Some days are better than others: Examining time-specific variation in the structuring of interorganizational relations.

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Abstract

The generative mechanisms controlling change in interorganizational relations are typically assumed to be time-independent, i.e., operate homogeneously and synchronously over time. In this paper we consider some of the implications of violating this assumption. We adopt and extend statistical models for relational events to reveal time-specific variations in mechanisms underlying interorganizational relations observed within a small community of health care organizations. We find that aggregate estimates of parameters associated with mechanisms of theoretical interest mask fine-grained temporal variation in relational events sequences. We discuss the implications of this result for studies of interorganizational relations – and social networks more generally.

Keywords: health care organizations; interorganizational networks; network dynamics; patient referral; relational event models; social mechanisms.

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1 Introduction

*"The Tuesday scowls, the Wednesday growls, the Thursday curses,
the Friday howls, the Saturday snores, the Sunday yawns,
the Monday morns, the Monday morns."'
Samuel Beckett (from "'Watt"')*

A major line of network research portrays the structure of interorganizational communities as an outcome of multiple micro-mechanisms embodying basic principles of organizational bonding (Laumann and Marsden, 1982; Laumann et al., 1978). Building on this view, more recent studies based on statistical network analysis have focused on the generative, self-organizing qualities of interorganizational networks (Lomi and Pattison, 2006). Longitudinal studies of interorganizational relations have emphasized the preferential tendencies of organizations to establish ties with partners embedded in specific local configurations of network ties (Koskinen and Lomi, 2013; Stadtfeld et al., 2016).

Despite fundamental differences in assumptions about the origins of dependencies among network ties (Block et al., 2016, 2018), current empirical studies are typically based on models that assume that the relational mechanisms underlying the dynamics of interorganizational systems are time independent, i.e., that these mechanisms operate homogeneously and synchronously across time periods, and over different time-frames (Kitts et al., 2017).

The purpose of this paper is to examine this assumption more closely, and assess its validity in the context of a realistically complex empirical analysis of time-stamped sequences of observed relational events – the raw material frequently used for the analytical reconstruction of network ties (Butts, 2009). More specifically, we adopt and adapt relational event models (Butts, 2008; Perry and Wolfe, 2013; Vu et al., 2017) to reveal time-specific variations in the effect of mechanisms of recognized theoretical relevance in interorganizational network research (Powell et al., 2005). Examples of such mechanisms include preferential attachment, inertia, reciprocity, assortativity, and various forms of triadic closure (Hollway et al., 2017; Lomi and Pallotti, 2012; Rivera et al., 2010).

The starting point of our work is the generic observation that much current research on the network dynamics of interorganizational systems is based on the useful, but somewhat paradoxical assumption that the mechanisms responsible for generating network ties operate in the same way over time. This assumption is useful because it reduces the complexity of empirical specifications by limiting the number of parameters to be estimated. This assumption is also paradoxical because it is difficult to imagine mechanisms of change that never change over time. Examining this assumption more closely allows us to ask new questions and extend previous research in at least two ways.

First, because the effects of social mechanisms are typically represented in terms of time-homogeneous parameters, issues related to their time-variation are ignored in studies of network change. In available studies, the effects of various social mechanisms on the structure of interorganizational networks are typically assumed not to change over time – or change only as a consequence of exogenous shocks (Corbo et al., 2016). With the possible exception of recent studies distinguishing between short-term and long-term effects of reciprocity (Kitts et al., 2017), studies of interorganizational relations continue to assume, implicitly, that the effects of relational mechanisms remain constant over time, and that they operate in synchrony. We are not aware of studies that have raised questions about time-specific variation in social mechanisms – i.e., about how such mechanisms operate differently at different points in time. We show how the average interpretation of network effects may mask time-specific variations that are essential to our understanding of network dynamics.

Second, exploring patterns of time-specific variation in network effects requires data on sequences of time-stamped events connecting sender and receiver units. We collected such data and use them to specify and estimate models that are able to reveal fine-grained temporal variations in patterns of interorganizational relations. We focus our modeling efforts on the time structure of relational event sequences connecting organizations – rather than network ties as one of their possible implications (Butts, 2009; Freeman et al., 1987). Prior research based on aggregation of repeated relational events into network ties has addressed issues of stability and change in interorganizational relations, but has ignored the possibility of time variations in high-frequency relational activities, i.e., in the micro-structure of network ties.

The opportunity to demonstrate the empirical value of an event-oriented analytical framework for exploring time-specific variations in relational mechanisms, is provided by data that we have collected on collaborative patient referral relations linking hospitals operating within a small regional community during the period 2005-2011. While the empirical setting has been the object of prior investigation (Kitts et al., 2017), these data are analyzed in this paper for the first time. Health care organizations provide a particularly appropriate empirical setting for examining time-specific variation in relational mechanisms because health care delivery activities are known to be extremely sensitive to the timing of treatment (Redelmeier and Bell, 2007; Zare et al., 2007). We focus on patient referral relations – a well-studied form of relational coordination between hospitals whereby the sender hospital involves the receiving hospital in the cooperative resolution of a clinical case (Iwashyna et al., 2009; Lomi and Pallotti, 2012; Veinot et al., 2012).

