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From network ties to network structures: Exponential Random Graph Models of interorganizational relations

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Abstract Theoretical accounts of network ties between organizations emphasize the interdependence of individual intentions, opportunities, and actions embedded in local configurations of network ties. These accounts are at odds with empirical models based on assumptions of independence between network ties. As a result, the relation between models for network ties and the observed network structure of interorganizational fields is problematic. Using original fieldwork and data that we have collected on collaborative network ties within a regional community of hospital organizations we estimate newly developed specifications of Exponential Random Graph Models (ERGM) that help to narrow the gap between theories and empirical models of interorganizational networks. After controlling for the main factors known to affect partner selection decisions, full models in which local dependencies between network ties are appropriately specified outperform restricted models in which such dependencies are left unspecified and only controlled for statistically. We use computational methods to show that networks based on empirical estimates produced by models accounting for local network dependencies reproduce with accuracy salient features of the global network structure that was actually observed. We show that models based on assumptions of independence between network ties do not. The results of the study suggest that mechanisms behind the formation of network ties between organizations are local, but their specification and identification depends on an accurate characterization of network structure. We discuss the implications of this view for current research on interorganizational networks, communities, and fields.

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1 Introduction

Contemporary research on interorganizational networks conventionally distinguishes between the individual (organizational) and the network level of analysis (Ahuja et al. 2011; Provan et al. 2007). The usefulness and face validity of this distinction are generally recognized (Brass et al. 2004). Less generally recognized is the fact that this distinction also introduces the additional need to specify how the coupling between these two levels may vary across empirical settings (Boorman and White 1976). This issue is very general and extends to a variety of substantive research domains that have adopted relational thinking (Pachucki and Breiger 2010). The generality of this problem motivates current efforts to derive models for network ties based on accurate characterizations of network structure (Pattison and Robins 2002; Snijders et al. 2006). In this paper we build on such efforts.

Empirical research based on assumptions of independence between network ties is logically—hence statistically—unable to clarify the issue of how different levels of action and structure might be linked (Pattison and Robins 2002). We know, for example, that under certain circumstances organizations with more similar attribute profiles or organizations that are more proximate in social or physical spaces are more likely to establish network connections (Rivera et al. 2010). We know little, however, about how individual ties that these various micro-mechanisms contribute to create and maintain are linked to structural features of interorganizational networks that are observed in specific empirical settings. This seems to be the case because models for network ties are typically specified to test a number of alternative mechanisms of tie formation. For example, it is common to link the presence of network ties between organizations to the level and type of uncertainty perceived by partners, their competitive interdependence, or to various types of resource complementarities and compatibilities (Beckman et al. 2004; Mitsuhashi and Greve 2009; Trapido 2007). However, no model for network ties we know of has been specified to test *also* its own ability to reproduce the structure of the overall network in which individual ties—however created—are embedded.

In this paper we address this issue directly. Building on recent research on interorganizational networks (Baum et al. 2003; Powell et al. 2005) we emphasize two salient dimensions of network structure: the network degree distribution and the level of network clustering. The former dimension is substantively interesting because significant departures from randomness in the network degree distribution suggest the presence of a status hierarchy sustained by differentials in relational activities (Ahuja et al. 2011). The latter dimension is substantively interesting because significant departures from randomness suggest that processes of network closure are at work to reproduce current structures (Kogut and Walker 2001).

We argue that these global structural features may help to identify specific assumptions about the dependence between network ties. We specify and test models for network ties based on such assumptions. Using computational methods we show that—other conditions being equal—models that incorporate correct dependence assumptions are consistent with the main structural features of the observed interorganizational network.

Our main goal in this paper is to demonstrate in a specific empirical setting the value of innovative analytical strategies that may be adopted to align models for network ties and features of network structure (Pattison and Robins 2002; Snijders et al. 2006). We rely on a newly derived class of Exponential Random Graph Models (ERGM) to demonstrate the ability of models for network ties that we estimate to reproduce with accuracy salient structural features of the observed interorganizational network. These models are based on the vision that social structures are constructed from the bottom up by concatenation of interactive local processes (Epstein 2007; Macy and Willer 2002; Robins et al. 2005).

The empirical context that we have selected to test the value of these ideas is based on original fieldwork and data that we have collected on patient sharing relations within a regional community of hospitals that we use to proxy the latent propensity of partner hospitals to establish collaborative agreements and arrangements (Lee et al. 2011). We organize the paper as follows. In the next section we start by reviewing the main empirical regularities in the structure of interorganizational networks. Then we argue that such regularities suggest specific patterns of dependence between network ties and we discuss how such dependencies may be linked to specific local configurations of network ties. In sect. 3 we introduce our empirical setting, discuss research design issues, and outline our analytical strategy. We present the results of the study in sect. 4. We conclude with a summary discussion of the main learning points supported by the analysis and of the general implications of our study for future research on interorganizational networks.

2 Motivation and background

2.1 Empirical regularities in the structure of interorganizational networks

Observed empirical regularities in the structure of interorganizational networks are interesting because they may be associated with a number of possible relational micro-mechanisms of tie formation which are not directly observable. According to Newman (2003, p. 9), for example: "Real networks are non-random in some revealing ways that suggest (…) possible mechanisms that could be guiding network formation." In an attempt to derive more contextual implications of this general claim, extant research has found that the structure of interorganizational networks departs from randomness in two major ways.

The first involves the overall distribution of network ties. In interorganizational networks the degree distribution is typically positively skewed with a limited number of high-activity (or high-popularity) organizational nodes and a long tail of nodes sending (or receiving) few or no connections (Powell et al. 2005). Skewness in the network degree distribution derives from the presence of higher interorganizational variation in relational activities than it would otherwise be expected by chance (Watts and Strogatz 1998). For example, it is well known that in random graphs the degree distribution follows a Poisson distribution (Britton et al. 2006). In directed networks skewness in the overall degree distribution may derive from organizational-level differences in activity—the propensity to send ties—or popularity—the tendency to receive ties (Greve 2005; Stuart 1998; Stuart and Yim 2010). In the study of interorganizational networks skewness in the degree distribution is important because differences in relational activities are frequently interpreted as reliable correlates of interorganizational differences in status, prominence and prestige (Ahuja et al. 2009). Skewness in the degree distribution is important also because it is associated with other structural properties of considerable interest to students of interorganizational networks such as, for example, centralization (Provan et al. 2007).

The second departure from randomness involves the recurrent finding that interorganizational networks are generally sparsely connected, but with a highly clustered internal relational structure (Baum et al. 2003; Robins and Alexander 2004). *Given* the degree distribution, clustering in interorganizational networks is typically much greater—and much more frequent—than what would be expected by chance. In studies of interorganizational networks this departure from randomness is interesting because it signals that social mechanisms of triadic closure may be at work to preserve structure and reproduce aggregate regularities (Laumann and Marsden 1982). Kogut and Walker (2001), for example, found that the network of ownership ties in Germany is characterized by sets of closely-knit clusters of companies that are highly reachable in the context of an overall sparse network of equity ties. Davis et al. (2003) develop similar observations in a study of intercorporate relations among US companies. Gerlach (1992) reaches similar conclusions for Japan. Picardi et al. (2010) characterize in similar terms the community structure in the inter-corporate network of companies listed in the Italian stock exchange.

