Investigating the Temporal Dynamics of Interorganizational Exchange: Patient Transfers among Italian Hospitals[1]

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Previous research on interaction behavior among organizations (resource exchange, collaboration, communication) has typically aggregated those behaviors over time as a network of organizational relationships. The authors instead study structural-temporal patterns in organizational exchange, focusing on the dynamics of reciprocation. Applying this lens to a community of Italian hospitals during 2003–7, the authors observe two mechanisms of interorganizational reciprocation: organizational *embedding* and resource *dependence*. The authors show how these two mechanisms operate on distinct time horizons: dependence applies to contemporaneous exchange structures, whereas embedding develops through longer-term historical patterns. They also show how these processes operate differently in competitive and noncompetitive contexts, operationalized in terms of market differentiation and geographic space. In noncompetitive contexts, the authors observe both logics of reciprocation, dependence in the short term and embedding over the long term, developing into population-level generalized exchange. In competitive contexts, they find no reciprocation and instead observe the microfoundations of status hierarchies.

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INTRODUCTION

Sociological research has left little doubt that organizations operate within extensive networks of other organizations. Most work has focused on coarse substantive relationships among organizations: patterns of joint ventures, strategic alliances, and other cooperative arrangements (Walker, Kogut, and Shan 1997; Powell et al. 2005); interorganizational networks formed by friendship or kinship among managers (Ingram and Roberts 2000; Ingram and Lifschitz 2006); links by shared directors (Galaskiewicz and Wasserman 1981; Palmer, Friedland, and Singh 1986; Roy and Bonacich 1988; Vedres and Stark 2010), founders (Hillmann and Aven 2011), members (Rosenthal et al. 1985; Cornwell and Harrison 2004), or investors (Hillmann 2008); or shared relationships with financial institutions (Mizruchi 1992; Moody and White 2003) or interorganizational coalitions (Ingram, Robinson, and Busch 2005; Rosenkopf and Schleicher 2008; Torfason and Ingram 2010). Instead of studying substantive relationships, some researchers have represented interorganizational networks by directly measuring interactive behaviors among organizations. For example, they record an interorganizational "tie" to represent communication observed among managers (Baker and Faulkner 1993; Fernandez and Gould 1994), organizations cosponsoring an event (Bearman and Everett 1993; Baldassarri and Diani 2007), firms lending money or trading personnel (Keister 2001), companies giving congressional testimony on the same policy issue (Dreiling and Darves 2011), ports being connected by a shipping trip (Erikson and Bearman 2006), or gangs murdering members of other gangs (Papachristos, Hureau, and Braga 2013). Even researchers observing organizational exchange events have conventionally aggregated these interactions over time into "ties," which they take as proxies for temporally stable and temporally continuous relationships (Kitts 2014; DeNooy 2015) defined on a time interval. In this way, interwoven sequences of interaction events are frozen into fixed structures ("networks") amenable to conventional social network analysis tools.

Although the concept of social structure seems to presuppose some stability in interaction patterns, the fine-grained sequence and timing of interaction also has profound importance for phenomena of interest to social scientists, such as diffusion and influence (Moody 2002; Moody, McFarland, and Bender-DeMoll 2005). Our work aims to address long-standing gaps in the understanding of how interorganizational networks change over time (Levinthal and Fichman 1988; Baker and Faulkner 2002; Rosenkopf and Padula

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2008). Notably, the temporal aggregation of exchange events reveals latent structures of exchange but may obscure our view of the generative forces underlying those structures. Even research that has considered the dynamics of interorganizational networks (as appearance or disappearance of ties) has yet to discriminate among time horizons in which different network mechanisms unfold. Empirical studies implicitly assume that mechanisms of network evolution operate in synchrony and depend on history in the same way. Finally, work focusing on local patterns in networks (e.g., reciprocity, transitivity) in isolation has limited potential to illuminate the macrostructures that emerge in organizational populations, communities, and fields.

We aim to understand the phenomenon of interorganizational resource exchange by focusing directly on the interdependent temporal dynamics of exchange events as they unfold in time. Avoiding temporal aggregation of exchange events into ties allows us to shed new light on the generative forces underlying exchange, gives purchase on identifying mechanisms, and offers a first look into the time horizons by which these mechanisms unfold. Directly analyzing exchange behavior also brings us in closer theoretical dialog with rich qualitative interpretations (Malinowski 1920; Mauss [1925] 1990; Levi-Strauss 1944) and informal discursive theory (Homans 1958; Blau 1964) on exchange dynamics. Methodologically, our approach draws on cutting-edge methods of relational event analysis (Butts 2008; Pilny et al. 2016; Stadtfeld, Hollway, and Block 2017), building on traditions in event history analysis (Tuma, Hannan, and Groeneveld 1979; Hannan 1989) and sequence analysis (Abbott 1990, 1995; Stark and Vedres 2006).

Here we take a first step toward an elementary structural theory of interorganizational social exchange. We focus on just one type of exchange among organizations, which has proven important to our understanding of interpersonal relationships: voluntary unilateral transfers of resources ("giving"). Unlike *negotiated exchange* (where both parties directly trade some goods or pay some price for services), in this case a unilateral transfer of resources from A to B may or may not be followed by a transfer from B to A at a later time. This situation of independent sequential choices is called *reciprocal exchange* (Molm 2010; Molm, Whitham, and Melamed 2012) or *reciprocity* (Homans 1958; Gouldner 1960; Blau 1964).

In developing this theory, we distinguish two basic bonding mechanisms that may underlie the process of reciprocal exchange among organizations (Laumann and Marsden 1982): first, organizations depend on each other for resources, and this dependence is greater if an exchange partner is an important source of resources (relative to other partners). When an organization gives more to exchange partners that are relatively important senders of resources to it (Emerson 1962; Cook 1977; Pfeffer and Salancik 1978), we call this *dependence reciprocation*. By contrast, organizational *embedding* implies that as organizations give a larger portion of their outgoing resources to particular partners, their operations and infrastructures gradually interweave: they develop better communication among personnel and more detailed and accurate information about partners' capabilities, and they gradually develop shared routines that make their exchanges more efficient and reliable than alternative neglected partners (Uzzi 1996). This gradual process yields a bias to give more to partners to which one has given in the past and a reciprocal bias to give to partners that have given relatively more to oneself in the past. We refer to these two forms of stickiness in exchange due to focus of activity as *embedding inertia* and *embedding reciprocation*.

Previous work on power and dependence has always conceived of those processes as operating on contemporaneous opportunity structures (i.e., the partners currently available; Cook 1977; Bonacich and Bienenstock 2009). Previous qualitative work on development of organizational relationships through reciprocation has informally described a process that plays out over time, even though analytical lenses rarely allowed direct analysis of temporal dynamics. Drawing on these earlier insights, we demonstrate that these two mechanisms of reciprocation (dependence and embedding) operate over distinct time horizons. Specifically, reciprocation due to organizational embedding develops gradually over a long time horizon, whereas reciprocation due to resource dependence operates contemporaneously on a set of active partners. This approach extends efforts to disentangle organizational dynamics operating in the short and long term (Hannan 1998; Kitts 2009).

We apply the theory to transfers of patients in a community of regional hospital organizations in the Abruzzo region of Italy over a period of five years (2003–7). In the Italian health care system, transferring patients implies flows of government funding (and other resources, as we will describe) from the patient-sending hospital to the patient-receiving hospital, so interhospital patient transfers in the Italian system can be represented as sender-initiated unilateral resource transfers. Our analysis of reciprocation in this system reveals a variety of clear patterns that are intelligible in light of our theory. As predicted, we observe both embedding and dependence reciprocation and show that the former develops over longer time horizons, whereas the latter is responsive to contemporaneous structures reflected on a shorter time horizon.

We present analytical extensions that validate our interpretations by showing how interorganizational exchange develops differently in competitive and noncompetitive exchange settings. Sending patients in competitive contexts (within the same medical specialty area and within the nearby geographic area) represents "deference" to competitors. Sending patients in noncompetitive contexts (across specialty areas and to distant geographic areas) allows for "complementary" exchanges. We show that the dynamics of reciprocation differ in intelligible ways for deference exchanges and complementary exchanges: for deference transfers within competitive exchange settings, we observe little or no reciprocation. For complementary transfers across exchange settings and geographic regions, we see reciprocation developing following the logics of dependence and embedding described above. Because competition diminishes continuously as geographic distance increases (Baum and Mezias 1992; Baum and Haveman 1997; Sorenson and Stuart 2001), we are able to demonstrate that reciprocation increases gradually as distance increases and show that processes of embedding and dependence drive reciprocation as competition diminishes.

Explicitly modeling the dynamics of social interaction will provide purchase on the emergence of community-level patterns, such as generalized exchange (Bearman 1997; Molm, Collett, and Schaefer 2007) and status hierarchy (Chase 1980; Gould 2002; Lynn, Podolny, and Tao 2009) as these broader systems develop through the confluence of dyadic (reciprocation) and triadic (closure) processes. The local dynamics that we theorize and analyze may then constitute a microlevel substrate that can lead to macrolevel structures. For deference transfers in competitive domains, we show that local exchange dynamics can lead to hierarchy formation in the population; for complementary transfers across specialties, we show that local exchange dynamics can lead to generalized exchange.

In summary, moving from conceptualizing "interorganizational networks" as reified structures to directly studying dynamics of resource transfers in time allows us to develop a deeper understanding of interorganizational exchange. Drawing on established literatures in resource dependence and in theories of organizational relationships, we develop novel implications for temporal dynamics of exchange. Specifically, we show that two distinct logics of reciprocation, dependence and embedding, operate over different time horizons and are contingent on the context of exchange (complementary vs. competitive). Importantly, we provide a coherent account that makes these nuanced patterns intelligible. Directly theorizing the dynamics of exchange in this way further allows a flexible and seamless bridge between micro- and macrostructures, including the relational foundations of hierarchy and generalized exchange.

THEORETICAL BACKGROUND

Although extant research on organizational networks has derived important insights from assuming the stability of interorganizational ties (Lomi and Pattison 2006), these networks do change over time as organizations establish (Beckman, Haunschild, and Phillips 2004; Rosenkopf and Padula 2008) or dissolve ties (Levinthal and Fichman 1988). Because the presence of prior network ties between organizations affects the evolution of future ties, research has focused on the endogenous dynamics of interorganizational networks (Gulati and Gargiulo 1999). This research has produced at least three general empirical regularities that we take as starting points (for a general review, see Rivera, Soderstrom, and Uzzi 2010). The first regularity concerns the inertia of network ties, or tie repetition. Current ties are more likely to be observed today if they existed in the past (Podolny 1994; Uzzi and Lancaster 2004), a pattern often interpreted as deriving from the reproductive forces of social structure or as a behavioral response to uncertainty and risk (Gulati 1995). The second regularity concerns reciprocity. A tie is more likely to be directed from one organization to another if the latter organization has directed a tie to the first (Larson 1992; Lincoln, Gerlach, and Takahashi 1992; Uzzi 1996)—an outcome consistent with basic behavioral principles of relational contract enforcement (Fehr, Gachter, and Kirchsteiger 1997). The third regularity concerns the tendency of organizations sharing common partners to be directly connected (Uzzi 1997; Kogut and Walker 2001; Baum, Shipilov, and Rowley 2003). Such patterns of triad closure are consistent with basic principles of organizational bonding (Laumann and Marsden 1982).

Inertia, reciprocity, and closure are often interpreted as social mechanisms capable of reproducing the aggregate regularities typically observed in empirical research (Powell et al. 2005), but key questions remain: How stable are these regularities? How do they change over time and on what timescale? How do these inferred social ties map onto underlying interaction behaviors? While occasionally recognized, such crucial issues are rarely addressed in empirical studies of organizational networks. Indeed, researchers have applied the same lenses and analytical tools to macrolevel and coarse-grained phenomena such as interorganizational relations determined by ownership and procurement that may evolve slowly over years (Gerlach 1997), as well as to microlevel and fine-grained phenomena such as radio communications among emergency responders that evolve over timescales of minutes or even seconds (Butts, Petrescu-Prahova, and Cross 2007). Conventional tools of network analysis tend to be agnostic to timescales, so developing a rigorous consideration of network dynamics requires us to think deeply about how relational processes play out over time.

Our focus on the temporal dynamics of reciprocation behavior builds on classic traditions of qualitative research. Indeed, decades of work in exchange theory have suggested that the temporal dynamics of reciprocal giving behavior play an important role in relationship formation, for individuals, clans, and tribes. Much of this work has employed qualitative fieldwork or informal reasoning and analysis, such as the classics in cultural anthropology (Malinowski 1920; Levi-Strauss 1944; Mauss 1990) and in sociological exchange theory (Simmel 1950; Homans 1958; Gouldner 1960). More recently, work in economics and evolutionary biology has explored the dynamics of reciprocation via game theory and laboratory experiments (Axelrod 1984;

Boyd and Richerson 1988; Fehr and Gachter 2000; Gintis 2000). Recent experimental (Bienenstock and Bianchi 2004; Kuwabara and Sheldon 2012; Molm et al. 2012) and observational (Willer, Sharkey, and Frey 2012) studies have pushed the frontiers of our understanding of interpersonal reciprocity. However, although there is interest in broadening the scope conditions of social psychological theories of reciprocity to include macro-organizational phenomena (Berger, Eyre, and Zelditch 1998; Molm 2010; Molm, Melamed, and Whitham 2013), it is not clear that affective or cognitive mechanisms developed to account for reciprocity at the interpersonal level will also apply to reciprocal exchange among large formal organizations over long timescales. In any case, despite the long-standing interest in applying exchange theory to organizational networks, an analysis of the temporal dynamics of the structure of reciprocal exchange among organizations has never been performed. Thus, we introduce a set of novel theoretical questions (indeed, a new kind of question to ask) as well as a set of new findings that will drive further theoretical development.

Embedding and Dependence Reciprocation in Transfer of Resources among Organizations

Our primary focus in the behavioral dynamics of interorganizational relations is on the phenomenon of reciprocation in exchange among organizations. Rather than studying reciprocity as a binary and static trait of a tie (i.e., reciprocated or unreciprocated), we examine reciprocation as a dynamic social process that takes the form of history dependence in exchange patterns.

For brevity, we refer to one organization giving resources to another organization as "giving," but this is shorthand for "unilateral voluntary transfer of resources, outside the context of negotiated quid pro quo exchange." It need not entail the semantic or cultural baggage of "gifts" in the interpersonal social world. To the extent that organizational resource transfers might be interpreted like conventional gifts, this invokes an analogy to classical cultural anthropology research (Mauss 1990), contemporary comparative and ethnographic research (Yang 1994; McLean 2007), and experimental social psychology research (Bienenstock and Bianchi 2004) on gift giving and implies cultural scripts such as a norm of reciprocity. A strong version of that interpretation is not plausible here, given that formal organizations do not "feel" obliged to reciprocate, and even reputational concerns would be compelling only if interorganizational resource transfers are public and salient. However, whether subtle tendencies to maintain and reciprocate resource transfers may operate at the organizational level through embedding of personnel, information flows, and operating routines—a process we call organizational embedding—is a distinct question that we are in a position to address.

Thinking of reciprocation dynamically, as a form of history dependence in behavior, generalizes the concept to allow richer theory. Resources transferred from actor i to actor j may depend in nuanced ways on temporal patterns of past transfers between j and i or even transfers between either actor and third parties k. This lens also allows us to consider how this history may be viewed and weighted in different ways by the actors. This extends an observation by Abbott (2001, p. 259) that what actors see as social structure is in fact a memory and reckoning of a dynamic pattern of past events: "Since at any time the given structure of relations is all that exists . . . all influence of the past works through the shape given to those relations by the actions of the past. Memory of course provides a symbolic record of the past, which then reinterprets and reshapes it as a foundation for current action. But in the first instance, social structure is itself the memory of the social process." We conceptualize two distinct social processes that drive changes in exchange rates over time: organizational embedding and resource dependence.

