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Does It Take Three to Dance the Tango? Organizational Design, Triadic Structures and Boundary Spanning across Subunits

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Does It Take *Three* to Dance the Tango?

Organizational Design, Triadic Structures and Boundary Spanning across Subunits.

Abstract.

In this paper, we investigate the processes of boundary spanning across subunits within organizational networks. We hypothesize that patterns of advice across organizational subunits are explained by different triadic mechanisms depending on the organizational design of the intra-organizational network. In organizational networks characterized by flat hierarchy, we found triadic cyclic closure to be positively associated to boundary spanning across subunits; but when the network reflects an organizational structure with formal hierarchical differentiation among members, then we found triadic transitive closure to be associated to boundary spanning across subunits. We test these predictions in two empirical studies consisting of two organizational networks that differ from each other in organizational design. We adopt a Bayesian parameter inference approach for ERGMs specifically designed for the statistical analysis of interpersonal relationships within and across subgroups or subunits. We suggest that the effects of informal, triadic network configurations on boundary spanning are contingent on formal organizational design.
Highlights.

- The effects of informal, triadic network configurations on boundary spanning are contingent on formal organizational design.
- In organizational networks characterized by flat hierarchy, we found triadic cyclic closure to be positively associated to advice boundary spanning across subunits.
- In organizational networks characterized by formal, hierarchical differentiation among members, we found triadic transitive closure to be associated to advice boundary spanning across subunits.
- We tested our arguments through two empirical studies of organizational networks differing from each other in organizational design.
- We adopt a Bayesian parameter inference approach for ERGMs in order to estimate posterior distribution of the model parameters.

Keywords.

Organizational social networks; Organizational Design; Transitive closure; Triadic cyclic closure; Boundary spanning; ERGMs; Bayesian inference.
Boundary spanning across organizational subunits is relevant for organizational processes and outcomes, including problem solving, knowledge recombination, development of new ideas and generation of innovation (Argote, McEvily, & Reagans, 2003). The importance of interconnection among subunits in fostering organizational functioning features studies of organizations since the beginnings of the discipline. In his *Administrative Behavior*, Herbert Simon (1947:24) claimed, “A major task in organizing is to determine, first, where the knowledge is located that can provide the various kinds of factual premises that decisions require,” and examined whether and how organizations can mobilize coordination and the transfer of knowledge and other resources, including social support, advice and information, among their subunits. In their foundational book *Organizations*, March and Simon (1958) argued that efficient organizations must be “highly programmed with respect to the specific steps needed to accomplish the task” (page 14), including inter-personal and inter-unit coordination as a way to “restrict the adaptiveness of the organization to the goals of the administrative hierarchy” (page 36). Modern organizational research pushed forward this early theorizing, acknowledging that “knowledge transfer typically occurs across a boundary” and that “the boundary could be between occupational groups… between organizational units… or between geographic areas” (Argote & Miron-Spektor, 2011: 1131).

Despite its undoubted relevance for organizational effectiveness, boundary spanning across organizational subunits has proven to be a difficult task. Organizations often mirror the “cavemen world” described by Watts (1999: 102), in which members live in dense isolated clusters (or “caves”) of strong, frequent, and redundant relations. Common membership in organizational subunits provides both frequent opportunities and stronger incentives to form within-subunit ties. Organizational subunits represent indeed social platforms (Pattison & Robins, 2002) that stimulate newcomers’ interaction (Morrison, 2002), facilitate interpersonal familiarity (Hinds, Carley, Krackhardt & Wholey, 2000), provide a repertoire of shared
experiences (Marsden, 1988), and also generate the development of shared memory and elaboration of past events (March & Olsen, 1975). Therefore, sharing knowledge across subunit boundaries is more costly, in terms of time and effort to cultivate and maintain cross-boundary relations, than transferring knowledge within the subunit (e.g., Lomi & Zappa, 2015).

However, organizations are rarely composed of isolated caves: Ties within organizational subunits can represent the majority, but typically not all the ties among members (e.g., Zappa & Lomi, 2015). As Brass, Galaskiewicz, Greve & Tsai (2004: 801) noted, “ties between people in different units are especially intriguing, because they create ties between organizational units.” So, what explains the likelihood to observe ties bridging between organizational subunits? This is the research question of this paper.

To answer this question, we bridge two ‘dualisms’ that have featured “organizational research in its historical evolution:’’ (i) Formal vs. informal organization; and (ii) hierarchical organizational structure (i.e. reflecting different hierarchical roles between its members) vs. flat organizational structure (i.e. with loose hierarchy and horizontal coordination) (McEvily, Soda, & Tortoriello, 2014: 300). By bridging the first dualism (i), we argue that formal organizational design can help explain informal processes of advice sharing across different subunits. “When managers impose new organizational structures, they invariably alter patterns of work” (Barley & Kunda, 2001: 76), including the structure of those informal ties that represent “the central nervous system that drives the collective thought process, actions and reactions” of organizational members (Krackhardt & Hanson, 1993: 104). By bridging the second dualism (ii), we show that the patterns of informal advice ties that span across subunit boundaries are contingent on the formal design of the organization. In summary, we suggest that, even if organizations can be conceived as unfolding patterns of interaction among its members (e.g., Tasselli, Kilduff, & Menges, 2015), yet the formal organization exerts a
remarkable influence on the structure of those informal and emergent structures by which organizational life is defined and evolves.

**Individual, Dyadic and Triadic Perspectives on Boundary Spanning across Subunits**

“What structural mechanisms will facilitate effective coordination among differentiated yet interdependent units?” This was the question formulated forty years ago by Tushman and Nadler (1978: 615), which attracted numerous but yet not conclusive answers. One possible reason making this celebrated research question still relevant today is that previous research has tended to answer this dilemma from different – and not always exhaustive -- levels of analysis.

From an *individual* lens, organizational scholars have investigated whether and how idiosyncratic attributes of single people can help knowledge transfer and coordination across intra-organizational boundaries. Building on this approach, empirical studies have shown that organizational members’ structural positions (e.g., Burt et al., 2013), their demographic attributes (including tenure) and their organizational roles (including hierarchical rank; e.g., Tasselli, 2015) can facilitate the ability to transfer and receive knowledge across boundaries. They have also shown that individuals with specific personality traits are more likely to span across intra-organizational divides (e.g., Mehra, Kilduff, & Brass, 2001). This research supports the view that individuals are active agents in bridging interpersonal and intra-organizational gaps (Burt et al., 2013).

From a *dyadic* perspective, research on organizational social networks has claimed that coordination among subunit boundaries can be explained looking at dyadic ties between organizational members. Empirical studies have shown that intra-organizational ties are more likely to be observed between two members of the same subunit than between members belonging to distinct subunits (Zappa & Lomi, 2015); and that ties across subunits are more likely to be observed between reciprocating organizational members (Caimo & Lomi, 2015).
This research supports the view that interconnection between subunits can be explained looking at the composition of dyadic ties between their members.

Previous organizational research has given relative less attention to the analysis of whether and how extra-dyadic, triadic structures affect processes of interconnection among subunit boundaries (for a notable exception, see Tortoriello & Krackhardt, 2010 on Simmelian ties and knowledge transfer). In the context of organizations, individuals are exposed to pressures arising from common membership of extra dyadic intra-organizational structures, including triads and cliques (Krackhardt, 1999). The likelihood to interact with others in triadic structures may vary to the extent that three people are co-members of the same organizational subunit or work in different subunits (Krackhardt, 1999). We may conceive triads as formed by network members working in the same subunit; or as formed by two people working in the same subunit and by a third individual working in a different unit; or as formed by three people who work in three different subunits (cf. Fernandez & Gould, 1994).