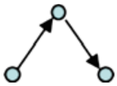
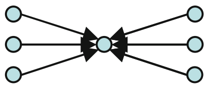
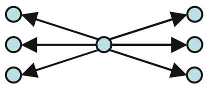
Considered together, empirical regularities related to skewness in the network degree distribution and to network clustering suggest the presence of systematic dependencies between network ties that require explicit modeling. In general, these dependencies are interesting because they suggest that *relations between network ties* may be as important as *relations between nodes* that network ties connect in explaining observed network structures. This is one of the fundamental theoretical insights produced by foundational research on social networks (Boorman and White 1976; Pattison 1993; White et al. 1976; White and Breiger 1975). In the next section we elaborate further our view that this fundamental insight is central to our understanding of interorganizational networks.

2.2 Network ties, motifs and structure

One possible strategy to link individual and network levels of analysis is to focus on intermediate patterns of dependence between network ties (Pattison and Robins 2002). Such patterns crystallize into configurations involving only small subsets of ties—or network *motifs*—that represent the functional building blocks of biological and organizational networks (Lomi and Pattison 2006; Milo et al. 2002). These local configurations represent *hypotheses* about dependence between network ties that may be dyadic, triadic, or extra-triadic (Snijders et al. 2006). Dependence hypotheses may be then specified as local constraints on network ties that—if satisfied—have direct implications for the overall network structure (Pattison and Robins 2002). What local constraints on individual ties are consistent with the observed skewness in the (observed) network degree distribution and with (observed) network clustering?

The propensity of organizations to collaborate by establishing bonds of collaboration has a broad interest in studies of interorganizational relations (Stuart 1998). If members of organizational populations or communities have a homogenously high tendency to establish network ties, the aggregate result will be a high network density. To explain such tendency, empirical studies of interorganizational networks based on dyadic data typically hinge on assumptions of local dependence between network ties (Rivera et al. 2010). Common patterns of local dependence that have been examined in empirical studies include reciprocity (Larson 1992), and various forms of correlation between tendencies to send and receive network ties (Stuart and Yim 2010). Assumptions of strictly local dependence are rarely consistent with observed structural features of interorganizational networks such as, for example, skewness in the distribution of network ties which suggest the presence of high degree nodes, or network "stars." (Powell et al. 2005). Because the number of stars in a network is a function of the degrees, accounting for star-like configurations in models for network ties is equivalent to modeling the network degree distribution (Snijders et al. 2006). Parameters for higher-order star-like network substructures are needed to capture the heterogeneity in relational activities revealed by differences in the propensity of individual organizations to be selected

Table 1 Degree-based sub-network configurations (or *network motifs*)

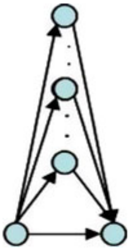
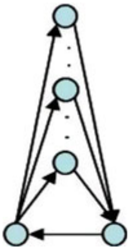
Network statistics	Qualitative pattern	Source of dependence	Network consequences
Density		Baseline tendency for a tie to occur	Tendency of network density to be high
Reciprocity		Reciprocity	Tendency of network structure to be symmetric
Simple connectivity		Propensity to send and receive ties	Tendency of in and out degree to be correlated
Popularity spread		Popularity	Tendency toward skewness of the in-degree distribution
Activity spread		Activity (expansiveness)	Tendency toward skewness of the out-degree distribution

as partner by many others (popularity), and in the propensity of individual organizations to select multiple others as partners (activity). Robins et al. (2009) call these effects *Popularity spread* and *Activity spread*, respectively, because their effect is to "spread" (i.e., to increase the variance of) the in and out-degree distributions. Popularity and activity are frequently portrayed as signals of underlying qualities that may affect the formation of network ties endogenously (Podolny 2005; Rivera et al. 2010). Whatever the underlying mechanism, the aggregate consequence of individual differences in relational susceptibility is network-level heterogeneity (Greve 2005). Both activity as well as popularity spread may arise from degree-based processes of preferential attachment or assortative mixing based on degree (Newman 2002). Table 1 provides a summary of the local configuration of network ties that we have discussed and that may be systematically associated with observed features of the network degree distribution.

Clustering is the second distinctive structural feature of interorganizational networks that we have discussed (Baum et al. 2003). Again we ask: what assumptions about dependence between network ties may be consistent with this observed structural feature of interorganizational networks? What constraints on the relation between network ties need to be satisfied to reproduce the level of network clustering that is actually observed? Theories of interorganizational relations provide rich material that may be used to identify empirically plausible constraints (Rivera et al. 2010).

While it may be defined in a variety of ways, the general idea behind network clustering involves a tendency toward path-shortening: actors connected to common thirds are more likely to become directly connected (Newman and Park 2003; Robins et al. 2009). Transitive closure—or the tendency of partners of partners to be partners—is perhaps the mechanism that is most commonly examined in empirical studied of interorganizational networks. Transitive closure represents a dominant mechanism underlying the creation of interorganizational ties that are "embedded in social attachments" (Uzzi and Lancaster 2003, p. 383). Transitive closure may be produced by path-shortening strategies whereby sharing multiple partners leads to a direct tie. Laumann and Marsden (1982), for example, consider

Table 2 Closure-based sub-network configurations (or *network motifs*)

Network statistics	Local pattern	Source of dependence	Network consequence
Generalized transitive closure		Path-shortening (transitivity)	Presence of clusters based on transitive closure
Generalized cyclic closure		Generalized exchange	Presence of clusters based on generalized exchange

transitivity in interorganizational networks as an outcome of what they call the principle of redundancy. The presence of transitive relations may serve as a form of insurance against disruption of resource flows and as a form of uncertainty reduction that may be adopted in order to facilitate access to multiple information sources. Laumann and Marsden (1982) predict that transitivity is likely to be detectable in networks of interdependent organizations sharing similar goals or views. Empirical research on interorganizational relations developed during the last thirty years has found systematic evidence in support of this prescient conjecture (Cropper et al. 2008; Gulati and Gargiulo 1999; Uzzi 1996). In general, the strength of transitive closure is considered proportional to the number of shared partners (Rivera et al. 2010).

A second mechanism that may act over and above transitive closure is cyclic (or intransitive) closure. Cyclical patterns are interesting in the study of interorganizational networks because they are the basic components of systems of generalized exchange where "Takers are obliged to be givers" (Bearman 1997, p. 1390). Generalized exchange involves the exchange of resources without the need of immediate reciprocity (Lazega and Pattson 1999). In the context of a study of US corporate elites, for example, Westphal and Zajak (1997) observe that systems of generalized exchange may function only under conditions of considerable trust between partners of equal status and prestige. The presence of cyclical patterns of exchange implies a tendency against local hierarchy in interorganizational relations or, alternatively, a tendency toward functional specialization—or interorganizational division of labor. According to Laumann and Marsden (1982) tendencies against generalized exchange in interorganizational networks may be due to an individual aversion to depend on others for resources and information. Table 2 summarizes our discussion on the closure-based mechanisms that may be associated with clustering in interorganizational networks.

