Network Dynamics and Organizations: A Review and Research Agenda

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ABSTRACT

This paper reviews the growing body of work on network dynamics in organizational research, focusing on a corpus of 187 articles -- both "micro" (i.e., interpersonal) and "macro" (i.e., interorganizational) -- published between 2007 and 2020. We do not see "network dynamics" as a single construct; rather, it is an umbrella term covering a wide territory. In the first phase of our two-phase review, we present a taxonomy that organizes this territory into three categories: *network change* (i.e., the emergence, evolution, and transformation of network ties and structures); the occurrence of *relational events* (i.e., modeling the sequence of discrete actions generated by one actor and directed towards one or more other actors); and *coevolution* (i.e., the process whereby network and actor attributes influence each other over time). Our review highlights differences between network dynamics based on relational states (e.g., a friendship) and relational events (e.g., an email message); examines the drivers and effects of network dynamics; and, in a methodological appendix, clarifies the assumptions, strengths, and weaknesses of different analytical approaches for studying network dynamics. In the second phase of our review, we critically reflect on the findings from the first phase and sketch out a rough agenda for future research, organized in terms of four overarching themes: the interplay between the dynamics of social networks conceived as relational states and relational events; mechanisms underlying network dynamics; outcomes of network dynamics; and the role of cognition.

Keywords: social networks; organizational networks; network dynamics; network change; coevolution.

A quarter century has passed since Salancik (1995), in his trenchant critique of organizational network analysis, challenged researchers to move beyond studies of network structure and its effects to offer a convincing account of how networks themselves come to be, how they are transformed, and how they disappear. This critique echoed others from outside the field arguing that, despite its many successes, network research failed to account for the formation, reproduction, and transformation of the very structures that make up the bedrock of its explanations (e.g., Emirbayer & Goodwin, 1994). These criticisms notwithstanding, much organizational network research continued to focus on "ties that are maintained over time, thus establishing a relatively stable pattern of network interrelationships" (Brass, Galaskiewicz, Greve, & Tsai, 2004: 795).

Over the last decade, however, there has been a discernible increase in the number of articles in management and organization studies that address network dynamics [1] and its implications for a broad range of organizational phenomena. Over the period covered by our review (2007-2020), the total number of papers on networks in management and organizational journals has grown (from a cumulative 1395 papers in 2007 to 1748 papers in 2020) and the share of network papers as a percentage of all papers published in leading management journals each year has hovered around 7 percent [2]. Of the network papers, roughly 10 percent have covered network dynamics (see Figure 1). Interest in network dynamics has been spurred by renewed calls in management journals (e.g., Ahuja, Soda, & Zaheer, 2007, 2012; Clegg, Josserand, Mehra, & Pitsis, 2016; Provan, Fish, & Sydow, 2007), the growing availability of time-stamped data, such as records of emails and online transactions (see Kitts & Quintane, 2020), and the emergence of new analytical tools for modeling network dynamics (e.g., Almquist & Butts, 2014; Snijders, 2001; Wasserman & Robins, 2005). We believe there is considerable

untapped value to be derived from categorizing and integrating this body of research. The study of network dynamics poses unique conceptual and empirical challenges even as it promises new insights into a broad range of organizational phenomena.

Insert Figure 1 about here

The topic of network dynamics has been taken up in previous reviews, [3] but ours is distinctive in several ways. First, this is a broad review unconfined to any particular topic or phenomenon of interest, such as network cognition (e.g., Brands, 2013), personality (Landis, 2016), brokerage (Kwon et al., 2020), entrepreneurial networks (Hallen, Davis, & Murray, 2020), or interorganizational ecosystems (Shipilov & Gawer, 2020). We cover a wide swath of research on network dynamics conducted by both "micro" organizational researchers interested in the dynamics of interpersonal networks and "macro" organizational researchers interested in the dynamics of inter-organizational networks [4]. Second, this is the only review of organizational network research that distinguishes between network dynamics as changes in "relational states" (e.g., the formation, transformation, or dissolution of a friendship tie) and network dynamics as the occurrence of "relational events" (e.g., emails exchanged over time among a set of actors) [5]. As we argue in the paper, these two types of dynamics focus on different kinds of phenomena, yet they are rarely distinguished in the research on organizational network dynamics. Much of the history of organizational network research has been about the study of relational states and their effects. When we study the dynamics of relational states, we are studying relationship change. By contrast, when we study the dynamics of relational events, we are studying sequence and timing of actions. Our review identifies questions for future research that could advance our

understanding of network dynamics and its effects by jointly considering networks as instantiated in relational states and relational events. We include a methodological appendix that compares and contrasts different analytical approaches used to model the dynamics of relational states and relational events. As we show, each analytical approach focuses on a different aspect of network dynamics, makes different assumptions about the underlying phenomenon, and is best suited to answering different kinds of questions. Third, we examine the relationship between network dynamics and outcomes of interest to management research, such as individual and organizational performance. Previous reviews have focused on the dynamics of the network rather than examining how changes in a network are related to outcomes of interest to organization scholars, such as the performance, behaviors, and cognition of actors.

Following recent editorial guidance (Parmigiani & King, 2019), we adopt a two-phase approach to clearly distinguish what our review found from the implications and directions for future research that we draw from our review (see Perrigino, Chen, Dunford, & Pratt, 2021, for a similar approach). In Phase I, we sift through the published papers in our sample and use a framework to categorize papers and summarize key findings. In Phase II, we take what we have learned from our review of the literature and identify key challenges and opportunities and suggest a research agenda.

PHASE I

METHOD AND SCOPE OF REVIEW

The process of literature search and paper selection consisted of four steps (see Figure 2). **Step 1**. We used the ISI Web of Science databases to search management journals for papers on network dynamics.[6] Search terms included: *network** in combination with *change**, *dynamic**, *evolution*, *development*, or *emergence*; OR *tie** in combination with *formation*, *persistence*,

maintenance, or *dissolution* [7]. The search encompassed articles published before January 2021, yielding 1246 articles.

Step 2. We next reviewed titles, keywords, and abstracts, and dropped less relevant papers using four criteria: (1) Did the paper specifically address social networks among individuals, groups, or organizations? This criterion led to the exclusion of studies that focused on networks of non-human, non-organizational entities, such as networks among computers, and artificial neural networks. (2) Was the paper relevant to management and organizations? This led to the exclusion of papers that, for example, focused exclusively on social media. (3) Did the paper substantially address (rather than mention in passing) network dynamics? (4) Was the paper a review or editorial essay? If so, we excluded the paper. There was some ambiguity about whether to include eighteen papers; this was resolved via independent coding and subsequent discussion as a team. The second step left us with 230 papers.

Step 3. Next, we retained papers that were published since 2007 because explicit calls for greater attention to network dynamics began appearing right around that time (e.g., Ahuja et al., 2007; Contractor, Wasserman, & Faust, 2006; Kilduff, Tsai, & Hanke, 2006; Provan et al., 2007). This step left us with 177 articles.

Step 4. We supplemented this corpus of papers with 10 additional papers from other journals.[8] All are either well-cited papers on this topic or provide additional insights beyond the papers from our journal-specific search.

The final sample consists of 187 journal articles on network dynamics. Our review focuses on these papers, but we occasionally refer to other papers, including a couple of papers that were published online in 2021, to contextualize and deepen our arguments.

Coding of papers. We coded each of the 187 papers for the categories used in Table 1. As a first step, three of the authors closely examined a sub-sample of 30 papers and forged consensus over how they should be coded. The 30 papers were a mix of macro and micro; and they were selected to represent the full period covered by our sample. Second, based on the consensus that was forged, the first author coded the remaining papers. Third, the full team reviewed the coding and flagged any papers whose coding was debatable -- there were 17 such papers. The team members then met to discuss and attained full consensus on the coding. [9]

Insert Figure 2 and Table 1 about here

CONCEPTUALIZING NETWORK DYNAMICS

Social network research offers a distinctive lens for studying social structure, which it represents as a set of entities connected by a set of relations. There are, of course, other ways that the elusive yet seemingly indispensable concept of social structure can be defined and studied (Sewell, 1992). What sets the network approach apart is that it seeks to "study social structures directly and concretely" by analyzing the arrangement of relations among members of a social system using a set of tools derived from graph theory (Wellman & Berkowitz, 1988: 3). The reductive nature of this representational model of structure has made it possible to develop network theories that are both mathematically precise and highly portable across disciplines. A broad range of phenomena, ranging from neural connectivity to the structure of the airline industry, have been fruitfully modeled as social networks. In organizational research, network theory and methods have long been used to examine the structure of both interpersonal (e.g., Brass, 1981) and interorganizational (e.g., Burt, 1983) relations, and to study their effects on

outcomes of organizational interest, such as job attitudes and performance (see Nohria & Eccles, 1992 for an early review).

Under the influence of structural sociology, early organizational network research tended to treat network structure as a stable "persisting order or pattern of relations among units" (Laumann & Pappi, 1976: 213). For example, Lincoln (1982: 26) asserted that what makes an organization a network is "the pattern of recurring linkages among its parts." [10] The emphasis on persistence was reinforced by empirical results showing that interpersonal relations, such as friendship, appear to stabilize quickly (Newcomb, 1961; cf. Moody, McFarland, & Bender-deMoll, 2005). This apparent stability does not mean, however, that networks are static. For example, networks can and do change in response to environmental shocks and disruptions (e.g., Barley, 1986). But networks may change and evolve even in the absence of disruptive external events. Indeed, network change may be a characteristic property of social networks, "something akin to the hum of a running engine" that produces "vibration and wiggle," and has implications for the accrual of advantage (Burt & Merluzzi, 2016: 370).

We are not claiming, of course, that previous research has completely ignored the possibility that networks change and evolve over time. Indeed, even some of the earliest work on organizational networks clearly appreciated that social networks do change (e.g., Homans, 1950; Kapferer, 1972). Much work since then has gone into developing a range of sophisticated models for studying network dynamics (e.g., Agneessens, 2021; Almquist & Butts, 2014; Doreian & Stokman, 1997; Kalish, 2020; Snijders, 2001). These dynamic models conceive of relationships (and, in some cases, nodes themselves) as evolving in time under the influence of forces whose presence and strength can be statistically estimated. But irrespective of whether social networks are modeled as static or as dynamic, most models assume that the ties in the network overlap in

time (i.e., are simultaneously co-present). Indeed, the co-presence of ties forms the basis of network structure. If the duration of ties becomes much shorter than the timescale of relationship formation, ties become a series of interactions with little or no temporal overlap. When this happens, "the usual notion of network structure breaks down, while alternative concepts of sequence and timing become paramount" (Butts & Marcum, 2017: 52). The ability to detect patterns in the order in which a series of interactions unfolds could provide fresh insight into social structure and its effects (Cornwell, 2015).

What are Network Dynamics? A Taxonomic Framework

The purpose of our taxonomic framework is to classify and organize research on network dynamics. We do not see "network dynamics" as a single construct; rather, it is an umbrella term covering a wide territory. The central panel in Figure 3 divides this territory into three distinct types of network dynamics.

Insert Figure 3 about here

The first type consists of work on what we refer to as *network change.* By network change, we mean change in who is connected to whom for specific kinds of tie—this work consists, in other words, of models of tie presence/formation and tie absence/dissolution. However, we also include resultant higher-order changes, such as those at the node level (e.g., the number of ties each node has) and at the network level (e.g., the extent to which the group has a centralized network structure). Higher order change implies lower-order change, but the reverse is not always true. For example, over time, the addition of new ties can close previously open structural holes in a network and the deletion of old ties can (re)open previously closed holes. Consider the

illustrative network presented in Figure 4. From the point of view of specific ties, the changed networks in the left and right panels are different — in the left panel, A drops her existing tie and adds a tie to F; in the right panel, B drops her existing ties and adds a tie to C. The resultant networks in the left and right panels are different at the level of ties, but the overall structure [11] of the network is the same in both panels. In our framework, each level of network change has some degree of autonomy and stability; yet each level is linked to and dependent upon other levels. Studies of network change either seek to understand the social processes that would lead certain nodes to be connected and other nodes to be disconnected (e.g., Clough & Piezunka, 2020; Tasselli, Zappa, & Lomi, 2020); or they attempt to explain change in network structures over time (e.g., Hernandez & Shaver, 2019; Kleinbaum, 2018).

Insert Figure 4 about here

A second type of network dynamic is the *occurrence of relational events*. Most ties studied in network research consist of what are termed relational states (Borgatti, Brass, & Halgin, 2014). Relational states are continuous and persistent and can be thought of as a relational role – something the node *is* with respect to another node. A common example in the interpersonal literature is when A is B's friend. In the interorganizational context, a common example is when a firm is in a joint venture with another firm. By contrast, relational events consist of relational behaviors (e.g., A sends B an email) and transactions (e.g., A buys goods from B)—see e.g., Quintane & Carnabuci (2016). Relational events are transitory and can be thought of as things a node *does* with another node (e.g., goes to a movie with) rather than something it *is* with another node (e.g., a friend). Whereas it makes sense to speak of relational

states changing over time, the episodic character of relational events means that they do not change as much as occur (or fail to occur). Studies of relational events, therefore, try to capture the characteristics of the stream of events that occur between pairs of nodes over time, such as the sequencing and spacing in time of electronic messages (e.g., Schecter & Quintane, 2021).

A third type of network dynamics consists of changes in nodes as a result of having ties and interacting with each other. There are many papers in the organizational literature that examine dynamic flows and influences. For example, an early study examined the diffusion of "poison pills," a corporate takeover defense, across the network of board interlocks (e.g., Davis, 1991). This is a well-established line of work, and over the years network researchers have developed rich and varied models of dynamics over a network (e.g., Burt, 1987; Fiss, Kennedy, & Davis, 2012; Rogers, 2003; Valente, 1996). However, most of the work on diffusion and adoption of innovation assumes dynamic flows over a fixed network. By contrast, the focus of this paper is on the dynamics of the network itself. Therefore, the only studies we review of network flows are *coevolutionary models*, which examine how the characteristics of networks and the attributes of the nodes in the network influence one another over time (see Kalish, 2020).

Network Change Based on Relational States

Table 1 classifies the papers in our sample using the framework depicted in Figure 3. Table 2 provides a list of illustrative studies. The table shows that "micro" and "macro" scholarship on network dynamics have proceeded along similar lines. In both micro and macro work, a clear majority of studies attend to the dyadic level of analysis (roughly 60 percent). There are fewer studies that address the node-level of analysis (36 percent) and fewer still that address the network level of analysis (19 percent). Micro and macro studies of network dynamics have both invoked actor attribute-based (80 percent) and relational (66 percent) explanations of network

change more often than changes precipitated by the (non-network) contextual factors (40 percent).[12] We begin by reviewing work that examines network change in terms of changes in relational states.

Insert Table 2 about here

Dyadic. Studies of dyadic change have sought to explain the formation and dissolution of ties; changes in tie strength; and the transformation of ties over time. For example, a recent study of managers sought to understand the formation of communication ties between managers from different units of a multiunit organization in the energy industry (Tasselli et al., 2020). Managers who shared similar "organizational vocabularies" were more likely to connect despite the fact they were rooted in different organizational units. Similarity in language trumped dissimilarity in unit membership in the formation of new ties. The influence of similarity and dissimilarity across a range of attributes on the formation and dissolution of interpersonal ties is a common topic of inquiry at the micro level. However, people sometimes also make instrumental decisions about which ties to retain and which ones to drop (e.g., Dahlander & McFarland, 2013; Kleinbaum, 2018). Interpersonal ties can change in strength over time as a function of socialization (e.g., Aven, 2015) and performance feedback (e.g., Parker, Halgin, & Borgatti, 2016). Less often studied are transformations in ties over time. A study that illustrates how such transformations can occur examined lawyers working on intellectual property cases: a history of collaboration between lawyers who later became rivals in court exacerbated conflict because salient others expected them to be antagonists (Uribe, Sytch, & Kim, 2020).

Research on interorganizational tie formation examines the formation of collaborative relationships, such as strategic alliances (e.g., Furlotti & Soda, 2018), co-investment syndicates (e.g., Zhelyazkov & Tatarynowicz, 2021), and board interlocks (e.g., Withers, Howard, & Tihanyi, 2020). Research on board interlocks (a board interlock tie arises when two firms have a board member in common) has played a central role in the interorganizational literature on dyadic tie changes. For example, research examining publicly traded U.S. firms has found that firms are more likely to form interlocking ties when their core technologies are aligned; and, once formed, board interlock ties can facilitate the subsequent formation of R&D alliance ties (Howard, Withers, & Tihanyi, 2017). Other studies have directly examined the formation of "negative" ties between firms, such as antitrust lawsuits (Sytch & Tatarynowicz, 2014b), competition (Downing, Kang, & Markman, 2019), and patent litigation (Howard et al., 2017). As in the interpersonal literature on dyadic change, tie dissolution has tended to receive less theoretical attention in the interorganizational research than tie formation [13]. A study of alliance in the global liner shipping industry found greater rates in the dissolution of ties as a function of market competition and time-dependent effects of earlier direct and third-party effects, suggesting that the factors that drive alliance dissolution differ from those that drive alliance formation (Greve, Mitsuhashi, & Baum, 2013). In addition to research on strategic alliances and board interlocks, market exchange ties have been a common topic in tie dissolution studies. For example, a study of state-level lobbyists and clients in the state of Texas found that ties between firms are more likely to dissolve when key employees who connected the firms through their interpersonal networks depart (Bermiss & Greenbaum, 2016). A different study examined a theory of vicarious performance effects on tie dissolution among firms and their suppliers in Formula One car racing (Clough & Piezunka, 2020).