By the embedding process, reciprocal resource transfers represent a gradual buildup of an interorganizational "relationship" over time. It may be tempting to view this relationship in psychological terms, but we need not assume that an organization has an affective attachment to another organization, feels grateful for a transfer, or feels loyal as a partner. Two organizations collaborating on mutual projects will develop routines and habits for cooperation and coordination and build acquaintances and familiarity at the personnel level that reduces transaction costs or uncertainty and facilitates organizational learning (Powell, Koput, and Smith-Doerr 1996; Keister 2001; Uzzi and Lancaster 2004). Meanwhile, successful exchanges will reduce uncertainty, and decision makers will build confidence in the competence and reliability of regular exchange partners.

Our use of the term embedding essentially represents a form of dyadic inertia in organizational exchange (Rivera et al. 2010), whereby an organization will tend to repeat transactions or exchanges with the same peer organization over time. Previous work on embedding among organizations emphasizes the interpersonal familiarity, affective bonds, and trust that build among personnel over time (Uzzi 1996). Personal affective attachments may indeed play a role in the interorganizational processes that we study, but we develop the theory at a higher level of abstraction and generality. When organization j elects to send resources to organization i, this collaboration may develop organizational bonds including shared routines and social and operational infrastructure for managing the ongoing exchange. The more focused j is on exchanging with i, the more j adapts its operations to specialize for exchange with i (reducing uncertainty on performance and operations).

Embedding inertia.—Actor i will give more to peer j now if in the past i has focused its giving on j (i has sent a greater proportion of its outgoing resources to j than to others).

An important insight we add here is that this relational focus developing gradually through habits, routines, or channels of communication may lead to resources flowing in either direction. Thus, gradual embedding and specialization is also manifested as reciprocation.

Embedding reciprocation.—Actor i will give more to peer j if in the past j has focused its giving on i (j has sent a greater proportion of its outgoing resources to i than to others).

By the dependence process, reciprocation reflects a current need for resources through an exchange partner (vs. the availability of resources through alternative partners). This connects directly to views on dependence in sociological exchange theory (Emerson 1962; Cook 1977), which are predicated on the notion of rational actors negotiating exchanges while embedded in networks, and to work in the resource dependence tradition in organization theory (Pfeffer and Salancik 1978). In both traditions, actors are seen as making exchange choices based on the set of available alternatives, and this contemporaneous structure of options results in power for some actors that is derived from the dependence of others.

In contemporary network exchange theory (Willer 1999), the actor optimizes its welfare by negotiating with network neighbors over terms of exchange (making offers, which may be accepted or rejected), and the mechanism driving power in these negotiated exchanges is the risk of exclusion. The network is an experimentally induced opportunity structure that sets the context for these bilateral negotiations, and the researchers are typically interested in the effect of exogenous network structures on realized power in exchange (measured as the magnitude of offers received).

Our approach is different. We are not directly interested in the exogenous opportunity structure, and we study an empirical population where there are no such hard constraints, so organizations may choose freely where to transfer resources. We also do not focus on negotiated exchanges (such as organizations trading money for other goods), and in fact we study a highly regulated organizational context in which exchange values are fixed by authorities. Our research site is well suited to study the realization of this relational resource dependence because we observe flows of resources—unilateral transfers among organizations—over a long time period in a fine time grain. We can observe, for example, that a large portion of organization i's incoming resource transfers come from organization j and interpret that i is more dependent on j for resources. Organization i is free to choose recipients of its outgoing transfers, but it cannot directly choose which other organizations send resources to it. When organization i becomes dependent on j for a large portion of its incoming resources, it may respond to this dependence by cultivating this relationship further (giving back to j), or it may respond by seeking alternative partners (giving to other organizations). This is an important choice that we are in a position to address.

In the contexts we study, the perceived network is the structure of ongoing unilateral transfers of resources among organizations. That is, organizations may conceive of their own dependence on others as the extent that their various partners are currently sending resources to them.

Dependence reciprocation.—Actor i will give more to peer j if i depends on j as a source of resources, that is, if i receives a greater proportion of its incoming resources from j (relative to other partners).

Retrospective Time Horizons

Embedding reciprocation and dependence reciprocation are both forms of relational history dependence, but we expect that they will exhibit different shapes over time. We model history dependence explicitly using shorter or longer *time horizons*, meaning the scope of history that an actor remembers and reckons in electing to reciprocate a transfer of resources. Our general argument is that embedding reciprocation at the organization level may be built and realized over a longer time horizon, whereas dependence reciprocation is a contemporaneous process, whose causes and consequences are realized in the short term.

The behavioral foundations of embedding reciprocation appear in the gradual "stickiness" of resource transfers, the development of routines and habits among regular organizational partners, reinforced by communication channels among administrative assistants, procurement officers, and other personnel. The more one organization focuses its resource transfers on another organization, the more it develops these dyadic organizational adhesions, but these relational processes all take time to play out. Previous ethnographic work on organizations has informally discussed how reciprocity develops into thicker and deeper embedding of organizations, including explicit assumptions about how this process transpires gradually over time. "An arms-length tie tends to be recast into an embedded tie if a trial period of reciprocal exchange results in voluntary contributions of new resources to the relationship and in a concretizing of cooperative expectations. Over time the iterative process progressively becomes independent of the initial economic goals, resulting in an embedded tie" (Uzzi 1996, p. 679).

Much of this work has stressed interpersonal affective attachments that develop among individual personnel through ongoing reciprocal exchange at the organization level. However, the same effect may be achieved by other means. What we call "embedding" as interorganizational affinities or adhesions may be composed not of personal friendships but of shared or mutually understood operating routines, established communication channels (phone and fax contact lists, e-mail distribution lists, etc.), familiarity among staff, adaptive habits, and similar coordinating mechanisms. These processes have also been discussed extensively in the work on interorganizational networks and organizational learning: "Firms deepen their ability to collaborate . . . by instantiating and refining routines for synergistic partnering. [For] the development of cooperative routines . . . firms must learn how to transfer knowledge across alliances" (Powell et al. 1996, pp. 119–20).

Much of this work examines the performance consequences of alliances and exchange, showing that organizations grow to work together better as they collaborate over time. The same argument is used to understand why organizations repeatedly choose particular peers as exchange partners. "As [firms] continue to work together from project to project . . . both parties can benefit from the somewhat idiosyncratic investment of learning to work together" (Eccles 1981, p. 340). By not assuming that organization-level embedding is necessarily due to interpersonal affective attachments, our theory is robust to issues—such as multidivisional organization structure or personnel turnover—that would interfere with personal attachments as a basis for organizational reciprocation.

Whereas the underlying logic of embedding reciprocation is about long-term stickiness due to organizational embedding, the logic of dependence reciprocation is about strategic choice based on resource dependence: exchange theory (Cook 1977) and resource dependence theory (Pfeffer and Salancik 1978) have universally regarded dependence as a property of a contemporaneous opportunity structure, not a force that accumulates as a function of history. "The dependence of one organization on another also derives from the concentration of resource control . . . whether the focal organization has access to the resource from additional sources" (Pfeffer and Salancik 1978, p. 50).

In this case, the present configuration of alternative partners (the perceived opportunity structure) is most relevant, and distant history plays little role. In fact, works on dependence in the early formulations of exchange theory (Emerson 1962; Blau 1964) and applications to interorganizational exchange (Cook 1977) have argued that dependence tends to actually decrease over time within an organizational exchange relation through a variety of "balancing mechanisms" (Cook 1977, p. 73), including changes in the network or changes in the value of goods exchanged. That said, at any moment, dependence is algebraically determined by the exchange structure and values of goods, so it is not a function of time and does not require time passing to be realized.

We have argued that our assumption that reciprocal exchange fosters mutual organizational embedding only slowly and gradually over a long time horizon reflects a universally held (if implicit) belief from previous research: scholars have assumed that interorganizational embedding (by any name) develops gradually through exchange over time. We have further shown that scholars have assumed that structural power and dependence are properties of a contemporaneous structure of exchange opportunities, not forces that develop gradually over time.

Thus, our key arguments that embedding reciprocation plays out over a longer time horizon and that dependence reciprocation reflects the contemporaneous structure of exchange represents an integration of two rich and longstanding bodies of work. Our focus on temporal dynamics allows and in fact requires us to develop these assumptions about time, which have otherwise remained implicit in previous work. Our studying the interdependent timing and sequence of interaction behavior allows us to develop this new frontier.

It will be instructive to consider how embedding and dependence reciprocation will respond differently to a change in the exchange context, such as the appearance of a new exchange partner. Following exchange theory (Emerson 1962; Blau 1964; Cook 1977) and resource dependence theory (Pfeffer and Salancik 1978), dependence of organization i on a peer j emanates from j's unique importance as a source of resources and so updates promptly with i's perception of the relative importance of alternative exchange partners for incoming resources. Thus, if a new partner k appears and rapidly becomes an important source of resources for i, this diminishes i's dependence on j. However, any embedding built up between i and k over time—including habits, routines, and relationships—responds slowly to repeated interaction over a much longer period and is not sensitive to short-term environmental changes such as the appearance of an alternative partner.

Here we operationalize the long-term time horizon as one year, and we operationalize the short-term time horizon as one month. We will describe how these are plausible time horizons for the population that we study, but note that the general theory is not wedded to this operationalization.

Dynamics of Closure in Transfer of Resources among Organizations

Our theoretical focus is on reciprocation—distinguishing the dependence and embedding perspectives on reciprocation and decomposing the timescales of those two processes. However, we can apply the same dynamic behavioral perspective to the pervasive phenomenon of *closure* at the level of organizational triads. A deep analysis of subprocesses and temporal dynamics of triad closure is beyond the scope of this article, but we must consider basic triad-level patterns because they are entwined with dyad-level patterns (Goodreau, Kitts, and Morris 2009; Wimmer and Lewis 2010; Block 2015). Because actors' choices to reciprocate may depend on their mutual embeddedness in exchange with other actors, failing to consider triads may then lead us to misunderstand processes at the dyadic level.

We consider two basic triadic dynamics.

Transitive triad closure.— Actor i gives more to actor j, to the extent that doing so contributes to a transitive pattern of exchange (i.e., to the extent that i gives to k and k gives to j).

Cyclic triad closure.— Actor i gives more to actor j, to the extent that doing so contributes to a cyclic pattern of exchange (i.e., to the extent that j gives to k and k gives to i).

Transitive triad closure may occur through various mechanisms. For example, the embedding processes that we described earlier may also apply at the organizational triad level. Just as routines, habits, and personnel familiarity may link organizations together, they also form the substrate for fostering exchange with third parties. An organization may refer one partner to another directly, or organizations may encounter and build familiarity, reputations, and trust through their shared embedded interaction with a third party (Uzzi 1996; Keister 2001; McLean 2007), all leading to closure at the triad level. Those triadic processes are analogous to what we have called embedding reciprocation at the dyad level. However, transitive closure may also reflect a very different mechanism: deference. If organization i signals deference to k by sending resources to k, and k similarly signals deference to j, then this may develop a status ordering of reputation that induces organization i to defer to j (Gould 2002; Lynn et al. 2009). That is, local acts of deference can crystallize into hierarchical population-level structures that convey status and thus socially construct the perceived quality of organizations in that structure (Lynn et al. 2009; Martin 2011; Manzo and Baldassarri 2014).

We have described two local micromechanisms leading to transitive triad closure: embedded relations including referrals or other shared interaction with third parties and also logics of hierarchy development through deference. Those mechanisms have similar implications for transitive closure, but they have opposite implications for cyclic closure. That is, extension of relations through third parties (e.g., organization i exchanges with organization k and encounters k's partner j through shared activities, observation, or direct referral) can result in transitive closure (i sends to j) as well as cyclic closure (j sends to i). This is not true for deference: extension of relations to third parties through status behavior (e.g., when organization i defers to organization k, k defers to j) results in transitive closure (i defers to j) but a negative tendency toward cyclic closure (j does not defer to i).

Extending our lens to the triad level gives us more purchase on the development of population-level structure, as dyads combine into triads, which then develop into larger structures of shared partners. A combination of positive reciprocity, positive transitive closure, and positive cyclic closure will lead to clusters of generalized exchange at the population level. In fact, any two of these processes is sufficient to produce generalized exchange (if the third is at least neutral). By contrast, if dyads do not tend to reciprocate and transitive triad closure is positive but cyclic closure is negative, then local patterns of exchange will aggregate into status hierarchies at the population level.

Our objective is not to develop a detailed theory of triadic dynamics, but we note that both transitive triad closure and cyclic triad closure plausibly operate on a longer time horizon. In fact, for structural processes operating above the dyad level, their dynamics should operate at least as slowly (and would require as least as much time to manifest) because they are constrained by the confluence of multiple microlevel processes that also take time. For phenomena such as the development of organizational clusters, or the development of reputational status among organizations, the underlying processes are notoriously sticky or inertial. We do not expect them to rapidly adjust to changes or fluctuations in the exchange environment. Thus, as we consider triad-level structural processes, we will focus our attention on the long-term time horizon.

RESEARCH DESIGN

Empirical Setting

To examine the proposed theory of resource transfers among organizations, we study data collected on all patient transfer events observed between 2003 and 2007 within a community of 31 hospitals providing health care services in Abruzzo, a region in southern Italy. Abruzzo extends over approximately 4,200 square miles, has a population of roughly 1,300,000 inhabitants, and is partitioned into four provinces (Chieti, L'Aquila, Pescara, and Teramo), which are further divided into 305 smaller municipalities. During the study period, only 10% of municipalities had more than 10,000 residents, 30% had fewer than 1,000 residents, and the largest city of Pescara (the capital city) had fewer than 120,000 residents.

The regional health system of Abruzzo is part of the Italian National Health Service, which provides universal health assistance to all citizens and residents free of charge at the point of service. The system is characterized by a federal structure organized at the regional level. Italian regional health care systems are financed mainly from regions' own revenues. Regional governments are granted broad discretion in planning and organizing health care services in their own territory (Toth 2014). Within each region, responsibility for the delivery of services rests on local health units (LHUs), which serve populations of roughly equal size. LHUs are well-defined territorial and administrative units responsible for coordinating services rendered by public as well as private accredited hospitals located in their reference geographical area. Patients are free to seek health care from any health care provider located within or outside their LHU of residence. The regional health system in Abruzzo is partitioned into six LHUs. We study all 10 private accredited hospitals and all 21 public hospitals (including two university teaching hospitals) that provide acute care services in the region. Figure 1 displays the population of hospitals and their geographic location. The figure also highlights hospital size, proximity to small urban areas, and form of ownership (public or private).