3 Research design models and methods

3.1 Setting

The opportunity to link our arguments to empirical examples is provided by data that we have collected on patient sharing relations within a community of public and private accredited hospitals located in Lazio, a large geographical region in central Italy. Extended over approximately 17,000 km^2, Lazio has a resident population of roughly 5,300,000 inhabitants, more than 60% of whom live in Rome, the capital city. Hospitals in Lazio are members of Local Health Units (LHU)—geographical-administrative areas in which the region is partitioned. LHU are well-defined territorial and administrative areas responsible for the financing, organization, and the provision of health care services within their jurisdiction defined in terms of zip codes. LHU represent the reference markets from which hospitals attract input resources—namely, patients and budgetary founds—and to which hospitals sell the services they provide to patients. In Lazio, the health system is partitioned into twelve LHU.

Because they operate in a sector that is jointly technical and institutional (Scott and Meyer 1983[1991]), hospitals represent an almost ideal example of organizations whose performance, status, and social legitimacy depend on their ability to involve partners in joint problem solving activities in the interest of patients' health (Iwashyna et al. 2009a; Provan and Milward 1995). For this reason, the ability to access knowledge resources across organizational boundaries and involve partners in joint problem-solving activities is particularly important for health care organizations in general, and for hospitals in particular.

One way in which two hospitals may be involved in joint problem solving activities is through patient sharing. Patient sharing is one of the most important forms of inter-hospital collaboration that is, however, only seldom investigated by the health care literature on interorganizational networks (Lee et al. 2011). Patient sharing typically occurs via direct inter-hospital patient transfers whereby patients discharged from one ("sender") hospital are admitted to another ("receiver") hospital. Connections between hospitals created by patient sharing are not possible in the absence of complex coordination activities between partner hospitals. Also because of legal concerns and other adverse consequences for either hospital and patients (Lee et al. 2011), such activities requite a significant level of reciprocity, information exchange, mutual understanding, and collaboration. In the absence of these conditions patient sharing becomes risky and ultimately unfeasible. In our analysis, we concentrate specifically on the sharing of in-patients. In-patients are individuals who have already acquired the status of "admitted patient" and, therefore, who have consented to follow the clinical and therapeutic paths proposed by professional medical staff who are clinically responsible and legally liable for their conditions. This is an important qualification because individual network ties induced by in-patients transfers are the outcome of organizational decisions over which patients have surrendered control at admission. Of course, patients retain the right to refuse transfer in the same way as they retain the right to refuse treatment. However, they cannot choose where they will be transferred—a decision that remains a prerogative of the individual organization in charge of the patient. Hence, the network structure of in-patient (henceforth simply "patients") transfer between hospitals in our sample can be legitimately seen—and modeled—as the outcome of interrelated interorganizational partner selection decisions. It may be useful to note that we are not dealing with the transfer of emergency (or critically ill) patients which is regulated by formal procedures and cannot be reduced only to an organizational decision. Therefore, these types of relations are hardly considered as randomly distributed across the network. Iwashyna et al.

Table 3 Descriptive network statistics

Network statistics	Observed value
Number of dyads	8,190
Density	0.136
Average degree	12.253
Proportion of reciprocated dyads	0.32
Average path length	2.197

(2009a) provide detailed information on inter-hospital networks in the context of critical care.

3.2 Data

In our analysis we rely on both primary as well as secondary data sources. We obtained secondary data on the patient sharing network from archival sources contained in the Regional Hospital Information System database (SIO). We supplemented official sources with a survey designed to collect information on specific dimensions of organizational structures, resources and hospital activities, and with a series of unstructured interviews that we conducted with hospital managers, senior executives and medical doctors in hospital trusts and university polyclinics of national reputation. At the end of the process, we obtained 91 usable questionnaires with no missing observations (83% response rate).

Using publicly available data on transferred patients observed during the year 2004, we constructed a patient mobility matrix ($V = \{v_{ij}\}$) of size 91×91. The matrix contains in each row (column) the sender (receiver) hospital, and in the intersection cells (v_{ij}) the number of patients transferred from the row to the column hospital. During the year of observation (2004) 15,307 patients were transferred between hospitals in our sample. The matrix of patient transfer relations is asymmetric, since for any hospital in the sample the number of patients sent typically differs from the number of patients received. Because we are interested in the existence of network ties, rather than their intensity, and want to model the propensity of individual organizations to select a specific network partner for patient sharing, we derived the binary matrix $A = \{a_{ij}\}$ by dichotomizing the matrix V using the mean number of transferred patients (1.87) as cut-off point. We also tested alternative dichotomization rules such as, simple dichotomization ($a_{ij} = 1$ if $v_{ij} \neq 0$), and dichotomizations based on more complex thresholds (like, for example $a_{ij} = 1$ if $v_{ij} >$ mean $(v_{ij}) + \text{sd}(v_{ij})$, and $a_{ij} = 1$ if $v_{ij} > \text{mean}(v_{ij}) + 2\text{sd}(v_{ij})$). The results of the analysis that we report were robust to alternative choice of dichotomization rule. Table 3 reports the main descriptive statistics of the network that we analyze.

3.3 Variables and measures

The dependent variable of theoretical interest is the network of patient sharing relations between hospitals in our sample. We distinguish between two broad categories of explanatory factors. We refer to the first with the generic term of actor-relation covariates to emphasize that we are interested in the association of a particular nodal attribute with the presence of network ties between pairs of organizations (Lusher et al. 2012). The second category is represented by endogenous network dependencies that we specify to link models for network ties to observed network structure.

3.3.1 Actor-relation covariates

Resource dependence, familiarity, resource complementarities, and geographical proximity are frequently identified as dominant logics associated with the presence of network ties between organizations. In the models that we estimate in the empirical part of the paper these general logics are represented by specific actor-relation covariates which may be monadic (when they refer to characteristics of individual organizations such as, for example, organizational size), or dyadic (when they refer to characteristics of pairs of organizations such as, for example, geographical distance).

Patients are one of the main source of interdependence between hospitals (Provan and Milward 2001; Sohn 2001; Lee et al. 2011). To control for *resource dependencies* we rely on a relational approach that is well-established in the study of organizational niches (Baum and Singh 1994). We adopt a measure of resource overlap specifically developed by Sohn (2001, 2002) to study competitive interdependence among hospitals. More specifically, for each pair of hospitals in our sample we computed a (dyadic) coefficient of overlap in patient pools between hospital i and hospital j (ω_{ij}) that measures the proportion of the patient pool of hospital i that is overlapped by hospital j. When $\omega_{ij} = 1$, then hospitals i and j depend exactly on the same patients across all local market areas (LHU) from which they receive their patients. When $\omega_{ij} = 0$, patient pools of hospitals i and j are disjoined.