Nodal. Network research distinguishes the overall network ("whole-network") from the network consisting of the node's direct contacts and the ties among them ("the ego network"). Network change at the node level consists of changes in the number and kinds of nodes that an individual is connected to (ego-network composition) as well as changes in the ego-network structure (e.g., who is connected to whom). Roughly 36 percent of both micro and macro studies in our sample examined network change at the nodal level. The composition of an ego-network can change as ties are formed and dropped and as the characteristics of the nodes in the network change over time. The structure of an ego network changes when the pattern of connections among those in the network changes. As an example of change in composition, a manager may experience a decrease in ties to women after transferring to a different division of the organization. As an example of change in structure, a manager's ego network may contain more structural holes (i.e., many contacts who are unconnected to each other) as she rises in the organization and has people from different divisions reporting to her. A study of change in friendship networks in a Dutch radiology department following the introduction of a disruptive new technology found that some people (high self-monitors) maintained the same (structural hole-rich) network pattern despite many changes at the level of their individual ties (Sasovova, Mehra, Borgatti, & Schippers, 2010). Studies have also examined changes in the size and density of individuals' social networks (e.g., Bensaou, Galunic, & Jonczyk-Sedes, 2014; Kleinbaum & Stuart, 2014b). In addition to examining changes in the structure of an individual's network over time, micro research has examined how the set of people in a network can change over time. For example, entrepreneurial network research has examined changes in the composition of an entrepreneur's core personal network caused by the entry of new network contacts (alters) or the exit of existing network contacts (Vissa & Bhagavatula, 2012: 274).

Macro research has examined stability/volatility in a firm's alliance network (e.g., Kumar & Zaheer, 2019). A study of corporate reputability found that the quality of corporate partners in a firm's network declines following unethical corporate behavior, with existing partners being replaced by low-quality ones (Sullivan, Haunschild, & Page, 2007). A different kind of nodal change involves the transformation of the nodes in a network. For example, a study of "node collapse" in the biotech industry found that acquiring firms can create synergies by gaining control over the network of the acquired firm (Hernandez & Shaver, 2019). When a firm acquires another, it also inherits its network ties. This means that the acquisition of one firm by another can lead to a sudden and significant change in the structure of the acquiring firm's network (Hernandez & Menon, 2018).

Network. Changes at the network level of analysis involve changes in the composition [14] and structure of the overall network. In the papers in our sample, studies of changes at the network-level are comparatively rare in both micro (15 percent) and macro (24 percent) research.

In organizations, the composition of an interpersonal network can change due to the entry and exit of employees (Methot, Rosado-Solomon, & Allen, 2018) or the redeployment of members (e.g., Stuart, 2017). More generally, human resource practices, such as recruitment, selection, and separation, can change the composition of workplace networks (Methot et al., 2018). External events, such as mergers and acquisitions, and internal reorganizations can trigger changes in both the composition and structure of networks at the interpersonal level (Woehler et al., 2021). For example, research has found that the density of communication networks between acquiring and target firms following firm acquisition initially increased as employees learned to adjust to one another and developed new routines for coordination; but as employees learned to coordinate with their new colleagues, the density of the overall communication network

decreased (Allatta & Singh, 2011). Changes in policies and procedures within the firm, too, can precipitate changes at the network level in interpersonal networks. For example, a study of inventor networks in a firm found that changes in a firm's R&D budget allocation created opportunities and incentives that led to changes in the patterning of the overall network as R&D staff started connecting with a more diverse set of colleagues to pursue projects (Argyres, Rios, & Silverman, 2020).

The composition of a firm's ego network can change for a variety of reasons, including environmental events, such as changes in government policies, or changes in the firm's goals and strategy. Changing the partners in an alliance network can help firms avoid getting locked into partnerships that are unproductive and have outlived their usefulness, and this may be why stability in the set of nodes that make up a firm's alliance network can be a drag on the firm's performance (Kumar & Zaheer, 2019). Changes in government regulations and corporate restructurings can also drive changes in the structure of interfirm networks (Aggarwal, Chakrabarti, & Dev, 2020). In industrial alliance networks, when many firms pursue mergers and acquisitions to access new structural holes, the overall industry network can shrink and become less modular (i.e., contain fewer cliques) (Hernandez & Menon, 2018).

Changes in the structure of interorganizational networks have been an important topic in macro network research (Provan et al., 2007). For example, macro research has tried to understand how industry-level networks over time acquire the structural characteristics of a "small-world", in which there are cohesive clusters linked together by bridging ties (Watts & Strogatz, 1998). In competitive and information-intensive industries, evidence suggests that the evolution of alliance networks follows an inverted U pattern where an initial increase in the small-world properties of the network is followed by a subsequent decline (Gulati, Sytch, &

Tatarynowicz, 2012). Other forms of network-level change in structure examined in macro research include changes in the extent to which a network is centralized around a few nodes (Paquin, & Howard-Grenville, 2013), changes in the extent to which a network exhibits a core-periphery structure (Aggarwal et al., 2020; Lomi & Pallotti, 2012), and changes in network modularity (Hernandez & Menon, 2021).

Occurrence of Relational Events

The work on network dynamics we have described thus far has examined networks where the ties are relational states—i.e., something that a node is with another node (e.g., a friend; an alliance partner). States have continuity over time; they are not permanent (nothing is) but they have a kind of "open-ended persistence" (Borgatti & Halgin, 2011: 1170). States can vary not only in terms of duration but also in terms of their strength and intensity. A far less frequently studied (constituting 9 percent of the micro papers and just 3 percent of the macro papers in our sample) kind of network dynamic focuses on relational events, which can be thought of as actions, things one node does to another (e.g., A sends B a note). Events are discrete and occur over relatively short time scales [15]. Whereas it makes sense to study how relational states change over time, relational events do not change so much as they occur and vanish [16]. The relational event model assumes that events occur at certain rates, where the rates are a function of the previous sequence of events and exogenous factors. Examples of relational events that have been examined in interpersonal networks include co-attendance of academic conferences (Chai & Freeman, 2019); physical interactions between scientists (captured using Bluetooth enabled sensors— e.g., Matusik et al., 2019); tactical communications in military teams (Schecter et al., 2018); and emails exchanged between employees (Quintane & Carnabuci, 2016). Examples of relational events that have been examined between firms include patient referrals between

hospitals (Kitts, Lomi, Mascia, Pallotti, & Quintane, 2017) and communications between organizations involved in the response to a natural disaster (Spiro, Acton, & Butts, 2013).

The focus of studies, both micro and macro, that examine network dynamics in terms of relational events has been on explaining the sequence and timing of events. A study of email communications among the employees of a knowledge-intensive organization used a relational events lens to show how "brokers broker" (Quintane & Carnabuci, 2016; see also Obstfeld, Borgatti & Davis, 2014). Individuals in sparse networks (the brokers) more often brokered information via short-term interactions (i.e., events) with colleagues who were outside their network of long-term relationships (i.e., states); and when doing so, brokers were more likely (than those in interconnected networks) to intermediate the flow of information between the parties they brokered. But when it came to brokering between colleagues in their long-term network of contacts, brokers were more likely (than those in interconnected networks) to facilitate direct information exchange between the parties they brokered. Similarly, macro studies have relied on event-based data to better understand the relational sequences that underlie brokerage and to assess how the resulting findings depart from what could have been inferred from examining brokerage as a static structure (e.g., Amati, Lomi, & Mascia, 2019; Spiro et al., 2013).

Event-based data do not have to be time-stamped but, when available, such data can offer rich insight into organizational processes. For example, using time-stamped data from 55 work teams of military personnel engaged in a tactical scenario, Schecter et al. (2018) showed that the temporal relationship between events in a sequence varied depending on how its members perceived the quality of coordination and information sharing among a team's members; and certain patterns of behaviors were repeated at different rates in teams with varying emergent

states. At the macro level, Kitts et al. (2017) examined interactions among organizations not as states but instead in terms of structural-temporal patterns. Using data from a sample of Italian hospitals, the study found evidence of different mechanisms of interorganizational reciprocation, one operating on a short time horizon and the other on a long-term horizon.

Coevolution Models

Coevolution studies examine the reciprocal and dynamic relationship between social influence processes and social selection processes. A first and basic type of coevolution model examines how actor attributes coevolve with networks. For example, employees' personal networks in the workplace may coevolve with their perceptions of team psychological safety (Schulte, Cohen, & Klein, 2012) and perceived stress (Kalish, Luria, Toker, & Westman, 2015). A study of 121 employees from eight healthcare organizations hypothesized that a person's intent to quit one's job and the social network around the individual shape each other over time (Tröster, Parker, van Knippenberg, & Sahlmueller, 2019). A second type of coevolution model examines how two different types of networks coevolve. For example, Ellwardt, Steglich, and Wittek (2012) showed that the sharing of gossip between two employees increased the likelihood of a future friendship tie forming between them. However, they also found that individuals with disproportionately high gossip activity have fewer friends in the network, suggesting that the use of gossip to attract friends has a limit.

At the macro level, Stadtfeld, Mascia, Pallotti, & Lomi (2016) studied the coevolution of internal organizational structures and interorganizational networks among hospitals in a mountainous region of Italy that collaborated on patient transfers between hospitals. The study proposed that assimilation mechanisms led collaborating hospitals to adopt the same portfolio of internal clinical practices, while reliance on functional differentiation mechanisms led hospitals

to maintain and even amplify differences in their internal clinical practices. Another macro study examined how the networks of trade agreements and investment treaties coevolve (Htwe, Lim, & Kakinaka, 2020). The study found evidence of cross-network dyadic influence, such that countries that signed a bilateral investment treaty (BIT) were willing to establish a regional trade agreement (RTA) but those that signed an RTA were reluctant to establish a BIT. Furthermore, the study found evidence of cross-network preferential attachment: countries tend to form RTAs with countries that have more BIT and RTA links; however, countries tend to form RTAs with partners who have more BIT links but are less likely to form RTAs with countries with many RTA links.

DRIVERS OF NETWORK DYNAMICS

Papers seeking to explain network dynamics have invoked a wide range of theories (Monge & Contractor, 2001). These theories tend to focus on one of three categories of factors, which we refer to as non-network contextual factors (e.g., the formal organization), actor attributes (e.g., personality) and relational factors (e.g., other ties). These are shown in the left panel of Figure 3. All three types are invoked to roughly the same extent in both micro and macro research on network dynamics (see Table 1). We interweave examples from both domains in this section. Table 3 lists illustrative studies for each of the three categories in the micro/ interpersonal and macro/ interorganizational domains. Later, in Phase II, we reflect on the work we reviewed in Phase I and identify a parsimonious set of generic mechanisms that underlie network change.

Insert Table 3 about here

(Non-network) Contextual Factors

In micro research, context-based drivers of network dynamics include formal organizational designs and work processes (e.g., Argyres et al., 2020; Caimo & Lomi, 2015; Clement & Puranam, 2018), geographic and physical location (e.g., Sailer & McCulloh, 2012), performance feedback (Parker et al., 2016), and disruptive events, such as corporate downsizing (Aalbers, 2020; Shah, 2000). In macro research, context-based drivers include changes in regulatory environments (e.g., Aggarwal et al., 2020; Zhang, Tan, and Tan, 2016), geographic proximity and colocation (e.g., Ghosh, Ranganathan & Rosenkopf, 2016; Kim, Howard, Pahnke, & Boeker, 2016; Kumar & Zaheer, 2021), and mergers and acquisitions (e.g., Hernandez & Shaver, 2019).

A prosaic contextual factor that can shape interpersonal network dynamics in work organizations has to do with work roles and projects. The nature of project-based work could require that a supervisor who had been working closely with a team in one country for some time shift her attention to a team in a different country, precipitating changes in her social network (see, e.g., Quintane, Pattison, Robins, & Mol, 2013; also see Kleinbaum, 2012, on the effects of having worked in headquarters on managers' subsequent social networks; and Jonczyk, Lee, Galunic, & Bensaou, 2016, on how patterns of career mobility shape interpersonal network dynamics). Formal organizational structures provide opportunities for interaction and inform employees' social identities, and thereby shape the formation and dissolution of interpersonal ties between employees (e.g., Kleinbaum, Stuart, & Tushman, 2013). The physical layout of workspaces, too, can substantially shape opportunities and incentives for interactions, and thereby influence the patterning of networks over time (e.g., Sailer & McCulloh, 2012). Changes in context, such as organizational restructurings, increase the uncertainty faced by employees,

and this can change who employees connect with in informal social networks (e.g., Srivastava, 2015). Uncertainty may be highest immediately following a disruptive event, such as an acquisition, but as time goes by, uncertainty recedes as employees learn who they need to connect with and rewire their networks accordingly (Mirc & Parker, 2020). Unplanned events, such as player injuries in professional hockey (Stuart, 2017), are another kind of contextual force that can shape interpersonal dynamics.

The idea that contextual forces shape patterns of network change is well established in the macro literature. Early research on alliance formation, for example, examined how organizations form alliances with other organizations in order to access resources and cope with environmental demands (Pfeffer & Salancik, 1978). Jolts and shocks in the external environment can influence an organization's alliance strategy and create opportunities for once marginal firms to move to a more central position in evolving industry networks (e.g., Corbo, Corrado, & Ferriani, 2016). Other contextual factors include cultural and institutional norms and regulatory environments, all of which can shape the attractiveness of alliance activity and thereby shape network dynamics (e.g., McDermott, 2007; Zhang et al., 2016). Contextual forces influence network dynamics because they help determine the "rules of engagement" that facilitate certain alliance activity and constrain other activity (Koka, Madhavan, & Prescott, 2006: 723). A different line of macro research has emphasized the role of geography and proximity in the formation of alliance networks (Ghosh et al., 2016) and board interlocks (e.g., Kim et al., 2016). Contextual forces shape not just the dynamics of an organization's network; they can shape the structure and composition of the networks for entire industries (e.g., Tatarynowicz, Sytch, & Gulati, 2016).

Actor Attributes

There are a variety of explanations of network structure that highlight actor (i.e., the node in a network) attributes as the engine of network dynamics. Some focus on generalized actor propensities, such as a preference for newcomers in organizations to form friendships with demographically similar others (e.g. Gibbons & Olk, 2003), and the general avoidance of unbalanced relationships (e.g., Tasselli & Caimo, 2019) [17]. Others have focused on actor-level tendencies that vary systematically across actors, such as personality (e.g., Kleinbaum, 2018), psychological orientations (e.g., Obstfeld, 2005), motivations (e.g., David, Brennecke, & Rank, 2020), identities (e.g., Lomi, Lusher, Pattison, & Robins, 2014), and attitudes towards networking (e.g., Kuwabara, Hilderbrand, & Zou, 2018). In some cases, these actor tendencies, such as personality, reflect a kind of routine agency that is unreflective and grounded in habit (e.g., Sasovova et al. 2010), whereas, in other cases, actors are depicted as deliberative and goal-oriented (e.g., Tröster et al., 2019). An inductive study of newly promoted service professionals over a 16-month period found evidence of differences across individuals in their approach to networking, ranging from the passive "purists" who let networks develop without any active intervention, to highly purposive and instrumental "devoted players" who devised clear game plans about who to connect with and how (Bensaou et al., 2014).

The demographic attributes of people have long been regarded as key drivers of tie formation and network evolution. For example, an employee's age at the time of hire had a curvilinear relationship with the number of friendships the employee maintained with former coworkers after leaving the organization, in part because mid-career is when such relationships are most valuable (Walsh, Halgin, & Huang, 2018). A well-known phenomenon related to demography is homophily, defined as the tendency for (positive) ties to occur between people

who are similar in terms of socially significant characteristics such as race, gender, age, education, occupation, and social class (McPherson, Smith-Lovin, & Cook, 2001). For example, Reagans (2011) found that teachers in five schools who were more similar in age had stronger ties. They also found that co-located teachers (i.e., spatially similar) communicated more frequently and felt more emotionally attached. Tasselli, et al. (2020) found that cultural similarity, in terms of managers sharing similar individual vocabularies in describing their organization, facilitates the formation of communication ties between formal organizational boundaries, nurturing informal task-related ties across subunits over time.