Unlike the majority of available studies in the specialized health care literature, in this paper we are not interested in time variations of clinical *outcomes* (as measured, for example, by the quality of health services rendered, or by change in patients' conditions caused by treatment), but in the time variation of organizational *processes* through which health care services are delivered to patients. Inter-hospital patient referral is one such process (Lomi et al., 2014). Adopting the distinction introduced by Borgatti and Halgin (2011), the modeling framework that we propose in this paper is inspired by "theories of networks" and not by "network theories." As such the models we estimate are designed to predict relational outcomes. The outcome of interest in our study is the probability of observing a single patient referral event connecting a sender and receiving hospital. This probability is modeled as conditional on the entire sequence of observed past events. Departing from prior studies, the focus of our analysis is neither on events linking patients to hospitals (i.e., patient choice), nor patient-level outcomes (e.g., health conditions following treatment). An extensive medical literature is available that deals with these specific issues. Our focus is on the dynamics of interorganizational relations reconstructed in terms of sequences of events linking hospitals through patient referrals. The study clarifies how the effect of some of the main social mechanisms underlying the dynamics of interorganizational networks affect relational activities in a way that is contingent on their timing.

2 Background

2.1 Network mechanisms and network times in the analysis of interorganizational relations

Interorganizational relations affect a variety of individual, organizational and field-level outcomes (Baker and Faulkner, 2002; DiMaggio, 1991; Galaskiewicz, 1985; Gulati and Gargiulo, 1999). Understanding how interorganizational relations change over time is important because such changes reveal, but at the same time promote, processes of large-scale historical, institutional and social transformation (Lomi et al., 2008; Padgett and Powell, 2012; Pescosolido and Rubin, 2000; Stark and Vedres, 2006).

Building on a longstanding tradition in the network analysis of interorganizational relations (Laumann et al., 1978; Laumann and Marsden, 1982), more recent research has emphasized the role that social mechanisms play in the reproduction and change of interorganizational networks (Lomi and Pattison, 2006; Powell et al., 2005; Stadtfeld et al., 2016).

Following recent advances in statistical models for social networks (Robins et al., 2009; Newman, 2001), much current empirical research reconstructs change in interorganizational relations in terms of two general classes of relational mechanisms (Baum et al., 2003; Davis et al., 2003; Kogut and Walker, 2001; Powell et al., 2005; Rosenkopf and Padula, 2008; Uzzi, 2008). The first class of mechanisms regulates direct connectivity – the propensity of organizations to choose and be chosen as partners. The second regulates closure, or path-shortening behavior – the tendency of organizations connected to the same partners to become directly connected.

In directed interorganizational systems, micro-mechanisms associated with change in connectivity include: (i) Preferential attachment (activity and popularity); (ii) reciprocity; (iii) inertia, and (iv) various forms of assortativity (Powell et al., 2005). Mechanisms that regulate closure involve (v) various forms of path-shortening behavior whereby the presence of indirect connections between two organizations makes them more likely to become directly connected (Lomi and Pallotti, 2013; Uzzi, 1997).

In directed interorganizational systems, activity (the tendency of organizations to establish relations with partners) and popularity (the tendency of organizations to be selected as partners) are aspects of preferential attachment – the preferential tendency of organizations that are central (in a "degree" sense) to become even more central (Stuart, 1998; Stuart and Yim, 2010). As a consequence of preferential attachment, network nodes accumulate new edges as a function of edges they already have (Newman, 2001). For this reason, in empirical research on interorganizational relations, preferential attachment is interpreted as a process that provides an "accumulative advantage" resulting in differential centrality, or '"prominence" within organizational fields (Powell et al., 2005; Rosenkopf and Padula, 2008).

Evidence of reciprocity, the tendency of social relations towards symmetry, is similarly common in empirical studies of interorganizational networks (Kitts et al., 2017). Reciprocity is frequently interpreted as a consequence of individual attempts to reduce or avoid uncertainty by establishing mutual obligations, expectations, and control (Coleman, 1988; Laumann and Marsden, 1982; Uzzi, 1997). Reciprocity is also associated with stability in interorganizational relations as non-reciprocated relations have an inherent tendency to become reciprocated or to dissolve (Rivera et al., 2010).