We suggest that different types of triadic configurations – namely, triadic cyclic closure or transitive triadic closure – can differently help explain processes of boundary spanning between subunits depending on the organizational design of the network. When organizations are designed as ‘flat’ networks, with limited hierarchical differentiation and horizontal coordination among members, then we hypothesize triadic cyclic closure to be associated to boundary spanning. Triadic cyclic closure implies that each actor provides without reciprocation social resources, including advice, to a second actor of the network who is member of a different unit, and receives the same kind of unreciprocated resources from a third actor who is member of a third unit in the organizational network (Block, 2015). But when networks reflect more classic, ‘hierarchical’ organizational structures with rank and role differentiation between members, then we hypothesize transitive triadic closure to be related to boundary spanning across subunits (e.g., Davis, 1970, for a classic argument connecting
local hierarchy and the tendency against transitive triadic closure in local network structures). In summary, we argue and show that the triadic mechanisms explaining boundary spanning across organizational subunits are contingent on the organizational design of the local network.

We found empirical evidence for our argument in two distinct studies. The first study focuses on a ‘flat’ organizational network and consists of 812 observations of advice patterns among the 29 employees working in four different subunits in a pharmaceutical company. The second study includes an organizational network including 420 observations of advice ties among the 21 managers having different formal hierarchical roles and working in the four distinct departments of a tech organization.

In line with recent research analyzing the arrangement of extra-dyadic network ties within organizations, we adopt a Bayesian parameter inference approach for exponential random graph models (ERGMs) specifically designed for the statistical analysis of social networks (cf. Robins, Pattison, & Wang, 2009; Snijders et al., 2006). ERGMs allow analyzing accurately the dyadic, triadic and extra-triadic structure of interactions involving the observed individuals, supporting the estimation of parameters associated with theoretically-relevant variables. Bayesian analysis of ERGMs (Caimo & Friel, 2011) is a promising approach to statistical network analysis because it yields a fully rich probabilistic picture of the uncertainty that is essential when dealing with complex statistical network models and heterogeneous relational data. Using a Bayesian framework leads directly to the inclusion of prior information about the network structure into the modelling framework, and provides immediate access to the uncertain ties by evaluating the posterior distribution of the parameters.

**Research contribution**

By analyzing the triadic structures of advice boundary spanning as contingent on the formal design of the organizational network, in this paper we aim to shed light on the nuanced processes by which *instrumental resources* and *interpersonal coordination* combine in
idiosyncratic organizational contexts. Despite numerous attempts to understand the social utility of network relationships (e.g., Burt, 1982; Coleman, 1988), research has tended to see instrumental resources -- including advice and knowledge (e.g., Podolny, Stuart, & Hannan, 1996) -- and subjective patterns of coordination (e.g., Durkheim, 1951) as two distinct ontological domains. By studying the patterns through which resources flow inside and across the organization, emphasis has been given to the most efficient ways by which ties can bridge organizational distance (Granovetter, 1973), and to the benefits accruing to those who can efficiently control the flow of resources (Burt, 1997). Conversely, patterns of interpersonal coordination have mainly been studied focusing on the egocentric motives behind social interaction, supporting a view of organizational networks as prisms reflecting actors’ qualities and contributing to the development of reputation, status and trust in the network (Podolny, 2001).

Our understanding of social networks, however, entails the “ability to make the micro-macro transition from pair relations to system” (Coleman, 1988: S98). Networks allow seeing regular patterns of behavior “even in situations that appear, at first glance, to approximate the classic higgling of a competitive market, as in the Moroccan bazaar analyzed by Geertz” (Granovetter, 1985: 491). Despite several limitations of this paper that we acknowledge, the argument that interpersonal micro-structures contribute to explain boundary spanning patterns helps bridge the competing sociological perspectives that interpret resource flow mainly through the lens of efficiency and interpersonal coordination mainly through the lens of status and reputation. Prismatic, status-related motives behind interpersonal coordination (hierarchical vs. horizontal, in this study) might indeed combine with the instrumental patterns of boundary spanning in providing a picture of organizational networks as ontological matrixes differently mixing status and efficiency motives depending on the interplay between formal organizational design and informal interaction. Thus, from a broader organizational
perspective, the apparently unsurprising finding that transitive closure is associated to hierarchy and cyclic closure to coordination offers a preliminary empirical ground to Stinchcombe’s (1968) intuition that “the processes that generate an institution are often different from those responsible for its reproduction” (in Powell, Packalen, & Whittington, 2012: 435). The meaning of organizational action at least partly derives from the often unfolding interplay between formalized structures, which prescribe efficient patterns of sharing resources across the organization (March & Simon, 1958), and the micro-structural interpretation that the actors forge through interpersonal patterns of coordination. A joint consideration of Talcott Parsons's (1937) concept of ‘social action’ as dependent on actors' embeddedness in idiosyncratic and often non-overlapping social contexts (Granovetter, 1985: 483) and organizational contexts (McEvily et al., 2014) can help organizational network research to highlight the “complex systems of exchange relationships” through which “boundaries around organizations and markets are shaped by a logic of mutual constitution” (Lomi & Pattison, 2006: 313).

Organizational Networks with Flat Hierarchy, Triadic Cyclic Closure and Boundary Spanning across Subunits

Triads have fascinated social scientists for decades. Simmel (1950: 138) claimed that “the addition of a third person completely changes” the dyad, because triads reduce the pursuit of individuals’ selfishness, limit the bargaining power of single people, and facilitate the resolution of interpersonal conflicts (Krackhardt, 1999). Burt (1982) added that the triad is a basic unit of theory and research that incorporates much richer possibilities of micro-macro extension than the dyad. As noted by a recent review (Tasselli et al., 2015: 12), within triads “the opportunities for individual decision making are shrunk by the social control exerted by coclique members.”
Despite this growing interest on triads, previous research has left relatively unexplored the striking social situation called *triadic cyclic closure*. In a triad of actors $i$, $j$, and $k$, the three-cycle is a network situation that describes the configuration where a tie from $i$ to $j$, a tie from $j$ to $k$, and a tie from $k$ to $i$ are present (Block, 2015: 164; see also Figure 1).

Figure 1 here

Empirical research has shown that the three-cycle parameter tends to be negative in network studies of social groups (e.g., Snijders et al., 2010; Steglich et al., 2012). Davis (1970) explained this evidence with the argument that the directionality of an unreciprocated tie indicates a difference in local hierarchy, in which the receiver is in a higher hierarchical position compared to the sender. We propose an *organizational explanation* to this sociological issue. Specifically, we consider three contingent conditions to argue that triadic cyclic closure can be positively associated to (i) boundary spanning relations across subunits in (ii) organizational networks (iii) characterized by ‘flat’ hierarchy.

(i) Most of previous research implicitly considered the interacting individuals as members of *social groups* — that is of “groups that are relatively small, informal and involve close personal ties” (Freeman, 1992: 152). This assumption is reflected by empirical studies of expressive interpersonal networks, such as friendship (Block, 2015), in which both the instrumental exchange of resources and organizational structure play little or no role.

(ii) However, when considering organizational networks — social networks in which the actors are organizational members exchanging instrumental resources, including advice or knowledge (Kilduff & Brass, 2010) -- informal relations between members are not autonomous from the more formal elements that define organizations as structured social settings (Dokko, Kane & Tortoriello, 2014). Organizations, indeed, differ from other kinds of informal social
groups. The tendency towards homophily of self-organized social groups tends to bring homogeneous sets of people together (McPherson, Smith-Lovin, & Cook, 2001). But individual membership in organizations, featured by goal-setting, resource exchange and task coordination, is “typically exogenous to the formation of network ties between individuals” (Lomi et al., 2013: 441). Dyadic, interpersonal connections alone are therefore unlikely to satisfy this search for resources, requiring extra-dyadic mechanisms of coordination (e.g., Tasselli & Kilduff, 2018).

(iii) When the organizational network is characterized by ‘flat’ hierarchy, with limited hierarchical differentiation among members (e.g., Atkinson & Moffatt, 2005; Carzo & Yanouzas, 1969), the need for horizontal coordination necessary to organizational functioning must support complex activities, which include the promotion of trust (Uzzi, 1997), the understanding of complex problems (Tortoriello & Krackhardt, 2010), and the transfer of information and critical knowledge resources (Gulati, Dialdin & Wang, 2002). In such types of networks, the limited role of formal hierarchy must be complemented by informal mechanisms of coordination to enable efficient organizational functioning.