Strategy research often portrays organizations as instrumental actors that use interorganizational relationships to secure advantage by reducing costs, minimizing risks, and gaining access to needed resources (e.g., Gulati, 1999). Actor characteristics that have been used to explain network dynamics in the literature on interorganizational networks include strategic orientations (e.g., Koka et al., 2006), risk reduction (e.g., Knoben & Bakker, 2019), resource complementarity (e.g., Furlotti & Soda, 2018), and status (e.g., Shipilov, Li, & Greve, 2011). Whereas some studies of interorganizational network dynamics have focused on characteristics that distinguish one firm from one another, others have emphasized general tendencies across firms, such as the general preference to build new ties with trusted partners (e.g., Baum, Rowley, Shipilov, & Chuang, 2005), a preference for partners who possess superior social capital (e.g., Hernandez & Shaver, 2019), and the quest for power and control (e.g., Howard et al., 2017). However, actor's attempts to develop ties that increase their power and control over other actors can trigger counteractions by those actors, suggesting that network dynamics evolve as a function of moves and countermoves rather than just unilateral action (e.g., Kumar & Zaheer, 2021; Rogan & Greve, 2015). Given the heightened possibility of opportunism in market

relations, risk reduction is a common reason for network change in macro research. For example, the motivation to reduce the leak of proprietary knowledge to other firms can lead firms to strategically prune and graft their network of alliances (e.g., Hernandez, Sanders, & Tuschke, 2015). Although the general tendency may be to form ties with trusted others, macro research has sought to understand the actor-level motivations behind the formation of clique-spanning ties that involve greater uncertainty but provide potential access to new ideas and novel resources (e.g., Baum, Cowan, & Jonard, 2010).

Studies of network dynamics among new venture firms have examined how differences in networking strategies are associated with differences in the speed and efficiency with which new ties are formed (e.g., Hallen & Eisenhardt, 2012). Macro research has also examined how the exit of a firm's managers can influence the dissolution of market ties between firms. A study of 232 dyadic ties between advertisers and New York City advertising agencies found that as the number of executives and exchange managers who leave increases, the chances of tie dissolution between the firms they represented also increases, although these effects varied as a function of the hierarchical level at which the exits occurred and the strength of market ties (Broschak & Block, 2014).

Relational Factors

Relational factors refer to the social environment surrounding a tie, reflecting the tendency for existing ties to affect the probability of other ties. For example, the probability of two strangers forming a friendship increases as a function of the number of friends they have in common (Cartwright & Harary, 1956): we tend to befriend our friends' friends (referred to as "transitivity"), whether because of increased opportunity, or, invoking balance theory (Heider, 1958), because doing so avoids the cognitive dissonance that results from disliking someone that

is liked by someone we like. Similarly, we often find that an actor is more likely to reciprocate connections over time: we are more likely to befriend a person in the future if that person has been friendly towards us in the past (i.e., "reciprocity"). Relational factors are sometimes referred to as "structural" or "endogenous" [18].

Other commonly studied structural tendencies include preferential attachment (i.e., the tendency to form ties with those actors that already possess many ties, in part because of their greater visibility), and cyclicality in triads [19]. Using four waves of sociometric data, a study of the employees of an organization used social status and social capital theories to forward competing hypotheses about the emergence and structure of advice relations (Agneessens & Wittek, 2012). In support of the social capital perspective, which posits an obligation to return favors, the study found that reciprocal advice relations were overrepresented. In support of the social status perspective, the study found that high status individuals tended to avoid asking for advice from low status others. These structural tendencies can vary over time as a function of the uncertainty that actors face (Mirc & Parker, 2020) and the kind of tie under consideration (Carnabuci, Emery, & Brinberg, 2018). Interpersonal network studies have also examined how the structure of a network influences subsequent network dynamics. For example, the presence of structural holes in a person's network influences the likelihood of subsequent tie formation and dissolution (e.g., Balkundi, Wang, & Kishore, 2019; Cannella & McFayden, 2016).

Similar structural tendencies have been documented by macro researchers studying alliances and other relationships between firms. Building on pioneering work on the topic (Gulati, 1995; Nohria & Eccles, 1992), macro studies have shown that network evolution among firms is conditioned by their prior network structure. For example, firms are more likely to form new alliance ties with firms they know through their previous collaborations and the partners of

the firms in the previous collaborations (Gulati, 1995; Gulati & Gargiulo, 1999). Existing relationships between two firms can influence the likelihood of tie formation with a third firm (Kim et al., 2016). The formation of syndicate networks is influenced by the structure and content of prior ties among potential members of the syndicate (Zhang, Gupta, & Hallen, 2017). And prior network embeddedness shapes subsequent changes in a firm's collaboration network (e.g., Zhang & Guler, 2020). These network effects can vary across industries (e.g., Ghosh et al., 2016), and they can vary as a function of actor attributes, such as an organization's age (Kim, Oh, & Swaminathan, 2006) and contextual events, such as the passage of the Sarbanes-Oxley legislation in the United States (Withers, Kim, & Howard, 2018).

OUTCOMES OF NETWORK DYNAMICS

Organizational scholars have produced a large body of work that builds and tests arguments describing how the characteristics of social networks shape the attitudes, actions, and performance of individuals, groups, and organizations (see, e.g., Kilduff & Brass, 2010). Our understanding of how network *dynamics* influence outcomes of organizational relevance is comparatively under-developed. The kinds of outcomes that have been studied vary: some have examined performance (e.g., Brennecke, 2020) and innovation (e.g., Kumar & Zaheer, 2019) as an outcome of network dynamics; other studies have focused on behaviors (e.g., de Klepper, Labianca, Sleebos, & Agneessens, 2017) and cognition and attitudes (e.g., Kalish et al., 2015) as the primary outcome of interest. Table 4 organizes micro and macro studies of network dynamics by the kind of outcome studied and describes some studies of each kind.

Insert Table 4 about here

Performance

Performance is a well-studied outcome in our sample papers (micro: 23%, macro: 20%, see Table 1; e.g., Burt & Merluzzi, 2016; Brennecke, 2020). It also includes some close variant of performance, such as creativity (e.g., Soda, Mannucci, & Burt, 2021), innovation (e.g., Lee, 2010), and, in the case of macro studies, such outcomes as firm valuation (e.g., Zheng, Liu, & George, 2010) and market share (e.g., Vissa & Bhagavatula, 2012).

The relationship between networks and performance is unlikely to be unidirectional because the relations that make up the network are endogenous and partly determined by performance (Jackson, Rogers, & Zenou, 2020). Endogeneity questions the causal prominence of network structure on individual outcomes, and, by implication, the degree of agency available to the individual nodes in the network to shape outcomes (Benasou, Galunic, & Jonczyk-Sedes, 2014). An influential example of organizational work that tries to sort out endogeneity at the micro level is Lee (2010). The study used data on the collaboration network of U.S. biotech inventors (1976-1995) to examine the possibility that although broker networks are often theorized to yield superior (patent) performance, it may be an inventor's superior performance in the past that enabled the inventor to possess a broker network. Lee (2010) found that inventors with past records of superior performance were more likely to form collaboration ties that enhanced their positions as network brokers; when past performance was controlled, the positive relationship between brokering position and subsequent performance was significantly weakened. Macro studies, too, have employed a range of approaches to sorting out endogeneity. For example, a study of production teams in the Italian TV production industry spanning 12 years found that prior status and centrality partly accounted for current structural holes; but even

accounting for this effect, spanning structural holes was associated with superior team performance (Zaheer & Soda, 2009).

A different stream of work has examined how the age of nodes (Zhang, Tan, & Tan, 2016; Kumar & Zaheer, 2019) and ties (e.g., Baum, McEvily, & Rowley, 2012; McEvily, Jaffee, & Tortoriello, 2012) in a network shape organizational performance. The age of ties can matter because age is related to the temporal and historical conditions under which ties were formed, producing an "imprinting" effect whereby the effects of certain ties and structures on performance can be long-lasting. In the context of Nashville's legal industry, McEvily et al. (2012) found that bridging ties produced network benefits over an extended period of time and could be traced back to the point of tie formation. In the context of the market for head coaches in NCAA basketball, Halgin, Borgatti, Mehra, and Soltis (2020) found that ties to star head coaches forged early in a coach's career were more likely to be recognized by others and allowed coaches to outperform their peers in the market for coaching jobs.

Although these studies provide important insights into the relationship between networks and performance over time, they do not directly examine how network dynamics shape performance. Only a handful of micro (8 percent) and macro (8 percent) papers in our sample examined how network change shapes performance. An influential micro paper on this topic used panel data on 346 investment bankers over a period of four years to show that the way an individual's network develops over time is related to the advantage it provides (measured as annual compensation; Burt & Merluzzi, 2016). Because summary measures of network volatility, such as the standard deviation of network scores, can conflate substantively different patterns of network change, Burt and Merluzzi examined network scores over time in terms of sequences and trajectories. Their paper distinguished four forms of network volatility: churn, variation,

trend, and reversal. They found that an oscillating pattern — consisting of closure (deep engagement in a group) for a period followed by a period of brokerage (connecting across groups) — enhanced performance. The overall conclusion one can draw from the pioneering work of Burt and Merluzzi is that "the way a network develops over time has implications for the advantage it provides" (p. 368).

A recent study drew on this insight and examined how the ability of individuals to benefit (in terms of creative performance) from their network depends on how their network changes over time (Soda et al., 2021). The study found that structural holes had a greater positive effect on individual creativity when the network structure was dynamic in the sense of adding new ties over time. Without changes in the ties that make up the structural holes in an individual's network, the creative advantages of structural holes were lost due to increasing rigidity in ways of thinking and coordinating (Soda et al., 2021). A different rationale for how network change shapes performance was proposed in a study of professional ice hockey teams that found that the unexpected injury-driven exits of players who were central in the team's interaction network decreased the likelihood that the team experimented with new network configurations — i.e., who co-plays with whom and for how long (Stuart, 2017). The paper speculated that network change (in terms of alternative configurations of players) can be difficult to pull off because it is perceived as risky. Teams failed to experiment with alternative network configurations despite the fact that, as the data showed, it was precisely such changes to network configurations that enhanced team performance (Stuart, 2017).

Macro studies have examined how network change influences the performance of firms (e.g., Sytch & Tatarynowicz, 2014a), acquisitions (e.g., Hernandez & Shaver, 2019), and alliances (e.g., Kumar & Zaheer, 2019). A study of the global computing industry during the

period 1981-2001 found that a firm gained the most benefit (in terms of invention productivity) when its own rate of movement across different network communities was moderate (Sytch & Tatarynowicz, 2014a). Another example is Knoben and Baker's (2019) study of alliance and board interlock networks among Australian mining firms. The study distinguished between three sequences: interlock-led relational pluralism (board interlock precedes the formation of a strategic alliance); alliance-led relational pluralism (strategic alliance formed prior to the board interlock); and concurrent relational pluralism (in which strategic alliance and board interlock were formed at the same time). Of these sequences, it was the interlock-led approach that had the strongest effect on firm performance. Although all firms benefited from forming multiplex, multifaceted ties with partners (dubbed "relational pluralism"), the best performing firms first formed board interlocks with promising partners and later added a strategic alliance. When board interlocks are formed first, this gives the start-up access to information about the vision and ethics of the partner before committing resources to the strategic alliance. Board members who sit on the board of both firms before the alliance is forged provide an informal communication channel that enhances familiarity and helps the firm distinguish trustworthy from untrustworthy partners, reducing the risk of future resource expropriations in strategic partnerships (Knoben & Baker, 2019). Similarly, there are distinct sequences discernible in how firm's forge alliances with other firms over time; and these sequences are related to firm performance (Shi & Prescott, 2011). The sequence of alliance activity can affect firm performance because it shapes when firms get access to critical resources and how they apply what they learn from their alliances.

A different kind of network dynamic that can shape performance has to do with changes in the composition of the network. Building on social resource theory (Lin, 1982) — which emphasizes the resources available to a firm through network composition, rather than through

network structure — Kumar and Zaheer (2019) argue that stability in the set of nodes in a firm's alliance network reduces the diversity of knowledge available to a firm for generating innovation. Stability in the set of alliance partners in a firm's network can be a drag on a firm's innovation performance because (a) it becomes harder for a firm to learn from its alliance partners after the initial period of assimilation; (b) given the rapid obsolescence of technological knowledge, it is difficult for a firm to remain innovative while remaining tethered to an unchanging set of alliance partners; and (c) learning over time means that initial complementarity in knowledge between a focal firm and its partners diminishes over time (Kumar & Zaheer, 2019: 693-694). However, too much change in network composition may be as bad as too little (Sytch & Tatarynowicz, 2014a).

Behavior

Studies that examine the effects of network change on behaviors and actions are rare, making up just 5 percent of the micro papers and 10 percent of the macro papers in our sample. The kinds of behaviors examined in the micro literature on the effects of network change include voluntary turnover (e.g., Woehler et al., 2021); attempts at controlling others' behaviors (de Klepper et al., 2017); and gossiping (Ellwardt et al., 2012). Using a combination of survey-based and email communication data between employees of two firms pre- and post-merger, Woehler et al. (2021) show that employees who change their personal networks by widening their cross-legacy connections during a corporate merger are less likely to leave the firm. This, they reason, is because by widening their networks during a merger, individuals are likely to gain useful information from connections in the counterpart legacy organization, thereby allowing them to better adjust to their changing environment. The other micro studies in our sample that examined the behavioral consequences of changes in networks adopted an explicitly

coevolutionary approach (Kalish et al., 2015; Kalish, 2020; Schulte et al., 2012; Tröster et al., 2019). Because we have discussed coevolution studies in an earlier section, we do not discuss them further here.

In the macro literature, researchers interested in the effects of network dynamics on behavior have examined such corporate actions as patent litigation and R&D collaborations (Howard et al., 2017), inter-organizational rivalry (Operti, Lampronti, & Sgourev, 2020), and changes in the hospital's portfolio of clinical specialties (Stadtfeld et al., 2016). However, of the nine macro studies in our sample that examined behaviors as an outcome of network dynamics, only two (Stadtfeld et al., 2016; Amati et al., 2019) examined behaviors as a function of changes in a network. We have previously described the Stadtfeld et al. (2016) study in the section on coevolution studies. The study by Amati and colleagues is a review of statistical models (especially ERGM models, which are described in the Appendix below) that can represent the global structure of an observed network in terms of underlying structural mechanisms. The paper defines the models and discusses model specification, estimation, and assessment.

Cognition

Of the twelve papers in our sample that examined cognition as an outcome of network dynamics, all were micro, examining such outcomes as thoughts of quitting (Tröster et al., 2019), perceived stress (Kalish et al., 2015), psychological safety (Schulte et al., 2012), and organizational commitment (Bensaou et al., 2014).

In one study of workplace friendships over time, the maintenance of friendship relations with former coworkers at a previous organization facilitated the perception of social integration in new workplaces (Walsh et al., 2018). A different study sought to understand the dynamic relationships between social networks and the vocabularies people use to describe and make

sense of their workplace experiences (Tasselli et al., 2020). The study found that, within organizational sub-units, individuals with task-related communication ties became more similar in their organizational vocabularies; and the more two members shared similar organizational vocabularies, the more likely they were to subsequently form a task-related communication tie. Focusing on perceptions of leadership, Balkundi, Kilduff, & Harrison (2011) used time-lagged data to examine the possibility that charisma is attributed to team leaders who are socially active in terms of giving and receiving advice. They found that formal team leaders who were central in a team's advice network were seen as charismatic by subordinates and this charisma was associated with high team performance.

Such studies provide insights into the effects of networks on cognition, but only five studies examined how changes in a network shaped cognition (Benasou et al., 2014; Carnabuci et al., 2018; Schulte et al., 2012; Tröster et al., 2019; Kalish & Luria, 2016). For example, Carnabuci et al. (2018) used stochastic modeling to examine how the likelihood that A perceives B as a leader depends on how frequently they interact and their pre-existing friendships; and Kalish et al. (2015) examined how self-reported stress and interpersonal communication networks coevolve. Because we have described coevolution studies in a previous section, we focus here on the one study that examined the effects of network dynamics on cognitive outcomes that was not a coevolution study: Using a grounded theorizing approach, Bensaou et al. (2014) identified, over a 16-month period, three networking strategies used by newly promoted service professionals in two firms. Using interview and ego-network data, the study examined how prior network positions influenced the networking strategies they observed; and how these networking strategies subsequently influenced the behaviors and cognition of the actors involved. The use of interviews was critical for learning how the beliefs and values of

individuals both shaped and were shaped via networking. In a similar vein, Methot et al. (2018) have argued, in a conceptual paper, that changes in social networks, precipitated by human resource practices, can influence individual cognition beyond mere attitudes by transforming individuals' self-concepts.

ANALYTICS

Some of the empirical results we have reviewed thus far are based on research designs and analytical approaches that do not explicitly model change yet have implications for and are discussed by their authors in terms of change (see, for example, Lomi et al, 2014). This is no different from when we estimate an ordinary cross-sectional regression $Y = b0 + b1X1 + b2X2 + \ldots$ and, having made causal assumptions based on theoretical grounds, expect Y to increase an average of b1 units if X1 increases by one unit. However, in addition to these implicit models, the field of network analysis has developed explicit models of dyadic dynamics based on longitudinal data. Table 5 identifies the main analytical approaches currently available for the study of network dynamics; summarizes the strengths and weaknesses of each approach; and identifies the kind of research question each approach is best suited to addressing. A fuller discussion of these analytical approaches can be found in the Appendix. We recognize that the set of analytical approaches available for the study of network dynamics will grow with time. Nonetheless, we believe that organizational scholars interested in network dynamics can benefit from an accessible summary of the analytical approaches currently available and guidance regarding their suitability for addressing different aspects of network dynamics.