Interhospital patient transfers are an integral component of the Italian health care system and of health care institutions more generally (Sethi and Subramanian 2014). Over recent decades the health care literature has devoted increasing attention to patient transfers by focusing not only on their associated costs and clinical risks but also on the critical role they play in en-

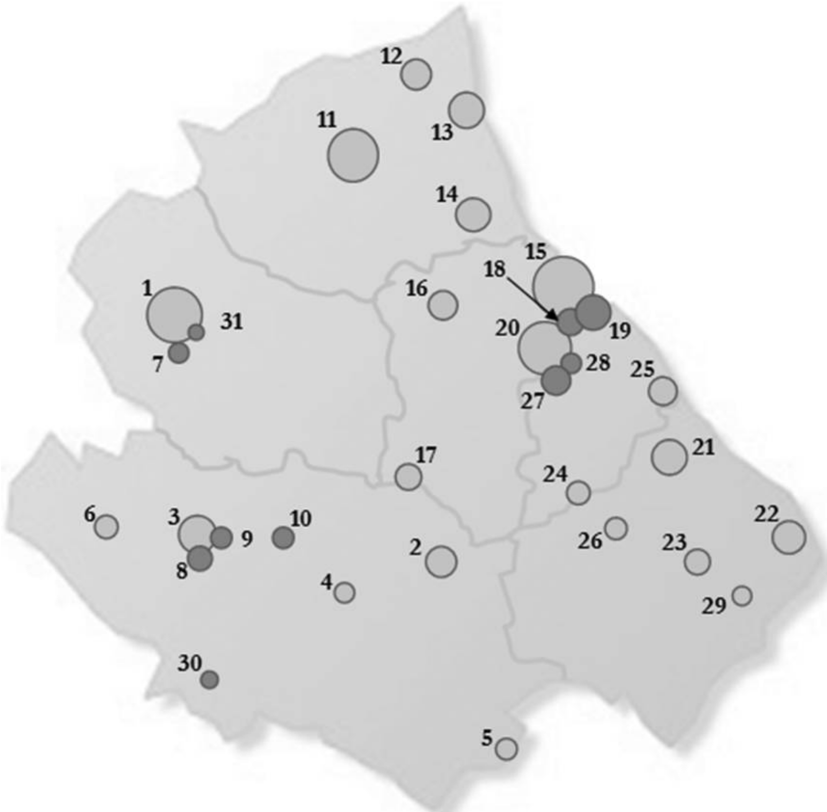


FIG. 1.—Map of Abruzzo hospitals, 2003–7. Public hospitals are light gray, private hospitals are dark gray, and the six LHUs are indicated by bounded regions. Nodes colocated in the same city are slightly separated for visual clarity, but hospitals 1, 7, and 31 are in L'Aquila (70,000 residents), 15, 18, and 19 are in Pescara (120,000 residents), 20, 27, and 28 are in Chieti (53,000 residents), and 3, 8, and 9 are in Avezzano (38,000 residents). All of these small cities are in separate LHUs.

suring the best possible care to patients (Hains et al. 2011). While it is now common to emphasize the economic aspects of hospitals as organizations competing for patients on price and quality (Gaynor and Vogt 2003), hospitals do differ from most conventional business organizations in the extent to which they operate in environments that are jointly technical and institutional (Scott and Meyer 1991; Ruef, Mendel, and Scott 1998). Hospitals must simultaneously optimize operational efficiency and follow elaborate institutional regulations and norms in order to maintain legitimacy. Their economic performance and social legitimacy depend on their ability to contribute to the health care system. Frequently, this involves collaboration with other hospitals for the benefit of patients (Mascia and Di Vincenzo 2011; Lomi and Pallotti 2012).

In Abruzzo, data on interhospital patient transfers are routinely collected for policy purposes to assess the geographical structure of demand for health care services and the institutional coordination requirements that demand imposes on hospitals (Ugolini 2001). Reliable high-quality data on the timing of patient transfer events are not publicly available but may be extracted from individual clinical records. The data for this study were derived from patient records provided by the Public Health Agency of Abruzzo, including all patients hospitalized over the study period.

A Network of Patient Transfer Events

Patient transfer is one of the most important forms of interhospital collaboration (Iwashyna et al. 2009; Iwashyna and Courey 2011; Lee et al. 2011; Lomi and Pallotti 2012; Veinot et al. 2012; Mascia, Pallotti, and Angeli 2016; Stadtfeld et al. 2016) and typically occurs via direct interhospital patient transfers whereby patients discharged from one ("sender") hospital are admitted to another ("recipient") hospital. To be sure, patient transfers are ostensibly intended to promote the patient's health: a transfer occurs when a hospital has patients with complex pathologies for which it does not have adequate diagnostic and therapeutic facilities or clinical competences, or patients with pathologies that may be treated more efficiently and effectively elsewhere. In the case of nonemergency transfers that we examine in this article, the choice of the destination hospital involves an explicit partner selection decision: the choice to send a patient is due to the clinical needs of the patient or limited capacity of the sender to meet those needs, but a sender hospital may choose from any number of recipient hospitals for the same patient, and this level of discretion for the sender invites the possibility that sociologically interesting processes may be at play.

One might suspect that clinical expertise may be so localized at particular hospitals that the demand for specific treatment capabilities and the distribution of capabilities across hospitals generates an exogenous structure of transfers, with little discretion for senders. Although this may be true in some contexts, in the case we study there is no major urban center, and these hospitals are relatively small with similar generalist profiles. Patient transfers are not generally driven by a need for specialist facilities. In fact, sensitivity analyses elaborated in the appendix show that our findings are consistent even if we fix the availability of specialties as an exogenous constraint and model transfer choices above and beyond that structure. Finally, the research literature on interhospital patient transfers (e.g., Bosk, Veinot, and Iwashyna 2011; Iwashyna 2012) suggests that transferring is a deeply social process that does not just send patients to the nearest or highest quality facilities.

Once the decision is made, completing a transfer requires not only a physical and technical infrastructure to make the transfer operationally possible (Iwashyna 2012) but also a relational infrastructure based on a complex coordination and information-sharing process between partner hospitals (Bosk et al. 2011). The correct functioning of these infrastructures is essential for avoiding delays and maintaining continuity of medical care (Hains et al. 2011).

In our analysis, we concentrate specifically and exclusively on transfers of elective patients, also known as inpatients. Inpatients are individuals who have already acquired the status of "admitted patient" and thus have consented to follow the clinical and therapeutic paths proposed by professional medical staff who are clinically responsible and legally liable for their conditions. This is an important qualification because patient transfer events are the outcome of organizational decisions over which patients have surrendered control upon admission. Of course, patients retain the right to refuse transfer in the same way as they retain the right to refuse treatment. However, patients cannot choose where they will be transferred—a decision that remains the exclusive prerogative of physicians in the sending hospital.

Our focus on patients qualified as "elective" intentionally excludes emergency patients. This is an important distinction as emergency transfers are governed by different mechanisms and are subject to different regulations and operating procedures. In Abruzzo, as well as in other regions in Italy, the transfer of patients between emergency rooms is often driven by overcrowding, lack of available beds, staffing shortages, and lack of comprehensive services. By contrast, for an elective patient a hospital bed has already been assigned; hence, crowding is seldom a driving factor for either sending or refusing an inpatient.

In terms of regulations and operating procedures, emergency transfers are managed by a centralized system, called "rete 118" (118 network), that provides real time information on bed availability to facilitate rapid selection of the nearest transfer targets that can accommodate emergency patients.

For inpatient transfer, however, a centralized superordinate system providing such information does not exist. As such, in this study we focus on a system of interhospital collaborative relations where social processes of interorganizational exchange are likely to be at work.

A distinctive feature of this study is its direct focus on patient transfer event sequences, rather than simple network ties defined in terms of aggregates of exchange events. However, for descriptive purposes (and comparability with previous studies), we can conventionally aggregate the transfers into a cross-sectional network, representing a flow of patients from hospital i to hospital j as a tie in that network. Figure 2 displays these aggregated exchange structures, arranging the nodes in the network to make their structure of exchanges easily visible (see fig. 1 for geographic location). The darkness of each tie indicates the intensity of the flow of patients within the study period.

The aggregated patterns of transfers partly reflect exogenous constraints that we must control for in our analysis. For example, although transfers occur throughout the region, there does appear to be a bias toward transferring to nearby hospitals and hospitals within the same LHU. Transfers also tend to happen along the highway system and other major roads, so it is clear that a simple control for geographic distance would be inadequate, and we must also consider travel times (including road topography and traffic congestion) just as the hospitals themselves would consider these features. There are also some apparent biases toward transferring to and among large hospitals, public hospitals, university hospitals, and urban hospitals. As these forces are exogenous influences on the structure of exchange, we will treat them as statistical controls in the context of our models.

The Inpatient Transfer Process

Transferring patients is an intensive and risky activity, and the transfer entails transaction costs to both parties (Bosk et al. 2011). Inadequate coordination between hospitals involved in patient transfers has predictable adverse consequences (Lee et al. 2011). For these varied reasons patient transfers produce signals of relational collaboration between hospitals (Van de Ven and Walker 1984; Bolland and Wilson 1994; Iwashyna et al. 2009).

Applying our theory of reciprocation requires us to think about interhospital patient transfer as a voluntary unilateral transfer of resources from one party to another. Transferring a patient entails at least some cost to the sender along with important substantive benefits to the recipient. In the Italian health care system, the budget "follows" the patient. In other words, patients are assigned cash values as a function of the care they receive. The

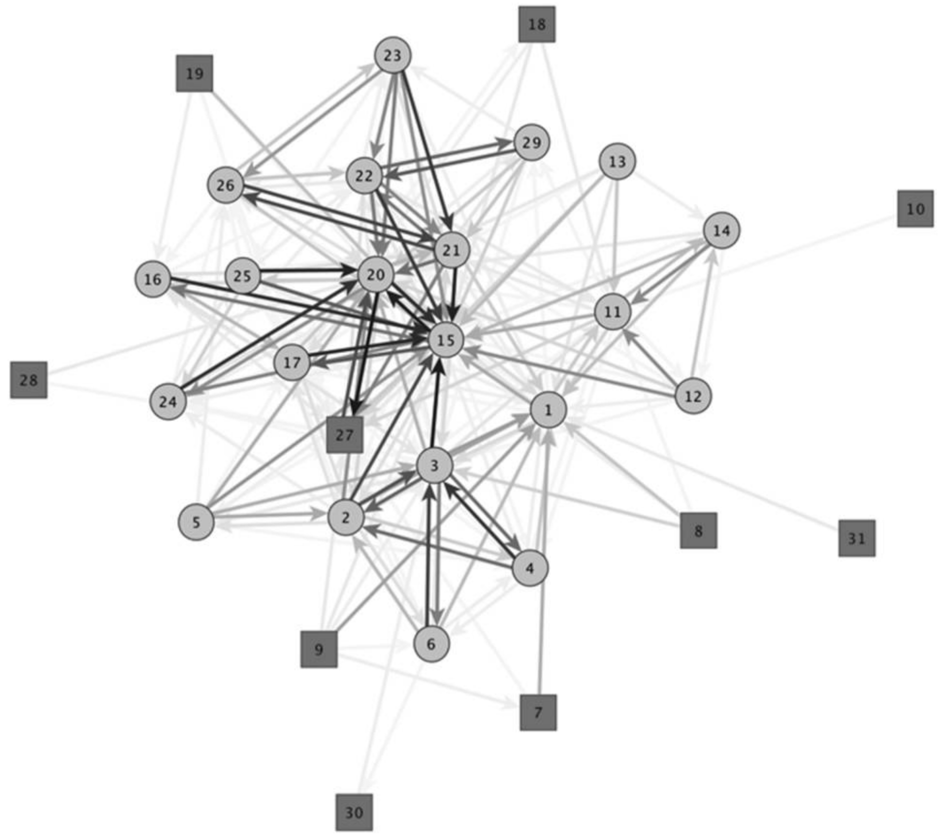


Fig. 2.—Aggregated network of patient transfers in Abruzzo, 2003–7. Public hospitals are circles, and private hospitals are squares. Arrow darkness represents the number of patients transferred between the two hospitals over five years.

corresponding resources are lost by the sender hospital and accrue to the receiving hospital. Accordingly, receiving a patient is regarded as a direct source of funding for the receiving hospital. This is what two physicians reported to us in an interview (translated from Italian):

> Physician A: Patients coming to us mean revenues for us. Also, the more we are able to use our available capacity, the less we run the risk that the region cuts the number of hospital beds at the end of the year.
>
> Physician B: The transfer of an elective patient always implies a loss for a given hospital since, once we decide to transfer a patient, we often need to reschedule and internally reallocate important hospital resources [e.g., surgical rooms] and staffed physicians' and nurses' availability, which were initially planned. In addition, we know that the regional authority is always attentive to cost-containment initiatives and has the possibility to use available admission [and transfer] data to eventually motivate decisions regarding the reduction of budgetary resources.

Just as patients represent funds that contribute to the bottom line for hospitals and clinical wards, patients represent reputational goods for physicians. Specifically, physicians signal their own expertise by reporting on their CVs and web pages the number of cases they have treated or the number of surgeries they have performed within specific pathologies. Thus, sending a patient entails a tangible opportunity cost in reputation, and receiving a patient entails a tangible benefit. Receiving transfers also brings prestige to the receiving hospital by the distinct quality-signaling value of transfers. A doctor recounted, "The flow of transferred patients we receive from other hospitals means that our expertise is recognized at the regional level. The fact that many hospitals transfer patients with complex cardiovascular problems to us is a clear sign of our expertise, professionalism and our ability to treat these types of patients."

Receiving a patient gives an opportunity to acquire new competencies. For example, the medical staff of the receiving hospital might learn from receiving a patient who underwent an innovative procedure or treatment protocol in the sending hospital. The director of a clinical ward in one of the hospitals in our sample revealed that "transferring patients is an important learning experience. Preparing the records that accompany the patient is an extremely delicate and important activity. The doctors who complete and sign the documents put a lot of effort into it. Sometimes they do it to impress the receiving hospital. These documents often contain hundreds of pages—containing information on referrals, diagnostic tests, and so on." A physician added, "For the receiving hospital the advantage is that, if done in an optimal way, the transfer increases the critical mass—that is, the number of cases treated—and allows the acquisition of skills—the hospital learns because often transfers concern complex and critical cases."

Although we use analysis of a data set on patient transfers to examine our hypotheses formally, our fieldwork provides considerable insight into the underlying social processes. For example, we have emphasized the role of collaborating on patient transfers as a source of familiarity and trust among personnel in the hospitals, as well as a source of routines or scripts that facilitate future association between the two hospitals (independently of the relations of particular personnel). Thus, the more hospital A transfers to hospital B, the more hospital B will be disposed to transfer to A by the same embedding processes that sustain ongoing transfers from A to B. The ward director also said, "We know some hospitals better because we receive from them. And it's much easier to activate time-consuming transfer processes with hospitals that we know better."

Another doctor who oversaw many patient transfers interestingly reported, "We need to carefully assess—and communicate—patients' conditions and everything has to be clear before the transfer is accepted and done. And this does not depend solely on the severity of patients' conditions; it actually depends on hospitals' mutual knowledge of resources, capabilities, as well as clinical and administrative procedures. Previous patient transfer experience enables the accumulation of such precious knowledge. But it needs to be exchanged and socialized among physicians before it can be integrated and become part of the 'memory' of a hospital's medical direction."

We have described how the same processes of embeddedness that lead to inertia—ongoing patterns of transfers that perpetuate further transfers in the same direction—also lead to reciprocal transfers in the reverse direction. A doctor speaks about the emergence of an informal organizational relationship between the surgical unit at one hospital and the rehabilitation unit at a nearby hospital: "Once this relationship is activated and repeated over time it becomes reciprocal. In other words, if the hospital providing rehabilitation services has patients who happen to need hospital care, this hospital will tend to send these patients to the hospital from which it receives patients."

Just as the mechanisms of organizational embeddedness work to channel inertia and reciprocation, they may similarly lead to triad closure. In discussing this phenomenon, another physician explained that "if the doctor in the contacted hospital cannot consent to receive the patient for whatever reason, the contacted hospital typically recommends another hospital about which they have information, such as the availability of that other hospital to receive patients or the competence of that hospital to treat that patient."