Specifically, in flat organizational networks, individuals might be expected to give knowledge to members of other units without direct pretention of interpersonal reciprocity. The argument is motivated by the expectation that subunit members will enable intra-organizational coordination by giving resources to members of other units, following a generalized tendency of the members of other units to share the same kind of resources. This claim is in line with balance theory, which argues that people seek balanced relationships in their networks (Cartwright & Harary, 1956). In the context of a flat, multi-unit organizational network, balance is achieved not only through interpersonal reciprocity or transitivity, but also through the perception of equity in gains and contributions among members. Individual members, indeed, represent not just themselves and their ‘private’ connections, but the unit to which they
belong too (Brass et al., 2004). Consequently, we expect the presence of cyclic triadic structures, in which boundary-crossing ties across subgroups provide the conditions of “conditional kindness” whereby knowledge is given in a subgroup under the expectation that it will be received by a member of another subgroup (cf. Fehr & Gächter, 2000). Thus, we hypothesize:

Hypothesis 1: In organizational networks with flat hierarchy, triadic cyclic closure will be positively associated to boundary spanning across organizational subunits.

Organizational Networks with Formal Hierarchical Differentiation, Triadic Transitive Closure and Boundary Spanning across Subunits

Different from the social situation described above is the context of boundary spanning across subunits in classic, ‘hierarchical’ organizational networks, which we defined as networks with formally assigned ranks and functional mandates. This kind of network is still common to most of modern organizations, in which hierarchical differentiation is functional to task assignment and coordination, control over activity performance and goal-orientation (e.g., Drazin & Van de Ven, 1985). In such organizational networks, the emphasis is usually on aspects of organizational functioning including “tasks, process workflow, work-unit composition, job design, and role structures” (Mc Evily et al., 2014: 308).

In this context, differently from flat networks, triadic cyclic closure is no longer likely to explain boundary spanning advice ties across subunits. As suggested by foundational work by Davis and Leinhardt (1970), “presence of a cyclic network configuration indicates a cyclic hierarchy, which is very unlikely as hierarchy is generally transitive” (in Block, 2015: 164). Differently from other types of network, such as friendship, advice ties intrinsically assume a status implication (e.g., Agneessens & Wittek, 2012), such that people who seek for advice tend to occupy a lower status position because they “expose themselves to denial and rejection”
and recognize their condition of dependence on others (Goffman, 1971: 114). “If people tend to seek help often, more often than they provide it, [indeed], they risk ruining their reputation as an exchange partner and undermining their status” (Flynn et al., 2006: 1124).

When advice ties spanning across subunits include members assigned with hierarchical ranks, the status implications of advice ties render unlikely advice searching between subunits without direct reciprocation. Consequently, three-cycles are also unlikely to be observed. Rather, we suggest positive effects of transitive triadic closure in explaining boundary spanning. The transitive triadic structure is similar to the transitive triplet, with the notable difference that the direction of the tie from $i$ to $k$ is reversed, mirroring the ‘hierarchical’ nature of the local network (Block, 2015: 164; see also Figure 1). Our suggestion is consistent with evidence that ‘advice networks tend to be both hierarchical and cohesive’, and that in such networks the hierarchical dimension tends to be stronger than the cohesive dimension (Lazega et al., 2012). In this sense, transitive clustering reflects the intrinsic natures of classic, ‘hierarchical’ organizational networks. Thus, we hypothesize:

Hypothesis 2: In organizational networks with hierarchical differentiation, triadic transitive closure will be positively associated to boundary spanning across organizational subunits.

METHODS

Research Settings

Organizational network with flat hierarchy. The network includes the 29 members of the four organizational subunits working in the strategic planning and administration department of a mid-size European pharmaceutical company, active in several therapeutic areas ranging from vascular and cardiac to respiratory and antibiotics. The company recently adopted a ‘flat’ organizational structure, such that the four subunits still maintain functional
differentiation while privileging and fostering functional integration, horizontal coordination and process-based informal ways of work. Hierarchical differentiation was also limited, as shown by the presence of managerial roles playing the role of ‘facilitators,’ with the main goal to ‘coordinate activities, reducing duplications and acting as catalysts to achieve intra-organizational harmony.’ In each unit, there was at least one facilitator. Differently from more traditional, hierarchical companies, in this company informal advice sharing across subunits was incentivized to facilitate processes of coordination, knowledge transfer and decision-making. Specifically, there was no formal need for facilitators to interact with other facilitators belonging to different units, but (as reported by a facilitator that we interviewed), “patterns of advice sharing within and across subunits are emergent, and all organizational members are empowered to disseminate their knowledge and expertise, irrespective of the formal role.” Therefore, we define this network as ‘flat’ because the company emphasized elements of ‘horizontal coordination’ and reduced hierarchical differentiation.

**Organizational network with hierarchical differentiation.** The organizational network with formal hierarchical differentiation among members consists of the network involving the managers of a “small organization” on the US west coast. The “10-year old entrepreneurial firm” produced “high-tech machinery for other companies.” They employed 100 people, 21 of whom were part of the management. The managers were formally assigned to three different ranks in the organizational hierarchy, from “supervisors up through president.” They belonged to four different departments. These data have been collected by David Krackhardt and analyzed several times in previous research (e.g., Krackhardt, 1987: 118; Wasserman & Faust, 1994). The dataset is publicly available in UCINET (Borgatti, Everett & Freeman, 2002) and in other open repositories with the name “Krackhardt High-Tech Managers.”

**Fieldwork and Data Collection**
**Organizational network with flat hierarchy.** We analyzed data on 29 members of the department (85% of the target sample). 6 of the 29 respondents were ‘facilitators’ in the flat organizational network. There were four integrated subunits, consisting respectively of 12, 5, 7 and 5 people. 38% of the members were women (SD = 0.49). The average tenure in the company was of more than 10 years (minimum = 2; maximum = 21); and 83% of members had a list a college degree (SD = 0.38).

**Organizational network with hierarchical differentiation.** These data were collected from the 21 managers of the high-tech company (Krackhardt, 1987). Attribute information for the managers includes managers’ age (M = 39.71; SD = 9.56), tenure (M = 11.71; SD = 8.11), level in the formal corporate hierarchy (coded 1, 2 and 3; 1 = CEO, 2 = Vice President, 3 = manager) and four departments, including respectively 5, 8, 3 and 4 managers, plus the CEO (Krackhardt, 1987: 118).

**Network data**

In the flat organizational network, we used the roster method to collect network data (Wasserman & Faust, 1994: 46), an approach that reduces the likelihood that respondents forget important contacts (Marsden, 2011: 372). For each actor, we collected data on the following question: “Please indicate those to whom you go for advice on knowledge relative to work related matters.” Building on field experience and previous interviews with key informants, the researchers also presented a list of concrete ‘matters’ that would require advice exchange among members. They included ‘coordination on problem solving and finding common solutions on strategic or administrative purposes’ and ‘alignment on decision making.’ In the classic, hierarchical network, network data were collected by asking each manager “to whom do you go to for advice” (Krackhardt, 1987: 118).

Each of the two networks can be represented as a \( n \times n \) binary adjacency matrix recording the presence or absence of relations for each possible pair of individuals in the
sample. Figure 2 and 3 report the networks of such relations between members of different subunits in the networks. Table 1 reports the main descriptive statistics for the two networks. On average, each member had approximately 3.2 ties with other members in the flat network and 9 ties in the classic, hierarchical network. Approximately 23% of all the ties observed were reciprocated in the flat network, and 24% in the hierarchical network.

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Figures 2 and 3, and Table 1 here

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**Variables and Measures**

*Dependent Variable.* Across the two samples, we report estimates of models for the probability of observing ties between members as a function of (i) dyadic covariate-based network statistics, based on actor-specific variables, or “covariate effects,” (ii) dyadic dependencies between network ties and (iii) extra-dyadic endogenous network statistics. The dependent variables of the study (advice ties) take the form of binary tie variables.