Insert Table 5 about here

PHASE II

CHALLENGES AND PROSPECTS FOR FUTURE RESEARCH

The term "network dynamics" covers a lot of ground, as our review has shown. There is already substantial work on how things — such as ideas, practices, resources — diffuse over fixed networks (e.g., Fiss et al., 2012; Rogers, 2003). The focus of our review, by contrast, is on the dynamics of the networks themselves, such as changes in the pattern of ties in the network, as well as sequences and timing of interactions. In Phase I, we have categorized and quantified the literature on organizational network dynamics, covering both micro (i.e., interpersonal) and macro (i.e., interorganizational) research over the last decade. In this second phase of our review, we critically reflect on what we have learned from our systematic review of the literature and identify key challenges and opportunities for advancing this line of work. We organize the discussion in terms of four major themes: the interplay between the dynamics of social networks conceived as relational states versus events; the mechanisms underlying network dynamics; outcomes of network dynamics; and the role of cognition. Challenges and prospects for future research are summarized in Table 6.

Insert Table 6 about here

The Dynamics of Relational States and Events

Within the category of network dynamics, our review has distinguished network change from relational event occurrence. Network change refers to a change in the relational state that characterizes a given dyad, such as the making of an enemy or the shift from acquaintance to friendship. These changes then have consequences for analytical constructs at higher levels of

analysis, such as (at the level of the node) the number of friends an individual has, or (at the level of the network), the shape of the network as a whole. A different kind of dynamic is the continuous stream of social acts, such as a sequence of moves and countermoves (e.g., between competitors in an industry). These relational events are transitory and discrete. They are things that, once they occur, are gone (although the consequences may persist for some time). The two dynamics involve two different kinds of "ties", which are often conflated. The tie that is a relational event is usually something that an actor does to or with another (a social act), whereas the tie that is a relational state is more like a role: it is something that the pair are, as in co-workers, supervisor and supervisee, or friends.

Much of the history of network research in organizational contexts is about the study of relational states. In the sample of papers we reviewed, only 6 percent of the papers examined network dynamics in terms of relational events. This is, in part, the result of methodological convenience. One can easily ask in a survey, "Who are your friends?" It is harder to track each utterance that an actor makes to another actor (but the growing availability of trace data, such as email and text-based communication, is making this easier -- see Kitts & Quintane, 2020). Often, relational event data are collected and analyzed as though it were a state, as when we ask the respondent "who do you usually seek advice from?" But the traditional focus on relational states has another reason as well, which is that the relative durability of states allows them to co-occur, creating a network of ties which are all present at the same time. This in turn creates structure, and the study of network structure -- and position within it -- has been one of the hallmarks of the field of network analysis.

Paradoxically, it is the continuously present aspect of relational states that enables the study of change. Relationships between actors do persist, but they also change. It is meaningful

to say that A and B were friends but are no longer friends. In contrast, a relational event such as the act of sending an email does not change: it happens, and is done (until it happens again). The content of the email, of course, persists, as does the effect of the email on the recipient. But if we are studying network dynamics, what we are studying with relational states is relationship change, whereas with relational events we are studying sequences over time. It would not distort reality too much to say that with relational states the network structure is "spatial," whereas with relational events the structure is temporal: one event leads to another, as in a conversation, and the analysis is about using the sequence and timing of communication acts to predict who will next communicate with whom.

Because relational states and relational events are different phenomena and, given that statistical tools now exist for the analysis of each (although the majority are for relational states), we could imagine these as two separate buckets -- different fields of inquiry no more closely related than two academic disciplines. Indeed, empirical research has tended to treat these phenomena as separate (notable exceptions include, e.g., Pilny, Schecter, Poole, & Contractor, 2016; Schecter et al., 2018). There are a few points of cross-over. First, as mentioned earlier, relational event data can be treated as states. We simply count up the number of interactions over a certain period and assume the dyads that interact a lot have an underlying relationship. If A frequently seeks advice from B, we say that A has an advice-seeking tie with B, and presumably (but not certainly), B has an advice-giving relationship with A. We then regard this as ongoing until, in subsequent periods, we see a drop in frequency, and then we say the relationship has changed. Second, the tools for analyzing relational events -- such as the Relational Events Model or REM (Butts, 2008) -- allow relational states to be used as (time-invariant) covariates. One can

model, for example, how the probability of an event (a call from A to B) depends on their relationship (supervisor-supervisee).

In theoretical work, a much deeper and tighter relationship between relational states and relational events has always been assumed. Relationships (i.e., states) carry with them a set of behavioral rights, obligations and expectations that derive from broad cultural norms as well as norms developed idiosyncratically over time by a given pair of actors (Mitchell, 1969; Argyle & Henderson, 1985: 36-63). Bosses are expected to tell their subordinates what to do, and subordinates are expected to do it. Interactions are expected to be cordial and certain behaviors, such as sexual harassment, are taboo. The relational states constitute dyadic roles that are continuously enacted by the participants as they behave toward each other. Failure to enact the roles properly ultimately leads to a change in the relational state, but this is also negotiated at the individual dyad level (White, 1992). In one dyad's friendship relationship, a certain amount of one-upmanship is tolerated, whereas in another dyad, it violates a core value.

Relational states and relational events continuously co-create each other in a process that resembles what Giddens (1984) described as "structuration." Networks are constituted through a process in which individuals draw on their knowledge of relational states as they interact, and their interactions, which are a series of events, dynamically (re)produce relational states. For example, when team members communicate with each other (e.g., phone calls), they draw upon their knowledge of existing relations within the group (e.g., friendships); and their acts of communication help shape these relations (Corman & Scott, 1994; Pilny et al., 2016). Social networks as states, from this perspective, are both medium and outcome of interaction events (what Giddens (1984) referred to as the "duality of structure"). Networks are both ongoing sequences of action (events) and a set of preexisting, institutionalized relations (states). But

states and events are not segregated realms; there is an interplay between them over time that is the process of structuring. Network states, moreover, are not deterministic; their relevance for action depends upon how actors make sense of changed states and the meanings they attach to their own and others' actions (Ranson, Hinings, & Greenwood, 1980).

The difficulty with all this is that it lacks specificity. There are few studies (especially quantitative ones) that generate specific hypotheses relating relational behaviors to relational states (cf. Barley, 1986). As a field, we do have ideas about the mechanisms relating the two phenomena. It seems clear that interpretation is critical. Parties in a relationship have expectations about how they should be treated by the other (Goffman, 1971). These expectations are derived from schemas and scripts that aid interpretation and sensemaking (e.g., Schank & Abelson, 1977; Weick, 1995). The relational state between two actors provides not only a causal context that alters the probability distributions of specific behaviors that will occur between specific pairs of actors, but also provides an interpretive context that changes the way events are interpreted. This is true for both the participants and third-party onlookers (White, 1992). An actor contradicting another is viewed differently if the relationship between them is boss-subordinate versus husband-wife. Agency in networks typically refers to relational actions, such as deliberately making ties to gain advantage and control, but perhaps the more common type of agency is the interpretive act, in which every actor scrutinizes every interaction, especially but not limited to those they are involved in themselves. Interestingly, it may well be that the principal objective in this constant interpretation is to obtain information about the state of the relationship. The relational state strongly determines how actions are seen, but at the same time the resulting interpretation is used to update the actors' understanding of what their relational state currently is. This suggests a folk theory that relationships are highly susceptible to change

and must constantly be managed either to maintain them or to move them to a more desirable state (Goffman, 1971).

The focus on interpretation does suggest an agenda for research. For example, we can investigate the consequences of variability in interpretive skill and cultural variations in relational norms. If culture is a toolkit of practices and styles that are used by actors to manage their networks (McLean, 2017), we can expect cultural differences in how people interpret the significance of events for underlying states and in how they draw prescriptions for actions based on an understanding of relational states. Obtaining the detail-level quantitative data to study these questions is daunting but promising. Qualitative methods, of course, are ideally suited to investigating questions of meaning and interpretation. It is also worth noting that, while relational event models (Butts, 2008) allow us to use relational states as explanatory predictors of relational events, the models do not allow us to model how relational events shape relational states; we hope this will be an area of future development.

Empirical work that seeks to understand the relationship between network states and events should be a priority. Few studies have investigated how traditional network measures of ties as relational states match up with event-based measures (for exceptions, see Matusik et al., 2019; Quintane & Kleinbaum, 2011). Wuchty and Uzzi (2011) examined dynamics in email communication and found that rapid response time (i.e., time elapsed between receiving and responding to an email) can accurately distinguish self-reported friendship/professional ties from non-ties. Specifically, shortest response time intervals indicated friendship ties while longer response times were strongly associated with professional ties. Scholars have attempted to retain and utilize both sequence and timing information in events networks to propose finer-grained temporal measures of network structure (Falzon, Quintane, Dunn, & Robins, 2018), because

aggregate estimates of structural parameters associated with social mechanisms of theoretical interest might mask fine-grained temporal variation in relational events sequences (Amati et al., 2019). Compared to static measures of network structure, temporal measures applied to interaction networks can illuminate meaningful differences in the way in which individual actors accumulate connections and reveal potential disconnections in the network without overestimating reachability and betweenness centrality, which are critical for accurately identifying key individuals in the network (Falzon et al., 2018).

The contemporary workplace, with its focus on project-based teams and shifting work roles, creates opportunities for the exchange of information and ideas among colleagues who may never become a part of the longer-term network of regular interactants that has been the focus of much previous network research. To model such events, a methodological challenge is the development of measures of positions in social networks that allow for the simultaneous consideration of both time and sequence in dyadic interactions. Typically, temporal network measures consider time and sequence separately, which can be an issue because it can be hard to determine when interactions are part of the same sequence. We call for the use of measures that jointly consider both sequence and time in order to gain a fine-grained understanding of how individuals enable and constrain the flow of information in a network (see Falzon et al., 2018).

Mechanisms of Network Dynamics

When reviewing an emerging field of study like network dynamics, a fundamental question we would like to answer is: “What are the key ideas about what drives the phenomena that defines the field?” In the case of network change, the fundamental question is what determines tie formation and dissolution. At a very specific level, there are almost as many answers to this question as there are studies. It is like turnover: the reasons people leave jobs are many and

varied. But the hope is that these myriad answers can be boiled down into a smaller number of underlying principles that have generality and fertility. So, here we consider what can be said more generally about the mechanisms of network dynamics, and in particular, network change.

There are numerous papers in the literature that attempt to list network theories and mechanisms. For example, Monge and Contractor (2001) list nine categories or "families" of theoretical approaches that can be found in published papers. They are summarized by Contractor, Wasserman and Faust (2006) as " (1) theories of self-interest, (2) theories of mutual interest and collective action, (3) cognitive theories, (4) cognitive consistency theories, (5) contagion theories, (6) exchange and dependency theories, (7) homophily theories, (8) proximity theories, and (9) theories of network evolution and coevolution." We note that these vary widely in terms of scope and type. Some are named in terms of the driving variable (e.g., proximity) and others by generic principles (e.g., self-interest). Still others are named by what they seek to explain (e.g. co-evolution). Some are primarily used to explain network outcomes like tie formation (e.g., cognitive consistency theories) while others discuss outcomes of having ties (e.g., contagion theories). More recently, Rivera, Soderstrom & Uzzi (2010) identify assortative (including homophily), relational (including transitivity), and proximity mechanisms. A variety of empirical papers -- especially those reliant on exponential random graph models (ERGMs, see Appendix) -- describe tendencies like reciprocity, homophily and transitivity as mechanisms (indeed, sometimes as "self-organizing mechanisms," as well as "social processes").

It is worth asking why these statistical tendencies are seen as mechanisms instead of the things to be explained. Recall that network dynamics can be studied at multiple levels of dynamics, including the dyad level, the node level, and the whole network (or group) level. The ERGM family of models is often described as a dyadic model because for estimation purposes it

is converted into a cousin of logistic regression predicting presence/absence of ties for each dyad, but fundamentally it is a model of the joint probability of all dyads having the states that they do. In other words, it is a network-level model. The concept is that the existing network is the result of a long term (unseen) process of adding and dropping ties in order to maximize an objective function, which is conceived of as a linear combination of parameters (to be estimated) and network-level statistics. These network statistics are typically counts of micro-configurations in the network, such as the number of dyads in which (a) each node sends a tie to the other (reciprocity), or (b) the nodes are tied and have the same gender (homophily), or (c) the nodes are tied and share ties to a common third party (transitivity), etc. These micro-configurations are presumed to be tied to social processes that engender them. In this sense, the overall pattern of ties in the network is "explained" as the product of multiple micro-tendencies working simultaneously to produce the network we actually observe. See the Appendix for more discussion on ERGMs.

Suppose, however, that we shift the level of analysis to the dyad. We want to explain, for any given dyad, why there is a tie from A → B. We may find that, in our data, a strong predictor is the existence of a tie B → A. We refer to this correlation as reciprocity, but it is important to note that this is a label, not an explanation. We still need to find a mechanism -- such as cultural norms, or feelings of gratitude -- that would explain why a tie in one direction would often entail a tie in the reverse direction. The same is true for homophily, transitivity, preferential attraction, and so on. At the tie level, these are all structural effects -- correlations -- in need of an explanatory mechanism.

Let us take homophily as an example. There are two generic mechanisms discernible in the literature. One mechanism -- particularly congenial to a structuralist perspective -- is opportunity.

If a male employee works in an office largely made up of men, it is likely that most of his office friends will be male, simply because there are many men and few women to choose from. The other mechanism is what we might call preference. Given a choice between two potential friends, individuals choose the ones most like themselves because they are easier to talk to: they have similar backgrounds, life experiences, conversational referents and so on (e.g., Byrne et al., 1971). This means homophily may yield an advantage in fitness because similar individuals may be able to coordinate more effectively (Fu, Nowak, Christakis, & Fowler, 2012). Similar individuals may also have aligned interests, reducing points of potential disagreement and competition. In macro contexts, homophily with respect to technical systems or culture can make it easier for organizations to work together. We can also invoke evolutionary psychological explanations, such as homophily being rooted in a healthy fear of strangers, who have no allegiance to you and who are also likely to be different from you (e.g., Haun & Over, 2015). All of these are preference mechanisms.

Now let us consider transitivity or closure -- the often-observed tendency for friends of friends to be friends. This too provides a dyad-level prediction for which ties will exist and which will not: when A → B, and B → C, a statistical model such as ERGM predicts A → C, because it has observed this pattern throughout the network. But what is the mechanism that creates this correlation? A classic psychological explanation is balance theory. According to Heider (1958), if A likes B, and B likes C, it would create aversive cognitive dissonance in A if she did not join B in also liking C. A different mechanism -- posited by Granovetter (1973) among others -- is that if B is close to both A and C, there will be many opportunities for A to hear of C, and indeed to meet them and grow to like them. This mechanism also applies to organizations, as a pair of organization's common ties to a third organization can facilitate

formation of a direct tie between them. Again, we have two classes of underlying mechanisms: preference and opportunity. Similar analyses can be conducted for reciprocity, preferential attachment, and a host of other tendencies observed in networks.

It is perhaps useful to reframe preference as agency. We can similarly rebrand opportunity as structure, and thereby fit our discussion into a well-known framework (Simmel, 1950). We can then see processes of tie formation in terms of the interplay between structure and agency. For example, a "networking" perspective views actors as players who may deliberately befriend someone (call them A) who is in a position to introduce them to someone else (B). This perspective combines structure and agency: structure/opportunity can be seen in the existing relationship between A and B, and agency can be seen in the player's deliberate befriending of A in order to meet B.

Discussions of agency often distinguish between agency as individual difference and agency as conscious choice (e.g., Tasselli & Kilduff, 2021). We can see this distinction in the mechanisms behind homophily and transitivity. The Heiderian aversion to dissonance is a built-in characteristic of individuals, not something the individual chooses, although their subsequent actions to avoid the dissonance may well be more deliberate. Similarly, the 'fear of the other' explanation for homophily is about the psychological make-up of the human mind, whereas choosing to partner with a firm that has a similar, compatible organizational culture is more likely the deliberate choice of a rational actor.

The rational choice paradigm is evident in a number of studies of organizational networks. Zaheer, Gözübüyük, and Milanov (2010) identified four "theoretical mechanisms" found in network research. These are resource access, trust, power/control, and signaling. The first of these, resource access, is the central theme of social capital. A person's ties potentially give them

access to the ideas, resources and efforts of others. While this is an argument for the consequences of social ties rather than their antecedents, these benefits in question provide powerful motivation for forming ties with those who can provide complementary resources, as theorized by Furlotti and Soda (2018). Similarly, Zaheer et al.'s (2010) signaling mechanism posits that perceived ties to high status players provide a signal of quality (Podolny, 1993). This again provides a rational actor with motivation to form ties with high status others. [20]

It should be noted that because ties in a network are interdependent, the existence of agency paradoxically creates a situation where much of what happens to an actor socially is, from their point of view, not caused by the actor. For example, an actor A may rapidly form bridging ties to people unconnected with their existing contacts, creating structural holes. But this provides opportunities for A's existing contacts to meet the new contacts as well, closing the holes back up again. Because there are many actors, the consequences of an individual's actions are contingent and uncertain. Moreover, any social behavior can have unintended consequences, leading to what might appear to be irrational agency. It is worth noting that actors act not only in the context of a social network around them, but also in the context of a mental model of the social structure (Kilduff & Krackhardt, 1994). For example, an actor might tell A something they would not like B to know, not realizing that A and B have a strong bond.