On the basis of our fieldwork and understanding, we expect that "cold" processes of embeddedness (operating mostly through scripts, routines, operating procedures, professional familiarity of clinical and administrative staff, ready access to information through frequent contact, etc.) underlie much of what looks like relationships among these hospitals. That is, we do not claim to observe deep affective bonds or normative obligations. However, we also saw evidence that some relevant decision makers may regard patient transfers as a "favor" and may have some inclination to reciprocate these favors. The medical director of one of the hospitals revealed to us that "the choice of destination hospital is often made on the basis of familiarity and mutual knowledge; that is, we give priority to hospitals that we know better by virtue of the elevated number of patients we receive from them. We are aware of being considered a reference organization in our institutional category by many hospitals and, in general, we tend to return the favor."

Indeed, clinical patient referrals serve as a classic empirical example of tacit reciprocity (Pfeffer and Salancik 1978, p. 149), and the possibility that hospital staff could be motivated by an apparent norm of reciprocity is intriguing. We note, however, that any such "norm of reciprocity" is likely to be much weaker than has been observed in other spheres such as gift giving (e.g., Yang 1994; Bourdieu 1998; Park and Kim 2017) and is unlikely to be acknowledged publicly. This is because the dominant professional norms are for optimal patient care and secondarily for efficient use of hospital resources, logics that seem incompatible with a political norm for reciprocal exchange of favors among organizations. Our fieldwork revealed no pervasive general norm for reciprocity in this context, and we do not believe such a force is driving the reciprocation we observe. Further, norms for patient care are so dominant in this context that cultural practices that shape gift-giving behavior—such as a norm against reciprocating too soon (Bourdieu 1998)—do not seem to apply.

Time Horizons for Interhospital Reciprocation

Inpatient transfers across hospitals are recurrent, institutionalized, and deeply social practices (Lee et al. 2011). Decisions to transfer patients are usually discussed during meetings that occur periodically. Thus, hospitals' attention to reciprocation issues in patterns of transfers over time may develop over longer periods of time. Our short-term time horizon defines statistics computed based on past patient transfers during the one month before the event being currently modeled. We operationalize long-term time horizons by computing statistics on all transfers over a time span of one year previous to the event being modeled. This implies that the time horizons are nested (i.e., a sequence of events that happens within a month also happens within a year) and that the monthly effects are marginal to the yearly effects when included together in a model.

One year is a natural choice for the long-term time horizon, as it corresponds to one organizational cycle of budgets, reviews, and performance assessment. One month is not as obvious a choice for the short-term time horizon. A patient transfer could happen on any day, and some staff meetings occur either weekly or monthly. Of course, the relevant scope would be the period of time that staff who oversee transfer decisions would naturally consider (implicitly) in evaluating a peer hospital as an exchange partner. Our fieldwork suggests that one month is a long enough time to observe a partner's recent behavior as an input to a transfer decision.

The social processes of organizational reciprocation seem unlikely to operate within a shorter time span of one to six days (as if organizations reciprocated on a weekly time horizon). The variability in transfers from one day to the next is noisy; such fine-grained variability in transfer volume is either random or is driven largely by exogenous forces (random shocks in medical demand, attending physicians' vacations, work schedules, state holidays, etc.). Thus, the day-to-day records of transfers are hardly diagnostic for actors wishing to assess their environment and exchange partners, whereas the monthly window reflects a more stable impression of the partner's recent behavior. A reviewer raises the intriguing question of fine-grained reciprocation, such as tit-for-tat exchanges of patients by hospitals (Axelrod 1984). We see no evidence of such fine-grained reciprocation in the immediate dynamics of patient transfers, in either our fieldwork or statistical analyses. Our implementation of reciprocation is an extension of Kollock's (1993) "relaxed accounting strategies," which respond to general patterns over time periods rather than mimicking a partner's most recent move.

Data

We examine the complete set of patient transfers observed between all 930 directed pairs of hospitals. The resulting data set features a total of 4,111 patient transfer events among the 31 hospitals over a period of five years from January 2003 until December 2007. On average, 2.26 patients were transferred each day (SD = 1.71) with 276 days in which there was no transfer and a maximum of 10 transfers on a single day. As figure 3 shows, the distribution of transfers is relatively stable over time, with predictable variations in daily transfer levels due to weekends or holidays, when fewer transfers of admitted elective inpatients typically occur.

The overall average number of patients sent per hospital in the data set is 132.61 (SD = 189.56) with a median of 76, a minimum of 1, and a maximum of 1,015 patients sent. The average number of patients received per hospital is 132.61 (SD = 258.80) with a median of 38, a minimum of 0, and a maximum of 1,056 patients received. The maximum value reflects a single outlier sender-receiver pair that is anomalous in volume and character (i.e., the receiving hospital is known to have conveyed cash bribes to entice the sender to transfer patients); we discuss this case later and control for this anomalous

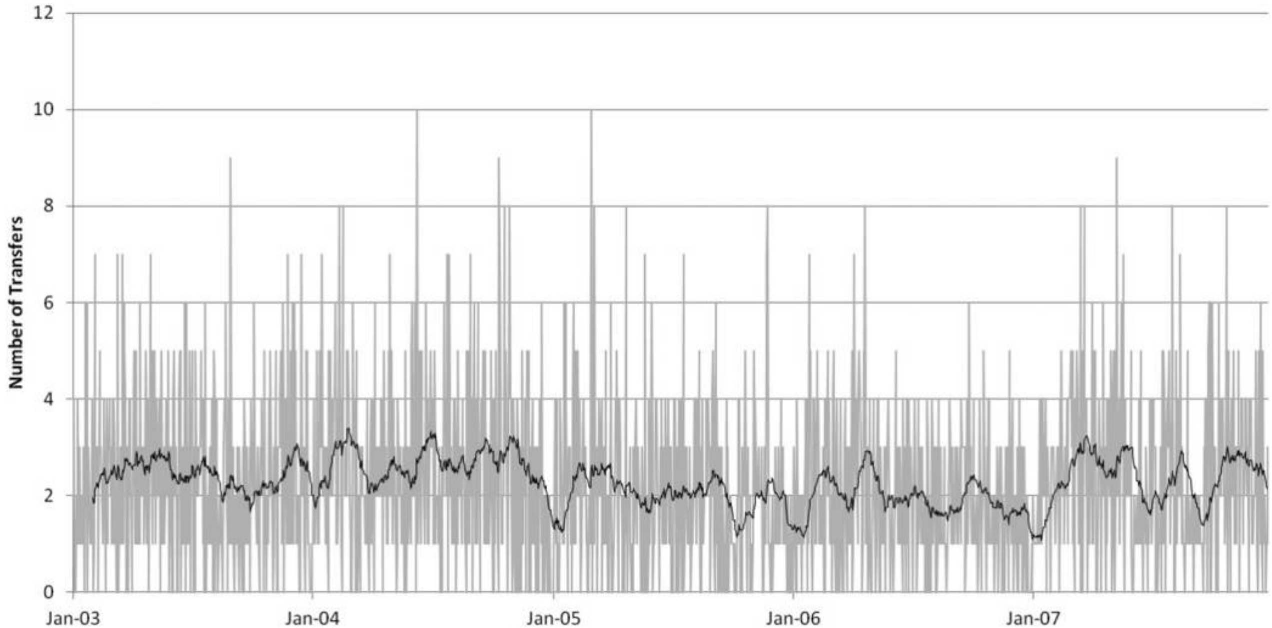


FIG. 3.—Number of daily patient transfers between 2003 and 2007 (with monthly moving average).

flow in statistical models. Most transfers (76%) are from one clinical specialty at the sending hospital to a different clinical specialty at the recipient. The median waiting time before a transfer is reciprocated is 34 days; the median waiting time before transitive triad closure is 68 days; the median waiting time before cyclic triad closure is 117 days.

Hypotheses

We have described a general theory of the dynamics of interorganizational exchange behavior, using insights drawn from theories of social exchange, resource dependence, and embeddedness. We now apply this theory by deriving and testing empirical hypotheses about the dynamics of patient transfers over the population of hospitals in Abruzzo, Italy, in 2003–7. In our empirical case, hospital *i*'s choice to reciprocate to hospital *j* depends on the history of giving among hospitals *i* and *j*, as well as with all shared exchange partners *k*.

Following from our argument about how interorganizational exchange events become embedded over a longer time horizon, we offer two hypotheses about patterns of inertia in patient transfers:

Hypothesis 1a.—*To the extent that hospital* i *has focused its patient transfers on another hospital* j *in the past, hospital* i *will be more likely to transfer patients to* j *in the future (embedding inertia).*

Hypothesis 1b.—*Embedding inertia will operate primarily in the long term (considering the past year) rather than in the short term (considering the past month).*

Building on the same mechanism of growing organizational embeddedness, we offer two corresponding hypotheses about embedding reciprocation:

Hypothesis 2a.—*To the extent that hospital* j *has focused its patient transfers on hospital* i *in the past, hospital* i *will be more likely to transfer patients to* j *in the future (embedding reciprocation).*

Hypothesis 2b.—*Embedding reciprocation will operate primarily in the long term (considering the past year) rather than in the short term (considering the past month).*

Some readers may wonder whether information about *j*'s other outgoing transfers is available to *i* in deciding whether to reciprocate to *j*. In fact, deidentified information about all transfers is available within the Italian hospital system, although there is no guarantee that physicians or other personnel involved in administering transfers will pay attention to this information. It is plausible that they are aware of coarse patterns of patient transfers among peer hospitals over a long time horizon, but it seems unlikely that they monitor the individual transfers or fine-grained patterns. Indeed, our fieldwork revealed little evidence that transfer agents kept close tabs on the outgoing transfer volume of their partners to decide how to weigh incoming transfers from those neighbors. Note that our theory does not require *i* to observe *j*'s outgoing transfers. Our proposed embedding mechanism is not an emotional drive or normative obligation to reciprocate due to recognizing *j*'s visible generosity in giving. It is a by-product of interorganizational routines, habits, personnel familiarity, and other organizational embedding that make *i*–*j* exchange (in both directions) easier, less costly, and less risky or uncertain. The proposed embedding inertia and embedding reciprocation mechanisms work in a reciprocal way, in which each organization's focus on the other partner gradually leads to the operational specialization that supports and reinforces ongoing exchange.

Whereas embedding inertia and embedding reciprocation represent a gradual buildup of relation-specific resources that enhance the quality or efficiency of exchange, dependence reciprocation represents investing in exchange partners that are important solutions to immediate resource needs, and thus it operates on the contemporary structure of exchange.

Hypothesis 3a.—*Hospital* i *will respond to its own dependence on exchange partners: it will reciprocate to hospitals* j *that are important sources of patients to* i *(dependence reciprocation).*

This hypothesis follows directly from the standard argument in exchange theory that organization *i* will transfer resources to organization *j* as a direct function of *i*'s dependence on *j*. In this work, resource transfers are called "balancing mechanisms" because they tend to increase dependence of *j* on *i* and thus balance dependence in the dyad (Cook 1977, p. 73). Following exchange theory, this force of dependence attends to the current balance of exchange, not long-term history.

Hypothesis 3b.—*Dependence reciprocation will operate primarily in the short term (considering the past month) rather than in the long term (considering the past year).*

This dependence mechanism does not require physicians or other personnel involved in administering transfers at hospital *i* to have information about *j*'s outgoing transfers, but it does require information about recent incoming transfers from other hospitals—which is readily available.

To recapitulate, we expect that the temporal scope for resource dependence applies to the current exchange structure (the most recent exchange patterns), whereas the temporal scope for organizational embedding applies to a longer history of exchange. Although our theoretical focus is on reciprocation, we recognize that we must also model triadic patterns of transfers because reciprocation is embedded in exchange with other hospitals. We expect to see transitive triad closure. We recognize that cyclic triad closure could be positive (yielding generalized exchange) or negative (yielding status hierarchy), but at this point we have no strong a priori expectation of either effect for the entire population of patient transfers, so we do not offer a triad-level hypothesis here.

METHOD

Using Retrospective Time Horizons to Weigh the History of Structure or the Structure of History

Extant research provides little guidance about the temporal patterns by which organizations weigh past relational events (such as giving by peers) in making their own decisions. This is because issues of timing in interaction sequences are rarely considered explicitly. In order to make the clearest contrast between the attention to the present-day structure of giving and attention to patterns over more distant history, we define the former as the set of events in the past month and the latter as the set of events in the past year. This is effectively a piecewise specification of time dependence: events older than the time horizon threshold (one month for short term and one year for long term) are not taken into consideration for present-day transfer choices. We show that our qualitative conclusions are not sensitive to the exact threshold by replicating the analysis with adjusted thresholds (using a quarter instead of a year as the long-term horizon and using a week instead of a month as a short-term horizon). Results are qualitatively similar for both of those analyses, although we observe that endogenous structural processes are predictably weaker in analyses based on a one-week time horizon.

Nor are our results sensitive to our using a strict threshold instead of smoother decay of importance between the present day (i.e., recent history) and distant history. We show this robustness by replacing the simple thresholds with continuous decay functions, so our short term is a rapid decay in weight over time, and long term is a slow decay. For this purpose, we drew a negated translated sigmoid memory decay function from research on sparse distributed memory (Ramamurthy, D'Mello, and Franklin 2006): $f(x) = 1 - [1/(1 + e^{-a(x-c)})]$ with $a = 1$. This model assumes a monotonic decay of importance of past events but includes parameters that can be tuned to allow history dependence to decay toward zero around a designated time horizon ($c = 30$ days for short term and $c = 365$ days for long term). This alternative specification replaces the strict time horizon threshold with a smooth curve but retains the qualitative distinction between immediate history and long-term history. Thus, our results do not depend on the exact boundaries of time horizons on the operationalization of time horizons as discrete boundaries but represent a more general contrast of the present-day relational environment and the long-term historical relational environment. In this article we present the simpler piecewise specification of time horizons for brevity and clarity.

Relational Event Model

As researchers shift focus from static patterns to dynamics of networks, some have applied event history analysis tools to investigate the appearance (Rosenkopf and Padula 2008) or dissolution (Levinthal and Fichman 1988) of interorganizational ties. Stochastic actor-oriented models (Snijders 2001) provide another promising lens, where researchers take repeated cross-sectional observations of networks and model the (unobserved) appearance and disappearance of ties during the time intervals between those observed networks. However, directly examining the interaction behavior among organizations offers unprecedented leverage for dynamic analysis, building on earlier static approaches to structural events (Ruef 2002). Instead of conceptualizing change in a network from one year to the next, we directly study the strength or rates of exchange behavior among organizations over time. Our research reported in this article applies a new class of models to investigate the sequence of exchange events connecting organizations. We know of no other study that has analyzed the temporal dynamics of interorganizational exchange, as this theoretical step is enabled by new analytical lenses.

The model presented here is based on the sequential form of Butts's (2008) relational event framework. This framework is suited to model sequences of relational events, which in this case represent social acts by individual parties directed at other individual parties (p. 159). Each event is assumed to be independent of all other events but conditional on the sequence of events that have occurred in the past. This assumption of conditional independence of events implies that "past history creates the context for present (inter)action, forming differential propensities for relational events to occur" (p. 160). The framework enables the estimation of the likelihood of particular patterns of past relational event sequences to be associated with a future relational event, without assuming that a future event is completely determined by these patterns.