Actor-specific variables control for the effect of the differences in individual characteristics among members on the presence (or absence) of ties. Dependencies at the local network level, instead, allow controlling for tendencies of subsets of network ties to organize themselves in what we can call “local configurations” (Pattison & Robins 2002). Actor-specific covariates and local dependencies representing subset of network ties are included in the empirical model specification as independent and control variables. Because advice ties among members are unlikely to be independent on one another, failure to include network effects in the modeling of empirical social networks may result in incorrectly specified models (Lomi et al. 2013).

*Independent Variables.* In our first hypothesis, we claim that patterns of advice across different subunits in flat networks can be sustained by triadic mechanisms of cyclic closure.
Using an example, it means that a member \( i \) of subunit \( X \) will be likely to give advice to a member \( j \) of subunit \( Y \), who will be likely to give advice to a member \( k \) of subunit \( Z \), who will be likely to give advice in turn to member \( i \), with no members being reciprocated in their advice giving (see also Figure 1). To test this hypothesis, we created a categorical variable recording the affiliation of participants to different subunits. We then used information on membership to build a \textit{Subunit homophily} covariate (statistic \( \theta_4 \) in the models). It is a dummy variable, with value 1 if two members are also members in the same subunit, and 0 otherwise. We also control for \textit{Subunit reciprocity} (statistic \( \theta_3 \) in the models), a variable assessing the density of mutual edges between nodes in the same subunit. Read together with the statistic measuring \textit{Reciprocity} in the whole network (parameter \( \theta_2 \) in the models), this variable allows testing whether reciprocal ties within – and, by exclusion, also between the subunits – exert any effect on the effects of theoretical significance that we hypothesized. Then, in order to capture the cyclic triadic effect involving actors with different subunits, we assessed the statistic called \textit{Triadic cyclic closure between units} (parameter \( \theta_{11} \)), which represents the number of cycles involving nodes belonging to different subunits. To allow disentangling the potentially different effects of cyclic closure as ‘generalized exchange’ in the networks and as ‘boundary spanning,’ we controlled for two directional \textit{gwesp} effects: \textit{Gwesp Outgoing Two-Path (OTP)} (parameter \( \theta_{13} \) in the models), which measures the effect of transitive shared partnership overall in the network; and \textit{Gwesp Incoming Two-Path (ITP)} (parameter \( \theta_{14} \) in the models), which assesses the effect of cyclical shared partnership in the network. The inclusion of both these directional \textit{gwesp} parameters in the models provides further confidence that the empirical specification that we adopt is able to tease apart general tendency towards triadic cyclic closure and to highlight the authentic effect of three cycles across subunit boundaries. Furthermore, to evaluate more in detail the probability to observe
cyclic configurations in the networks, we also control for the presence of Four cycles, assessing the number of cycles involving four nodes overall in the network.

In our second hypothesis, we suggest that patterns of advice across subunits in classic, hierarchical networks are explained by triadic transitive closure. Using an example, it means that in a closed triad composed by actor i (belonging to subunit X), actor k (belonging to subunit Z) and actor j (belonging to subunit Y), actor j gives advice to actor k, and actor i gives advice to both actor j and actor k. To test this hypothesis, we assessed a network statistic called Closed triadic structures between units (parameter $\theta_{10}$ in the models), which represents the number of directional transitive triads involving nodes belonging to different subunits. This statistic allows us to control for the presence of closed transitive structures between units, therefore also facilitating the interpretation of the Triadic cyclic closure between units statistic (parameter $\theta_{11}$ in the models). We also control for the presence of directional closed triadic structures (cyclic and transitive) overall in the network, and not only between subunits, including also in this models $gwesp.OTP$ and $gwesp.ITP$ parameters, and for the presence of four cycles in the network. Read together, these statistics allow interpreting in a more comprehensive way the patterns involving triadic clustering effects within and between subunits in the networks.

Control Variables. The dyadic covariate-based network statistics include homophily effects involving different nodal covariates: The number of edges involving actors with the same subunit (Subunit homophily), and the number of edges involving actors with the same demographic and organizational attributes, including gender, age, tenure and education. In all networks, subunit membership is measured as a categorical variable, based on the exclusive membership in one of the subunits. We assessed the number of edges involving actors with the same hierarchical organizational rank, to test for whether actors were managers (facilitators) or did not have any rank. Similarity in demographic traits and other
individual or organizational characteristics is important because can predict basic characteristics featuring social relationships between individuals (Tasselli et al., 2015).

Members’ propensity to go for advice to each other is likely to be affected not only by individual characteristics, but also by forms of local dependencies between network ties (Lomi et al., 2013). Dyadic endogenous network statistics include the number of edges (edges, statistic $\theta_1$) measuring the density of the network, and the number of mutual edges (reciprocity, statistic $\theta_2$) measuring the tendencies toward reciprocity. As specified above, we also controlled for reciprocity within the subunits. More in detail, reciprocity models the likelihood that the existence of an advice tie in one direction leads the receiver to build a tie in the opposite direction.

An additional set of control variables captures extra-dyadic endogenous network statistics. They include geometrically weighted in- and out-degree statistics ($\text{gwidegree}$; and $\text{gwodegree}$) measuring centralization of in- and out-edges. Geometrically weighted edgewise shared partner statistics ($\text{gwesp}$), which consist of two directional parameters, OTP, assessing the tendency towards transitive closure, and ITP assessing the tendency towards cyclic closure overall in the network. And geometrically weighted non-edgewise shared partner statistics ($\text{gwnsp}$), measuring the presence of open triadic structures overall in the network. As noticed above, we also control for the presence of four cycles in the network.

Table 2 summarizes our discussion of the independent variables and of the control variables that we incorporate in the empirical model specification that we discuss next.

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| Table 2 here |
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**Empirical Model Specification: Bayesian Estimation**

The interdependence between observations typical of network data makes standard
statistical modeling inappropriate to test association between advice ties. To account explicitly for these interdependences, in both studies we adopt a Bayesian (so called after Reverend Thomas Bayes, 1763) parameter inference approach for ERGMs using the approximate exchange algorithm (Caimo & Friel, 2011; Caimo & Friel, 2013) implemented in the Bergm package for R (Caimo & Friel, 2014). ERGMs are statistical models for social networks that are becoming increasingly popular in studies of interpersonal relationships within and across organizational subunits and between organizations (e.g., Lomi et al., 2013). Bayesian ERGM analysis is particularly appropriate for small and medium network samples, like the ones analyzed in this paper (Zyphur & Oswald, 2015). By adopting a Bayesian approach for ERGMs, we provide a reliable and systematic fully-probabilistic assessment of the uncertainty of the model parameters by incorporating prior information on their expected behavior and evaluating their posterior distribution conditional on the data (Caimo & Lomi, 2015). In the context of network analysis, priors are important to ensure that posterior-based decision rules have good frequentist properties; for example, we can ensure network sparsity by concentrating most (or all) of the probability mass of the edges parameter on negative values or specifying a positive correlation between density (edges) and transitivity (e.g., transitive triads).

For all the network models that we analyzed, we specify a vague prior parameter distribution by setting all the parameters to be following a vague normal distribution with mean 0 and standard deviation equal to 5 except for the following parameters: $\theta_1 \sim N(-3, 2)$ assuming negative density (edges) effect; $\theta_2 \sim N(1, 2)$ assuming positive reciprocity effect (reciprocity); $\theta_{12} \sim N(1, 2)$ assuming positive closed transitive triadic effect (gwesp.OTP).

For each of the 20 MCMC chains used to perform the analysis with the adaptive direction sampling approximate exchange algorithm, we set the number of burn-in iterations equal to 300 and the number of main iterations after the burn-in to 3,000. The number of auxiliary
iterations for each main iteration is set to 3,000 and the adaptive direction sampling factor $\gamma$ is set so as to get about 20% acceptance rate.