In organization studies, network researchers have begun to examine agency in the guise of characteristic motivations as reflected in networking styles (e.g., Vissa, 2012), skills (e.g., Grosser et al., 2018), the networking strategies of different actors (e.g., Bensaou et al., 2014; Ozcan & Eisenhardt, 2009), and, more generally, in how people approach social networking (e.g., Casciaro, Gino, & Kouchaki, 2014). Of course, it is important not to reduce agency to routine, purpose, or judgement; what matters is the dynamic interplay between these elements of

agency within different and changing structural contexts of action (Emirbayer & Mische, 1998: 963). Moreover, largely missing from the literature is recognition of the temporally embedded nature of human agency, which is both informed by the past and oriented towards the future. We have, for example, indirect evidence (Hernandez & Shaver, 2019) to suggest that actors may look into the future to see how an acquisition might reshape a firm's network (in terms of network status and number of structural holes). Few network studies examine how actors imagine the future while taking actions in the present to shape their networks [21].

Outcomes of Network Dynamics

Most of the papers in our review of organizational network dynamics have examined how the network at one point in time shapes the network at a subsequent point in time (see Table 1 for details). A central preoccupation of this work has been to sort out the issue of endogeneity that "plagues causal analysis" (Kleinbaum & Stuart, 2014a: 363). Because actors are not randomly assigned to their networks, it could be that previous performance influences the characteristics of the networks that actors end up with, which they then use to boost performance. Indeed, research has found that accounting for past performance can significantly reduce the effects of network structure on subsequent performance (Lee, 2010). There are ways to ameliorate this issue statistically through the use of fixed effects models and instrumental variables. But it is unlikely that statistical fixes of this kind will ever match the controlled environment of the lab for persuasively establishing causal direction. Results obtained in the laboratory, however, can be difficult to generalize. Ultimately, there may be no perfect solution. We believe that endogeneity "is not a problem we are likely to solve, whether in network analysis or any other field of human inquiry" (Borgatti et al., 2014: 20).

As noted in Phase I, another stream of work has tried to sort out how the age of nodes, ties, and network structures shapes outcomes (e.g., Baum et al., 2012; McEvily et al., 2012; Soda, Usai, & Zaheer, 2004). One reason that age is likely to matter for network-based advantage is that timely access to information matters for advantage. This is one reason that the benefits of bridging ties may be short-lived (Soda et. al., 2004). Another reason is that the networks that convey benefits are themselves vulnerable to decay, which means that the benefits they provide are unlikely to persist (Burt, 2002). A contrasting perspective argues that "networks retain much of their structure over time, evolve gradually, and have extended time horizons within which valuable resources could be acquired" (McEvily et al., 2012: 548). The implication of this contrasting perspective is that the resources networks provide accumulate rather than dissipate over time. It is also possible that the conditions that prevail at the time of network formation leave a lasting, "imprinted" effect that shapes outcomes for the actor long afterwards (e.g., Halgin et al., 2020). Networks that are formed during a formative period in an individual's (or organization's) development may be particularly conducive to learning (McEvily et al., 2012) and may therefore have a lasting effect on individual performance. A different route whereby imprinted ties may have long-term effects on success is through third-party perceptions: observers tend to put disproportionate weight on the influence of ties forged early in a career on the ability of the actor to perform well in the future (e.g., Kilduff et al., 2006). A promising area of inquiry for future work is to disentangle the effects of the age of a network from the length of time it continues to shape outcomes. It may be that some networks dissipate and decay yet their influence on outcomes stretches over years, whereas other networks may only deliver value while they are active.

Studies that examine historical and temporal effects of networks on outcomes represent a new and exciting line of inquiry, but they do not examine how network *change* shapes outcomes. Coevolution research, which examines the influence of attributes on networks, and vice versa, is well suited to studying the reciprocal effects of changes in networks on changes in actor performance. None of the coevolution papers in our sample, however, have examined performance as an actor attribute, focusing instead on attitudes and behaviors. Few papers, moreover, examine how characteristics of network change, such as its pace and trajectory, shape performance outcomes. To the extent that superior performance derives from a match between environmental threats and opportunities and the characteristics of an actor's network, the agility with which an actor is able to adapt the network to changes in the environment should be related to the actor's performance. For example, faced with the Coronavirus epidemic, companies that are able to quickly (re)configure their supply and distribution networks to respond to the environmental jolt may be outperforming those who have been slower to change their networks (e.g., Dykes, Hughes-Morgan, Kolev, & Ferrier, 2020). Network transformation, however, can be difficult and risky. It can be costly and time-consuming for an organization to discard old ties and build new ones due to a number of constraints, such as those that arise from intraorganizational networks, tie-specific constraints, and external constraints rooted in the interorganizational field (Kim et al., 2006). Firms may vary in their rates of "network responsiveness," with fast and slow responsiveness each suited to different conditions (Kleinbaum & Stuart, 2014a). This means that the speed of network change has the potential to erode performance not just enhance it, but we need more empirical research on when and how network transformation can prove detrimental for individual and organizational performance.

As we noted in Phase I, a pioneering study of how network dynamics shape individual performance found that an "oscillating" sequence of deep engagement in a group followed by a period of connecting between groups was related to higher annual compensation in a sample of investment bankers (Burt & Merluzzi, 2016). However, Burt and Merluzzi noted that the mechanism responsible for this effect remains a matter of speculation and pointed to three possibilities. One possibility is that embeddedness in a closed network for a period of time allows the actor to develop a local reputation as trustworthy and this local reputation is key to the actor benefiting from subsequently moving ideas and practices from one group to another. A second possibility is that oscillating between closed and open networks enhances human capital. A person who oscillates between open and closed networks may become adept at noticing and effectively responding to opportunities in the surrounding environment, developing, over time, the mindset and personality of a network entrepreneur -- an argument that is consistent with White's (1992) claim that identity emerges from actors' attempts at managing the turbulence created by flows of cross-cutting expectations and constraints. A third possibility is that network oscillation allowed people to build a larger, more diverse network, and it was because of this resultant network that network oscillation was advantageous. Of course, if one were to oscillate back and forth between the same set of people, the state-like properties of the network would not change; it would be the sequence of events that oscillated. We need further research, both macro and micro, to sort out which of these plausible mechanisms apply and under what conditions they apply.

What we currently know about the relationship between network change and outcomes is largely based on the study of relational states. The relationship between sequences of events that underlie the state-like conception of ties and outcomes of interest has not been a focus of

organizational network research. This may be because, as we have noted previously, it is easier to gather data on states rather than on the procession of events that underlie the states. But beyond data, what is needed is advances in theory that allow us to connect the sequence and timing of events with outcomes of interest. Individual performance in a work-team may be related to the timing and sequence of communication with team members rather than, say, the individual's friendship network, yet none of the studies in our sample address this possibility. We call for research that characterizes performance by the underlying sequence of actions associated with it. An actor in a closed network position that appears to offer no brokerage opportunities may in fact have a chance to control the flow of information between alters so long as the actor interacts with the alters before they interact with each other (Spiro et al., 2013). Moreover, future research could advance our understanding of the relationship between network dynamics and outcomes by considering networks as instantiated in states and events jointly. The implications of a sequence of events for outcomes may only make sense when one also considers the more enduring network of states. For example, to explain why one country attacks another (an event), it is important to consider not just the past sequence of events (in terms of who attacked whom when) but also the more enduring (state-like) network of alliances between countries (Robbins, 2016). Future organizational research that seeks to understand how network dynamics shape outcomes can benefit from the joint consideration of networks as states and events.

Cognition and Network Dynamics

Social networks exist not just as patterns of relations in the world; they are also cognitive representations in the mind. Although there is a long line of work on network cognition in organization studies (see Brands, 2013, for a review), research has neglected how individuals

(and audiences) perceive, anticipate, or recall network *dynamics*. In the set of papers covered in this review, only one empirical paper examines the possibility that network dynamics are driven to some extent by actors' anticipation of what a future network might look like (Hernandez & Shaver, 2019; cf. Hernandez & Menon, 2021). In the context of inter-firm acquisitions, it seems reasonable that firms attempt to estimate how the position they currently occupy in the industry-wide network would be improved by acquiring a target firm and its network and their estimations inform the actions they take and the network dynamics that ensue (Hernandez & Shaver, 2019: 175-176). Yet work that directly examines the role of cognition in the context of network dynamics is rare.

We see great potential for new research. For example, building on the theory of loss-aversion, it is possible that actors are more prone to noticing the loss of a tie in their network than the addition of a new tie. On the other hand, new ties, because they require effort to nurture and build, may be more salient than older ties. The perception of gain/loss triggered by network change may help us better understand what leads actors to engage in instrumental networking, an activity that most people find unpleasant and prefer to avoid (Casciaro et al., 2014). Switching from the network perceptions of focal actors to those of the audience, we know that investors tend to notice gestalt patterns in the competitive actions of firms to infer their future success (e.g., Ariely & Carmon, 2000; Rindova, Ferrier, & Wiltbank, 2010). Is it possible that similar gestalt principles guide how investors register the dynamic patterning of firms' alliance networks over time? We know from previous research that investors track the dynamic sequences of competitive actions that firms take and they perceive some sequences as more desirable than others (Rindova et al., 2010). It therefore seems plausible that audiences track trajectories and patterns that networks -- both as states and as sequences of events -- take over time and they

reward those actors whose trajectories fit their mental models of success and resilience (Stark & Vedres, 2006). A trajectory whereby an actor moves from the margins of the network to its core versus one where an actor has been in the core from the start might signal that the first actor is a rising star whereas the second is stagnant (Mehra et al., 2014). Indeed, this is yet another plausible explanation for the study by Burt and Merluzzi's (2016) discussed above: audiences may notice the oscillating pattern of an actor's network and associate the pattern with future promise and success. Audience beliefs about an actor's potential informed by their perceptions of the dynamics of the actor's network could prove self-fulfilling. The question of how audiences perceive and react to changes in an actor's network represents rich but largely uncharted territory.

In considering the cognitive representation of network dynamics, the role of memory raises new questions. Network ties can stretch and change over different time horizons, which makes possible the overlaying of ties of different duration, such as transient employment ties overlaid on enduring organizational ties. The resultant "temporal multiplexity" (Shipilov et al., 2014) can leave a relational residue that shapes future attitudes and behaviors. This process, moreover, can connect past interpersonal ties with future interorganizational ties. For example, a personal tie forged between two employees when they worked for the same firm in the past can subsequently facilitate the forging of a tie between the different firms that they go on to work for (e.g., Somaya, Williamson, & Lorinkova, 2008). More generally, ties to past employers can continue to influence both employees and their past employers (cf. Godart, Shipilov, & Claes, 2014). Although the idea that the overlaying of ties of different durations can shape network processes and outcomes has been raised in several papers (e.g., Kilduff et al., 2006), empirical evidence has been sparse (e.g., Soda et al., 2004), and only recently has work started to illuminate the

mechanisms involved in the process. On the one hand, the overlaying of career mobility on organizational networks can create conflict between the demands of the organization and the interests of the employee, as happens, for example, when an employee leaves a firm to go work for a rival firm. On the other hand, it may be that temporal overlaying of this sort can be beneficial in that it "makes actors less willing or less capable of implementing the conflict-inducing demands of their employers, thus reducing the likelihood of conflict" (Operti et al., 2020: 3). It is also possible, however, that a history of collaboration between two people who subsequently represent rival organizations can exacerbate conflict because salient others expect them to display loyalty to their current organizations (Uribe et al., 2020).

This emphasis on the role of memory on network dynamics and outcomes is shared by a growing body of work on "dormant ties" (Levin, Walter, & Murnighan, 2011). Dormant ties are defined as ties that were active in the past, but have become inactive in the present. For example, a pair of colleagues -- even close friends -- may lose touch with each other when one moves to another organization or city. Truly dormant (versus changed or lost) ties can be reactivated. When being reactivated, they may offer advantages over current ties (because changes in life experiences will have brought novel perspectives) and new ties (because the past relationship with the dormant tie makes it easier to communicate and share complex knowledge). From the point of view of relational states and events, a dormant tie can be viewed as one in which the relational state (e.g., amicable colleagues) remains the same, but the relational events normally associated with the relationship have declined in frequency. So long as the relational state remains substantially the same, the dormant tie can be reactivated. This distinguishes a dormant tie from a lost tie. Other work in the dormant tie tradition has argued that simply recalling and reflecting on relationships from the past can deliver value (McCarthy & Levin, 2019). In

emphasizing how people recall and reflect on relationships, it is important to distinguish between clock time and time as it is subjectively perceived. An exclusive focus on networks as a sequence of events that unfolds in clock time neglects the possibility that the human mind tends to register not a series of isolable events but instead stitches events together into more enduring, state-like relationships (cf. Bergson, 1960). This possibility raises new questions about how social networks, as both states and events, are retained in memory and the conditions that influence when and how they are recalled.

Our review found that micro and macro research on network dynamics has proceeded along remarkably similar lines [22]. Because organizational network research has traditionally emphasized relations rather than the characteristics of nodes, network theory and methods seem as relevant to the study of interorganizational network dynamics as they do to the study of interpersonal network dynamics. However, given the role of cognition in network dynamics, it may be fruitful for scholars to more carefully distinguish the characteristics of nodes that are individual persons from nodes that represent organizations. A sense of obligation, for example, may explain the tendency for individuals to reciprocate ties over time. But in the more instrumental context of interorganizational ties there may be no such sense of obligation and network dynamics may be more a function of calculated self-interest (cf. Belmi & Pfeffer, 2015). Of course, one can treat the interorganizational network as though it were an interpersonal one. The founder of an entrepreneurial startup, for example, is a reasonable stand-in for the organization itself. But such substitution makes less sense for larger, more mature organizations where no one top officer holds exclusive decision-making authority. Studies that systematically compare interpersonal with interorganizational networks are rare, but one study found that interorganizational networks do not exhibit the tendency to connect with well-connected others

(often referred to as “preferential attachment”), which, by contrast, is a common feature of interpersonal networks (Powell, White, Koput, & Owen-Smith, 2005). Network research has emphasized the applicability of the principles of network dynamics irrespective of whether the nodes in the network are individuals or organizations. We call for theory and research to examine possible differences in network dynamics when the node is a person versus an organization.

CONCLUSION

The pre-Socratic philosopher, Heraclitus, observed that one cannot step into the same river twice [23]. There are many interpretations of this famous observation. Heraclitus may have been suggesting that everything is changing all the time; or that everything changes at least some of the time; or, at minimum, everything is subject to change. This bit of ancient wisdom is of direct relevance to organizational network research. Social network ties can run the gamut from relatively long-lasting relational states (e.g., a friendship between two coworkers) to instantaneous events (e.g., an email communication between two coworkers). In a strict sense, network change is about changes in relational states. By contrast, events do not change; they happen, and then they are gone. Yet these ephemeral events keep shaping the states. It is this ongoing interplay of relational states and relational events that we must more fully understand if we are to finally address Salancik’s (1995) critique and offer a convincing account of how networks come to be, are transformed, and disappear.

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FOOTNOTES

1. As we explain more fully in the section "A Taxonomic Framework," we see network dynamics as an umbrella term that covers a broad territory consisting of: (a) *network change* (i.e., the emergence, evolution, and transformation of the nodes/actors, ties, and structures that comprise social networks); (b) *the occurrence of relational events* (i.e., discrete actions generated by one actor and directed towards one or more other actors); and (c) *coevolution* (i.e., the process whereby network and actor attributes influence each other over time).
2. See the section "Method and Scope of Review" for details on how we identified and tabulated relevant articles on network dynamics.
3. Reviews that are relevant to organizational network dynamics include Ahuja et al., 2012; Brands, 2013; Carpenter, Li, & Jiang, 2012; Hallen et al., 2020; Kwon et. al., 2020; Landis, 2016; Rivera, Soderstrom, & Uzzi, 2010; Shipilov & Gawer, 2020; Tasselli, Kilduff, & Menges, 2015.
4. It is common in the field of management to use the terms "macro" and "micro" to distinguish studies that focus on organizations from those that focus on individuals (and teams) within organizations. In this paper, we retain this usage but, as explained more fully below, we separately distinguish three levels of analysis: node, dyad, and network. Our usage highlights differences between the dynamics of networks where the nodes of the network represent individuals and the dynamics of networks where the nodes represent organizations, but it obscures the fact that the distinction between levels can be blurry, as, for example, when a change in the personal network of an entrepreneur precipitates a change in the alliance network of the firm headed by that entrepreneur-- see Payne, Moore, Griffis, and Autry, 2011.