We include a dyadic covariate recording the number of patients transferred between every pair of hospitals in the previous year to account for *familiarity*, or the tendency of network ties to reproduce themselves over time that is so often revealed by empirical studies (e.g., Gulati and Gargiulo 1999). To account for the tendency of organizations controlling *complementary resources* to establish network ties, we include in the model a dyadic covariate recording the Euclidean distance computed on a 2-mode matrix of hospitals by the clinical specialties they contain. We do so to control for possible complementarities in the typology of services offered to patients—which may be associated with network-independent selection of partners (Baum et al. 2010). According to this argument, the closer two hospitals are in the space of clinical specialties—i.e., the more similar are the health care services they provide—the less likely is that patient transfer can be justified on clinical grounds. We also include a covariate capturing possible institutional compatibilities due to complementary roles that hospitals play in the overall health care system. We classified hospitals in the community as providers of specialized consultative care (i.e., tertiary care), or providers of secondary care. Hospitals playing the same *institutional role* in the regional health system (i.e., hospitals providing the same level of care) should be less likely to exchange patients. Hence we expect the corresponding estimate to be negative. We control for *geographical distance* (in kilometers) between hospitals to account for the joint effect of transportation costs and clinical risks inherent in patient transfer. Following extant research we expect cooperative relationships to be more likely to be established among organizations that are closer in space (Sorenson and Stuart 2008). The variable number of employees is included to take the effect of organizational *size* into account (Fennell 1980). This variable is computed as the sum of all the medical doctors, paramedics, nurses, and administrative staff working within hospitals. To control for the possible effects of *capacity constraints* we also included occupancy rate, measured as the average percentage of beds occupied in hospitals.

Finally, we control for general institutional factors that may influence patterns of collaboration between hospitals. The categorical variable *organizational form* captures the institutional diversity of hospitals in the community and reflects the official classification of hospital ownership forms adopted by national health authorities. A second powerful categorical distinction between hospitals concerns their membership in the various LHU. *LHU* *membership* is a categorical variable, uniquely assigning each hospital to its reference geographical/administrative area. Table 4 reports the descriptive statistics of all the actor-relation covariates that we include in our empirical model specifications. Measures of all the actor-relation covariates refer to the year prior to the observation of the interorganizational network ties.

The actor-relation covariates we have discussed enter model specification in three different ways (Lusher et al. 2012). Given a tie variable y_{ij} and an exogenous attribute x, the first way is as a "sender effect" (or attribute-based activity $= \sum_{i,j} x_i y_{ij}$). The second is as a "receiver effect" (or attribute-based popularity $= \sum_{i,j} x_j y_{ij}$). The third is as a "difference effect" defined as $h_{ij}(x) = \sum_{i,j} y_{ij} \left| x_i - x_j \right|$, where $\left| x_i - x_j \right|$ is the difference in the level of attribute x between actors i and j. When $\left| x_i - x_j \right| = 0$ organizations i and j are identical with respect to attribute x. For real-valued variables (e.g., size) a negative estimate of the corresponding difference effect indicates a tendency of similar organizations to interact. For categorical (e.g., LHU membership) and binary variables (e.g., institutional role) a negative sign of the corresponding difference effect has the opposite interpretation (Lusher et al. 2012).

3.3.2 Network dependencies

The dependence assumptions corresponding to the various sub-network configurations that we have discussed may be directly measured in terms of the corresponding network statistics as summarized in Table 5. Interested readers may find the derivation of these various network statistics in Snijders et al. (2006), and Robins et al. (2009). Additional discussion may be found in Goodreau (2007) and Lusher et al. (2012). In Table 5, x_{ij} denotes the presence of a network tie from i to j, S_{k_in} and S_{k_out} are the number of in-star and out-star-like configurations of size k, respectively, L_2 denotes the number of two-paths between i and j, and λ is a positive parameter that may be estimated from the data and that acts as a (geometrical) smoothing factor.[1]

As reported in Table 5, *Arc* is the network statistic that captures the individual propensity to establish network ties. *Reciprocity* captures the tendency of network ties to be reciprocated. *Simple connectivity* (or *mixed 2-path*) captures the tendency of incoming and outgoing ties to co-occur or, in other words, the tendency of in and out degree to be correlated. These three parameters correspond to specific forms of dyadic tie dependence that are commonly found in interorganizational networks. *Activity spread* and *popularity spread* capture the tendency of actors to select and be selected by multiple others, respectively. To capture the global tendency toward clustering we control for dependencies induced by closure as summarized in Table 2. More specifically, we include a parameter corresponding to *generalized transitive closure* which captures the tendency toward path-shortening, or the tendency of organizations sharing multiple partners to be directly connected. To counterbalance the effects of closure we include a parameter corresponding to *multiple connectivity,* expressing the propensity of organizations sharing multiple partners *not to* develop direct connections. Because a two-path that is not closed is a "structural hole,"*multiple connectivity* may be interpreted as capturing a tendency toward brokerage. *Multiple connectivity* is the precondition for closure as it involves multiple open triangles (Snijders et al. 2006). When interpreted together with a positive estimate of the *generalized transitive closure* parameter, a negative estimate of the *multiple*

[1] The strength of the tie between i and j increases when they share multiple partners, but the increase is not linear and, beyond a certain number of shared partners (which depends on the value of λ), an additional partner in common (k) does not add much to the likelihood of the multiple 2-paths between i and j becoming closed. Snijders et al. (2006) and Hunter (2007) provide further elaboration on this specific point.

Table 4 Descriptive sample statistics

Variable	Measure	Type	Unit of measure	Mean	SD	Min	Max
Resource interdependence	Patient pool overlap	Dyadic	Dimensionless	0.09	0.16	0	0.98
Familiarity (network $t-1$)	Number of transferred patients in time $t-1$	Dyadic	Units	1.61	12.69	0	525
Resource complementarity	Euclidean distance between clinical profiles	Dyadic	Dimensionless	2.92	1.02	0	5.92
Institutional role	Secondary and tertiary care	Monadic	Binary category	0.12	0.33	0	1
Distance	Geographical distance	Dyadic	Kilometers	50.77	39.50	0	220.60
Size	Number of employees	Monadic	Units	398.25	483.90	11	2,494
Capacity constraint	Occupancy rate	Monadic	Dimensionless rate	80.38	15.59	22.34	106.64
Organizational form	Type of ownership–governance structure	Monadic	Dimensionless index	–	–	1	6
Group (LHU) membership	Dependence on common LHU	Monadic	Dimensionless category	–	–	1	12

Table 5 Summary table of endogenous network effects

Network statistics	Measures
Density	$\sum y_{ij}$
Reciprocity	$\sum y_{ij} y_{ji}$
Simple connectivity	$\sum_{ijk} y_{ji} y_{ik}$
Popularity spread	$\sum_{k=2}^{n-1} (-1)^k \frac{S_{k\_in}}{\lambda^{k-2}}$
Activity spread	$\sum_{k=2}^{n-1} (-1)^k \frac{S_{k\_out}}{\lambda^{k-2}}$
Generalized transitive closure	$\lambda \sum_{i<j} y_{ij} \left\{1 - \left(1 - \frac{1}{\lambda}\right)^{L_{T2ij}}\right\}$
Generalized cyclic closure	$\lambda \sum_{i<j} y_{ji} \left\{1 - \left(1 - \frac{1}{\lambda}\right)^{L_{C2ij}}\right\}$
Multiple connectivity	$\lambda \sum_{i<j} \left\{1 - \left(1 - \frac{1}{\lambda}\right)^{L_{2ij}}\right\}$

connectivity parameter would provide additional evidence that closure occurs because of the completion of the basis of multiple triangles, rather than because of completion of the sides. Finally, Table 5 reports the network statistic that captures the tendency within the network toward generalized exchange (*generalized cyclic closure*). We note that the generalized parameters included in the model imply dependence structures that are extra-triadic (Robins et al. 2009). To assist interpretation of the estimates we note that a large positive (negative) parameter associated with a particular local dependence structure suggests that the corresponding configuration is observed in the actual network more (less) frequently than what would be expected by chance—conditional on the presence of configurations associated with other effects in the data.