Inertia refers to the tendency of ties between partner organizations to persist, or relational events connecting a sender and a receiver organizations to be more likely if an event in the same direction occurred in the past (Vu et al., 2017). In empirical studies, inertia in interorganizational relations is frequently interpreted as a precondition for the development of trust between partners (Gulati and Nickerson, 2008). Similarly common is the link between relational inertia and the so called principle of exclusivity, according to which organizations respond to uncertainty by reinforcing collaboration with known partners (Podolny, 1994). Persistency of network ties, or in patterns of repeated events is one of the core feature of social networks, and indeed of relational social systems more generally (Freeman et al., 1987).

Assortativity refers to the preferential tendency of network nodes to develop relations on the basis of similarity or dissimilarity in their degree (Snijders et al., 2010) or level of activity (Vu et al., 2017). Relational systems in which connections are more likely between nodes with similar degree are called assortative. Relational systems are disassortative if the opposite happens, i.e., if association is more likely between organizations with different number of partners (Newman, 2002), or different levels of activity (Lomi et al., 2014). Interorganizational networks have been occasionally found to be disassortative (Zhao et al., 2010). Other studies report evidence of assortative mixing (Stadtfeld et al., 2016). The empirical variability in patterns of assortative mixing observed empirically is often due to difference in patterns of interorganizational differentiation and division of labor and other institutional arrangements (Hollway et al., 2017).

The second class of mechanisms that have been shown to affect the structure of interorganizational systems includes forms of closure, or path-shortening behavior underlying the tendency of organizations separated by one or more intermediaries to become directly connected (Kogut and Walker, 2001; Uzzi, 1997). In directed interorganizational systems closure has a number of antecedent configurations and component elements that may be specified and estimated empirically (Laumann and Marsden, 1982; Lomi and Pallotti, 2013; Robins et al., 2009). In consequence, closure in directed interorganizational systems may be produced by a variety of mechanisms, including transitivity, generalized exchange and different local forms of structural equivalence (Block, 2015; Lomi and Pallotti, 2013; Robins et al., 2009). Tendencies toward closure may be conceptualized in a similar way when relations are reconstructed in terms of events connecting sending and receiver organizations, or volume of activity flowing between them (Vu et al., 2017).

The concatenation of connectivity and closure mechanisms has been repeatedly shown to be capable of producing and reproducing the empirical regularities that are commonly observed in interorganizational fields (Baum et al., 2003; Powell et al., 2005; Sorenson and Stuart, 2008). However, questions about the stability of these mechanisms in interorganizational relations have been posed only recently, and have typically been restricted to the dynamics of reciprocity (Kitts et al., 2017). In the typical empirical study, issues of time scales at which network mechanisms operate are generally ignored by aggregating observed relations into convenient, but otherwise arbitrary, time periods. With few partial exceptions (Ingram and Morris, 2007), mechanisms of network change have been implicitly assumed to operate uniformly over time, i.e., to affect interorganizational systems in the same way at different points in time[1].

This assumption seems at odds with recurrent evidence of time-specific variations in "network times" (Stark and Vedres, 2006), internal "rhythms" of relational processes

[1]Existing statistical tests have been designed to reveal the presence of time heterogeneity in network effects (Lospinoso et al., 2011). But such tests tell little about the form that time heterogeneity may take – i.e., how the effect of relational mechanisms on network change vary systematically over time.

(Golder et al., 2007), and cycles in the life of individuals and organizations (Golder and Macy, 2011; Zerubavel, 1979). Increasingly, empirical studies document the time-specificity of events underlying the flow of organizational activities (Butts et al., 2007; DuBois et al., 2013; Kitts et al., 2017; Lerner and Lomi, 2017; Marcum et al., 2012). As classic theories of organizations have long recognized (Cohen et al., 1972), patterns of time-specificity are produced by the sequential constraints that shape both intra- as well as interorganizational relations (Abbott, 1990; Chase, 1982; White, 1970). Examples of sequential constraints are well illustrated by the most common relational mechanisms such, for example, reciprocation: a directed event connecting a sendere and a receiver node must have occurred at a prior time, if a current event in the opposite direction is to generate reciprocation. A similar argument holds for more complex events involving path-shortening behavior: in order for an event connecting a sender and a receiver node to generate closure, other events must have happened before that have established a two-path-like structure between the same two nodes. This argument extends directly to more complex mechanisms, i.e., mechanisms based on more complex precursor event-sequences.

Under conditions of time-specificity and sequential constraints, models that "detach cases from the network of other cases and prior times" (Abbott, 1995, p.94) are clearly inadequate. This mixture of empirical evidence and theoretical considerations suggests that there may be some value in testing the pervasive, but typically implicit assumption that network effects arising from sequences of relational events operate independently of the timing of the events that they supposedly produce.