5. Relational states represent things you are with someone (e.g., a friend); they are continuous and persist until they end. By contrast, relational events are discrete behaviors, directed at one or more others, that take place over shorter time scales (e.g., A sends B an email; Butts, 2008). We unpack this distinction in greater detail in the section titled "Occurrence of Relational Events."
6. We used the Financial Times FT-50 list to identify core management journals. We also included the journal *Social Networks* because it is a core journal for network research across disciplines, including management. Here is the final list of journals in our review: *Academy of Management Journal, Academy of Management Review, Administrative Science Quarterly, Entrepreneurship Theory and Practice, Human Relations, Human Resource Management, Journal of Applied Psychology, Journal of Business Venturing, Journal of International Business Studies, Journal of Management, Journal of Management Studies, Journal of Organizational Behavior, Management Science, Organization Science, Organization Studies, Organizational Behavior and Human Decision Processes, Organizational Research Methods, Strategic Entrepreneurship Journal, Strategic Management Journal*.
7. To achieve a broad search, we did not include quotation marks with the search terms. This meant the search did not require that the search terms be found in a specific order, allowing for different combinations of terms. Thus, the search terms can appear separately in any of these fields; e.g., *network* may appear in the title while *dynamics* is in the abstract.
8. *American Journal of Sociology* (2 papers); *Academy of Management Discoveries* (3); *Academy of Management Perspectives* (1); *Long Range Planning* (2); *Psychological Science* (1); and *Journal of Occupational and Organizational Psychology* (1).

9. The goal of the coding is to lend greater precision to the claims we make about the kinds of research on network dynamics being conducted in the micro and the macro literature; we are not attempting to mount a formal quantitative review, e.g., a meta-analysis.
10. As we clarify below, this early work seems to have confused relational states with relational events: it is the events (e.g., knowledge exchange) accompanying the states (e.g., friendships between people or alliances between firms) that have a recurring, ordered persistence, not the states themselves.
11. In other words, the networks are isomorphic. Any structural measure such as centralization or density would give the same value to the two networks.
12. The section "Drivers of Network Dynamics" discusses each of these explanations in detail.
13. However, some models of tie formation implicitly model dissolution as well, even when that is not the theoretical focus.
14. A network purist might argue that changes in the nodes in a network do not constitute network change. We see the point but adopt a broader perspective. After all, even when there is no change in a network's structure, a change in the composition of the nodes that make up the network can have consequences for the knowledge available in the network (e.g., Rodan & Galunic, 2004), the coordination challenges it presents (e.g., Tröster, Mehra, & van Knippenberg, 2014), and therefore its performance (Kumar & Zaheer, 2019).
15. For a fuller exposition, see, e.g., Borgatti & Halgin, 2011; Butts, 2008.
16. A source of confusion, however, is that the onset of a relational state, if well-defined, is a relational event. Moreover, some studies use the language of tie formation and dissolution (events) but actually study the presence/absence of ties (states) using cross-sectional data.

17. In the Phase II discussion, we describe and build on a handful of organizational studies that are explicit about how people's anticipations of future network states, and their memories of past ones, play a role in network dynamics. We do not describe those studies here to avoid redundancy.
18. Here, "endogenous" means that we are using features of the network itself to explain other features of the network.
19. A triad is described as a cycle if i → j, j → k, and k → i. Hierarchical relations, such as "is the boss of," do not contain cyclical triads.
20. See below our discussion of cognitive factors influencing network dynamics.
21. Although, to be fair, something like this is an explicit feature of stochastic actor-oriented models (SAOM). In these models, actors make connection choices to maximize a utility function that, while shared, is evaluated separately from the point of view of each actor and without knowledge of what changes other actors are making. For example, if the model has a high closure parameter, the actor forms ties that would maximize closure around it (not in the network as a whole), although the effort could be unsuccessful as the changes made by others could nullify the expected closure.
22. There are three notable differences: there has been greater attention to the dynamics of relational events in the micro literature than in the macro literature; ERGMs have been less often used in the macro literature than in the micro literature; and, not surprisingly, the micro literature has more often examined attitudes and cognition as an outcome of network dynamics (see Table 1).

23. Cratylus, a follower of Heraclitus, took this emphasis on flux a step further and argued that one cannot step into the same river even once. According to Cratylus, it is not that all things are changing, so we cannot encounter the same thing twice. Rather, it is that a precondition for identity is flux: things stay the same only by changing.
24. To clarify, a node-level study might regress individual performance on the number of ties they have. A group or whole network level study might regress team performance on the density of ties within each team. In the former, the cases are actors (individual nodes), and in the latter the cases are teams (collection of nodes), but both studies use the same statistical method.
25. This is not to say that specialized methods could not be used. Some node-level network measures, for instance, are expected to suffer from non-independence of observations. For these situations, researchers should consider autoregressive (Doreian, 1981) and autologistic models (Daraganova & Robins, 2013).
26. We note that in this and all other models we will discuss, the dyads may be ordered or unordered pairs. Ordered pairs accommodate directed ties. A directed tie is one in which direction has meaning, as in A is the boss of B, or A lends money to B. An undirected tie is one for which direction doesn't make sense, as in A and B are co-authors. If we are modeling a directed tie, such as "seeks advice from", the dyads are ordered pairs, such that (A, B) is one case and (B, A) is another case, and variables like difference in age retain sign (e.g., if A is older than B then Age(A)-Age(B) is positive but Age(B)-Age(A) is negative).
27. While simple, this model is also known to be degenerate. In actual practice, practitioners would replace the triangles effect with either an alternating triangles effect or a geometrically-weighted edgewise shared partner term (GWESP) effect (Snijders et al, 2006).

28. It may be useful to consider that the concept and representation of a network only makes sense in the case of relational states, since, for relational events, at any given moment the network would be almost entirely empty and the notion of network structure would be meaningless. Of course, if we observe sequences of relational events within a number of dyads, we might use the frequencies of certain kinds of interactions, such as sharing confidences, as indicators of an underlying relational state, such as friendship (or, indeed, as predictors of a future friendship).

Table 1. Coding Counts

	Total counts	% in all papers	Interpersonal network papers	% in Interpersonal papers	Interorganizational network papers	% in Interorganizational papers
Network change						
Dyadic level	117	63%	63	66%	54	59%
Nodal level	67	36%	35	36%	32	35%
Network level	36	19%	14	15%	22	24%
Relational event	12	6%	9	9%	3	3%
Network coevolution	7	4%	5	5%	2	2%
Drivers of network dynamics						
Contextual	74	40%	43	45%	31	34%
Actor Attributes	150	80%	71	74%	79	87%
Relational Factors	123	66%	55	57%	68	75%
Outcomes of network dynamics						
Performance	40	21%	22	23%	18	20%
Behavior	14	7%	5	5%	9	10%
Cognition	12	6%	12	13%	0	0%
Analytic models						
Regression	104	56%	50	52%	54	59%
QAP	3	2%	3	3%	0	0%
ERGM	22	12%	17	18%	5	5%
SAOM-SIENA	20	11%	10	10%	10	11%
REM	9	5%	6	6%	3	3%
Simulation	9	5%	4	4%	5	5%

Notes. QAP = Quadratic Assignment Procedure, ERGM = Exponential Random Graph Models, SAOM = Stochastic Actor-Oriented Models, REM = Relational Event Models. Also, one paper may involve multiple topics.

Table 2. Major Research Foci of Organizational Network Dynamics and Illustrative Studies

Research Foci	Key Topics	Interpersonal network studies	Interorganizational network studies
Network change			
Dyadic level	Tie formation, dissolution, & strength change		
	• Tie formation	David, Brennecke, & Rank, 2020	Hallen & Eisenhardt, 2012
	• Tie dissolution & persistence	Kleinbaum, 2018; Walsh et al., 2018	Bermiss & Greenbaum, 2016; Greve et al., 2013
	• Tie strength change	Aven, 2015; Levin et al., 2011	Mariotti & Delbridge, 2012
	Tie content transformation		
	• Multiplexity	Brennecke, 2020; Methot et al., 2018	Howard et al., 2016; Operti et al., 2020
	• Changing tie content & nature	Riza & Higgins, 2019; Sullivan & Ford, 2014	Uribe, Sytch, & Kim, 2020
Nodal level	• Ego network composition change	Burt & Merluzzi, 2016; Cannella & McFadyen, 2016; Sasovova et al., 2010; Small, Pamphile, & McMahan, 2015	Bakker & Knoben, 2015; Kumar & Zaheer, 2019; Zhang, Tan, & Tan, 2016
	• Ego network structure change	de Klepper et al., 2017; Kleinbaum, 2012; Newbert, Tornikoski, & Quigley, 2013; Sasovova et al., 2010	Hernandez & Menon, 2018; Hernandez & Shaver, 2019; Kumar & Zaheer, 2021; Ozcan, 2018; Schilling, 2015

Network level	• Whole network composition change	Methot et al., 2018; Stuart, 2017	Sytch & Tartaraynowicz, 2014a; van den Ende et al., 2012; Zhang & Guler, 2020
	• Whole network structure change	Argyres et al., 2020; Clement & Puranam, 2018; Stuart, 2017	Gulati et al., 2012; Hernandez & Menon, 2018; Schilling, 2015; Tatarynowicz et al., 2016
Relational event occurrence	• Sequences of interactions	Matusik et al., 2019; Quintane & Carnabuci, 2016; Quintane et al., 2013; Schecter et al., 2018	Spiro et al., 2013
	• Timing of interactions	Falzon et al., 2018; Wuchty & Uzzi, 2011	Amati et al., 2019; Kitts et al., 2017
Network coevolution	• Coevolution models	Kalish, 2020; Kalish et al., 2015; Schulte et al., 2012; Tröster et al., 2019	Amati, Lomi, Mascia, & Pallotti, 2021; Stadtfeld et al., 2016

Notes: This table is not exhaustive; it merely lists illustrative studies. One paper may involve multiple categories.

Table 3. Drivers of Organizational Network Dynamics

	Interpersonal network studies	Interorganizational network studies
Contextual	• Formal organizational structures and geography delimit social interaction such that homophilous ties are more likely to form within rather than across formal boundaries (Kleinbaum et al., 2013). • Organizational restructuring leads employees to detach from formal ties and rely more on semiformal and informal ties (Srivastava, 2015).	• Environmental shock (An industry-wide dramatic event considerably shapes industrial alliance network evolution, Corbo et al., 2016). • Institutional change (Legislation regulatory transformation reinforced reciprocity but not transitivity in board interlock networks, Withers et al., 2018).
Actor Attributes	• Personality (Self-monitoring shapes the amount and pattern of network change in terms of tie addition and structural holes, Sasovova et al., 2010). • Past performance (Productive inventors are more likely to form collaboration ties that enhance brokerage position, Lee, 2010.)	• Strategy and actions (Corporate strategy and node-modifying actions lead to different network changes, Hernandez & Menon, 2021). • Resources (Firms pursue homophilous alliance ties for domain-specific knowledge but heterophilous ties for architectural knowledge, Yayavaram, Srivastava, & Sarkar, 2018).
Relational Factors	• Preexisting network structures (Inter- and intra-team brokerage positions lead to subsequent tie formation and dissolution, Balkundi et al., 2019). • Endogenous structural tendencies (Reciprocity, transitivity, and popularity are predictive of network dynamics. Mirc & Parker, 2020; Rank, Robins, & Pattison, 2010).	• Prior ties and networks (Prior ties shape subsequent tie dynamics and network formation, Uribe et al., 2020; Zhang et al., 2017). • Endogenous structural tendencies (Reciprocity, transitivity, popularity, and activity are predictive of network dynamics. Howard, Boeker, & Andrus, 2019; Kim et al., 2016).

Notes: This table is not exhaustive; it merely lists illustrative studies. One paper may involve multiple categories.

Table 4. Outcomes of Organizational Network Dynamics

Outcomes	Interpersonal network studies	Interorganizational network studies
Performance	• **Individual performance** (Brennecke, 2020; Burt & Merluzzi, 2016; Methot et al., 2018; Soda, Mannucci, & Burt, 2021). • **Team performance** (Briscoe & Tsai, 2011; Stuart, 2017; Zheng, Zhao, Liu, & Li, 2019). • **Organizational performance** (Clement & Puranam, 2018; Kleinbaum & Stuart, 2014a).	• **Financial & operational outcomes** (Beckman, Schoonhoven, Rottner, & Kim, 2014; Hernandez & Menon, 2018; Ozcan, 2018; Shipilov & Li, 2008; Uribe et al., 2020; Young-Hyman & Kleinbaum, 2020). • **Firm growth & market share** (Baum et al., 2012; Knoben & Bakker, 2019; Mitsuhashi & Greve, 2009; van den Ende et al., 2012; Vissa & Bhagavatula, 2012; Zaheer & Soda, 2009). • **Corporate innovation** (Baum et al., 2010; Howard et al., 2019; Kumar & Zaheer, 2019; Schilling, 2015; Sytch & Tatarynowicz, 2014a).
Behavior	• **Individual behavior**: gossiping behavior (Ellwardt et al., 2012); quitting a job (de Klepper et al., 2017; Woehler et al., 2021). • **Collective behavior**: inter-unit collaboration (Kleinbaum & Tushman, 2007); corporate coordination and adaptability (Kleinbaum & Stuart, 2014a).	• **Cooperative action**: forming alliance (Ahuja, Polidoro, & Mitchell, 2009; Howard et al., 2017; Rosenkopf & Padula, 2008), mergers & acquisitions (Hernandez & Shaver, 2019), interfirm employee mobility (Sgourev & Operti, 2019), formal organization change (adopting partner hospitals' clinical activities, Stadtfeld et al., 2016). • **Competitive action**: patent litigation (Howard et al., 2017), competitive encounter (Downing et al., 2019), collective violence (Operti et al., 2020).

Cognition	• **Person-oriented**: perceived stress (Kalish et al., 2015), job/task embeddedness (Bensaou et al., 2014). • **Relation-oriented**: team psychological safety (Schulte et al., 2012), social integration perception (Bensaou et al., 2014; Walsh et al., 2018), relational identity disruption (Methot et al., 2018), leadership attribution (Carnabuci et al., 2018; Kalish & Luria, 2016). • **Organization-oriented**: org. commitment (Bensaou et al., 2014; McCarthy & Levin, 2019), thoughts of job quitting (Tröster et al., 2019).	• NA.

Notes: This table is not exhaustive; it merely lists illustrative studies. One paper may involve multiple categories.

Table 5. Key Analytic Approaches to Network Dynamics

	MR-QAP	ERGM	SAOM	REM
Summary description	A form of multiple regression in which cases are dyads and the dependent variable is presence/absence or strength of tie. Significance of parameters assessed via permutation test rather than classical inferential	A model of the probability of an observed network, given a set of network statistics reflecting the prevalence of various micro-configurations & other properties. Observed data viewed as long-term outcome of a set of tendencies working in combination	A model for longitudinal network data. Simulates actors making sequences of choices to change or maintain relationship status with every other actor as they maximize a common objective function. Actors control only their outgoing ties	A model of sequences of discrete dyadic events, such as text messages. The dependent variable is each event in the sequence, modeled as a function of the past sequence of events, along with static covariates, including states.
Sample research question	Simple QAP: Are managers more likely to seek advice from others of the same gender? Is this relationship moderated by having friends in common? Panel QAP: Are new ties more likely to be within gender while lost ties more likely to be between genders?	Simple ERGM: Controlling for homophily, do managers have a tendency to start seeking advice from their advisors? LERGM: Do actors who cite patents of many others tend to be highly cited themselves, and does this effect increase over time?	Basic model: What are the forces that seem to be driving actors' choices to form or dissolve ties? Co-evolution model: Do disgruntled employees seek each other out as friends, or do friends influence each others' attitudes toward the company, or both?	How do communication norms and formal roles interact to determine who will next call whom?
What is modeled	Presence/absence or strength of ties (assumed to be relational states) among dyads. Can also model diverse dyadic outcomes such as similarity of behavioral profiles	Presence/absence of ties (assumed to be relational states)	• Presence/absence of ties (assumed to be relational states) • (optional) Change in node-level attributes such as behaviors	Occurrence of the next relational event. Specifically, who will direct an interaction to whom.