While the general form of a relational event model is a continuous-time event history model, the ordinal version of the model we use can be represented as a familiar conditional logistic regression (Butts 2008). Indeed, we focus on the sequence of events and not on the precise time at which events occur. Each new event defines a stratum, and the possible events within the stratum are the set of possible pairs who may be linked as sender and recipient of the next event. The probability of each possible event within the stratum is conditional on the relational statistics computed from the prior sequence of events, and there are $m(m - 1)$ possible next events if m actors are potential participants in the next event. As the parameterization of the model is specific to relational exchanges, the model predicts the realization of the next event in the sequence on the basis of individual attributes of the sender and recipient, attributes of the dyad, and the prior history of relational events. This prior history is composed of configurations of actors linked by events. These configurations are counted across a time horizon to explore the tendency of future events to be triggered by past events. We model such history dependence over longer time horizons (counts of events over the past year) and shorter time horizons (counts of events over the past month).

The statistics are inspired by exponential random graph model statistics (Goodreau et al. 2009; Harris 2014), and functional forms generally follow Butts (2008). Statistics are scaled across all values for observed and potential events, based on calculating a proportion of previous events rather than a raw count. For instance, the statistic for embedding inertia is the proportion of previous patient transfers from the sender to the recipient out of the count of patients transferred by the sender, rather than the count of past transfers from the sender to the recipient. It can be interpreted as the extent that hospital i focuses its outgoing patient transfers on hospital j.

While parameterization of the model draws from network analysis, the use of event sequences avoids some problems associated with traditional methods of network analysis. First, we do not need to aggregate all patient transfers into one or more cross-sections or make event streams into binary ties so we do not lose information on the sequence of the underlying events. Second, because we retain the sequencing of the events we can avoid the standard problem of nonindependence of observations that affects network analysis and model the probability of one event happening conditional on covariates that include prior states of the system. As Butts (2008, p. 192) expresses, “The ability to impose sequential dependence on all events, in particular, avoids the more complex, simultaneous structures of dependence that emerge from realistic models with concurrent relationships” and that often require special statistical techniques, such as exponential family random graph models with Markov chain Monte Carlo estimation (Goodreau et al. 2009; Wimmer and Lewis 2010).

The approach has similarities with sequence analysis (Abbott 1995). We model a specific type of event sequence, where a single behavior recurs in a sequence across many dyads in a population. Yet, our covariates differ from a typical sequence analysis because they capture configurations of actors that are linked by events, rather than a pattern of events that occurred during the lives or careers of actors. The aim of a relational event model is to fit a limited number of parameters in order to derive a parsimonious explanation of patterns in the whole sequence of events, rather than finding a limited number of clusters that identify prototypical patterns of event sequences, as is more common in sequence analysis (Abbott and Hrycak 1990; Stovel, Savage, and Bearman 1996). We focus on structural dependence (across actors), whereas most sequence analysis work has assumed independence of actors and focused in richer detail on the temporal sequencing of independent chains of events (Abbott 2001). Stark and Vedres (2006) and Bothner, Smith, and White (2010) also applied sequence analysis within social networks research, but these were more similar to conventional network analysis (in focusing on a set of cross-sectional snapshots of network ties) and closer to conventional sequence analysis (in studying characteristic sequences of network positions, held by actors). By contrast, we are examining the sequence of behavioral interaction events as they enact structural forces and mutually constitute the observed network.

Finally, we differentiate our approach from the rich study of dyadic and triadic exchange patterns in conversation analysis, such as the work on turn taking by Gibson (2012). A set of strong rules applies to conversations, in that parties must take turns speaking, avoid silence, and respond directly to the immediately preceding talk, and the sequence of exchanges must compose a coherent and intelligible narrative for which the sequence is essential for the conversation meaning. Again, the dependencies in the exchange patterns we observe do not take the form of direct sequential reciprocation, there is no need for turn taking and no avoidance of silence, and any exchange patterns emerge implicitly over time. A patient is transferred at a particular time because the patient needs to be transferred, not because the hospital needs to reply to another hospital or maintain a conversation. Above all, recall that we are not studying the timing of transfer choices (which reflects the needs of the patient), but instead we are studying the development of relational transfer patterns over time. Further details about the estimation of the relational event model and the preparation of the data set are available in the appendix.

Variables and Controls

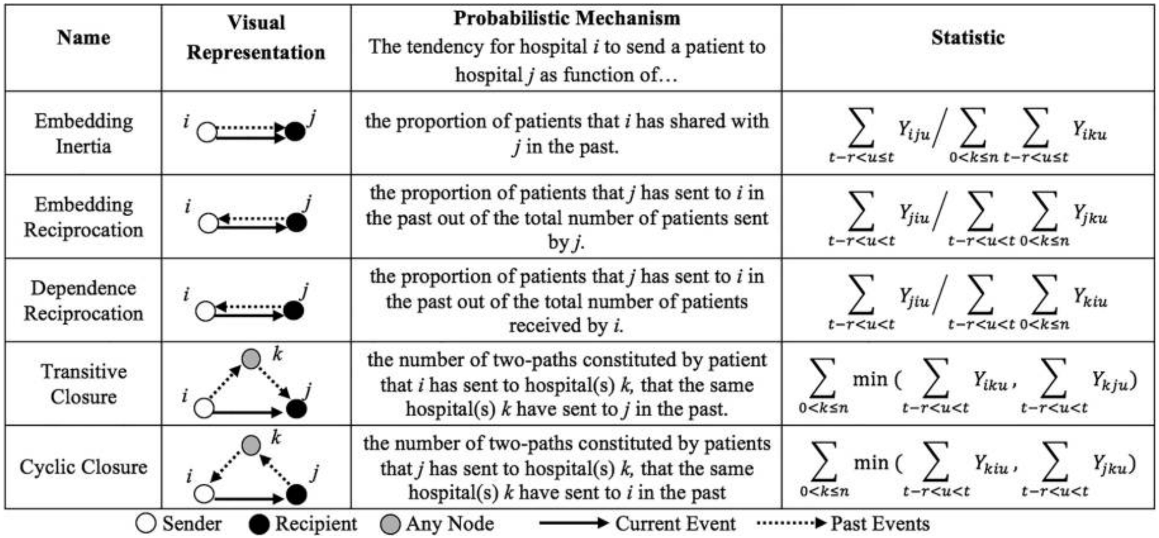
Dependent variable.—We model the transfer of a patient from hospital i to hospital j. More specifically, given features of hospitals and their environments, and a historical sequence of transfer events, the dependent variable is the next event in the sequence. For each patient transfer event, the dependent variable is a binary variable containing the set of possible patient transfer arcs (ordered pairs of hospitals) and takes the value 1 if the event actually occurred between the hospitals in the arc and the value 0 if it did not occur.

Independent variables.—Our independent variables capture the history of patient transfers between j and i, as well as the history of their exchanges with all other neighbors k. To represent *embedding inertia* for hospital i, we compute the proportion of patients sent by hospital i to hospital j out of all the patients sent by hospital i. A positive (negative) parameter estimate indicates that the higher the proportion of patients that i sent to j in the historical time horizon, the higher (lower) the probability that i will send a patient to j now. To represent *embedding reciprocation*, we compute the proportion of patients sent by hospital j to hospital i out of all the patients sent by hospital j. For *dependence reciprocation*, we compute the proportion of patients sent by hospital j to hospital i out of all the patients received by hospital i. *Transitive closure* represents the tendency for hospital i to give to hospital j as a function of the extent that doing so will constitute a transitive triadic pattern of giving (i.e., to the extent that i gives to k and k gives to j).[2] We compute this as the number of two-paths that occur when patients are sent by hospital i to hospital(s) k and patients are also sent by the same hospital(s) k to j. Following Butts (2008), we assume that a two-path is no stronger than its weakest link (the lesser of the number of patients transferred from i to k or from k to j). *Cyclic closure* represents the tendency for hospital i to give to hospital j as a function of the extent that doing so will constitute a cyclic pattern of giving (i.e., to the extent that j gives to k and k gives to i). We compute the weight of two-paths that occur when patients are sent by j to hospital(s) k and patients are also sent by hospital(s) k to i, again assuming that a two-path is no stronger than its weakest link (the lesser of the number of patients transferred from j to k or from k to i). A definition of each of the statistics is given in figure 4. All statistics are standardized to facilitate comparison across parameters.

Three categories of control covariates are incorporated into the models that we estimate: individual organizational controls, dyadic organizational controls, and endogenous structural controls.

Individual organizational controls.—We control for a number of organization-specific attributes that may provide alternative explanations for the tendency of hospital organizations to send or receive patients. We might suspect, for example, that larger hospitals have a higher activity level in the transfer community simply because they treat more patients or that hospitals are more attractive as recipients if they have low occupancy (less crowding) or better efficiency. We thus include total number of staffed beds (*size*) to control for the higher activity level of larger hospitals and the average percentage of beds occupied (*occupancy rate*) to control for interhospital differences in capacity management and availability. To control for the possibility that more efficient hospitals are preferred recipients, we use the standard comparative performance index (CPI) as a measure of operational

[2] Note that the patients sent by i to k are typically not the same patients as those sent by k to j. Thus, we are talking about triadic patterns of transfer decisions for hospitals, not sequences of admissions for individual patients.



Name	Visual Representation	Probabilistic Mechanism The tendency for hospital i to send a patient to hospital j as function of…	Statistic
Embedding Inertia	i j	the proportion of patients that i has shared with j in the past.	$\sum_{t-r<u\le t} Y_{iju} \Big/ \sum_{0<k\le n} \sum_{t-r<u\le t} Y_{iku}$
Embedding Reciprocation	i j	the proportion of patients that j has sent to i in the past out of the total number of patients sent by j.	$\sum_{t-r<u<t} Y_{jiu} \Big/ \sum_{t-r<u<t} \sum_{0<k\le n} Y_{jku}$
Dependence Reciprocation	i j	the proportion of patients that j has sent to i in the past out of the total number of patients received by i.	$\sum_{t-r<u<t} Y_{jiu} \Big/ \sum_{t-r<u<t} \sum_{0<k\le n} Y_{kiu}$
Transitive Closure	i j k	the number of two-paths constituted by patient that i has sent to hospital(s) k, that the same hospital(s) k have sent to j in the past.	$\sum_{0<k\le n} \min\left(\sum_{t-r<u<t} Y_{iku}, \sum_{t-r<u<t} Y_{kju} \right)$
Cyclic Closure	i j k	the number of two-paths constituted by patients that j has sent to hospital(s) k, that the same hospital(s) k have sent to i in the past	$\sum_{0<k\le n} \min\left(\sum_{t-r<u<t} Y_{kiu}, \sum_{t-r<u<t} Y_{jku} \right)$

FIG. 4.—Mechanisms of theoretical interest. Let $Y_{ijt} = 1$ if i sends a patient to j at time t ($Y_{ijt} = 0$ otherwise), where i denotes the sender, j the recipient, t the time of the event, r the time horizon (one month and one year), n the number of hospitals, u an index over time steps within the time horizon, and k an index over all hospitals.

inefficiency.[3] Because daily measures are not available, when organization-specific attributes change over time, their measure is taken yearly. This periodization is broadly consistent with the yearly budget and performance evaluation cycle that regulates change in resource stocks available to hospitals. Resources available to hospitals like, for example, staffed hospital beds change across years as a function of changes in the regional budget and in the performance of the hospital but are more or less constant within years.

Given that public and private hospitals may differ in their tendencies to send and receive patients, and urban or rural hospitals may also differ, we include *public* and *urban* controls for both sender and receiver. Some transfers may target a clinical specialty unit (e.g., cardiology) that is not offered in the sending hospital. We include a binary variable *in-house capability* to indicate that the sender has a named specialty unit to treat in the area targeted by the transfer. Finally, given the special role of university *teaching hospitals* in providing health care, we include a dummy variable to control for their activity as senders or popularity as receivers.

Dyadic organizational controls.—Having controlled for the above features of senders and receivers, we also need to control for features of particular dyads that may affect the likelihood of transfers. For example, we expect that patients will be transferred more frequently between hospitals that are closer in geographic space (Sorenson and Stuart 2001). We thus control for *distance* between each hospital to account for the joint effect of transportation costs and clinical risks inherent in distant patient transfers. We measure distance in driving minutes, rather than geographic distance, in order to capture the various constraints (topography, driving routes, and traffic congestion) that hospitals must consider in making transfer decisions. Or it could be that patients tend to be transferred more frequently between hospitals offering complementary services, because in this way hospitals may be able to exploit economies of scale deriving from interorganizational division of labor. To control for the effect of dependence on common resources for which hospitals compete (i.e., patients), we include the variable *niche*

[3] The CPI measures a hospital's efficiency—in terms of length of stay—relative to the average efficiency of a reference set of hospitals with an analogous composition of cases treated, where cases are categorized into diagnosis related groups (DRGs). CPI is computed as $\mathrm{CPI}_j = \Sigma_{i=1}^{n_c}[d_i \times N_i]/\Sigma_{i=1}^{n}[D_i \times N_i]$, where d_i indicates the average length of stay of DRG_i numbered in hospital j, D_i indicates the average length of stay of DRG_i numbered in the reference set of hospitals with an analogous composition of cases treated, N_i indicates the number of discharges of DRG_i numbered in the reference set of hospitals, n indicates the number of DRGs in the reference set of hospitals, and n_c indicates the number of common DRGs overlapping between hospital j and the reference set of hospitals (Gianino et al. 2006). The CPI takes the value 1.0 for hospitals whose service efficiency is on par with all other hospitals in the region. The CPI takes values that are smaller (greater) than 1.0 for hospitals that are less (more) inefficient than comparable peer hospitals.

overlap, as conceptualized by Podolny, Stuart, and Hannan (1996) and as adapted by Sohn (2002) specifically for representing competitive interdependence in a hospital dyad.[4] We also control for *service differentiation* in a dyad by reconstructing a two-mode matrix of hospitals by the clinical specialties they provide. We then computed the Euclidean distances between hospitals in the space spanned by all the clinical specialties. Geographic and administrative reasons may make patient transfers more likely within rather than between LHUs. We thus control for *same LHU* in our models. In addition to sender and receiver effects for urban and public, we use an indicator for shared urban and public status (*both urban, both public*) to allow for the possibility of homophily or heterophily on these features.

Finally, we also compute dyadic differences on a number of the organization-level controls (*size difference, occupancy difference, inefficiency difference*) to allow that hospitals may transfer patients to larger, less crowded, and better performing hospitals, compared to themselves. It seems intuitive to include model terms for sender size, recipient size, and size difference, but this implies a linear dependence, as the difference is obviously determined by the other two terms. We could instead omit difference terms to include both sender and receiver size (both would be significant and positive, as larger hospitals send and receive more patients) but present the most intuitive parameterization here. How we deal with this parameterization of the controls has no effect on other results.

Our last concern is an exogenous interference in the normal exchange dynamics in the form of bribery of one hospital by another hospital (which resulted in prosecution and conviction shortly after our study period). This bribery led to an anomalously high transfer rate from the bribed hospital to the bribing hospital. We include a binary variable to control for this one arc—*bribery*—which reflects a different process from the dynamics of reciprocation in patient exchange. To be sure, bribery is an interesting topic, and it obviously affects patient exchange in this case. However, of 930 directed ties observed in this study, there was only one observed corrupt tie, and thus

[4] Niche overlap among hospitals is measured as follows. Patient discharges are first stratified into 25 major service diagnostic categories and aggregated to the zip code level to construct one patient origin-destination matrix for each service category. In the Abruzzo region there are 305 zip code areas. For each service category, niche overlap is computed as $\omega_{ij} = \sum_k w_{ik} \min(p_{ik}, p_{jk}) / \sum_k w_{ik} p_{ik}$, where $\min(p_{ik}, p_{jk})$ indicates the overlap (or "intersection") in patient pools between hospital i and hospital j in zip code k, and the weight w_{ik} indicates the proportion of all patients admitted to hospital i who come from zip code k. In the equation above, the numerator expresses the overall sum of niche overlaps between hospital i and j across all zip code areas, while the denominator simply tells the niche width of the ith hospital, i.e., the total number of patients admitted by hospital i across all zip code areas. The (dyadic) niche overlap coefficient, ω_{ij} may then be interpreted as the proportion of the patient pool of a hospital overlapped by another hospital. The term $\min(p_{ik}, p_{jk})$ requires that ω_{ij} lies between 0 (no overlap) and 1 (maximum overlap).

we do not have sufficient data to study the emergence of corrupt exchange (of cash given for patients received) as a distinct process. This one tie was both independently confirmed in its criminal activity and also anomalous in its volume and pattern of exchange, so after extensive study and sensitivity analysis we confirmed that the most appropriate way to deal with this one directed tie was to control for the anomalous flow.