3.4 Empirical model specification and estimation

To link our argument to appropriate statistical models, we consider each individual tie between organizations as a random variable. More precisely, for each pair of organizations i and j we define a random variable Y_{ij} so that $Y_{ij} = 1$ if hospital i transfers patients to hospital j, and $Y_{ij} = 0$ otherwise. Because transfer relations give rise to directed ties, Y_{ij} may be different—in general—from Y_{ji}. We define y_{ij} as a given value of the variable Y_{ij}, and we let $\boldsymbol{y}$ be an instantiation of the set of all variables Y, e.g., the observed network is one such y and can be represented as an adjacency matrix containing the observed y_{ij} for all i and j. By considering each individual network tie as a random variable, we link our data structure directly to a class of ERGM, also known as p-star (p*) models (Wasserman and Pattison 1996). All ERGM follow the general form (Robins et al. 2009; Snijders et al. 2006):

$$\Pr\left(Y = y \mid X = x\right) = \frac{1}{\kappa} \exp\left(\sum_{Q} \lambda_Q Z_Q\left(y\right) + \sum_{R} \lambda_R Z_R\left(y, x\right)\right), \tag{1}$$

where (i) Q refers to possible local configurations of network ties; (ii) λ_Q is the parameter corresponding to configuration of type Q; (iii) $Z_Q\left(y\right) = \prod_{y_{ij} \subset Q} y_{ij}$ is the network statistic counting the frequency of configurations Qin the graph $\boldsymbol{y}$ (as defined in Table 5), and (iv) κ is a normalizing quantity included to ensure that (1) is a proper probability distribution.

The summation is taken over all possible network configurations (Q) included in a given model. Finally, the term $Z_R(y, x)$ is the model component that defines the actor-relation covariates, or the effects of the interaction between network variables (y) and individual attributes (x) on the probability of observing a tie. The second summation is over all possible configurations R of ties and attributes. As established in previous sections a "configuration" is a sub-graph structure representing specific patterns of local dependence for which there is a parameter in the model.

3.5 Model estimation and evaluation

Reliable parameter estimates of ERGM may be obtained via Markov Chain Monte Carlo Maximum Likelihood (MCMCML) or similar simulation-based techniques (Hunter and Handcock 2006; Snijders 2002; Wasserman and Robins 2005). When convergent maximum likelihood parameter estimates are successfully obtained, it is possible to use these estimates to simulate the distribution of graphs implied by the model. Any feature of the observed network that can be expressed as a network statistic may be compared to the estimated distribution of that feature that is implied by the model. If a measured network statistic is close to the corresponding mean value of the statistic produced by simulation, then we may infer that the specific feature of the observed network structure that the statistic represents is consistent with the model. For example, if networks randomly sampled from the distribution of graphs simulated on the basis of the estimates do not have a large clustering coefficient, but the observed network does, then we may conclude that the model is unable to reproduce with high fidelity this particular (global) feature of the data. Goodreau (2007) and Hunter et al. (2008) provide the statistical argument for this approach to comparing structural statistics of the observed network with the corresponding statistics on networks simulated from the fitted model. In the empirical part of the paper we follow this simulation-based strategy to examine the ability of our models to reproduce salient global features of the observed network.

4 Results

4.1 Empirical analysis

We organize the presentation of our empirical results around Table 6 which reports the MCMCML estimates of models for network ties.

Model M1 reports the baseline local dependence model controlling only for the tendency to establish network ties (*arc*), the tendency toward reciprocation (*reciprocity*), and the tendency of incoming and outgoing ties to co-occur (*simple connectivity*). Model M1 is a Markov model because it confines the dependence between ties to ties that have a node in common (Pattison and Robins 2002). Model M1 is therefore a possible empirical specification of the p-star (p*) model of Wasserman and Pattison (1996). Unlike the original p-star model, however, the estimation procedure implemented here produces maximum likelihood estimates (Lubbers and Snijders 2007).

The estimated effects of parameters associated with actor-relation covariates are consistent with expectations. The effect of *familiarity* is significantly positive: the strength of past ties is a reliable predictor of the presence of current ties. *Resource interdependence* has a strong positive effect: network ties are significantly more likely to be observed between hospitals with overlapping patient pools. The effect of interdependence should be interpreted as net of the predictably negative effect of *geographical distance*. Larger hospitals tend to send

Table 6 Approximate maximum likelihood estimation of ERGM parameters (SE in parentheses)

	Local dependence model (restricted M1)	Partial conditional dependence model (Full M2)
Actor-relation effects		
Resource interdependence	2.1658*	1.5114*
	(0.2267)	(0.2070)
Familiarity	0.0084*	0.0088*
	(0.0033)	(0.0031)
Resource complementarity	0.0398	0.0015
	(0.0571)	(0.0556)
Institutional role	−1.1927*	−0.9142*
	(0.2895)	(0.2480)
Geographical distance	−0.0172*	−0.0097*
	(0.0017)	(0.0013)
Size (sender)	0.0023*	0.0017*
	(0.0003)	(0.0002)
Size (receiver)	0.0027*	0.0018*
	(0.0002)	(0.0002)
Size (difference)	−0.0014*	−0.0005*
	(0.0001)	(0.0001)
Capacity constraint (sender)	0.0197*	0.0130*
	(0.0039)	(0.0035)
Capacity constraint (receiver)	0.0152*	0.0109*
	(0.0038)	(0.0033)
Capacity constraint (difference)	0.0116*	0.0095*
	(0.0038)	(0.0036)
Organizational form	0.4219*	0.3746*
	(0.0887)	(0.0829)
LHU membership	0.8152*	0.7932*
	(0.1142)	(0.1003)
Endogenous network effects		
Arc (Outdegree)	−6.3914	−5.8914*
	(0.5297)*	(0.7646)
Reciprocity	1.0447*	1.0984*
	(0.1356)	(0.1456)
Simple connectivity	−0.0196*	−0.0191*
	(0.0096)	(0.0085)
Popularity spread	–	−0.6367*
		(0.2168)

Table 6 continued

	Local dependence model (restricted M1)	Partial conditional dependence model (Full M2)
Activity spread	–	0.3197 (0.2052)
Generalized transitive closure	–	0.9695* (0.1152)
Cyclic closure	–	$-0.0773^{\dagger}$ (0.0395)
Multiple connectivity	–	−0.0742* (0.0089)

* $p < 0.01$; † $p < 0.05$

and receive more network ties. The significantly negative effect of difference in hospital *size* suggests that hospitals tend to prefer similarly sized others as exchange partners. The effect of the *institutional role* is significant in the expected direction: hospitals providing the same level of care are less likely to exchange patients. Ties are more likely between organizations subjected to the same administrative authority (because they are member of the same LHU). Considered together, the estimated effects of *capacity constraint* suggest that inter-hospital patient sharing activities are shaped—at least in part—by *occupancy rate*: hospitals with differences in occupancy rates are more likely to share patients. The fact that hospitals closer to their full capacity are more likely both to send as well as receive patients may be due to constraints induced by rules of reciprocity operating over and above capacity constraints. The presence of network ties is also more likely to be observed between hospitals with the same *organizational form*.