2.2 Empirical setting: Calendar effects and time-specific outcomes within and between health care organizations

In the empirical part of the paper, we address issues of time-specificity and sequential constraints in network effects in the context of health care – a field where the fine-grained timing of organized activities is intimately and delicately linked to their outcomes. Extant research typically explains the existence of this link in terms of the fact that reactions of patients to treatment is highly sensitive to the timing of treatment itself. Both medical research, as well as clinical practice demonstrate that: "The consequences of adverse events cannot always be offset by working harder on subsequent days (...) If the patient dies on the weekend, no heroics on Monday will suffice" (Redelmeier and Bell, 2007, p. 1164). In this sense, the time moments over which care processes unfold cannot, in general, be permuted without consequences. In spite of general agreement on this view, time-specificity is a pervasive feature of health care organizations. While in our analysis we are not concerned with clinical outcomes, available studies on the time-specific consequences of clinical practices invites careful analysis of time-variability in health care delivery processes such as, for example, interhospital patient referral – the specific relational process that we examine in this paper.

One aspect of the time-specificity in health care outcomes is revealed by the so called "weekend effect," a general label used to summarize the statistical association between the day in which patients are admitted in hospitals, the quality of care they receive, and the clinical outcomes that they eventually experience (Bell and Redelmeier, 2001; Cram et al., 2004).

For example, weekend admissions have been found to be associated with a significantly higher mortality than regular weekday admissions for a wide variety of pathologies including, among others, myocardial infarction (Becker, 2007; Martin et al., 2017), stroke

(Saposnik et al., 2007; Hoh et al., 2010; Palmer et al., 2012), prostate cancer (Schmid et al., 2015), and gastrointestinal hemorrhage (Ananthakrishnan et al., 2009). Higher rates of mortality are also observed for patients admitted during holidays and other "special" periods (Berger et al., 2008; Jneid et al., 2008).

Time-specific variation in outcomes is not restricted to "weekend effects." Barnett et al. (2002, p. 530) found that "adjusted odds of death were higher (P<0.001) for patients admitted on Monday (OR 1.09) or Friday (OR 1.08)." Forms of "calendar effects" operating on a weekly basis seem to affect other important dimensions of health services delivery such as appropriateness and efficiency of care, readmission rates (Becker, 2007), and length of hospital stay (Barnett et al., 2002). This body of evidence suggests that outcomes of health care services are characterized by significant and widespread "calendar effects" (Thaler, 1987a,b) determining a variety of time-specific patient outcomes. In general, empirical studies report that calendar effects in health care unfold on a day-of-the-week basis. Available evidence of hour-of-the day variation in outcomes is less consistent (Jneid et al., 2008).

Despite the solid evidence of "day-of-the-week" variation, available studies concentrate almost exclusively on health care outcomes measured at the patient level, rather than health care processes defined at the organizational level. Partial exceptions are represented by studies on patient handoffs within hospitals (Cohen and Hilligoss, 2010), and studies on the time pattern of staffing of physicians in the restricted context of critical care (Pronovost et al., 2002). Issues of timing figure prominently this research. However, no studies are available about the time-specific variation of patient services involving coordination between – rather than within – hospitals. In the empirical part of the study we show for the first time that time-specific variation in health care delivery processes also affects patterns of interhospital coordination which we reconstruct in terms of the main relational dependencies that we have discussed in the prior section.

In the next section, we build on the main insights of this medical literature, to specify and estimate statistical models that admit time-specific variations in health care delivery process. Because we are interested in time-specific variation in relational mechanisms rather than individual outcomes, in the analysis that follows we focus on structured sequences of interhospital referral events as a recognized example of health care process characterized by significant relational components produced by coordination and collaboration between hospitals (Lomi et al., 2014; Veinot et al., 2012; Mascia et al., 2017).

3 Data, Models and Measurements

3.1 Data

The empirical context for our study involves collaborative patient referral relations between health care organizations within Abruzzo – a small region in central Italy with a population of approximately 1.3 million people distributed over a territory covering approximately 4,200 square miles. Two hospitals are connected by a patient referral event when a sender hospital refers a patient to a receiving hospital (Mascia et al., 2015; Vu et al., 2017). Because patient referral typically requires a considerable level of coordination and communication between partner hospitals (Iwashyna, 2012), patient referral events are reliable indicators of the presence of an underlying collaborative relation between the hospitals involved. Patient referral relations also represent a clear example of how hospitals may collaborate to improve the quality of care that they can deliver to patients, and ensure better clinical outcomes (Lee et al., 2011; An et al., 2018). Successful and effective patient referral relations depend directly on the information about the patient exchanged between sender and receiver hospitals (Mascia and Di Vincenzo, 2011). This kind of information may be highly sensitive, and for this reason the quality of the relation between partner hospitals is of paramount importance (Lomi et al., 2014). Time-specificity in patient referral relations is richly demonstrated by the extensive literature on critical care (Iwashyna and Courey, 2011) – where the timing of patient transfer has direct implications for the survival of patients being transferred (Cooke et al., 2011).