**RESULTS**

**Bayesian Model Interpretation**

Bayesian analysis has many advantages compared to classical inference as it provides rich diagnostic information about the unknown model parameter values, and allows a fully reliable assessment of the uncertainty of all model parameters. Bayesian inference makes use of probability intervals (quantile-based highest posterior density) called credible intervals to state the probability that the parameter values are between the two limits of the interval. For these reasons, Bayesian analysis is becoming a common methodology used in several disciplines in the social sciences, including sociology (Demeulenaere, 2011; Western, 2001), organization and management studies (Andraszewicz et al., 2015).

We present and discuss the results of the Bayesian analysis conducted in the two studies in Tables 3 and 4. The tables report estimated posterior means, medians and 95% credible intervals (bounded by the 2.5th and the 97.5th percentiles) for each parameter. For the selected significance level (in our case, 0.95), credible intervals report the interval of values that are likely to be included by the parameters of a model based on the analyzed data. Intervals are modelled so that the probability of a given parameter to have value within the interval (marked by the 2.5% quantile and 97.5% quantile of the posterior distribution) is 0.95. Posterior parameters distributions provide therefore information on the parameters after observing the data; specifically, they give quantitative value to the effects included in the ERGMs, by taking into account information on the specific model given by the prior distribution. To give an example of how these models can be interpreted, a credible interval for a selected parameter reporting only positive value means that the effect associated with
the parameter tends to be common, and therefore likely to be observed, in the network (Caimo & Lomi, 2015: 677-678).

**Organizational network with flat hierarchy**

Table 3 reports the posterior results of our analysis of the flat organizational network. The model incorporates both individual-specific covariates and local dependencies (dyadic and extra-dyadic) that are likely to affect engagement in advice interactions between members of the department.

Table 3 here

Dyadic network effects show a negative value of the posterior estimates of the credible intervals associated with the *edges* parameter (-6.43; -2.79), and a positive value of the credible intervals of the *reciprocity* parameter (0.29; 2.77). Among the actor-level covariates, we notice the positive value of the credible intervals of the *subunit homophily* parameter, which vary from 0.43 to 1.97, and suggest that ties tend to be concentrated within rather than across subunits (e.g., Caimo & Lomi, 2015). We also see a positive value of hierarchical *rank homophily* (0.24; 1.69), which suggests that facilitators are more likely to interact informally with each other than with other employees, and of *education homophily* (0.09; 1.43), suggesting that members tend to connect with others with the same educational background. Among the extra-dyadic effects, of note are the non-significant – from a non-Bayesian interpretation -- *out-degree* and *in-degree* parameters. Because 0 is included in the credible intervals of the parameter, indeed, this suggests that the probability to observe in the network positive or negative effects for these parameters is not different from what would be observed in a random graph with tie probability equal to 0.5. We also notice that the posterior
estimates of the four cycles parameter are negative (-0.80; -0.10), suggesting that four cycles are unlikely to be observed in the network.

Moving to the effects of theoretical interest, the credible intervals associated with the parameter testing for Triadic cyclic closure between subunits vary between 0.06 and 3.22, supporting the arguments of Hypothesis 1. Of the 25 cycles present in the network, 17 involve ties between subunits. The posterior distributions of the effects of the Closed triadic structures between units parameter lace an amount of probability to 0 (the credible intervals vary from -0.35 to 0.60), meaning that the corresponding effects are indistinguishable from zero. Of note, the effects of gwesp.OTP are positive and significant (0.00; 0.80), suggesting that there is an overall tendency towards transitivity; the effects of gwesp.ITP, instead, included 0 in their credible intervals, suggesting, from a non-Bayesian perspective, non-significant findings for the effects of cyclical shared partnership overall in the network. Read together, these findings suggest that boundary spanning between subunit tends to be explained, in flat organizational networks, by triadic cyclic, rather than transitive, closure; and that triadic cyclic closure is positive and significant exclusively while looking at boundary spanning triads between subunits, and not overall in the network.

Organizational network with hierarchical differentiation

The results of the Bayesian analysis in the classic organizational network involving ties between managers with different formal hierarchical roles working for a high-tech company are reported in the model in Table 4.

Table 4 here

The model suggests that the posterior distributions of the effects of edges include 0 in their credible intervals (-0.38; 0.40), meaning that the corresponding (directional) effects are
indistinguishable from zero. Consistent with the previously analyzed network, the posterior distributions of the reciprocity parameter are positive (0.02; 0.41), suggesting that ties are likely to be reciprocated overall in the network. Because the posterior distribution of the parameter associated with the subunit reciprocity place a significant amount of probability to 0 (-0.31, 0.33), this parameter can be considered, using a non-Bayesian interpretation, as ‘not statistically significant.’ In other words, managers are unlikely to establish reciprocated more or less advice relations within units than expected by chance.

The analysis of the actor-level covariates shows that the posterior distributions of tenure absolute difference are negative and significant (-0.08; -0.01), meaning that members are more likely to form ties with others similar to themselves in tenure. On the contrary, the effects of age and hierarchical rank have 0 falling in their credible intervals, thus suggesting that the likelihood of these covariates to explain tie formation is indistinguishable from what would be expected by chance.

Among the extra-dyadic dependences, the posterior distributions for in-degree and out-degree distributions include 0 in their credible intervals, thus suggesting that the lack of statistical probability to observe tendencies towards specific actors’ activity and popularity in the network. Consistent with the previous, flat organizational network, the value for open triadic structures (gwnsp statistic) is not significant, because 0 falls inside the credible intervals (-0.29; 0.19). And the posterior distributions of the effect of gwesp.OTP in the overall network are positive and significant (0.06; 0.44), suggesting that there is a positive tendency towards transitive closure; the distributions of the gwesp.ITP parameter, instead, can be assessed, in non-Bayesian terms, as non-significant. Read together, these two effects suggest that there is a tendency in the overall network to clustering due to transitive relations among actors. The posterior distributions of the four cycles parameter also have 0 falling in their credible intervals (-0.06; 0.01), so they can be interpreted as ‘non-significant.’
The analysis of the triadic effects of theoretical relevance confirms our predictions. Recall Hypothesis 2, stating that triadic mechanisms of transitive closure are likely to be positively associated to advice boundary spanning between subunits in hierarchical organizational networks. The credible intervals associated with the parameter testing for Closed triadic structures between subunits ($\theta_{10}$ statistic) vary between 0.08 and 0.18, supporting the hypothesis. More in detail, the conditional probability that a tie spanning between subunits is included in a transitive triad is more likely than the probability that this kind of tie is embedded in a different triadic structure.

Differently from the previous study on a flat network, in this hierarchical organizational network the parameter associated with triadic cyclic closure between units is negative, with values of the credible intervals that vary from -0.63 to -0.03. These findings suggest a specular interpretation to the one described in the first study: Despite the relatively high likelihood in the network to observe triadic clustering overall, while looking at boundary ties between subunits, triadic clustering is sustained by mechanisms of transitive, rather than cyclic, closure.

**Robustness Checks**

*Friendship networks*. The effects that we show all pertain a particular type of instrumental and potentially asymmetrical network: The advice network, in which organizational members share resources that are instrumental for organizational functioning and that are functional to hierarchical differentiation (for calls to analyse triadic structural configurations in such network, see Block, 2015). What about the effects on boundary spanning of expressive ties, assessing long-standing personal relationships that develop alongside work relationships and can potentially trigger advice ties (e.g., Tasselli & Kilduff, 2018)? For this reason, we tested our predictions with a sample of friendship ties in the classic organizational network (Data from the High Tech dataset from David Krackhardt,
publicly available in the UCINET database repository. For what concerns the effects of theoretical relevance, we did not find positive effects for the *triadic cyclic closure between units* parameter, in line with previous research envisaging negative or no effects of three cycles in expressive networks (Block, 2015).