Table 1 reports definitions, measures, and descriptive statistics of all the organization-specific covariates that are control factors in the models that we estimate in the next section. We note that for variables whose values change over time (all but geographic distance, LHU membership, and institutional type) descriptive statistics are given in this table as average values over the five years, but the longitudinal data are used in the analyses.

Endogenous structural controls.—We have controlled for features of hospitals and hospital dyads that seem to exert force on the transfer process. In order to control for otherwise unobserved heterogeneity in the tendency for hospitals to send or receive patients, we also include degree-based effects. Specifically, we control for historical *activity* (overall tendency to send patients) and *popularity* (overall tendency to receive patients) for both sender and recipient over the short term and long term, as they may affect their likelihood to send or receive another patient. Definitions of these statistics are given in figure 5.

There are surely correlations among the variables of theoretical interest and controls, but multicollinearity diagnostics do not raise concerns. The maximum correlation of our variables of theoretical interest with each other or with our control variables is 0.626, and all variance inflation factor coefficients for our variables of theoretical interest are below 2.5 in all models reported. There is some multicollinearity among some of the controls (e.g., *size sender* and *size difference*), but this does not affect our results.

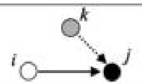
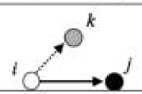
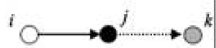
The base model includes control variables and should be considered as a null model against which subsequent models can be compared. Goodness of fit is reported as deviance, or −2 times the log of the ratio of likelihoods for the estimated model to a saturated model. Decreases in deviance for nested models can be compared to a chi-squared distribution with degrees of freedom equal to the number of additional parameters. Note that all models reported represent a significant reduction deviance compared to the model including only controls.

RESULTS

Maximum likelihood estimates for three models are presented in table 2. Model 1 is the base with only control variables. Model 2 introduces endogenous structural variables of theoretical interest transitive closure and cyclic closure in the long term, along with the embedding inertia and sender-scaled

TABLE 1
DESCRIPTIVE STATISTICS OF THE ORGANIZATIONAL CONTROL COVARIATES INCLUDED IN THE MODEL

Variable	Measure	Mean	SD	Min	Max
Size	Number of staffed beds	188.45	150.55	30	730
Occupancy rate	Average percentage of beds occupied	71.57	15.15	6	100
Inefficiency	CPI of relative efficiency (reverse scaled)	1.045	.264	.437	3.432
Distance	Driving distance (in minutes) between every pair of hospitals within the region	66.26	28.82	0	146
Niche overlap	Patient pool overlap between every pair of hospitals as measured by Sohn (2002)	.0157	.029	0	.383
Service differentiation	Euclidean distance computed on (*n*) hospitals by (*m*) specialties matrices	3.174	.984	0	5
LHU membership	Membership in local health unit	. . .	. . .	1	6
Urban/rural	1 = urban hospital; otherwise 0	32% urban	. . .	0	1
Public/private	1 = public hospital; otherwise 0	32% public	. . .	0	1
In-house capability	For each event, 1 if the sending hospital has a specialty unit in the patient's needed specialty (indicated by receiving unit); otherwise 0	.31	. . .	0	1
Bribery	1 = arc convicted of bribery; otherwise 0	827 events	. . .	0	1
Teaching	1= teaching hospital; otherwise 0	2 hospitals	. . .	0	1

Name	Visual Representation	**Probabilistic Mechanism** The tendency for hospital i to send a patient to hospital j as function of…	Statistic
Popularity of Sender		the extent to which i has received patients from hospital(s) k in the past.	$\sum_{0<k\le n}\sum_{t-r<u\le t} Y_{kiu} \Big/ \sum_{0<k\le n}\sum_{0<l\le n}\sum_{t-r<u\le t} Y_{klu}$
Popularity of Recipient		the extent to which j has received patients from hospital(s) k in the past.	$\sum_{0<k\le n}\sum_{t-r<u\le t} Y_{kju} \Big/ \sum_{0<k\le n}\sum_{0<l\le n}\sum_{t-r<u\le t} Y_{klu}$
Activity of Sender		the extent to which i has sent patients to hospital(s) k in the past.	$\sum_{0<k\le n}\sum_{t-r<u\le t} Y_{iku} \Big/ \sum_{0<k\le n}\sum_{0<l\le n}\sum_{t-r<u\le t} Y_{klu}$
Activity of Recipient		the extent to which j has sent patients to hospital(s) k in the past.	$\sum_{0<k\le n}\sum_{t-r<u\le t} Y_{jku} \Big/ \sum_{0<k\le n}\sum_{0<l\le n}\sum_{t-r<u\le t} Y_{klu}$

○ Sender ● Recipient ◉ Any Node ⟶ Current Event ⋯⋯▸ Past Events

FIG. 5.—Endogenous structural controls. Let $Y_{ijt} = 1$ if i sends a patient to j at time t ($Y_{ijt} = 0$ otherwise), where i denotes the sender, j the recipient, t the time of the event, r the time horizon (one month and one year), n the number of hospitals, u an index over time steps within the time horizon, and k an index over all hospitals.

TABLE 2
Parameter Estimates of Relational Event Models for All Transfers between 2003 and 2007

	Model 1		Model 2		Model 3	
Variable of theoretical interest:						
Long term:						
Embedding inertia			.33**	(.02)	.32**	(.02)
Embedding reciprocation			.17**	(.02)		
Dependence reciprocation					−.02	(.01)
Transitive closure			.24**	(.01)	.23**	(.01)
Cyclic closure			.13**	(.02)	.05*	(.02)
Short term						
Embedding inertia			.03**	(.01)	.04**	(.01)
Embedding reciprocation			.02*	(.01)		
Dependence reciprocation					.02*	(.01)
Organizational control:						
Size sender	1.45**	(.09)	1.40**	(.10)	1.25**	(.10)
Size difference	−.92**	(.10)	−.74**	(.10)	−.57**	(.10)
Occupancy recipient	−.30**	(.07)	.05	(.07)	−.03	(.07)
Occupancy difference	−.01	(.07)	.15*	(.07)	.11	(.07)
Inefficiency recipient	−.03	(.04)	−.04	(.04)	−.02	(.04)
Inefficiency difference	−.14**	(.04)	−.12**	(.04)	−.09*	(.04)
Geographic distance	−.51**	(.04)	−.36**	(.05)	−.44**	(.04)
Niche overlap	.26**	(.02)	.11**	(.02)	.08**	(.02)
Service differentiation	−.13**	(.03)	−.17**	(.03)	−.09**	(.03)
Same LHU	1.82**	(.05)	1.03**	(.07)	1.31**	(.07)
Both urban	.25**	(.06)	.30**	(.06)	.31**	(.06)
Sender urban	−2.29**	(.17)	−2.11**	(.18)	−2.22**	(.18)
Recipient urban	−.48*	(.19)	−.28	(.19)	−.17	(.19)
Both public	1.82**	(.42)	1.18**	(.42)	1.24**	(.42)
Sender public	−.79	(.42)	−.50	(.42)	−.78	(.42)
Recipient public	.49	(.41)	.53	(.41)	.87*	(.41)
In-house capability	−.33**	(.3)	−.37**	(.03)	−.35**	(.03)
Bribery	4.56**	(.20)	2.71**	(.21)	2.87**	(.22)
Sender teaching	−.18	(.19)	.29	(.18)	.54**	(.18)
Recipient teaching	.74**	(.13)	.54**	(.13)	.48**	(.13)
Endogenous structural control:						
Long term:						
Popularity sender	.27**	(.05)	−.05	(.06)	.13*	(.06)
Activity sender	.10*	(.04)	−.02	(.04)	.01	(.04)
Popularity recipient	.37**	(.04)	.01	(.05)	.08	(.05)
Activity recipient	.00	(.03)	−.08*	(.03)	−.10**	(.04)
Short term:						
Popularity sender	.05	(.04)	−.01	(.04)	.04	(.04)
Activity sender	.12**	(.03)	.09**	(.03)	.10**	(.03)
Popularity recipient	.09**	(.03)	.05	(.03)	.06*	(.03)
Activity recipient	.01	(.03)	−.00	(.03)	−.00	(.03)
Goodness of fit:						
Null deviance			44,388			
Residual deviance	28,014		27,231		27,354	
Observed events (potential events)			3,247 (3,016,463)			

Note.—SEs are in parentheses.
* $P < .05$.
** $P < .01$.
*** $P < .001$.

embedding reciprocation in both the short term and long term. Model 3 uses the alternative receiver-scaled weighting (dependence reciprocation).

Parameter estimates in model 1 indicate that larger hospitals tend to send more patients (positive *size sender*), and also patients are more likely to be transferred when the receiving hospital is larger than the sender (negative size difference). Hospitals with higher occupancy (more stringent capacity constraints) are generally less likely to receive patients, but dyadic differences in occupancy rates do not appear to be important. We take this as evidence that patient transfer does not follow a straightforward logic of capacity management. We find no evidence that inefficiency of the recipient has an independent effect, and patients are slightly more likely to be transferred from more efficient hospitals to less efficient hospitals (negative inefficiency difference).[5] Estimates suggest that a hospital is more likely to transfer patients to a more proximate hospital (negative distance effect). The estimates also indicate that niche overlap has a positive effect: patient transfers are more likely between hospitals with overlapping patient pools. The effect of service differentiation is significantly negative: patient transfers are less likely between hospitals offering different types of services. Also, patient transfers are more likely between organizations facing the same administrative constraints, opportunities, and institutional partners (because they are members of the same LHU). Urban hospitals tend to send to each other (positive both urban) and generally send less (negative sender urban) than nonurban hospitals. The apparent tendency for public hospitals to receive more patients in general seems to be captured by other control variables, especially a tendency for public hospitals to send to each other (positive both public) and for teaching hospitals to receive patients (positive *recipient teaching*). Consistent with intuition, hospitals are less likely to send patients if they have the specialty that the patient requires for her treatment (negative *in-house capability*). Finally, we control for the high volume of transfers in the one directed tie that was investigated and convicted of corruption for the period we study (*bribery*).

As for the structural controls, see that historically *popular* hospitals (which have received more patients over the historical time horizon) in the long-term past are more likely to both send and receive patients, although

[5] We control for inefficiency to avoid spurious effects that could be due to unmeasured heterogeneity. The observed pattern suggests that more efficient (low-CPI) hospitals are more likely to transfer patients. However, their choice of recipient hospital is clearly not driven by differences in efficiency of the receiving hospital (they are not sending to more efficient hospitals or even to particularly efficient hospitals), and this leaves open the possibility that sociologically interesting processes (such as reciprocation) may be at play.

this pattern is not as robust in the short term. Historically active hospitals (which have sent many patients over the time horizon) are more likely to send patients but not to receive them.

Model 1 controls for a large number of important features of senders and receivers (urban, public, size, occupancy rate, inefficiency, capability, research/teaching hospital) and of hospital pairs (geographic distance, niche overlap, service differentiation, LHU membership, differences on organization-level attributes), as well as popularity and activity controls that likely capture remaining unobserved heterogeneity at the sender and receiver level. Models 2 and 3 in table 2 allow us to focus on the results of theoretical interest. In both models, we do see evidence of reciprocation for hospitals (i.e., hospitals tend to give back patients to other hospitals that give to them). This is true for both embedding and dependence reciprocation, but we also see preliminary evidence that timescale matters; that is, distinct social processes depend differently on history. Model 2 includes embedding inertia (the tendency for i's historical focus on giving to j to be reproduced in future transfers from i to j) and embedding reciprocation (the tendency for j's historical focus on giving to i to lead i to give to j). Both effects are significant and positive (supporting hypotheses 1a and 2a), and both are more strongly positive in the long term than in the short term (supporting hypotheses 1b and 2b).

Model 3 shows a positive effect for dependence reciprocation (supporting hypothesis 3a), and this effect is more positive in the short term than in the long term (supporting hypothesis 3b). That is, dependence reciprocation takes present alternatives into account (e.g., "is this partner important to me relative to my current alternative partners?"). After controlling for dependence in the short term, dependence in the long term has no significant effect. No such effect was predicted, and our focus is on the short-term effect of dependence.

We did not develop hypotheses for the triad level at this stage. In models 2 and 3, we observe that transitive closure is strongly positive in the long term, a result that is robust across all models. However, this result fails to discriminate between our two target mechanisms—local generalized exchange or local status processes—because positive transitive closure is consistent with both mechanisms. Cyclic closure could indicate either generalized exchange (if positive) or status hierarchy (if negative). We observe that it is positive and significant here, suggesting generalized exchange. Our next analysis will shed more light on both dyad-level and triad-level patterns.

EXCHANGE IN COMPETITIVE AND MUTUALISTIC CONTEXTS

Moving beyond studying interorganizational ties to directly theorize and analyze temporal patterns in exchange behavior has allowed us to draw more deeply on resource dependence theory and organizational theories of embeddedness and to explicate temporal implications of both theories. In our main contribution, we suggested two different mechanisms of reciprocation and also showed how they depend on history over different time horizons, with dependence reciprocation operating on contemporaneous exchange structures and embedding reciprocation operating on long-term histories of exchange. The unique value of our approach is to afford identification of these differences.

In this section we examine the same research context and data on Italian hospitals, but we exploit an important form of heterogeneity in patient transfers to further validate the theory and demonstrate the value of the method. On the basis of our extensive fieldwork, we propose that interhospital patient transfers within the same clinical specialty are driven by different logics of exchange than transfers across specialties. Let us define these terms:

Across-specialty transfers occur when hospital A sends a patient from one specialty at hospital A to a different specialty at hospital B (transferring to receive a different kind of care).

Within-specialty transfers occur from hospital A to hospital B within the same care specialty (providing equivalent and potentially competing services).

We present hypotheses and results separately for these two kinds of exchange. In considering this form of heterogeneity in kinds of patient transfers, we do not aim to show that our results are robust to this heterogeneity. Instead, we show that findings depend on this heterogeneity in systematic ways that support and validate the theory. In order to employ richer data on treatment specialties, the following analyses focus on 2005–7 because detailed specialty data are not available for 2003–4. There appear to be no systematic differences in the structure of exchanges or the operation of exchange processes, so we employ the longer time period and larger data set for the previous analysis that did not require specialty-level data. (Replicating the previous analysis restricting to 2005–7 yields the same results.)

Exchange in Complementary Service Domains (Transfers across Specialties)

Transfers between hospitals across specialties, such when as a juvenile heart patient in pediatrics at hospital A is transferred to a cardiology unit at hospital B, do not signal deference because their services are complementary. For these complementary transfers, we expect the same dyadic patterns of embedding inertia (hypotheses 1a and 1b), embedding reciprocation (hypotheses 2a and 2b), and dependence reciprocation (hypotheses 3a and 3b) as we had predicted and observed for the full set of exchanges.