Model M2 reports the estimates of the full ERGM accounting for multiple degree-based and closure-based dependencies between network ties. Following Lubbers and Snijders (2007) we refer to this model as the partial conditional dependence model because—unlike the prior model M1—dependencies in model M2 may involve disjoint pairs of actors (Pattison and Robins 2002). The pattern of statistical significance of actor-relation effects remains unaltered. However, the magnitude of the effects is considerably decreased—a result that may be interpreted as evidence that organizational and institutional factors affect the likelihood of network ties at least in part through local network structures. The significantly negative *arc* parameter indicates that individual ties that are not reciprocated and are not embedded in more complex sub-network configurations are highly unlikely. In other words, random network ties are unlikely to be observed in this network ($\exp(-5.89) = 0.003$). The estimated *reciprocity* effect implies that the odds of a reciprocated tie are approximately three times the odds of a non-reciprocated tie (because $\exp(1.098) = 2.998$). The negative parameter associated with *simple connectivity* may be interpreted as indirect evidence of specialization: it is unlikely to observe hospitals that at the same time send and receive patients. The parameters corresponding to multiple stars configurations capture the effect of high degree nodes. The negative parameter associated with *popularity spread* indicates that highly popular nodes are unlikely to be observed in our network and provides evidence of a tendency against skewness of the in-degree distributions. The (weakly significant) negative estimate of the parameter associated to *generalized cyclic closure* indicates a tendency against generalized exchange

Table 7 Model comparison and goodness of fit diagnostics

Network statistics	Observed	Restricted model (M2)	t-ratio	Full model(M3)	t-ratio
Standard deviation	13.654	18.141(0.398)	−11.270	12.569(0.585)	1.855
Int-degree distribution					
Skewness	1.905	1.313(0.071)	8.385	1.740(0.114)	1.448
In-degree distribution					
Standard deviation	10.528	7.271(0.377)	8.649	8.210(0.574)	4.042
Out-degree distribution					
Skewness	1.100	0.142(7.909)	7.909	1.024(0.186)	0.405
Out-degree distribution					
Global clustering	0.255	0.381(0.012)	−10.843	0.255(0.008)	−0.093
(Transitive closure)					
Global clustering	0.216	0.258(0.006)	−7.224	0.245(0.008)	−0.090
(Cyclic closure)					
Mahalanobis distance		272.192		108.835	

Estimated standard errors in parentheses

and provides evidence of local hierarchization of network ties preventing the formation of cycles. The parameter corresponding to *generalized transitive closure* is positive and very strongly significant indicating a definite tendency toward clustering: connectivity in the form of multiple two-paths leads to a direct tie. Read in conjunction with the significantly negative estimate of the parameter associated to *multiple connectivity*, the positive estimate of the *generalized transitive closure* parameter implies an overall tendency toward “clumping”: clustering in the network is due to multiple triangles simultaneously formed by a completion of the common base (Robins et al. 2009).

Interpreted together, the full model (M2) estimates seem to imply a global network structure characterized by densely connected triangulated cores that arise from closure-based mechanisms rather than from network-level heterogeneity in the degree distribution.

4.2 Simulation analysis

How well do the estimated models reproduce salient structural features of the overall network? We believe that this is a relevant question because the models that we have estimated contain no information about the global structure of the network that we have actually observed. For this reason simulation analysis based on empirical estimates is appropriate. Following the approach suggested by Robins et al. (2005) and illustrated by Robins et al. (2009), we used the empirical estimates to simulate 10 million random graphs out of which we sampled 2,000.[2] Table 7 compares the network statistics estimated from this sample and the corresponding network statistics calculated on the observed network.

Building on Goodreau (2007) and Robins et al. (2007) we rely on t-ratios for a comparative assessment of the ability of the restricted (M1) and full (M2) models to reproduce theoretically interesting structural features of the overall interorganizational network. The t-ratios are calculated on the basis of differences between the statistics describing the observed

[2] Monte Carlo Markov Chain simulations performed to obtain the graph distribution are based on the Metropolis-Hastings algorithm. Alternative algorithms are discussed in Snijders (2002).

network and their mean value computed on the sample of simulated graphs. For an observed graph feature not included in the model, a conventional t-ratio less than two in absolute value is typically taken as evidence that the observed feature is not unusual in the estimated graph distribution (Hunter et al. 2008). The figures reported in Table 7 support the following conclusions. First, the restricted model (M1) is unable to capture the skewness and variance of the degree distributions and misses the degree of clustering in the network. Second the full model displays a significantly improved ability to capture skewness in the degree distribution, and clustering that may be due to transitive and cyclic closure. Third, in all cases the full model outperforms the restricted model, suggesting that the model implied by the estimates is more consistent with the overall network structure that was actually observed. While considerably improved, the standard deviation of the outdegree distribution implied by the full model is still less than satisfactory. This results may suggest the need to introduce additional repressors in the model as activities of sending network ties may be affected by organization-specific factors that we have been unable to incorporate in this model.

Heuristically, the considerable difference in Mahalanobis distance between the restricted and the full model indicates the improvement in the overall ability of the model to reproduce the data when local dependencies among network ties are correctly specified. Clearly, what changes across model specifications is the ability of the model to reproduce the data, and not its ability to estimate the effect of exogenous covariates on the likelihood to observe network ties between organizations.

5 Discussion and conclusions

Exchange is the building block of interorganizational networks (Stuart 2007). This view invites consideration of networks as social structures built from the bottom up through concatenation of individual acts of exchange. Our understanding of interorganizational networks, therefore, hinges crucially on our ability to link network ties to network structure (Pattison and Robins 2002). Our starting point in this paper was the observation that current attempts to understand the antecedents of individual acts of exchange taking the form of network ties are unable to explain the global network structures which these acts contribute to create. In our view, this motivation has methodological and substantive implications that are indissolubly intertwined and that need to be addressed jointly. Separating the methodological and substantive aspects of this problem leads to models that are analytically convenient, but empirically implausible. The new specifications of ERGM that we have adopted in this paper help to reconcile models, data, and theories of interorganizational networks by: (i) representing explicitly the micro-relational processes that underlie the distribution of observed network ties; (ii) suggesting testable hypotheses about the dependence between network ties, and (iii) linking patterns of local dependence that such hypotheses imply to salient features of global network structures.

We have demonstrated the value of this general analytical approach in the specific context of patient sharing within a regional community of hospital organizations. We have shown that models that incorporate general dependence assumptions are more informative than models that assume strictly local forms of dependence between network ties. We have shown that ERGM satisfy theoretical expectations about the organizational and structural antecedents of network ties between organizations, while at the same time producing empirical estimates that are consistent with the global structure of the interorganizational network that was actually observed.