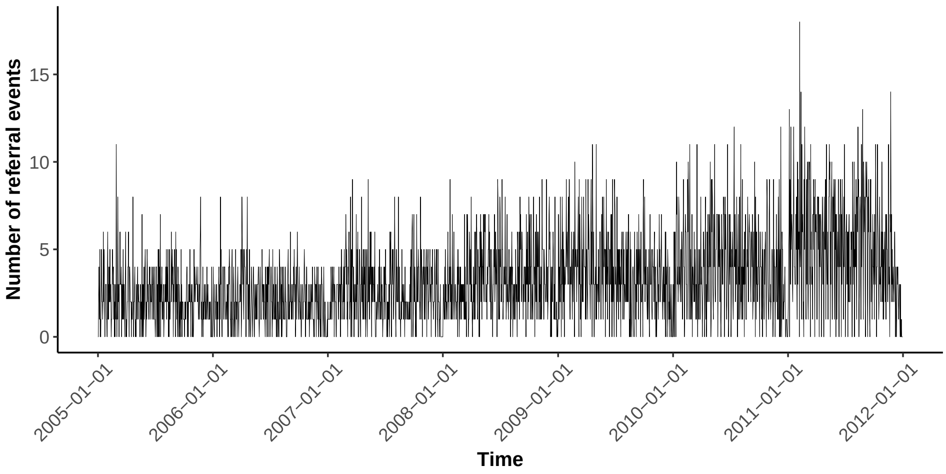
The relational event data we analyze in the empirical part of the paper were made available by the regional Agency of Public Health, an agency whose institutional mandate is to collect and manage patient discharge data for assessing regional hospitals' activities and performance. The data consists of 8,363 referral events connecting all the 35 hospitals located in the Italian region Abruzzo over a period of seven years from 01.01.2005 to 31.12.2011. During the observation period 5 hospitals were closed and thus dropped out of the study. Information on their specific closure dates was available and allowed us to define an accurate risk set for the events.

Each referral event was associated with the date it occurred (precise to the day), the name of the hospital referring the patient (sender), and the name of the target hospital admitting the referred patient (receiver). An increasing number of referral events per day was observed during the sample period, as indicated by the time series of inter-hospital patient referral events depicted in Figure 1a. The daily number of referral events ranged between 1 and 18 with a mean of 3.67 (s.d. 2.31).

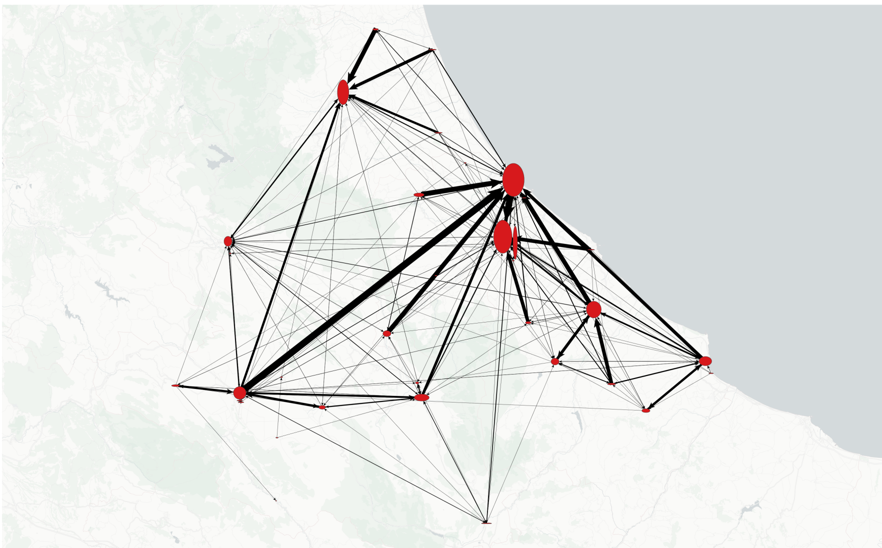
Figure 1b aggregates the events over the entire sample period into network ties and plots the resulting relations among the hospitals in the region. The location of the hospitals is assigned on the basis of geographical coordinates. The width of the network ties is proportional to the number of patient flowing from a sending to a receiving hospital (ranging between 0 and 595 transfers). The width and the height of the nodes are respectively proportional to the number of the outgoing (ranging between 3 and 1528) and incoming (ranging between 0 and 1586) events. The picture shows that transfers between hospitals geographically close were more frequent than transfers between hospitals far apart, albeit two thick and long-distance ties connect the hospitals located in the left lower part of the picture to the hospitals located in the right upper part. Moreover, some hospitals were more likely to receive than send referral events. With a few exceptions, the receiving hospitals were those with a larger size (measured by the number of beds) and a higher number of specialties.

Table 1 and Figure 2 show the frequency distribution of the referral events aggregated by day of the week. Although patient referral events may – in principle – occur at any time and in any day of the week, patient referral events during weekends (27% of all the transfer events) tended to be fewer than during regular weekdays (83% of all the transfer events). The frequency of patient referrals was higher during the first four days of the week and then decreased from Friday on. The same trend held for the mean and median of the number of referral events per day of the week, but not for the maximum.