Kinds of effects / independent variables	Principally used to examine effects of exogenous covariates such as proximity, similarity of attributes, other kinds of ties, etc. Can also test certain endogenous effects (e.g., reciprocity) if a dyadic variable can be constructed to capture the idea (e.g. transpose of the adjacency matrix.	Modelling endogenous effects such as tendencies to reciprocate, to send ties to friends of friends, etc. Can also include any exogenous variables such as other kinds of ties or actor characteristics	See ERGM. Additionally, can be used to simultaneously model selection (e.g., how actors choose their friends) and influence (e.g., how actors adopt the styles of their friends) as a coevolutionary process	Use of past sequence of events to predict future events. Also includes a subset of analogues to ERGM parameters, such as reciprocity, transitivity, cyclicality, preferential attachment, along with exogenous covariates.
Meaning of parameters	Positive parameter for X indicates that larger values of X are associated with greater probability or strength of tie.	• Exogenous variables: change in log odds of tie given unit increase in X • Endogenous variables: Positive parameter for X (e.g., # of transitive triples) indicates that odds of a tie is higher to the extent that its presence contributes to change in X (e.g., change in # of transitive triples)	See ERGM	How much the risk of an event is multiplied by a unit increase in X. E.g., the increase in likelihood that the next event is A sending to B that is due to the relationship A has to B
Approach to change	Implicit. Model gives the effect of X on Y. Hence, we predict change in Y given a change in X. *But see also panel variants below.*	Implicit. Model gives the effect of X on Y. Hence, we predict change in Y given a change in X. *But see also temporal variants below*	Explicit. Continuous time framework updates dyadic dependencies as each dyad changes. Ordering of tie changes makes a difference. But actual minute-by-minute changes to the network are imputed, not observed	Explicit. The model is about the next (social) event to happen. This is about network dynamics even if it is not about tie change per se
Approach to non-independence of observations in dyadic data	Permutation method automatically controls for all sources of dyadic dependence (known and unknown)	Researcher explicitly identifies and models sources of dependence between dyads	See ERGM	Relational events dependent on past events, but since events assumed to be non-simultaneous, no dependence at same time

Goodness of fit	Dyadic. Sum of squared differences, across all dyads, between observed Yij and predicted Yij	Whole network. Check whether networks simulated from the model have the same overall network statistics as the observed network	Like ERGM	Dyadic. For each dyadic event that actually occurred, did the model assign a high probability to that (sender, receiver) pair?
Minimum input data requirement	DV: an observed network IVs: dyadic covariate (possibly constructed from node attributes).	An observed network at one point in time.	A network measured at two or more time points.	A set of time-ordered sender-receiver pairs representing social acts between a finite number of actors.
Testing of purely endogenous effects	Variables representing endogenous effects must be constructed and input as IVs by the researcher. E.g., to test reciprocity, the transpose of the network must be added as an IV	Built-in to model	Built-in	Several built-in
Actor Agency	Agnostic	Agnostic	Assumed	Agnostic
Strengths	• Easy to understand and interpret parameters • Easily customizable • Requires relatively little computational power • No problems fitting model • No problem predicting strength of tie, frequency of interactions, etc.	• Specifically designed for modeling network data • Can include some endogenous effects that would be difficult in MR-QAP • Can include any dyadic covariates that can be used in MR-QAP • Provides the most complete understanding of the endogenous processes in a given social network	• Specifically designed for modeling network data • Can include some endogenous effects that would be difficult in MR-QAP • Can include any dyadic covariates that can be used in MR-QAP • Can model coevolution of ties and node attributes	• Only model reviewed here that is appropriate for relational events • Can model sequences of events without a priori aggregation (and therefore losing information about sequence and timing) • Ability to change the duration of the history of observed events in predictors • Ability to handle change in the composition of the

				actor membership over time.
Issues	• Only a limited set of endogenous effects can be modeled with cross-sectional data • Variants such as logistic or negative binomial not well studied yet	• Problems getting models to converge • Interpretation of parameters is complex • Computationally demanding with networks above a certain size	• Difficult to extrapolate the network past the last observed time • Can only account for a moderate amount of change in the network	• Computational issues in calculating the risk set for sequences with many actors (but possibility to do sampling) • Limited range of statistics available off the shelf
Temporal variants	• Can include lagged versions of both Xs and Y as controls, as in panel regression • Can explicitly model Y(t) - Y(t-1)	• TERGM: Essentially an ERGM that includes lagged version of network as dyadic covariate • STERGM: a TERGM with separate models for tie formation and dissolution • LERGM: something like a tie-wise version of SAOM	Not applicable	Not applicable

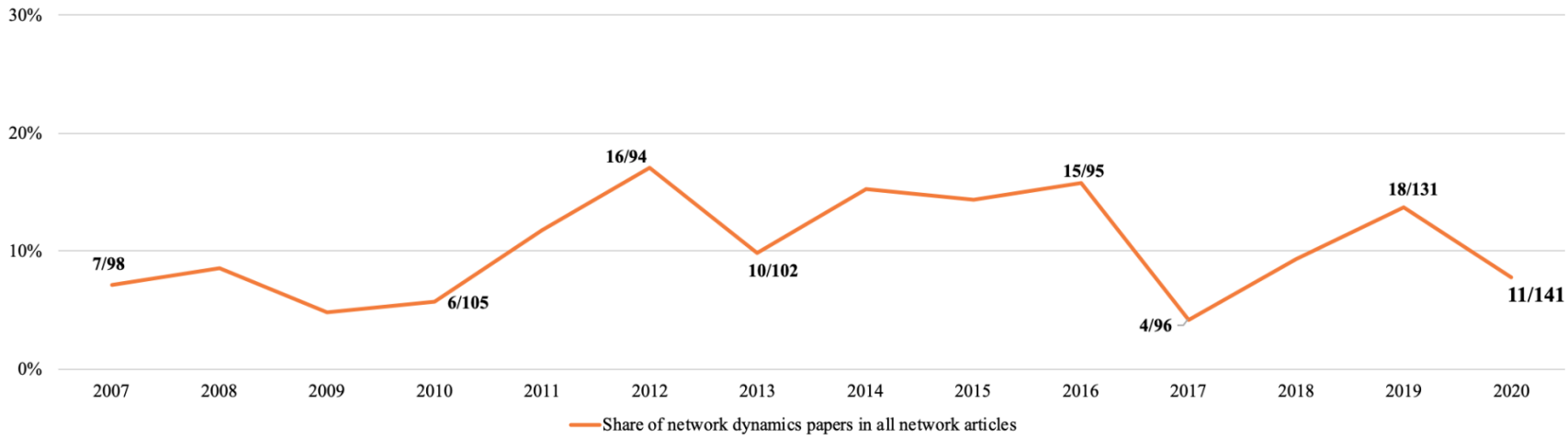
Notes. MR-QAP = Multiple Regressions with Quadratic Assignment Procedure, ERGM = Exponential Random Graph Models, SAOM = Stochastic Actor-Oriented Models, REM = Relational Event Models.

Table 6. Key Questions for Future Research on Network Dynamics

Topic	Key Research Questions
The interplay of relational states and relational events	● How are the probabilities of relational events (e.g., person A sends person B an email) shaped by the nature of the relational states (e.g., friendship; coworkers) in which they are embedded? ● How does the occurrence, sequence and timing of relational events shape the evolving network of relational states? ● What is the role of interpretation and sensemaking in the dynamic relationship between relational states and relational events? How does variation in interpretive skills and cultural norms influence this relationship? ● Need for the further development of event-based measures (and analytic techniques) that simultaneously account for the sequence and timing of network dynamics to complement existing state-based measures.
Mechanisms of network dynamics	● Avoid confusing statistical regularities with explanatory mechanisms. We need greater attention to the "how" behind network dynamics — that is, we need readily understandable causal accounts that explain observed statistical regularities. ● How best to account for the agency of others in network dynamics? Different analytical approaches, implicitly or explicitly, take different approaches to this question. ● Are some mechanisms underlying network dynamics different when the nodes in the network are individuals versus firms/collectivities? ● We know little about the mechanisms that explain the timing and sequence of relational events.

Outcomes of network dynamics	● How and why do network dynamics (as compared to the simple presence/absence of ties) influence outcomes (such as performance) other than the network itself? More generally, we need to learn more about the coevolution of networks and outcomes. ● How short-lived are the effects of network dynamics? ● To what extent are the outcomes of network dynamics associated with changes in relational states versus the sequence and timing of events? ● How does the speed and/or periodicity of network change influence outcomes and what explains this influence? ● How are network trajectories (sequences of relational states and/or relational events) related to outcomes?
Cognition and network dynamics	● How do individuals/firms/audiences encode and recall the dynamics of networks as states and events? Are certain kinds of dynamics more easily noticed than others? What kinds of cognitive scripts do people use to organize their perception of the order and sequence of relational events? ● How are perceptions of network dynamics related to networking behaviors? ● What is the role of memory in channeling the influence of past networks on actions and outcomes in the present and the future? ● What are the cognitive processes underlying the reactivation of ties that have fallen dormant over time? ● How do differences in the cognitive capacities and propensities of firms versus individuals shape “macro” and “micro” network dynamics?

Figure 1. Percentage of Network Dynamics Papers among Overall Network Papers in Major Management Journals



Notes: The fraction examples along the line give the count of network dynamics papers and the count of overall network papers respectively in a specific year. The count of overall network papers was based on a search that used the word "network*" in the title, abstract or author keywords in any of the management journals (see footnote 6 for list of journals).

Figure 2. Literature Search and Inclusion Criteria

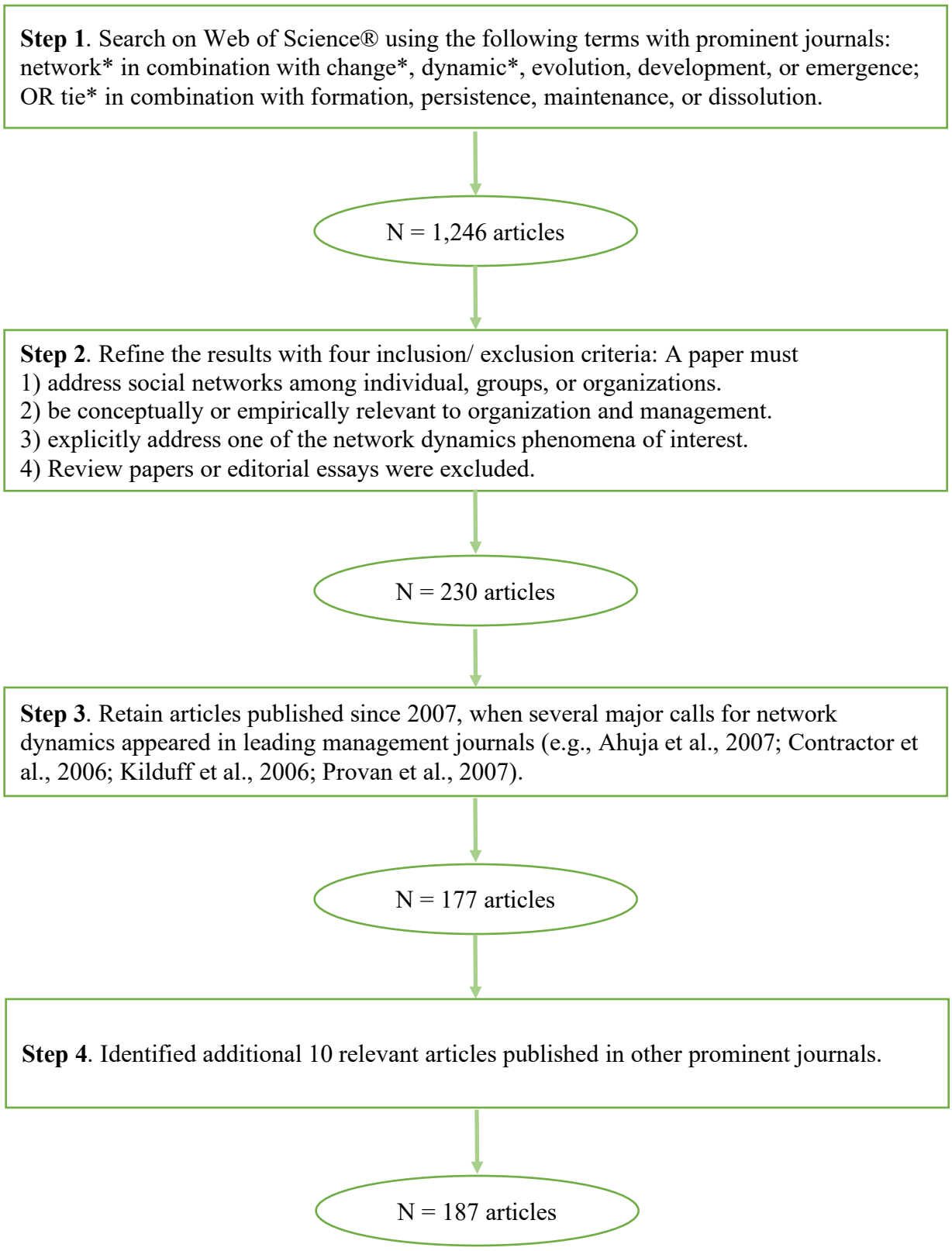
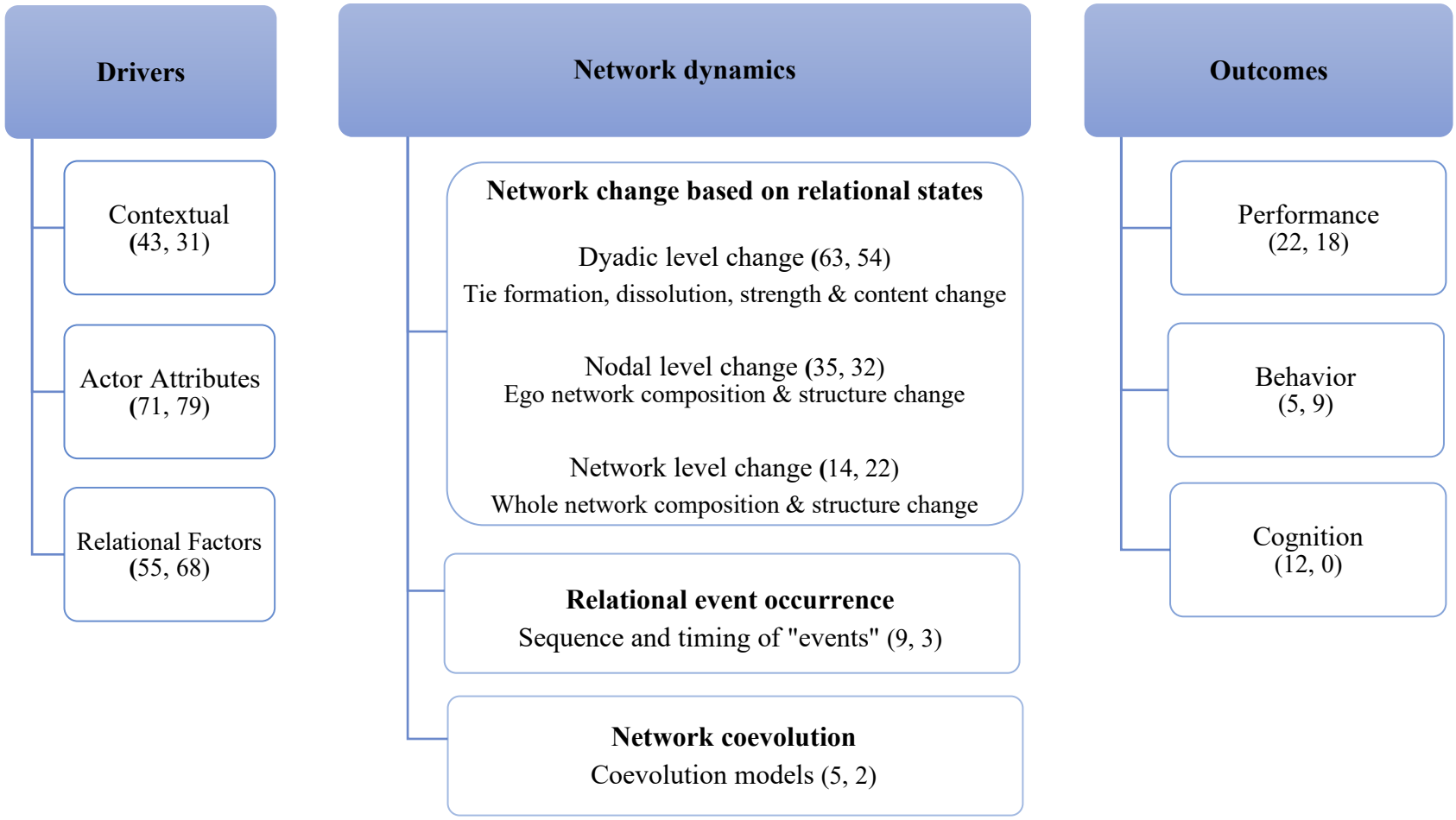
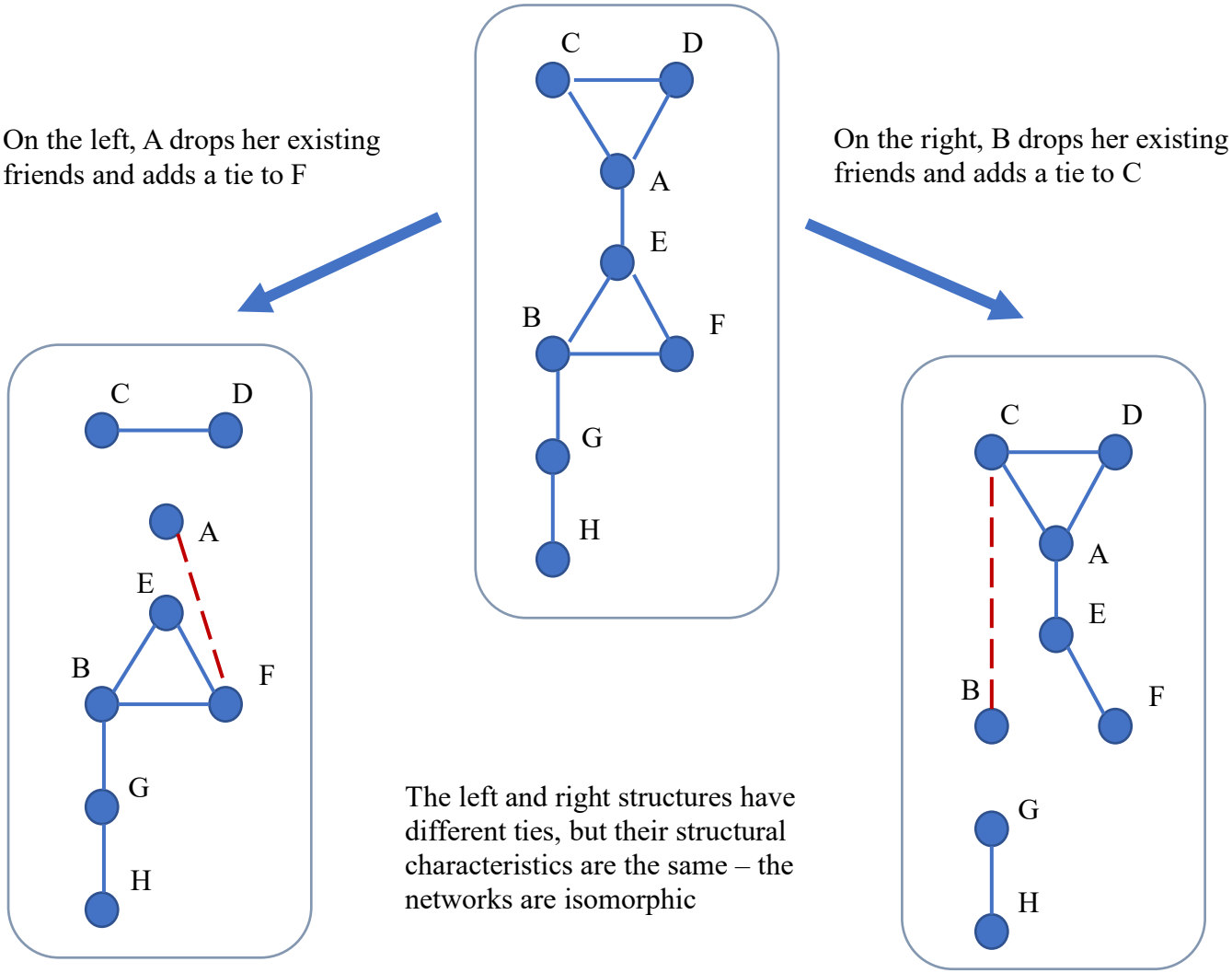


Figure 3. Network Dynamics: A Taxonomic Framework



Note. Numbers in parentheses are counts of micro (interpersonal) and macro (interorganizational) papers respectively.