Our study still suffers from a number of limitations that require—and at the same time invite further developments. The first is that we have selected one specific relation for analysis, but many others are typically possible. While our field experience and extant research gives us confidence that patient sharing reveal important dimensions of collaboration (Lee et al. 2011; Iwashyna et al. 2009a), hospitals collaborate in other ways as well. Cross training of medical staff, capacity sharing contracts, centralization of ancillary services, and technology transfer all come to mind as possible relational contexts that may reveal and at the same sustain collaboration between hospitals. Future studies will have to pay attention to the multiplexity that interorganizational collaboration is likely to involve (Lomi and Pattison 2006) and to the logics underlying the transposition of network ties across relational contexts (Dahlander and McFarland 2009; Trapido 2007). Second, we focused on path-shortening behavior as a possible source of transitivity in interorganizational networks. But in directed networks there is little reason to believe that transitivity will be the only or even the main source of network clustering. Future studies should make a serious effort to identify different mechanisms that may be at work to produce observed clustering in interorganizational networks. The recent work of Robins et al. (2009) offers more complete parameterizations that would help to adjudicate among different, and possibly competing mechanisms of closure underlying observed patterns of network clustering. Third, our focus in this paper has been on the presence of network ties rather than on the change in network ties. The development of appropriate models for change requires a substantial modification of the analytical framework that we have adopted and, obviously, different data structures. Recent progress in the analysis of network panel data suggests cautious optimism about the possibility to extend our current analysis to network evolution (Van de Bunt and Groenewegen 2007). Fourth, and finally, hospitals may hardly be considered a random sample of the organizational world at large, and some may consider patient sharing relations as unrepresentative of interorganizational relations at large. Extant research, and our own fieldwork suggest otherwise (Iwashyna et al. 2009b). Inter-hospital patient transfers are simply not possible without systematic interorganizational collaboration and coordination. Hospitals, however, remain highly idiosyncratic organizations facing a variety of institutional, competitive, and organizational constraints that do not operate in the same way and with equal strength in other regions of the organizational world (Ruef and Scott 1998; Scott and Meyer 1983[1991]; Thompson 1967). Yet, understanding how different micro-relational mechanisms combine to give rise to local dependencies, and how such dependencies connect local and global network structures remain issues of general relevance for students of interorganizational fields, communities, and networks. Similarly general is the applicability of the analytical approach that we have implemented to address these issues.

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References

Ahuja, G., Polidoro, F. Jr., Mitchell, W.: Structural homophily or social asymmetry? The formation of alliances by poorly embedded firms. Strateg. Manag. J. **30**, 941–958 (2009)

Ahuja, G., Soda, G., Zaheer, A.: The genesis and dynamics of organizational networks. Organ. Sci. (2011) (forthcoming).

Baum, J.A.C., Singh, J.V.: Organizational niches and the dynamics of organizational mortality. Am. J. Sociol. **100**, 346–380 (1994)

Baum, J.A.C., Shipilov, A.V., Rowley, T.J.: Where do small worlds come from? Ind. Corp. Change **12**, 697–725 (2003)

Baum, J.A.C, Cowan, R., Jonard, N.: Network-independent partner selection and the evolution of innovation networks. Manag. Sci. **56**, 2094–2110 (2010)

Bearman, P.: Generalized exchange. Am. J. Sociol. **102**, 1383–1415 (1997)

Beckman, C.M., Haunschild, P.R., Phillips, D.J.: Friends or strangers? Firm-specific uncertainty, market uncertainty, and network partner selection. Organ. Sci. **15**, 259–275 (2004)

Boorman, S.A., White, H.C.: Social structure from multiple networks. II. Role Structures. Am. J. Sociol. **81**, 1384–1446 (1976)

Brass, D.J., Galaskiewicz, J., Greve, H.R., Tsai, W.: Taking stock of networks and organizations: A multilevel perspective. Acad. Manag. J. **47**, 795–817 (2004)

Britton, T., Deijfen, M., Martin-Löf, A.: Generating simple random graphs with prescribed degree distribution. J. Stat. Phys. **124**, 1377–1397 (2006)

Cropper, S., Ebers, M., Huxham, C., Smith Ring, P. (ed.): The Oxford Handbook of Inter-Organizational Relations. Oxford University Press, New York (2008)

Dahlander, L., McFarland, D.A.: Intellectual tie formation: multiple networks and refunctionality. Working Paper, Stanford University (2009)

Davis, G.F., Yoo, M., Baker, W.E.: The small world of the American Corporate Elite, 1982–2001. Strateg. Organ. **8**, 43–68 (2003)

Epstein, J.M.: Generative Social Science: Studies in Agent-Based Computational Modeling. Princeton University Press, Princeton (2007)

Fennell, M.L.: The effects of environmental characteristics on the structure of hospital clusters. Adm. Sci. Q. **25**, 485–510 (1980)

Gerlach, M.L.: The Japanese corporate network: a blockmodel analysis. Adm. Sci. Q. **37**, 105–139 (1992)

Goodreau, S.M.: Advances in Exponential Random Graph (p*) models applied to a large social network. Soc. Netw. **29**, 231–248 (2007)

Greve, H.R.: Interorganizational learning and heterogeneous social structure. Organ. Stud. **26**, 1025–1047 (2005)

Gulati, R., Gargiulo, M.: Where do interorganizational networks come from? Am. J. Sociol. **104**, 1439–1493 (1999)

Hunter, D.R.: Curved exponential family models for social networks. Soc. Netw. **29**, 216–230 (2007)

Hunter, D.R., Handcock, M.S.: Inference in curved exponential family models for networks. J. Comput. Graph. Stat. **15**, 565–583 (2006)

Hunter, D.R., Goodreau, S., Handcock, M.: Goodness of fit of social network models. J. Am. Stat. Assoc. **103**, 248–258 (2008)

Iwashyna, T.J., Christie, J.D., Kahn, J.M., David, A.: Uncharted paths: hospital networks in critical care. Chest **135**, 827–833 (2009a)

Iwashyna, T.J., Jason, D.C., Moody, J., Kahn, J.M., Asch, D.A.: The structure of critical care transfer networks. Med. Care **47**, 787–793 (2009b)

Kogut, B., Walker, G.: The small world of Germany and the durability of national networks. Am. Sociol. Rev. **66**, 317–335 (2001)

Larson, A.: Network dyads in entrepreneurial settings: a study of the governance of exchange relationships. Adm. Sci. Q. **37**, 76–104 (1992)

Laumann, P., Marsden, P.V.: Microstructural analysis of interorganizational systems. Soc. Netw. **4**, 329–348 (1982)

Lazega, E., Pattson, P.E.: Multiplexity, generalized exchange and cooperation in organizations: a case study. Soc. Netw. **21**, 67–90 (1999)

Lee, B.Y., McGlone, S.M., Song, Y., Avery, T.R., Eubank, S., Chang, C.-C., Bailey, R.R., Wagener, D.K., Burke, D.S., Platt, R., Huang, S.S.: Social network analysis of patient sharing among hospitals in Orange County, California. Am. J. Public Health **4**, 707–713 (2011)

Lomi, A., Pattison, P.: Manufacturing relations: an empirical study of the organization of production across multiple networks. Organ. Sci. **17**, 313–332 (2006)