Daily differences were also evident when looking at the networks represented in Figure 3. These networks were obtained by aggregating the interhospital patient referral events over the entire sample period by day of the week. In analogy with Figure 1b, the width of a link is proportional to the number of referral events from the sending to the receiving hospital (range: 0 - 144). The number of connected dyads in the networks



(a)



(b)

Figure 1: *a) Time series of (daily) patient referral events b) Aggregate interorganizational network.*

Day	Count	%	Max	Median	Mean	s.d.
Monday	1460	17.4	18	4	4.23	2.48
Tuesday	1403	16.8	11	4	4.04	2.24
Wednesday	1470	17.6	14	4	4.29	2.51
Thursday	1387	16.6	12	4	4.03	2.32
Friday	1254	15.0	14	3	3.73	2.16
Saturday	1001	12.0	11	3	3.12	1.89
Sunday	388	4.6	7	1	1.61	0.90
All week	8363	100	18	3	3.62	2.31

Table 1: *Number of the referral events by day of the week and in total.*

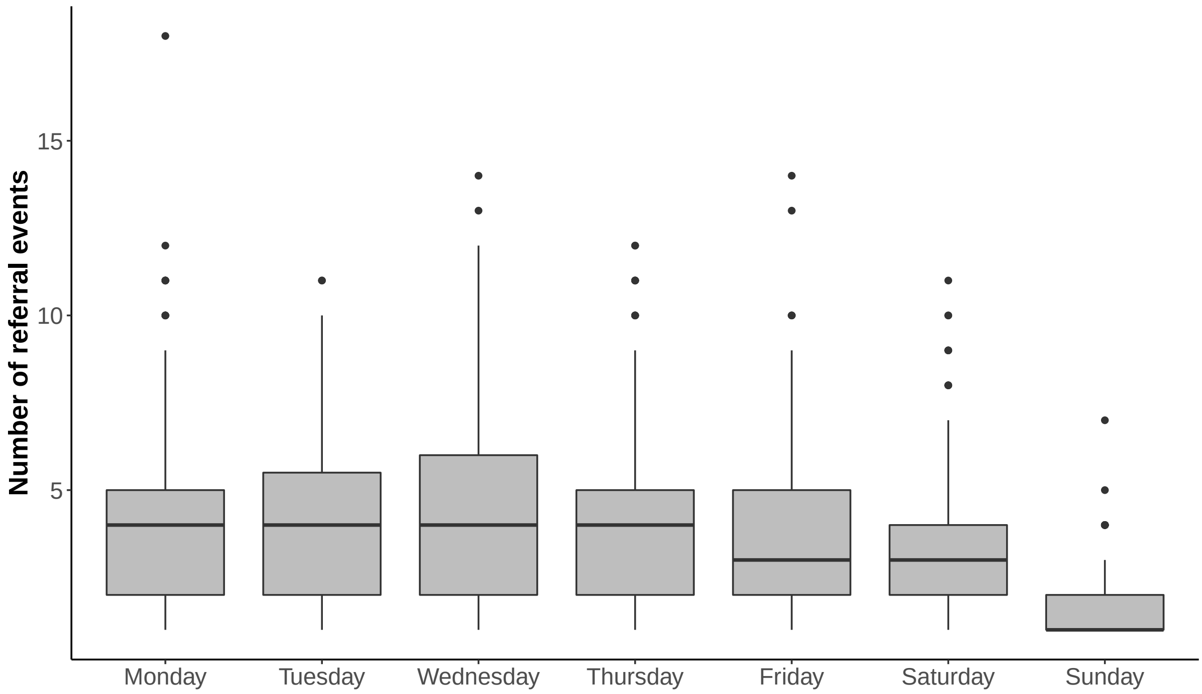


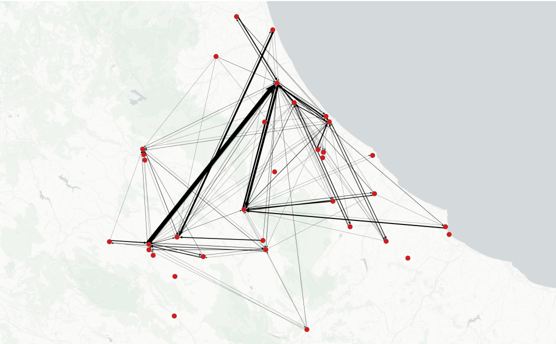
Figure 2: *Boxplot of the referral events by day of the week.*

Variable	Description	Type	Range	Mean	s.d.
Local health unit (LHU)	Membership of single hospitals to the different administrative units in which the region is partitioned	Nominal	1–6	-	-
Distance (geo.dist)	Geographical distance (Kilometers)	Continuous	2–146	69.0	28.8
Hospital size (n.beds)	Total number of staffed beds	Continuous	[20–661]	155.4	138.6
Occupancy rate (occ.rate)	Proportion of bed occupied	Continuous	[5–217]	74.5	23.9