We further develop predictions at the triad level. For these complementary transfers across clinical specialties, we expect generalized exchange at the triad level, implying the following two specific hypotheses:

Hypothesis 4a.—*In across-specialty transfer choices, triadic patterns in patient transfers will exhibit (a tendency toward) transitive closure. The more hospital* i *transfers to hospital* k *and hospital* k *transfers to hospital* j, *the more hospital* i *will send across-specialty transfers to hospital* j.

Hypothesis 4b.—*In across-specialty transfer choices, triadic patterns in patient transfers will exhibit (a tendency toward) cyclic closure. The more hospital* j *transfers to hospital* k *and hospital* k *transfers to hospital* i, *the more hospital* i *will send across-specialty transfers to hospital* j.

Again, it is not necessary that hospitals monitor patient exchanges among third-party hospitals (although this information is available to them) for these triad closure patterns to obtain. We have described how the gradual embedding of the transfer process may develop through organizational embedding (operating routines, communication channels, contact lists, familiarity among staff, habits, and the like), and some of these adhesions spread to third parties just as they operate reciprocally (for embedding inertia and embedding reciprocation). Table 3 presents relational event models to test the six dyadic and two triadic hypotheses for choices to transfer across specialties.

The findings for embedding reciprocation and dependence reciprocation in across-specialty transfer choices are substantively similar to those reported for all exchanges. Model 4 shows that embedding inertia and embedding reciprocation are generally positive but consistently more positive in the long term than in the short term (supporting hypotheses 1a, 1b, 2a, and 2b), whereas model 5 shows that dependence reciprocation also operates but more in the short term (supporting hypotheses 3a and 3b). Again, we are interested in documenting embedding reciprocation and showing that it operates more strongly in the longer term and documenting dependence reciprocation and showing that operates more in the short term. Whether embedding reciprocation is still significant in the short term or dependence reciprocation is still significant in the long term is not theoretically important.

Models 4 and 5 show positive transitive closure (hypothesis 4a) and positive cyclic closure (hypothesis 4b) for across-specialty transfers. The combination of positive transitive and cyclic closure at the triad level leads to a pattern of clustered generalized exchange at the population level.

For the case of complementary exchange (across-specialty transfers, with minimal direct competition), we thus see the same patterns of reciprocation that we identified in the main part of this article: embedding reciprocation operates more strongly on the long-term and dependence reciprocation operates more strongly on the short-term time horizon. Net of dyadic effects,

TABLE 3

PARAMETER ESTIMATES OF RELATIONAL EVENT MODELS FOR ACROSS-SPECIALTY TRANSFERS BETWEEN 2005 AND 2007

	Model 4	Model 5
Variable of theoretical interest:		
Long term:		
Embedding inertia	.29** (.02)	.26** (.02)
Embedding reciprocation	.19** (.02)	
Dependence reciprocation		.02 (.01)
Transitive closure	.24** (.02)	.23** (.02)
Cyclic closure	.21** (.03)	.11** (.03)
Short term		
Embedding inertia	.03** (.01)	.03* (.01)
Embedding reciprocation	.03* (.01)	
Dependence reciprocation		.03** (.01)
Organizational control:		
Size sender	1.68** (.14)	1.50** (.14)
Size difference	−.79** (.15)	−.52** (.14)
Occupancy recipient	−.08 (.09)	−.16 (.09)
Occupancy difference	−.03 (.09)	−.07 (.09)
Inefficiency recipient	−.02 (.04)	.00 (.04)
Inefficiency difference	−.11* (.05)	−.09* (.04)
Geographic distance	−.57** (.06)	−.66** (.06)
Niche overlap	.11** (.03)	.08* (.03)
Service differentiation	−.06 (.04)	.04 (.04)
Same LHU	1.11** (.10)	1.37** (.10)
Both urban	.66** (.08)	.64** (.08)
Sender urban	−2.26** (.25)	−2.48** (.26)
Recipient urban	.07 (.27)	.27 (.27)
Both public	2.47** (.52)	2.49** (.52)
Sender public	−1.52** (.51)	−1.93** (.51)
Recipient public	.13 (.46)	.63 (.46)
In-house capability	−.92** (.04)	−.90** (.04)
Bribery	3.55** (.34)	3.90** (.34)
Sender teaching	.45 (.24)	.74** (.24)
Recipient teaching	.46* (.18)	.41* (.18)
Endogenous structural control:		
Long term:		
Popularity sender	−.15 (.08)	.01 (.08)
Activity sender	−.03 (.06)	.01 (.06)
Popularity recipient	−.10 (.06)	−.01 (.06)
Activity recipient	−.06 (.05)	−.10* (.05)
Short term:		
Popularity sender	−.03 (.05)	.05 (.05)
Activity sender	.08* (.04)	.10** (.04)
Popularity recipient	.03 (.04)	.05 (.04)
Activity recipient	−.03 (.04)	−.03 (.04)
Goodness of fit:		
Null deviance	23,732	
Residual deviance	13,968	14,066
Observed events (potential events)	1,736 (1,612,744)	

NOTE.—SEs are in parentheses.

* $P < .05$.

** $P < .01$.

*** $P < .001$.

we see the predicted pattern of generalized exchange at the triad level in positive transitive and cyclic closure.

Exchange in Competitive Service Domains (Transfers within Specialties)

Hospitals should only engage in transfers that benefit the patient, and these elective inpatient transfers represent patients who already have a bed in the same specialty at the sending hospital. Thus, in contrast to across-specialty transfers, within-specialty transfers imply a public signal by hospital *i* that hospital *j* will offer the patient superior care. Thus, in addition to the financial costs of losing a patient, sending within-specialty transfers entails a greater reputational cost. We have no reason to believe that the processes of embedding and dependence reciprocation are deactivated for within-specialty exchanges. However, we note that a logic of strict meritocracy (based on objective quality of care or of socially constructed reputation or both) is in conflict with reciprocation for within-specialty inpatient transfers, and we expect this logic of meritocracy to dominate the transfer process for within-specialty exchange, blocking all reciprocation and cyclic closure and replacing generalized exchange with a strict merit hierarchy.

Hypothesis 5.—*For within-specialty transfer choices there will be no embedding reciprocation, either in the short term or in the long term.*

Hypothesis 6.—*For within-specialty transfer choices there will be no dependence reciprocation, either in the short term or in the long term.*

Hypothesis 7a.—*For within-specialty transfer choices, triadic patterns in patient transfers will exhibit transitive closure. The more hospital* i *transfers to hospital* k *and hospital* k *transfers to hospital* j, *the more hospital* i *will send within-specialty transfers to hospital* j.

Hypothesis 7b.—*For within-specialty transfer choices, triadic patterns in patient transfers will exhibit negative cyclic closure. The more hospital* j *transfers to hospital* k *and hospital* k *transfers to hospital* i, *the less hospital* i *will send within-specialty transfers to hospital* j.

Note that positive transitive closure (hypotheses 4a and 7a) leads to clustering, which can be consistent with either generalized exchange or hierarchy. However, positive cyclic closure (hypothesis 4b) generates local generalized exchange, while negative cyclic closure (hypothesis 7b) generates local hierarchy.

Table 4 presents relational event models to test these two dyadic and two triadic hypotheses for within-specialty transfers. For the case of deference/competition (where transferring patients implies superiority), we do not see reciprocation for either embedding (supporting hypothesis 5) or dependence (supporting hypothesis 6) reciprocation. Embedding reciprocation never matters, and dependence reciprocation does not matter in the short term

TABLE 4
PARAMETER ESTIMATES OF RELATIONAL EVENT MODELS FOR WITHIN-SPECIALTY TRANSFERS BETWEEN 2005 AND 2007

	Model 6	Model 7
Variable of theoretical interest:		
Long term:		
Embedding inertia	.35** (.04)	.37** (.04)
Embedding reciprocation	.03 (.06)	
Dependence reciprocation		−.14** (.03)
Transitive closure	.24** (.03)	.22** (.03)
Cyclic closure	−.05 (.06)	−.07 (.06)
Short term:		
Embedding inertia	.00 (.02)	.01 (.02)
Embedding reciprocation	.01 (.03)	
Dependence reciprocation		−.01 (.02)
Organizational control:		
Size sender	1.02** (.28)	.89** (.27)
Size difference	−1.06** (.27)	−1.15** (.27)
Occupancy recipient	.25 (.22)	.14 (.22)
Occupancy difference	.20 (.19)	.07 (.19)
Inefficiency recipient	−.24 (.15)	−.29 (.15)
Inefficiency difference	−.30 (.19)	−.30 (.19)
Geographic distance	−.05 (.10)	−.05 (.10)
Niche overlap	.08 (.08)	.06 (.08)
Service differentiation	−.43** (.07)	−.41** (.07)
Same LHU	.91** (.19)	1.47** (.20)
Both urban	−.79** (.15)	−.82** (.15)
Sender urban	−.38 (.43)	−.042 (.44)
Recipient urban	−1.05* (.47)	−1.09* (.48)
Both public	.61 (1.10)	.78 (1.11)
Sender public	.81 (1.11)	.83 (1.11)
Recipient public	.29 (1.10)	.25 (1.10)
In-house capability	2.01** (.27)	2.04** (.27)
Bribery	2.27** (.56)	1.78** (.56)
Sender teaching	−.64 (.38)	−.62 (.38)
Recipient teaching	.52 (.31)	.55 (.31)
Endogenous structural control:		
Long term:		
Popularity sender	.22 (.16)	.31* (.16)
Activity sender	.09 (.09)	.13 (.09)
Popularity recipient	.04 (.12)	.03 (.117)
Activity recipient	−.18* (.09)	−.14 (.087)
Short term:		
Popularity sender	−.18 (.11)	−.15 (.11)
Activity sender	.16* (.07)	.15* (.07)
Popularity recipient	.06 (.06)	.07 (.07)
Activity recipient	.07 (.07)	.06 (.07)
Goodness of fit:		
Null deviance	7,628	
Residual deviance	4,337	4,323
Observed events (potential events)	558 (518,382)	

NOTE.—SEs are in parentheses.
* $P < .05$.
** $P < .01$.
*** $P < .001$.

and is sometimes negative in the long term. That is, i is less likely to send within-specialty transfers to j if i receives a great proportion of incoming transfers from j. This strongly supports hypothesis 6 and again suggests that meritocratic hierarchy is the overarching logic for within-specialty exchanges. Although we did not predict that dependence reciprocation would be dampened much more than embedding reciprocation for within-specialty exchange, this makes sense from the interpretation of the exchange structure as socially constructed meritocracy. Interpreting patient transfers as deference for the sender and dominance for the recipient, then i's negative dependence reciprocation on j means i is reluctant to defer to i's crucial source of status. This is to say, reciprocating deference is unlikely overall, but near the bottom of the pecking order (e.g., if one receives status from only a single peer), one is particularly unlikely to do so.

Meaningful patterns emerge at the triad level over the long term. Specifically, for within-specialty transfers in competitive contexts, we see positive transitive closure (hypothesis 7a) just as we had seen for across-specialty transfers in complementary contexts. Unlike across-specialty transfers, cyclic closure is negative as predicted in models 6 and 7 (hypothesis 7b), although this fails to reach statistical significance in these models. This reveals limited evidence of the microfoundations of hierarchy emergence at the triad level: if i gives to k and k gives to j, then i also sends deference to j (supporting hypothesis 7a) and j is not more likely to send deference to i. The fact that the negative parameter estimate on cyclic closure fails to reach statistical significance in models 6 and 7 fails to provide full support for hypothesis 7b (i.e., that j is less likely to send deference to i), but the contrast with the significant positive cyclic closure pattern for across-specialty transfers in models 4 and 5 is notable, as is the negative reciprocation result described above.

Although it is reasonable to assume that different processes drive the choices to reciprocate within or across specialties, and this motivates our modeling those choices separately in tables 3 and 4, we have not assumed that hospitals keep ledgers of other hospitals' transfers and differentiate within- and across-specialty transfers in that perceived network. We have conservatively assumed that gradual processes of embedding through repeated interaction occur similarly for within- and across-specialty transfers and that the distinct choices to transfer patients within and across specialties operate within a single overarching structure of exchanges for all peer hospitals, even as they respond differently to that structure. If we assume that within- and across-specialty transfers are separate networks (i.e., hospital i's choice to reciprocate to hospital j within specialty attends only to j's and k's within-specialty transfers, which requires strong assumptions about hospitals' monitoring and keeping track of each other's transfers), then results are similar overall, but the long-term cyclic closure for within-specialty transfers is statistically significant (negative) as predicted. We conservatively report the weaker result that does not require such strong assumptions.

To recapitulate our comparison of exchange in competitive (within-specialty) and mutualistic (across-specialty) contexts: for complementary transfer choices across specialties, we observe reciprocation at the dyad level and transitive and cyclic closure at the triad level, which together lead to generalized exchange at the population level. For deference transfer choices within specialties, we observe no reciprocation (or even antireciprocation) at the dyad level, and we see transitive closure without cyclic closure (or even negative cyclic closure), which collectively suggest hierarchy formation at the population level.

CONSIDERING COMPETITION OVER GEOGRAPHIC DISTANCE

In the main analysis of patient transfers, we developed a theory of interorganizational exchange that differentiated embedding and dependence reciprocation and showed that embedding operates over long time horizons (responds to long-term history) and dependence operates contemporaneously (responds to short-term history) in patient flows. In a follow-up analysis above, we considered exchange in two different contexts—transfers within service specialties (competitive contexts, where transfers are taken as a sign of deference) and across service specialties (in complementary or nonoverlapping contexts, where transfers can represent cooperation). Supporting our interpretation of embedding and dependence reciprocation, this extension to heterogeneity in exchange behaved in an intelligible manner. For complementary transfers (across specialties), we observe reciprocation following the same patterns that we had described and discussed in the primary analysis: embedding over the long term and dependence in the short term, with generalized exchange at the population level. For deference transfers (within specialties), we do not observe reciprocation. The structure of exchanges appears to be unidirectional at the dyad level, and transitive (not cyclic) at the triad level, implying a basic tendency toward hierarchy. In this section, we elaborate the analysis and give a further validation of our interpretation, now considering the role of geographic distance in moderating the two mechanisms of organizational reciprocation (embedding and dependence).

We earlier reported that no reciprocation occurred in within-specialty transfers, and we attributed this failure of reciprocation to competition. As we have detailed location information on these hospitals, we can use geographic distance between hospitals to verify that the breakdown of reciprocation for within-specialty transfers is in fact due to competition. This seems particularly appropriate in the case we examine because competition in service industries (such as hotels, restaurants, and hospitals) is known to attenuate with distance (Baum and Mezias 1992; Mascia et al. 2016). If competitive dynamics are indeed the driving force for the lack of reciprocation for within-specialty transfers, then geographic distance should moderate the findings we attributed to competition. At short distances, competitive dynamics should erase reciprocation for within-specialty transfers (as we found above), but great distance will attenuate competition, allowing reciprocation to emerge even within each specialty market.

HYPOTHESIS 8.—*Reciprocation will increase with geographic distance for within-specialty transfers.*

We do not report the full tables of coefficients for within-specialty transfers for brevity, but those results are available upon request. To present this result more intuitively, we plot the predicted multiplier of the exchange rate as distance increases, for embedding and dependence reciprocation in the short term versus the long term (see fig. 6).

For within-specialty transfers, we again see that reciprocation appears to be negligible (multiplier near 1.0) for short-distance or medium-distance hospital pairs (under about a 40-minute drive). However, over great distances, reciprocation does in fact emerge even for within-specialty transfers. Further, this reciprocation at great distances actually matches the pattern of reciprocation that we had reported for the entire population (in table 2) and for across-specialty transfer choices (in table 3): *long-term embedding reciprocation* and *short-term dependence reciprocation* are strongest. Supporting our interpretation that the failure of reciprocation in within-specialty transfers had been due to competition, we confirm that increasing *geographic distance* (which attenuates competition) restores reciprocation, including the characteristic pattern of time-dependent reciprocation.