Lubbers, M:J., Snijders, T.A.B.: A comparison of various approaches to the exponential random graph model: a reanalysis of 102 student networks in school classes. Soc. Netw. **29**, 489–507 (2007)

Lusher, D., Koskinen, J., Robins, G.: Exponential Random Graph Models for Social Networks. 2012. Theory, Methods and Applications. New York. Cambridge University Press. (Forthcoming)

Macy, M.W., Willer, R.: From factors to actors: computational sociology and agent-based modeling. Annu. Rev. Sociol. **28**, 143–166 (2002)

Milo, R., Shen-Orr, S., Itzkovitz, S., Kashtan, N., Chklovskii, D., Alon, U.: Network motifs: simple building blocks of complex networks. Science **298**, 824–827 (2002)

Mitsuhashi, H., Greve, H.: A matching theory of alliance formation and compatibility. Acad. Manag. J. **52**, 975–995 (2009)

Newman, M.E.J.: Assortative mixing in networks. Phys. Rev. Lett. **89**, 208701 (2002)
Newman, M.E.J.: The structure and function of complex networks. SIAM Rev. **45**, 167–256 (2003)
Newman, M.E.J., Park, J.: Why social networks are different from other types of networks. Phys. Rev. E **68**, 036122 (2003)
Pachucki, M.A., Breiger, R.L.: Cultural holes: Beyond relationality in social networks and culture. Annu. Rev. Sociol. **36**, 205–224 (2010)
Pattison, P.: Algebraic Models for Social Networks. Cambridge University Press, New York (1993)
Pattison, P., Robins, G.: Neighborhood-based models for social networks. Sociol. Methodol. **32**, 301–337 (2002)
Picardi, C., Calatroni, L., Bertoni, F.: Communities in Italian corporate networks. Physica A **389**, 5247–5258 (2010)
Podolny, J.M.: Status Signals: A Sociological Study of Market Competition. Princeton University Press, Princeton (2005)
Powell, W.W., Koput, K.W., White, D.R., Owen-Smith, J.: Network dynamics and field evolution: the growth of interorganizational collaboration in the life sciences. Am. J. Sociol. **110**, 1132–1205 (2005)
Provan, K.G., Milward, H.B.: A preliminary theory of interorganizational network effectiveness: a comparative study of four community mental health systems. Adm. Sci. Q. **40**, 1–33 (1995)
Provan, K.G., Milward, H.B.: Do networks really work? A framework for evaluating public sector organizational networks. Public Adm. Rev. **61**, 414–423 (2001)
Provan, K.G., Fish, A., Sydow, J.: Interorganizational networks at the network level: a review of the empirical literature on whole networks. J. Manag. **33**, 479–513 (2007)
Rivera, M.T., Soderstrom, S.B., Uzzi, B.: Dynamics of dyads in social networks: assortative, relational, and proximity mechanisms. Annu. Rev. Sociol. **36**, 91–115 (2010)
Robins, G., Alexander, M.: Small worlds among interlocking directors: network structure and distance in bipartite graphs. Comput. Math. Organ. Theory **10**, 69–94 (2004)
Robins, G.L., Pattison, P., Woolcock, J.: Small and other worlds: Global network structures from local processes. Am. J. Sociol. **110**, 894–936 (2005)
Robins, G.L., Snijders, T.A.B., Wang, P., Handcock, M., Pattison, P.: Recent developments in Exponential Random Graph (p*) models for social networks. Soc. Netw. **29**, 192–215 (2007)
Robins, G., Pattison, P., Wang, P.: Closure, connectivity, and degree distributions: Exponential Random Graph (p*) models for directed social networks. Soc. Netw. **31**, 105–117 (2009)
Ruef, M., Scott, W.R.: A multidimensional model of organizational legitimacy: hospital survival in changing institutional environments. Adm. Sci. Q. **43**, 877–904 (1998)
Scott, W.R., Meyer, J.W.: The organization of societal sectors. In: Meyer, J.W., Scott, W.R. (eds.) Organizational Environments: Rituals and Rationality, pp. 129–153. Sage, Newbury Park (1983)
Snijders, T.A.B.: Markov chain Monte Carlo estimation of exponential random graph models. J. Soc. Struct. **3**, 1–41 (2002)
Snijders, T.A.B., Pattison, P.E., Robins, G.L., Handcock, M.S.: New specifications for Exponential Random Graph Models. Sociol. Methodol. **36**, 99–153 (2006)
Sohn, M-W.: Distance and cosine measures of niche overlap. Soc. Netw. **23**, 141–165 (2001)
Sohn, M-W.: A relational approach to measuring competition among hospitals. Health Serv. Res. **37**, 457–483 (2002)
Sorenson, O., Stuart, T.E.: Bringing the context back in: settings and the search for syndicate partners in venture capital investing. Adm. Sci. Q. **53**, 266–294 (2008)
Stuart, T.E.: Network positions and propensities to collaborate: an investigation of strategic alliance formation in a high-technology industry. Adm. Sci. Q. **43**, 668–698 (1998)
Stuart, T.E: The formation of Inter-organizational networks. In: James, R. (ed.) The Missing Links: Formation and Decay of Economic Networks, Russell Sage Foundation, New York (2007)
Stuart, T.E., Yim, S.: Board interlocks and the propensity to be targeted in private equity transactions. J. Financ. Econ. **97**, 174–189 (2010)
Thompson, J.D.: Organizations in Action: Social Science Bases of Administrative Theory. McGraw-Hill, New York (1967)
Trapido, D.: Competitive embeddedness and the emergence of interfirm cooperation. Soc. Forces **86**, 167–191 (2007)
Uzzi, B.: The sources and consequences of embeddedness for the economic performance of organizations: the network effect. Am. Sociol. Rev. **61**, 674–698 (1996)
Uzzi, B., Lancaster, R.: Relational embeddedness and learning: the case of bank loan managers and their clients. Manag. Sci. **49**, 383–399 (2003)
Vande Bunt, G.G., Groenewegen, P.: An actor-oriented dynamic network approach: the case of interorganizational network evolution. Organ. Res. Methods **10**, 463–482 (2007)

Wasserman, S., Pattison, P.E.: Logit models and logistic regressions for social networks: an introduction to Markov graphs and p*. Psychometrika **61**, 401–425 (1996)

Wasserman, S., Robins, G.L.˙: An introduction to random graphs, dependence graphs, and p*. In: Carrington, P.J., Scott, J., Wasserman, S. (eds.) Models and Methods in Social Network Analysis, pp. 148–161. Cambridge University Press, New York (2005)

Watts, D.J., Strogatz, SH.: Collective dynamics of 'small-world' networks. Nature **4**, 440–442 (1998)

Westphal, J.D., Zajak, E.J.: Defections from the inner circle: social exchange, reciprocity, and the diffusion of board independence in U.S. corporations. Adm. Sci. Q. **42**, 161–183 (1997)

White, H.C., Breiger, R.L.: Pattern across networks. Society **12**, 68–74 (1975)

White, H.C., Boorman, S.A., Breiger, R.L.: Social structure from multiple networks. I. Blockmodels of roles and positions. Am. J. Sociol. **81**, 730–780 (1976)