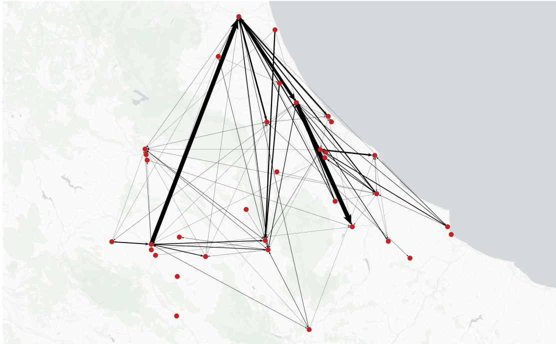
Table 2: *Description of the covariates.*

range between 78 (Sunday) and 126 (Tuesday). The structure of the networks varies on a daily basis due to variations in both the magnitude and the direction of the event flows. Common patterns are visible, however. In the networks aggregating referral events happening on Tuesday and Saturday (Figure 3b and Figure 3f), patient transfers between more distant hospitals seem to be more common than in the networks obtained by aggregating referral events happening on the other days of the week. Furthermore, in the networks referring to Wednesday, Thursday and, partially, Friday (Figure 3c, Figure 3d and Figure 3e), the ties concentrate in the center and in the right area of the maps (East).

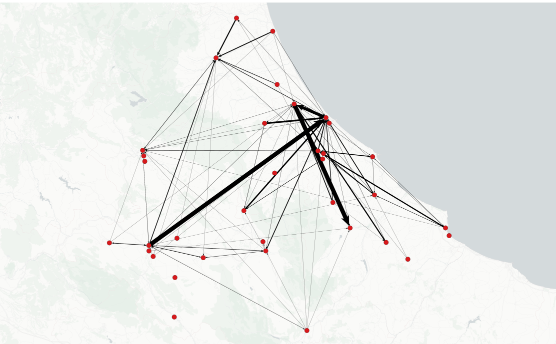
Additional information was collected over and above the time series of referral events: the administrative units which a hospital belongs to, the geographical distance in kilometers between hospitals, the number of beds measuring the size of a hospital, and the mean occupancy rate. All the variables but the distance among hospitals, are monadic and time-varying due to administrative changes. Table 2 provides a summary of the covariates that are included in the model we use in the empirical part of the paper.