**The spurious nature of three cycles.** Previous research suggests that the negative effect of the triadic cyclic closure parameter reported by several studies of social groups may have spurious nature, such that “the tendency against forming three-cycles decreases or disappears” “when controlling for the tendency towards reciprocation in transitive triplets” (Block, 2015: 166). In the flat organizational network, we found and reported positive effects for the three-cycle parameter between subunits even when the tendency towards reciprocation within boundary spanning triads is not explicitly modelled. Therefore, in our models the test for the positivity of the boundary spanning three-cycle effect tends to be more conservative. Indeed, “the parameter that models the formation of three-cycles should pick up the effect of the omitted network structures” (Block, 2015: 166), thus accounting for the expected tendency against reciprocation within triadic structures.

**Bayesian versus non-Bayesian ERGM estimation.** In the methodological section of the paper, we described the advantages and conditions under which using Bayesian ERGM analysis. To allow further comparability between Bayesian and non-Bayesian estimation, we replicated the analysis using non-Bayesian ERGM models. There is an asymptotic equivalence of Bayesian and maximum likelihood (ML) estimation when vague or non-informative priors are used for posterior estimation. In this paper, we did not make use of strong informative priors so the maximum-a-posteriori (MAP) estimates obtained by the approximate exchange algorithm are similar to the ML estimates (as also shown in Caimo & Friel, 2011). Therefore, we replicated the analysis with non-Bayesian ERGM estimates using flat priors; as expected, the results for the patterns of theoretical significance were
comparable with those obtained through Bayesian ERGM analysis, providing further confirmation on the validity of our results. More in general, because Bayesian analyses do not assume large samples, as is the case with ML estimation, typically smaller data sets (like the ones in this paper) can be analyzed without losing statistical power while retaining precision. As Lee & Song (2004) showed, Bayesian estimation requires a much smaller ratio of parameters (number of network effects) to observations (number of network dyads). Bayesian estimation makes thus it possible to use smaller datasets compared to ML estimation (Gelman, Carlin, Stern, & Rubin, 2004; Zyphur & Oswald, 2015).

Model Assessment

In order to evaluate the model's goodness of fit in terms of posterior predictive assessment, the observed network is compared to a set of networks simulated from the estimated posterior distribution of the parameters of the model (Caimo & Friel, 2011). This comparison is carried out in terms of general network statistics distributions (Hunter et al., 2008) in order to check how well the estimated posterior parameter distribution is able to reproduce networks resembling the general structural features of the observed network. GOF distributions commonly used in statistical analysis to describe directed network structures include the in-degree distribution, the out-degree distribution, the minimum geodesic distance distribution and the edgewise shared partner distribution. Model assessment involves comparing the GOF diagnostic statistics distributions of the observed network data with the ones of the network data simulated from the estimated posterior density. The plots with the results of the GOF diagnostic statistics for the two networks are reported in Figures 4 and 5, in which the red line represents the observed data is inside the 95% predictive interval (delimited by the two gray lines) for any GOF diagnostic statistic considered. The GOF diagnostics of our models demonstrate that the posterior parameter estimates support our
prediction and reproduce with accuracy important structural features of the observed networks.

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Figures 4 and 5 here

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**DISCUSSION**

We designed this study to answer one main question of importance for theory and research on organizational social networks: Under what conditions is advice embedded in idiosyncratic, dyadic relationships likely to reach across intra-organizational boundaries and thus to be shared among distinct organizational subunits? Through the analysis of advice ties in a flat and in a hierarchical organizational network, we assessed the nuanced effects of organizational design and triadic network structure on the likelihood to observe informal advice ties spanning between organizational subunit boundaries. We have shown that looking at triadic configurations among organizational members belonging to distinct subunits can answer our research question, and that these effects are contingent on the degree of hierarchy in the intra-organizational network. In the flat organizational network that we examined, we found triadic mechanisms of cyclic closure to be positively associated to boundary spanning; in the classic, hierarchical network, instead, the effects of triadic transitive closure were associated to the transfer of advice across subunits.

These results extend evidence discussed in prior research on advice and knowledge sharing ties across the formal and informal boundaries of organizations (e.g., Caimo & Lomi, 2015; Tasselli, 2015). We know from classic research on the duality of groups and individuals in social structure (Breiger, 1974) that, “when two individuals interact, they not only represent an interpersonal tie, but they also represent the groups of which they are members” (Brass et al., 2004: 801). Most of attention has been paid to the structural side of
boundary spanning (e.g., Tortoriello et al., 2012), but the role that both formal organizational structures (including the membership of different subunits) and organizational design choices (including the degree of hierarchy in the network) play in processes of knowledge exchange has been surprisingly downplayed (McEvily et al., 2014). We show that patterns of advice across organizational boundaries are contingent on the interplay between formal and informal structures in enabling interpersonal interaction across subunits. Different structural, informal network configurations (triadic transitive closure and cyclic closure) combine with both the formal organizational configuration of units (subunit membership) and hierarchies (flat vs. hierarchical network) in affecting the processes by which advice patterns flow within and across the social space of the organization. We suggest that the understanding of organizational social networks as the “company behind the chart” (see Krackhardt & Hanson, 1993) should incorporate into analysis the ‘organizational chart’ itself, in terms, as in our case, of subunit and hierarchy configuration.

Building on this insight, we contribute on research on two different triadic configurations, transitive closure and cyclic closure, as structural configurations that help describe and interpret processes of knowledge sharing and boundary spanning within and across local structures in organizational networks. The positive value of transitive closure across subunit boundaries in hierarchical organizational networks suggests that advice sharing ties in the context of local hierarchies are positively associated to clustering mechanisms in which players occupying hierarchical positions are likely to play pivotal roles between otherwise unconnected others. As noted by recent research on knowledge sharing in triads, this result reminds us how “the existence of common third-party ties around a focal bridge substantially changes the nature of the bridging relationship” (Tortoriello & Krackhardt, 2010: 168). Further research is needed to understand whether and how the
leadership abilities of those occupying hierarchical positions in the local network facilitate or hamper the process of knowledge spread (e.g., Balkundi & Kilduff, 2006).

In the flat organizational network, instead, we found effects of positive triadic cyclic closure in explaining boundary spanning advice ties. These findings suggest that, when hierarchy is absent or limited, the presence of an overarching organizational purpose requires members to coordinate their activities and interactions for a unique goal that transcends the individual and dyadic utility of social interactions. This reason goes beyond the classic argument that the negative tendency against triadic cyclic closure reflects the tendency against reciprocation in triads (e.g., Davis, 1970). Using the words of James March and Herbert Simon (1958: 178), in flat networks individual members tend to behave as "organizational men" (p. 135), contributing to the achievement of superordinate organizational goals. This result should inspire further research on the work of formal leadership in influencing coordination across boundaries (Balkundi & Kilduff, 2006).

We cannot infer the causality patterns behind our results – that is, what’s the causal mechanism whereby knowledge is transferred cyclically across subunits without direct reciprocation in flat organizational networks. Previous research has shown that, in hierarchical organizational networks, reciprocity in boundary spanning ties tends to be positive (Caimo & Lomi, 2015). The study of a hierarchical organizational network that we report also confirms the negative effect of cyclic triadic structures in explaining patterns of advice between subunits. Read together, those findings seem to suggest our argument concerning the ‘fit’ between specific organizational design solutions and idiosyncratic advice patterns. Further work is needed to understand better whether, in these different organizational networks, members seek balance or whether the advice ties that we observe are the mere result of structural determination.
In summary, we confirm and extent the argument of classic literature in organizational design (e.g., March & Simon, 1958) that the peculiar nature of organizational networks derives from evidence that both their formal and informal structures make resonant the patterns of interpersonal connections among their members – something that makes peculiar organizations compared to other social groups. The interplay between those dimensions (formal vs. informal organizational structure, and flat vs. hierarchical structure) would guide, in our view, further work on coordination across organizational boundaries.