Also supporting that competition is driving the failure of reciprocation for within-specialty transfers, we did not find that distance increases reciprocation for across-specialty transfers. Reciprocal exchange across specialties is strong locally and diminishes as distance increases (for short-term and long-term dependence and short-term embedding), an intuitive pattern due to greater costs and risks of distant transfers. It is unsurprising that reciprocation in complementary patient exchanges is less likely over great distances, and this result is not relevant to our theory, so we do not focus on this result here. However, the fact that distance decreases reciprocation for complementary exchanges provides a contrast that highlights how distance increases reciprocation for competitive exchanges.

CONCLUSION

Previous work has considered interorganizational networks either as binary ties among organizations or as time-aggregated flows of resources among

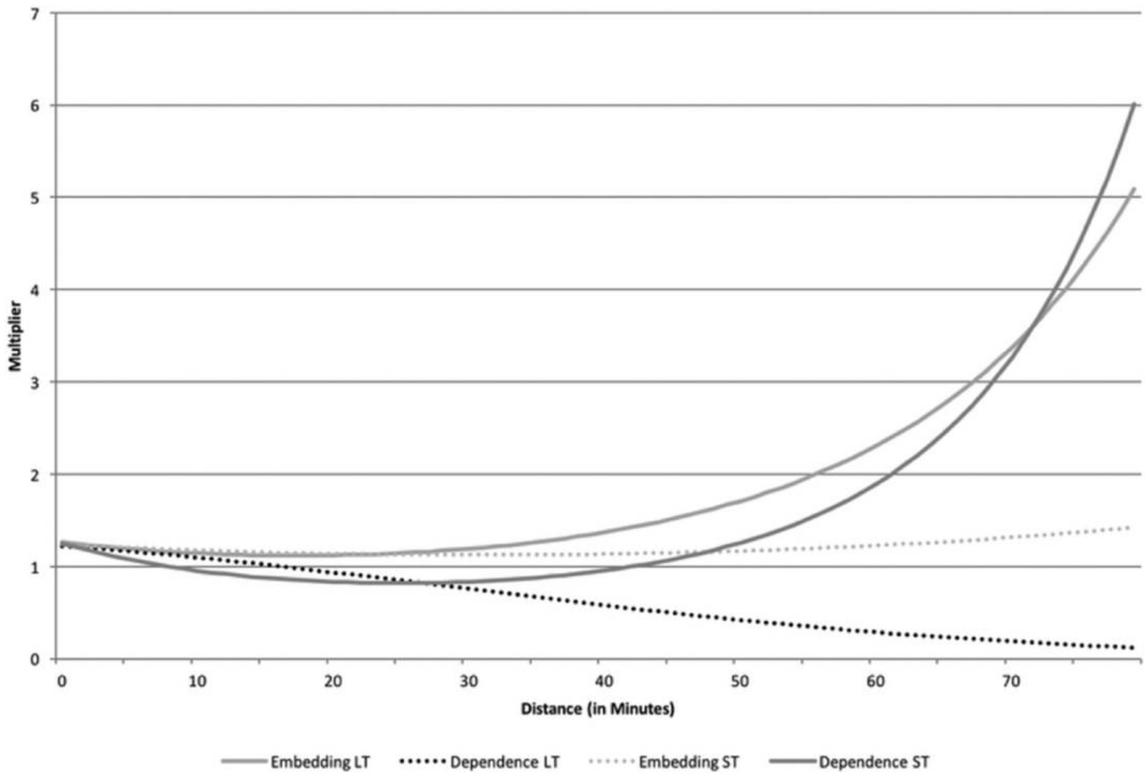


FIG. 6.—Forms of reciprocation across space in within-specialty transfers (2005–7)

organizations. Researchers have typically assumed an equivalence of interaction behavior and observed relationships, having measured one and taken it as a proxy for the other. We extend that work by directly studying the interaction behaviors, developing an integrated theory for the structural-temporal dynamics of interorganizational exchange. Moving from a dyadic/binary ties perspective to direct analysis of interaction behavior allows us to consider new kinds of questions, considering for the first time how two prominent logics of organizational exchange (previously seen as static patterns) fit together dynamically.

Drawing on resource dependence theory and theories of organizational embeddedness, in our primary contribution we develop and defend the following theoretical claim: when looking at the contemporaneous structure of interorganizational exchange (recent patterns of giving), organizations tend to reciprocate resource transfers according to a logic of dependence (i gives more to peers j that are relatively important sources of resources to i). When looking over the long-term historical structure of exchange, organizations tend to give according to a logic of interorganizational embedding (i gives to peers j that focus their giving on i), which we call embedding. At any given time, the organization's giving choices reflect these two forces, which operate as two distinct forms of history dependence on distinct clocks. Developing and testing novel hypotheses for the temporal dynamics of these two reciprocation mechanisms operating on patient exchanges among Italian hospitals, we show that embedding reciprocation is driven by long-term historical patterns and dependence reciprocation is driven by the contemporaneous structure (recent history) of exchange.

In our secondary contribution, we investigate a scope condition for the above theoretical claim about reciprocation. We show how local exchange dynamics differ in competitive environments, where exchanges may be interpreted as deference by the sender to a superior recipient. Specifically, we show that competitive intensity (using two distance-based measures) moderates the forces of reciprocation: reciprocation follows the pattern hypothesized above only when competitive intensity is low. As a categorical measure of competitive intensity, we distinguish patient transfer choices within service specialties (competitive contexts, where transfers may be interpreted as dominance or deference) from transfer choices across specialties (where transfers may be interpreted as complementarity and cooperative differentiation). We use driving distance between hospitals as an alternative continuous operationalization of competitive intensity, assuming conventionally that competitive intensity varies inversely with geographic distance. This supplementary analysis yields consistent conclusions: in contexts where organizations are located near each other in market space and in geographic space, competitive interdependence leads a distinct logic of deference/dominance to overwhelm the above tendencies toward reciprocation, so reciprocation does not appear at all. For complementary transfers across specialties or over great geographic distances, reciprocation does develop and follows the pattern predicted by our theory: strongest for long-term embedding reciprocation and short-term dependence reciprocation. For across-specialty exchange (where there is little competition), reciprocation unsurprisingly decreases with geographic distance. This interaction with geographic distance (distance increases reciprocation within markets and decreases reciprocation across markets) strongly supports the theory and its scope condition.

Our third contribution is to suggest how local exchange dynamics can serve as microfoundations of macrolevel social structures. For example, we show how local logics of mutualism can lead to population-level generalized exchange when competitive intensity is low (resource transfers signal collaboration) and local status dynamics can lead to hierarchy when competitive intensity is high (resource transfers signal deference). For complementary resource transfers, we show strong reciprocation at the dyad level and positive transitive and cyclic closure at the triad level, which leads to generalized exchange in the population. For deference transfers within competitive contexts, we find no reciprocation (or antireciprocation) for dyads and transitive closure without cyclic closure for triads, which collectively suggest tendencies toward hierarchy at the population level. We thus show that the dyadic and triadic patterns in this article will tend to lead to reciprocation and generalized exchange in less competitive contexts and will lead to linear transitive hierarchies of dominance and deference in more competitive contexts. Thus, competitive intensity determines when a population will develop into generalized exchange (reciprocation, cyclic and positive transitive exchange) and when a population will develop into hierarchy (no reciprocation, no cyclic exchange, instead transitive dominance relations). Although intuitive, this result has never before been demonstrated with this level of granularity at the level of temporally situated interorganizational exchange events.

In fieldwork, we discussed the observed patterns with some physicians from Lazio, Marche, and Abruzzo. They found our observations of reciprocation for across-specialty exchange, as well as nonreciprocation at the dyadic level and transitive anticyclic exchange at the triad level, to be intelligible for within-specialty exchange, in terms consistent with our account here. They explicitly described the expressions of deference that physicians enact through transferring patients and the status hierarchies that result in the local population. The one pattern that they found puzzling was the appearance of positive cyclic closure in exchanges, which we had observed for across-specialty transfers. This appearance of a regular structure (cyclic exchange) outside the awareness of the individuals who enact those patterns recalls the findings by Bearman (1997), who also observed robust cyclic exchange (transfers of wives among subsections of an aboriginal tribe) in a population that neither prescribed nor recognized this cyclic pattern. Further research is needed to verify this suggestive result.

Our study of temporal-structural dynamics of exchange behavior goes beyond conventional network analysis and revisits insights from classical exchange theory, drawing inspiration from qualitative ethnographic fieldwork and experimental research on exchange. This new lens allows us to reincorporate the idea that the event history of exchange may play a crucial role in the development of exchange structures, an insight that has been too often ignored because it could not be rigorously considered with conventional social network analysis. Disaggregating the structure of interaction into the dynamic structure of underlying interaction events also opens a world of opportunities to examine the content of interaction that constitutes that structure. For example, McLean (2007) analyzed the text of patronage letters among Florentines in the Italian Renaissance, showing how templates developed and were reproduced through the exchange of letters over time. Similar lenses could be applied to analysis of text in the documents accompanying patient transfers. We look forward to future work that will apply this lens and more nuanced theory to other research contexts.

APPENDIX

Additional Information about the Relational Event Model

Model Estimation

In the general (continuous) form of the model each relational event is assumed to have a piecewise constant hazard of occurrence (λ) given a particular history of prior relational events. The piecewise constant rate function λ is assumed to depend on a variety of characteristics of the actors, the prior history of relational events within some specified sociotemporal envelope and exogenous covariates, and is parameterized in the form $\lambda = \exp(\sum_h \theta_h (u_h)_{i(m)j(m)})$, where each statistic $(u_h)_{i(m)j(m)}$ depends on characteristics of the actors, the prior history of events relevant to the mth event, $a_m = (i(m), j(m))$ and/or exogenous covariates. The θ_h are corresponding parameters.

In cases in which only the sequence of events is known or when the timing of events is less relevant than the information about the order of the events, as it is here, Butts (2008) shows that the probability that the mth event will be next in the sequence is the occurrence rate for that event divided by the sum of the rates for events $(k, l) \in \Omega(m)$ that might occur, including the mth event itself. The model therefore considers the probability of events that did occur as well as the probability of events that could have occurred at time t

but did not. The probability of the next event in a sequence is described by the function $p(m) = \lambda_m/(\Sigma_{m'}\lambda_{m'})$, where λ_m is a rate parameter associated with event m and the events m' run over all possible events that may occur next in the sequence. Hence, full formulation of the function that characterizes the probability that an event is the next in a sequence is as follows:

$$\frac{\exp\left(\sum_h \theta_h (u_h)_{i(m)j(m)}\right)}{\sum_{(k,l)\in\Omega(m)} \exp\left(\sum_h \theta_h (u_h)_{kl}\right)}, \tag{A1}$$

with the probability of the sequence of events being

$$p(A_t) = \prod_m \left[\frac{\exp\left(\sum_h \theta_h (u_h)_{i(m)j(m)}\right)}{\sum_{(k,l)\in\Omega(m)} \exp\left(\sum_h \theta_h (u_h)_{kl}\right)}\right]. \tag{A2}$$

In words, we compute the probability that an event is next in a sequence of events by comparing its rate of occurrence in the past (as characterized by the statistics in the model) to the rate of occurrence of all the potential events (eq. [A1]). The probability of the sequence itself is the product of the probabilities of each event (eq. [A2]). The final version of the model takes the form of a familiar conditional logistic regression model (e.g., Agresti 2002), specifying each event as a stratum within the model.

Data Preparation

Our data set is structured as a discrete ordered sequence of relational events (patient transfer), each of which can be expressed in the form $a_m = (i(m), j(m))$ signifying that the mth event is a patient being sent by hospital $i(m)$ to hospital $j(m)$. The hospitals $i(m)$ and $j(m)$ are members of a known set $N(m)$ relevant at each event (m). (It is also convenient to write $Y_{i(m)j(m)t} = 1$ to indicate $i(m)$ sending a patient to $j(m)$ at time t and $Y_{ijt} = 0$ otherwise; we use this more precise timing in the computation of statistics). The sequence of events is assumed to be of length M and may be written in the form $(a_1, a_2, \ldots, a_M)$. The sequence of events up to and including the mth event may be written as $A_m = \{a_h: h \leq m\}$. While $a_{\mathrm{m}} = (i(m), j(m))$ denotes the mth event, we also defined the set of potential events for the mth event as $\Omega(m) = \{(k,l): k \neq 1$ and $k, l \in N(m)\}$. Variable $\Omega(m)$ then includes the actual mth event and all the potential events that could have occurred as the mth event. We employed a custom-developed Java application to compute potential events and relevant preconfigurations based on the actual events contained in the patient exchange data set.[6]

We recorded the transfers as they occurred each day. Because more than one transfer may occur on the same day and because we did not have the exact time of day at which each transfer occurred, some transfers are simultaneous in our raw data. In fact, there are approximately two transfers per day, on average. As is standard in event history analysis, we deal with such simultaneous events by randomizing the sequence of events within each day. Although this introduces a minor source of error due to uncertainty about the true order of events within a particular day, such tiny differences (due to time perturbations of hours or minutes) can hardly affect results on our time horizons of months and years; indeed, sensitivity tests showed no change in results for replications of this random assignment. Also, the transfer process for individual patients takes many hours, so the exact timing within the day is arbitrary, and we found no evidence of statistical dependence for transfers on such a short time horizon (i.e., hospitals do not reciprocate patient transfers on the same day).

Alternative Consideration of the Risk Set

The models presented in the article use a set of potential events (or risk set) composed of all potential dyadic combinations between all hospitals in the sample. That is, any hospital could conceivably send a patient to any other hospital, even if the sending or receiving hospital does not have a distinct clinical specialty unit that matches the patient's actual admission category at the sender or receiver. An alternative version would be to assume that only hospitals that include the exact named clinical specialty of the actual sender could have sent the patient and only hospitals that have the specialty of the actual recipient could have received the patient. We replicated the analysis with this "restricted" risk set—composed of all hospital pairs where the potential sender (receiver) has a named specialty unit of the actual sender (receiver)—and results are robust. We report the unrestricted version not only because it is simpler and more parsimonious but also because assuming that only a hospital with specific named specialty unit could send or receive a patient is a very strong (and not always reasonable) assumption. In fact, hospitals may admit and treat patients even if they do not have a specific named specialty unit (such as neonatology or neonatal intensive care), and patients often have multiple intersecting medical problems and features that could apply to a number of different specialties (e.g., a child with a sim-

[6] The code used to calculate the statistics and to estimate the model are available on request from Eric Quintane. It is also possible to estimate relational event models using the relevent package in R; see Marcum and Butts (2015).

ple sports injury could be evaluated and sent to orthopedics and trauma, sports medicine, pediatric surgery, or surgery at various hospitals, depending on the judgment of the sender). Patient transfers are complex decisions that involve ambiguity and human judgment, and leave open the possibility that social processes (such as organizational reciprocation, generalized exchange, and status behavior) may be part of the story. It is notable that our results are similar whether we use the extreme restricted risk set or the unrestricted risk set. In another robustness check, we used the unrestricted risk set but included dummy variables to indicate whether the potential sender includes a clinical specialty matching the patient's admission in the actual sender hospital and another dummy variable indicating whether the potential recipient includes a specialty unit matching the patient's admission in the actual recipient hospital. Again, results were the same. Thus, we are in no way concerned that our results for social process of interorganizational exchange are an artifact of the structure of organizational specialties or capabilities.

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