Figure 4. Tie Dynamics and Network Structure



APPENDIX.

ANALYTICAL APPROACHES TO NETWORK DYNAMICS

As we have noted, research on networks is conducted at three levels of analysis: the dyad, the node, and the group (also called "network"). In general, the methods used to explore hypotheses at the node and group levels are the same as in any area of organizational research. [24] Hence, we do not discuss these kinds of hypotheses further, except when discussing the coevolutionary capabilities of SAOMs (described below).[25] Where specialized models are routinely used (and unquestionably needed) are at the dyadic level. This is because the dependent variable consists of measurements on a set of dyads that are not independent of each other. For example, all the dyads which feature a given node as the sender are not independent of each other because they share the same sender. If sender A is very gregarious, then the likelihood of a tie A → B is increased, as is the likelihood of a tie A → C, and so on. The situation will be familiar to anyone working with multi-level data. Similarly, dyads featuring a given receiver tend to be interdependent as well. The sources of dependence do not end there. Given norms of reciprocity, not to mention gratitude, a tie from A to B tends to provoke a tie from B to A. In addition, balance theory (Heider, 1958) suggests that if A likes B, and B likes C, A will experience some aversive cognitive dissonance if A did not like C. This would tend to either increase the probability of an A to C tie or increase the probability of dissolving the A to B tie. Either way, the states of all three dyads have some level of interdependence. More complex dependencies have been formulated as well (Snijders, Pattison, Robins, & Handcock, 2006).

Analytical Models with Cross-sectional Data: QAP and ERGM

There are two main approaches to dealing with dyadic dependence. We discuss these in a cross-sectional context first, and then add in a longitudinal component. The simplest approach is

the Multiple Regression Quadratic Assignment Procedure, known as MR-QAP (Krackhardt, 1988; Dekker, Krackhardt, & Snijders, 2007). As used in this context, MR-QAP is a form of regression in which the cases are dyads, the dependent variable is the state of the dyad (i.e., presence/absence or strength of tie), and the independent variables are dyadic properties such as the difference in age between the nodes in the dyad, whether they are the same gender, their physical proximity, and so on. [26]

Where MR-QAP differs from ordinary regression is that the p-values are calculated via a permutation method that generates the distribution of beta coefficients on the fly (like bootstrapping) rather than assuming a mathematical distribution (which would not be safe in the presence of non-independence of observations). The consequence of the permutation method used in MR-QAP, specifically the double semi-partialling method developed by Dekker et al (2007), is that the structure of dependencies among dyads is held fixed (i.e., controlled for). See Allatta and Singh (2011) for an example of a study using MR-QAP to predict amounts of communication between pairs of workers.

When used to predict a binary dependent variable – the presence or absence of tie – the MR-QAP technique implements the linear probability model (LPM) often used in econometrics. It has the advantage that the beta coefficients can be interpreted directly as expected changes in probability of the dependent variable as a function of one-unit change in independent variable. However, it does have the disadvantage that in principle the predicted values could be smaller than 0 or larger than 1. Logistic regression QAP models (Martin, 1999) are available in software such as UCINET (Borgatti, Everett, & Freeman, 2002), but to our knowledge there are no published studies that explore the mathematical properties of these models. See Gulati and Gargiulo (1999) for an example applying QAP to probit regression models in studying strategic

alliance tie formation. Note that for cross-sectional data, the MR-QAP model is best viewed as a model of tie existence, which is informally thought of as modeling tie formation.

The second fundamental approach to testing dyadic hypotheses is the family of exponential random graph models, known as ERGM (see Lusher, Koskinen & Robins, 2013, for an approachable introduction). Whereas MR-QAP implicitly controls for sources of dependence among dyads, ERGM explicitly models individual sources of dependence (such as transitive triples) by including them as independent variables. Hence a model predicting friendship ties as a function of a covariate such as physical distance would also include a variety of terms to capture the local dependencies between dyads. In these models, the effects capturing these dependencies are known as endogenous effects, because they can be calculated from the network being modeled -- the dependent variable -- without needing to reference additional information about the actors. In turn, characteristics of the nodes, such as gender, or other dyadic data, such as physical distance or the presence of some other kind of tie (e.g., advice-seeking ties when modeling friendship ties), are termed exogenous effects. This terminology should not be taken to mean that phenomena like reciprocated ties and transitive triples are inherent in networks, nor that they would occur independently of (a) actor psychologies and goals, or (b) contextual factors such as norms of behavior and incentive structures. As an aside, some authors refer to the endogenous effects in ERGM as “self-organizing”. But it is not these effects (which represent micro social processes) that are self-organizing. Rather, it is the structure of the network as a whole that is emergent (a less misleading word than “self-organizing”) as a consequence of these micro processes operating over time.

An ERGM can be formulated as a logistic regression in which the log odds of a tie, conditional on the rest of the network, is modeled as a function of a set of parameters

representing both endogenous and exogenous effects. For the endogenous effects, the variables represent changes in a graph statistic (such as the number of transitive triples) that would occur if the tie were present versus not, and the parameters represent the change in log odds for a unit of change in the difference between graph statistics. For example, suppose we have estimated the following model, chosen for its simplicity [27]:

$$\text{Logit}\,(X_{ij}=1) = -2.0\,(\Delta \text{ ties}) + 0.3\,(\Delta \text{ triangles})$$

Insert Figure A about here

Given this model, let us use the network in Figure A to consider the probabilities of a tie forming between various pairs of nodes, starting with the (a, b) dyad. If a tie is added between these two actors, the change in the number of ties in the network is 1, and the change in the number of triangles is 0. So the log odds of a tie is -2, which corresponds to a probability of a tie of 0.12. Now consider the (c, d) dyad. Adding a tie here would add one triangle to the network, so according to the model the log odds of a tie in this situation is -2 + 0.3 = -1.7, which corresponds to a probability of 0.15. Thus, ties that would create a closed triangle are slightly more probable than ties that would not. Finally, consider the (b, c) dyad. Adding a tie here adds two triangles, yielding a log odds of -2 + 2*0.3 = -1.4 which in turn yields a probability of 0.20. The differences in probabilities are not large, but it is clear that the positive parameter on triangles means that ties that contribute multiple triangles to the network are more likely, which is to say that a network generated by this model would have more triangles than a network in which the triangle parameter was zero.

An interesting feature of ERGMs is that goodness of fit is not assessed at the dyad level. Rather, the estimated model is used to generate hundreds of simulated networks and overall network statistics (such as number of reciprocated ties) are calculated for each one. If the average value of each statistic is close to the corresponding statistic in the observed network, the model is said to fit. All the statistics included in the model are evaluated, as well as additional statistics not associated with the model parameters, such as, say, the degree distribution (the number of nodes with exactly *k* friends, for all possible *k*). The idea is that a good model generates simulated networks that look like the observed network on a variety of dimensions. This also means that, in the absence of exogenous covariates (reflecting node-specific information), ERGMs should not be expected to do a good job of predicting ties between specific pairs of nodes. Recent organizational network studies applying ERGM in examining tie formation include Brennecke (2020), de Klepper et al. (2017) and Tasselli & Caimo (2019) for interpersonal networks, and Ghosh et al. (2016) and Kim et al. (2016) for interorganizational networks.

It is worth noting that a cross-sectional ERGM is a model of the presence/absence of ties, not change. However, if we assume the observed network is the outcome of a long-term process of patterned tie changes, then we can view the parameters of the model as providing evidence for which kinds of social processes might have been operating to shape the network.

Analytical Models with Longitudinal Data

While these cross-sectional models do establish the correlates (theorized as antecedents) of ties, it is clear that they do not explicitly model change. However, if a network Y is measured at two points in time, MR-QAP can be used to model Y(t)-Y(t-1), effectively predicting changes in ties between the two time periods. Alternatively, one can model Y(t) as a function of the X

variables and include Y(t-1) as a control, as in a panel regression. The latter approach can be done with ERGM, and this is essentially what the temporal ERGM, known as TERGM, does (Robins and Pattison, 2001). A variation of TERGM is STERGM – separable temporal ERGM – which effectively fits two models, one for tie formation and one for tie dissolution (Krivitsky & Handcock, 2014). While TERGM and STERGM assume that the network observations are the outcome of discrete-time Markov process, other ERGM variants (e.g., LERGM) analyze network panel data by considering the observed networks as the outcome of a continuous-time Markov process defined by a series of micro-steps in network change. See Kalish and Luria (2016) for an example of applying longitudinal ERGM in studying leadership perception network evolution in a military assessment boot camp.

A different model – designed specifically for modeling the process of network change – is the stochastic actor-oriented model, or SAOM (Snijders & Van Duijn, 1997; Snijders, 2001). Unlike a purely statistical model that is agnostic to what is being modeled, the SAOM implements basic elements of a sociology of tie change. In the simplest case – where ties are directed -- it assumes that actors control only their outgoing ties, and that they make changes in their relationships with others over time in accordance with a set of goals/preferences (such as preferring to reciprocate incoming ties, or to minimize cognitive dissonance by closing transitive triples). These preferences are modeled as an "evaluation function" (a linear combination of parameters and local graph statistics) that the actor seeks to maximize (consciously or not). The data consists of a network measured at multiple points in time, though the model assumes an unseen process of tie changes that unfold continuously between observations. In the model, the actor is viewed as taking a series of unobserved, one-at-a-time, relational decisions that maximize the evaluation function. This means that the dependence structure among dyads

changes after each tie decision is made, rather than as a slate of changes from one wave to another, as would be the case in a panel MR-QAP or a TERGM. In addition, the statistics used in the evaluation function (such as the number of triangles or the number of ties to women) are calculated from the actor's point of view, not globally as in ERGM. This means, for example, that when calculating the evaluation function for actor A, the triangles counted are only those involving A's alters. However, the model parameters – the effects – are common to all alters. This means all actors have the same degree of striving for, say, reciprocating ties. Goodness of fit for SAOMs are calculated as in ERGMs -- i.e., ensuring that networks simulated by the model resemble the observed network with respect to network statistics such as the degree distribution and the triad census. Organizational network studies applying SAOMs include: Agneessens and Wittek, 2012; Carnabuci et al., 2018; de Klepper et al., 2017; Kalish et al., 2015; Schulte et al., 2012; Tröster et al., 2019 on interpersonal network change and Corbo et al., 2016; Howard et al., 2017; Sgourev and Operti, 2019; Withers et al., 2020 on interorganizational network change.

The ties modeled in an MR-QAP, ERGM or SAOM are assumed to be relational states rather than relational events. A relational state characterizes the relationship between two actors (e.g., friends or coworkers) and is continuously present until the state changes. A relational event is something that happens between two actors, and refers to a discrete, transitory occurrence, such as sending someone an email. From a statistical point of view, one way to think about the difference is in terms of whether the primary dependencies between dyads are sequential or simultaneous (Butts & Marcum, 2017). Relational events occur quickly and frequently within the same dyad and are strongly auto-correlated over time. For example, a pair of friends speak frequently with each other, and each utterance is highly dependent on previous utterances. An utterance between A and B, however, may be unrelated to one between C and D, and, at any

instant in time, there may only be one utterance happening anywhere in the network. In contrast, the relational state of friendship is simultaneously occurring across many dyads, leading to autocorrelation across dyads at a single point in time. [28]

MR-QAP, ERGM and SAOM all require relational states rather than events. There are two reasons for this. First, it seems obvious that for something to change, it really has to have continuity over time. A relationship can change over time. But it seems awkward to refer to something that is discrete and instantaneous (such as an email X sent from A to B) as changing, because once X has happened, it no longer exists. It is a different kind of network dynamics. Second, ERGMs and SAOMs assume simultaneity. What is modeled is the joint probability that all of the dyads have the states they do. Without simultaneity, there is no social structure to model.

However, there is a very different family of models that is specifically defined for relational events. This is the relational event model or REM (Butts, 2008). In a REM, the dependent variable is the occurrence of the next event (conceived of as an ordered pair of actors), which is modeled as a function of the sequence of past events, along with more static covariates, such as actor characteristics. For example, we might study abusive comments like put-downs. Effectively, the model is told that a put-down event is coming up and its job is to predict, based on what's happened before, who will put down whom. A large volume of past put-downs may predict future put-downs, just as a history of having been put-down may predict a continuation of that tendency. In addition, reciprocity may be negative in that, within the same dyad, put-downs from A to B may tend to be associated with a lack of put downs from B to A. We might also anticipate a negative cyclic effect where if A → B, and B → C, then only rarely would we find C → A.

A relational event model allows a researcher to examine social behaviors over time in the context of social structure. For example, following the general logic of Burt (1992), we might expect actors to actively seek the perspectives of their unconnected actors on the theory that these would be more likely to provide diverse views than contacts who are connected to each other. Is this what actually happens? Together with a dataset of time-ordered requests for inputs (such as emails), a relational event model would make it possible to answer this question. See Quintane and Carnabuci (2016) for an empirical study along these lines. Similarly, in a conversation, we might expect whoever has recently been vocal to be the target of present communications. See Schecter, Pilny, Leung, Poole, and Contractor (2018) for an example examining communication network dynamics in teams.

In the model, each event is assumed to occur alone (not simultaneously with other events). What is modeled is the appearance of an arc at a given time. Essentially, the model predicts who will do something to whom at each event time. Goodness of fit is assessed at the event level, in the sense that, for a given event, the model assigns a probability to every possible combination of (ordered) sender-receive pairs. If the model is good, the ordered pair that actually occurred is one that the model assigned a high probability to. In addition, we can assess how often the pair with highest probability is the one with the correct sender and the correct receiver. Thus, we can count up how often the model got the sender right, and how often it got the receiver right.

As summarized in Table 5, there are a number of analytical models that can be used to study presence or absence of ties. These range from cross-sectional MR-QAP and ERGM, which models change only implicitly, to panel versions of these same models, to fully temporal models that actively model change. Clearly, then, an important factor in choosing an analytical method is whether one has cross-sectional or longitudinal data. Another big divide is between the relational

event model (REM), which is designed for relational events, and all the other models, which are designed for relational states. Both model network dynamics, but of different kinds. The former models occurrences of social acts, while the latter models change in relationships. In the extreme, the relational events model assumes streams of instantaneous events that occur one after another with no simultaneity, whereas relational state models assume all of the ties (in a given wave) are present simultaneously, giving rise to paths that link together distant nodes and enabling us to speak of network structure. As Moody (2002) points out, problems arise when we treat time-ordered relational events as if they were relational states by aggregating over time periods. Each of the different models makes different assumptions about the underlying nature of network dynamics and is best suited to addressing a different question (see Table 5).

Figure A. Excerpt of a Network for Illustrating ERGM