**Limitations and Future Directions**

Despite clear boundary conditions and limitations (e.g., two idiosyncratic types of organizations, the focus on small networks, and the choice of the advice network), the results of this paper investigate and strengthen an intuition of direct relevance to social network research. The ability of specific structural configurations (such as, in this case, transitive and cyclic triadic closure) to associate to patterns of interpersonal interactions (in this case, cross-boundary ties) is contingent on the organizational design of the particular social network that is taken into account. This intuition calls for future empirical research in different social and organizational settings, including social groups with a clear goal-orientation (e.g., activists who are part of a social movement for civil rights), organizational networks that follow serendipitous rather than goal-oriented trajectories (e.g., Kilduff & Tsai, 2003) or organizations that are changing their strategies, identities and activities (e.g., Tasselli, 2019). Looking how different kinds of social environment make resonant specific structural configurations would help understand more in detail the extent to which structural properties are contingent on the idiosyncratic social environment in which network data are collected.

Moreover, future research is needed to explore whether individual attributes play any significant role in understanding what kinds of people are more likely to engage in structural configurations, such as triadic cyclic closure, in which they give social resources to other
network members without dyadic reciprocation. Recent research is exploring the relevance of specific personalities and motivations in explaining patterns of interpersonal interaction within and outside the workplace (e.g., Burt et al., 2013). Self-monitoring personality, for example, has been shown to explain both an individual’s propensity to form open triads (e.g., Sasovova et al., 2010) and an individual’s skills in managing membership of closed triads (e.g., Tasselli & Kilduff, 2018). There is also interest in recent social network research in communal motivation, defined as the extent to which people manifest a social need to get along with others and can thus be prone to give help and support to network co-members (Barrick, Stewart, & Piotrowski, 2002). Is it the case that individuals high both in self-monitoring personality and communal motivation are more prone and able to form directional and unreciprocated ties within triadic configurations, so combining the ability to manage behavioral pressures arising from triad membership with the propensity to give social resources to others without the need of reciprocation?

In this study, we presented samples consisting of cross-sectional network data. For future research, it would be interesting looking at the processes by which triadic configurations are formed or evolve over time. We know that the acquaintances that people make in changing social environments tend to ‘freeze’ soon towards stability, like shown in a classic natural experiment on a student living group (Newcomb 1978). However, under this apparent ‘glacier’ of stability, when social settings change, people also change their networks such that they seem to “dance” between acquaintances (Moody, McFarland, & Bender-deMoll, 2005: 1229). The ‘network metrics’ of individuals often do not have a linear pattern: They ‘rise and fall through time’ – a process called ‘oscillation’ because resembles a pendulum ‘in which a period of deep engagement in a group is followed by a period of connecting across groups’ and so on (Burt & Merluzzi, 2016: 35). These phenomena are even more salient in contemporary societies in which technology offers to opportunity to broaden
and change the composition of our social interactions almost instantaneously. Is it the case that triadic cyclic structures are likely to be relatively stable over time -- differently from precarious open triadic structures including structural holes (e.g., Burt, 2002) – because they imply interpersonal trust between triad members? Or, perhaps, will unbalance in the actual or perceived patterns of advice seeking and giving within the triad push people to activate reciprocity mechanisms over time, thus making the triadic cyclic structure short-living and making triadic transitive closure more stable? These reflections still need to be matched by empirical research.

In conclusion, in this study we have shown that the effect of two celebrated structural configurations (transitive and cyclic triadic closure) on outcomes is contingent on the degree of hierarchy of the organizational networks taken into account. Overall, this study, and the directions for future research that we have suggested, can help better understand the often-nuanced mechanisms underlying both the composition and the functioning of organizational social relations.

**Footnotes**

The code for implementing the *localtriple* statistic using the ERGM package is available at: [https://github.com/acaimo/ergm-terms](https://github.com/acaimo/ergm-terms).

**REFERENCES**


Kilduff, M., & Brass, D. J. (2010). Organizational social network research: Core ideas and key debates. *Academy of Management Annals, 4*(1), 317-357.


TABLES AND FIGURES

Table 1.
Main Descriptive Statistics for the Networks.

<table>
<thead>
<tr>
<th></th>
<th>Organizational Network with Flat Hierarchy</th>
<th>Organizational Network with Hierarchical Differentiation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Density</td>
<td>0.12</td>
<td>0.45</td>
</tr>
<tr>
<td>Average degree</td>
<td>3.24</td>
<td>9.05</td>
</tr>
<tr>
<td>Standard deviation indegree</td>
<td>2.03</td>
<td>4.07</td>
</tr>
<tr>
<td>Standard deviation outdegree</td>
<td>1.60</td>
<td>5.45</td>
</tr>
<tr>
<td>Reciprocity</td>
<td>0.23</td>
<td>0.24</td>
</tr>
<tr>
<td>Number of mutual dyads</td>
<td>22</td>
<td>45</td>
</tr>
<tr>
<td>Number of asymmetric dyads</td>
<td>50</td>
<td>100</td>
</tr>
<tr>
<td>Number of null dyads</td>
<td>334</td>
<td>65</td>
</tr>
<tr>
<td>Clustering coefficient</td>
<td>0.29</td>
<td>0.73</td>
</tr>
<tr>
<td>Average path length</td>
<td>2.79</td>
<td>1.64</td>
</tr>
</tbody>
</table>
Table 2. Description of the Network Statistics included in Empirical Model Specifications.

<table>
<thead>
<tr>
<th>Statistic</th>
<th>Description</th>
<th>Interpretation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Edges</td>
<td>number of edges in the network</td>
<td>density of edges</td>
</tr>
<tr>
<td>Reciprocity</td>
<td>number of mutual edges $y_{ij}, y_{ji}$</td>
<td>density of mutual edges</td>
</tr>
<tr>
<td>Subunit reciprocity</td>
<td>number of mutual edges $y_{ij}, y_{ji}$, for which subunit$i = subunit(j)$</td>
<td>density of mutual edges between nodes in the same unit</td>
</tr>
<tr>
<td>Subunit homophily</td>
<td>number of edges for which subunit$i = subunit(j)$</td>
<td>density of edges between nodes in the same unit</td>
</tr>
<tr>
<td>Gender homophily</td>
<td>number of edges for which gender$i = gender(j)$</td>
<td>density of edges between nodes with the same gender</td>
</tr>
<tr>
<td>Years of experience homophily</td>
<td>number of edges for which experience$i = experience(j)$</td>
<td>density of edges between nodes with the same years of experience</td>
</tr>
<tr>
<td>Education homophily</td>
<td>number of edges for which education$i = education(j)$</td>
<td>density of edges between nodes with the same education</td>
</tr>
<tr>
<td>Age absolute difference</td>
<td>sum of absolute differences $</td>
<td>age(i) - age(j)</td>
</tr>
<tr>
<td>Hierarchial rank absolute difference</td>
<td>sum of absolute differences $</td>
<td>rank(i) - rank(j)</td>
</tr>
<tr>
<td>Tenure absolute difference</td>
<td>sum of absolute differences $</td>
<td>tenure(i) - tenure(j)</td>
</tr>
<tr>
<td>In-degree; $gwidth$</td>
<td>geometrically weighted in-degree statistic</td>
<td>tendency towards centralisation in in-degree distribution</td>
</tr>
<tr>
<td>Out-degree; $gwidth$</td>
<td>geometrically weighted out-degree statistic</td>
<td>tendency towards centralisation in out-degree distribution</td>
</tr>
<tr>
<td>Closed triadic structures</td>
<td>number of triangles among units</td>
<td>number of triads involving nodes of different units</td>
</tr>
<tr>
<td>between units</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Triadic cyclic closure</td>
<td>number of cyclic triangles among units</td>
<td>number of cyclic triads between nodes of different units</td>
</tr>
<tr>
<td>between units</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Four cycles</td>
<td>number of four cycles</td>
<td>number of cycles involving four nodes</td>
</tr>
<tr>
<td>$Gwesp.OTP$</td>
<td>geometrically weighted edgewise shared partners (Outgoing Two-path)</td>
<td>tendency towards transitive clustering overall in the network</td>
</tr>
<tr>
<td>$Gwesp.ITP$</td>
<td>geometrically weighted edgewise shared partners (Incoming Two-path)</td>
<td>tendency towards cyclic clustering overall in the network</td>
</tr>
<tr>
<td>Open triadic structures; $gwnsp$</td>
<td>geometrically weighted nonedgewise shared partner statistic</td>
<td>tendency of non-directly-connected nodes to be connected through multiple others</td>
</tr>
</tbody>
</table>
Table 3.
Results: Estimated Posterior Means, Medians and Credible Intervals for Each Parameter in
the Organizational Network with Flat Hierarchy.

<table>
<thead>
<tr>
<th>Parameter (statistic)</th>
<th>Mean</th>
<th>2.5%</th>
<th>50%</th>
<th>97.5%</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\theta_1$ (edges)</td>
<td>-5.04</td>
<td>-6.43</td>
<td>-5.13</td>
<td>-2.79</td>
</tr>
<tr>
<td>$\theta_2$ (reciprocity)</td>
<td>1.52</td>
<td>0.29</td>
<td>1.52</td>
<td>2.77</td>
</tr>
<tr>
<td>$\theta_3$ (subunit reciprocity)</td>
<td>0.17</td>
<td>-1.51</td>
<td>0.17</td>
<td>1.81</td>
</tr>
<tr>
<td>$\theta_4$ (subunit homophily)</td>
<td>1.23</td>
<td>0.43</td>
<td>1.24</td>
<td>1.97</td>
</tr>
<tr>
<td>$\theta_5$ (gender homophily)</td>
<td>0.15</td>
<td>-0.29</td>
<td>0.15</td>
<td>0.59</td>
</tr>
<tr>
<td>$\theta_6$ (education homophily)</td>
<td>0.76</td>
<td>0.09</td>
<td>0.76</td>
<td>1.43</td>
</tr>
<tr>
<td>$\theta_7$ (hierarchical rank homophily)</td>
<td>0.99</td>
<td>0.24</td>
<td>1.00</td>
<td>1.69</td>
</tr>
<tr>
<td>$\theta_8$ (In-degree; $gw_{degree}$)</td>
<td>0.64</td>
<td>-1.40</td>
<td>0.60</td>
<td>3.16</td>
</tr>
<tr>
<td>$\theta_9$ (Out-degree; $gw_{degree}$)</td>
<td>1.60</td>
<td>-0.72</td>
<td>1.45</td>
<td>4.72</td>
</tr>
<tr>
<td>$\theta_{10}$ (closed triadic structures between units)</td>
<td>0.12</td>
<td>-0.35</td>
<td>0.11</td>
<td>0.60</td>
</tr>
<tr>
<td>$\theta_{11}$ (triadic cyclic closure between units)</td>
<td>1.61</td>
<td>0.06</td>
<td>1.62</td>
<td>3.22</td>
</tr>
<tr>
<td>$\theta_{12}$ (four cycles)</td>
<td>-0.42</td>
<td>-0.80</td>
<td>-0.41</td>
<td>-0.10</td>
</tr>
<tr>
<td>$\theta_{13}$ (closed triadic structures; $gw_{esp}.OTP$)</td>
<td>0.25</td>
<td>0.00</td>
<td>0.31</td>
<td>0.80</td>
</tr>
<tr>
<td>$\theta_{14}$ (closed triadic structures; $gw_{esp}.ITP$)</td>
<td>0.15</td>
<td>-0.29</td>
<td>0.15</td>
<td>0.51</td>
</tr>
<tr>
<td>$\theta_{15}$ (open triadic structures; $gw_{nsp}$)</td>
<td>0.06</td>
<td>-0.19</td>
<td>0.07</td>
<td>0.23</td>
</tr>
</tbody>
</table>
Table 4.

Results: Estimated Posterior Means, Medians and Credible Intervals for Each Parameter in the Organizational Network with Hierarchical Differentiation.

<table>
<thead>
<tr>
<th>Parameter (statistic)</th>
<th>Mean</th>
<th>2.5%</th>
<th>50%</th>
<th>97.5%</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \theta_1 ) (edges)</td>
<td>0.01</td>
<td>-0.38</td>
<td>0.02</td>
<td>0.40</td>
</tr>
<tr>
<td>( \theta_2 ) (reciprocity)</td>
<td>0.04</td>
<td>0.02</td>
<td>0.07</td>
<td>0.41</td>
</tr>
<tr>
<td>( \theta_3 ) (subunit reciprocity)</td>
<td>0.02</td>
<td>-0.31</td>
<td>0.01</td>
<td>0.33</td>
</tr>
<tr>
<td>( \theta_4 ) (subunit homophily)</td>
<td>0.03</td>
<td>-0.37</td>
<td>0.05</td>
<td>0.37</td>
</tr>
<tr>
<td>( \theta_5 ) (age absolute difference)</td>
<td>-0.02</td>
<td>-0.05</td>
<td>-0.02</td>
<td>0.00</td>
</tr>
<tr>
<td>( \theta_6 ) (hierarchical rank absolute difference)</td>
<td>-0.18</td>
<td>-0.64</td>
<td>-0.16</td>
<td>0.16</td>
</tr>
<tr>
<td>( \theta_7 ) (tenure absolute difference)</td>
<td>-0.05</td>
<td>-0.08</td>
<td>-0.06</td>
<td>-0.01</td>
</tr>
<tr>
<td>( \theta_8 ) (In-degree; gwdegree)</td>
<td>-0.03</td>
<td>-0.35</td>
<td>-0.05</td>
<td>0.33</td>
</tr>
<tr>
<td>( \theta_9 ) (Out-degree; godegree)</td>
<td>-0.00</td>
<td>-0.33</td>
<td>0.01</td>
<td>0.29</td>
</tr>
<tr>
<td>( \theta_{10} ) (closed triadic structures between units)</td>
<td>0.13</td>
<td>0.08</td>
<td>0.13</td>
<td>0.18</td>
</tr>
<tr>
<td>( \theta_{11} ) (triadic cyclic closure between units)</td>
<td>-0.33</td>
<td>-0.63</td>
<td>-0.35</td>
<td>-0.03</td>
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<tr>
<td>( \theta_{12} ) (four cycles)</td>
<td>-0.02</td>
<td>-0.06</td>
<td>-0.02</td>
<td>0.01</td>
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<tr>
<td>( \theta_{13} ) (closed triadic structures: gwesp.OTP)</td>
<td>0.09</td>
<td>0.06</td>
<td>0.11</td>
<td>0.44</td>
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<tr>
<td>( \theta_{14} ) (closed triadic structures: gwesp.OTP)</td>
<td>0.04</td>
<td>-0.15</td>
<td>0.05</td>
<td>0.35</td>
</tr>
<tr>
<td>( \theta_{15} ) (open triadic structures; gwnsp)</td>
<td>-0.03</td>
<td>-0.29</td>
<td>-0.03</td>
<td>0.19</td>
</tr>
</tbody>
</table>
Figure 1.

Triadic Transitive and Cyclic Configurations in the Advice Network across Subunit Boundaries.
Figure 2.

The Network of Advice Ties in the Pharmaceutical Department, and the Membership of Actors to Subunits
Figure 3.

The Network of Advice Ties in the High-Tech Company, and the Membership of Actors to Subunits
Figure 4.

Graphical Goodness of Fit Diagnostics for the Organizational Network with Flat Hierarchy.

Bayesian goodness–of–fit diagnostics

Note: The red line representing the observed data is inside the 95% predictive interval (delimited by the two gray lines) for any GOF diagnostic statistic considered.

Figure 5.
Graphical Goodness of Fit Diagnostics for the Organizational Network with Hierarchical Differentiation.

Bayesian goodness–of–fit diagnostics

Note: The red line representing the observed data is inside the 95% predictive interval (delimited by the two gray lines) for any GOF diagnostic statistic considered.