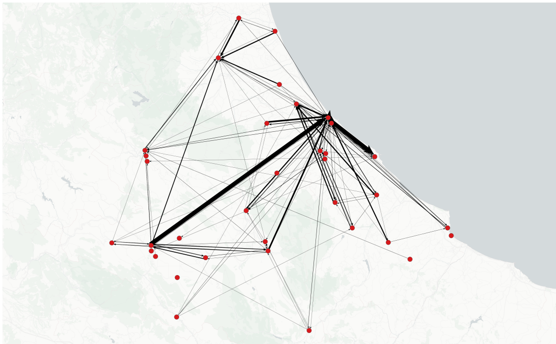
(a) Monday



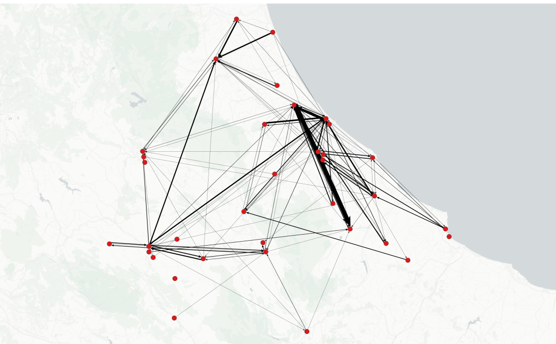
(b) Tuesday



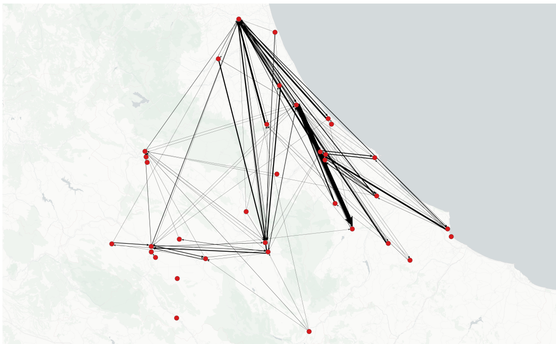
(c) Wednesday



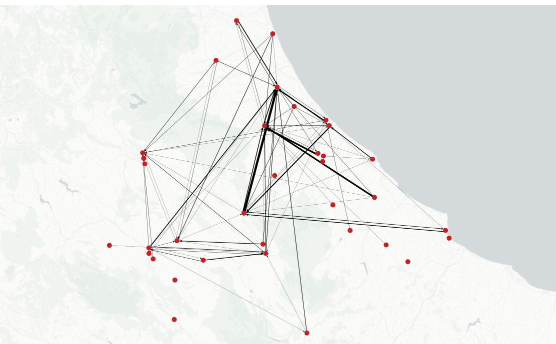
(d) Thursday



(e) Friday



(f) Saturday



(g) Sunday

Figure 3: *Aggregate interorganizational network by day of the week.*

3.2 Model

The model we outline in this section provides an analytical framework for analyzing time-ordered sequence of relational events, i.e., series of exact times at which interactions among our units (organizations) were observed. While most of the statistical models developed in the past thirty years have focused on the analysis of cross-sectional and panel network data, in the past decade or so much effort has been devoted to the formulation of models for analyzing event networks. Models drawing on event history analysis (Butts, 2008; Brandes et al., 2009), event-based actor-oriented models (Stadtfeld, 2012), and point-process models for social interaction data (Vu et al., 2011; Perry and Wolfe, 2013) have been proposed. Compared to previous approaches based on the aggregation of network events across time, these models allow to fully represent the temporal variation of the relational events at the same granularity level of the observed time-stamped data.

In the empirical part of the paper we adopt the relational event model originally proposed by Vu et al. (2011) and Vu (2012) and recently summarized in Vu et al. (2017). The model has been recently adopted in empirical studies by Vu et al. (2015) and Lomi et al. (2014). We apply this model to analyze the sequence of referral events, and to show how the mechanisms regulating the network sequencing operate differently over time. As already mentioned in Section 2.1, we are interested in the systematic variation of the effects of relational mechanisms over the regular days of the week, rather than in the variation of the effects of relational mechanisms over a long observation period (Lospinoso et al., 2011).

In the next sections, we define the model based on the empirical setting introduced in the previous paragraph, but a more general description can be obtained by replacing the words "hospitals"and "referral events", by "entities" and "relational events", respectively.

3.2.1 Model definition

The model assumes that the observed sequence of network events is a realization of a marked temporal point process, a stochastic process whose realization is an ordered set of points representing the time of an event (Jacobsen, 2006). Marked temporal point processes are an extension of temporal point processes allowing to account for *marks* – additional information collected along with each event point.

In our setting, an event is a patient referral from hospital i to hospital j. We denote by t_e the time at which a referral event e occurred, and by j_e the mark of the event, which is the receiving hospital of the referral event e.

Let $\mathcal{V} = \{1, \ldots, n\}$ be the set of hospitals in the network. Given an ordered pair of hospitals $(i, j),\ i, j \in \mathcal{V}$, we denote by $E_i = \{(t_e, j_e),\ t_e \in \mathbb{R}^+,\ j_e \in \mathcal{R}_i(t_e), e \in \mathbb{V}\}$ the series of referral events initiated by the hospital $i \in \mathcal{V}$, where $\mathcal{R}_i(t_e)$ is the set of the hospitals that are "at risk" of receiving the referral event e from hospital i at time t_e. Hereafter, we refer to this set as the *risk set* at time t_e. Let $N_{ij}(t)$ be the number of referral events from i to j up to time t and H_{t^-} the history of all events happening right before t.

The marked point process is modeled by the *conditional intensity function* defined as

$$\lambda_i(t, j|H_{t^-}) = \lambda_i(t|H_{t^-}) \times p_i(j|H_{t^-}) \times \mathbb{I}_{\{i,j \in \mathcal{R}_{ij}(t)\}} \tag{1}$$

where $\lambda_i(t|H_{t^-})$ is the *ground intensity* function, modeling the time at which hospital i initiates a referral event, $p_i(j|H_{t^-})$ is the *mark distribution*, modeling the probability that the receiving hospital is the hospital j, and $\mathbb{I}_{\{i,j \,\in\, \mathcal{R}_{ij}(t)\}}$ is an indicator function taking value 1 if a referral event between the hospitals i and j can happen at time t, and 0 otherwise. This term has been introduced in the model to account for changing in composition of the node set which in our empirical study is due to the closure of some hospitals during the observation period.

The formulation of the model in (1), indicates that, in line with other approaches (Stadtfeld, 2012; Perry and Wolfe, 2013; Stadtfeld and Block, 2017), the proposed model is a two-step process. The first step, accounts for the rate at which hospitals initiate referral events, whereas the second step determines the receiving hospitals of the referral events.

The ground intensity function accounts for time-varying event rates among the hospitals and is defined as a conditional proportional hazard model:

$$\lambda_i(t|H_{t^-}) = \lambda_0(t)\exp[\theta' s(t,i)] \times \mathbb{I}_{\{i \,\in\, \mathcal{R}_{ij}(t)\}} \tag{2}$$

where $\lambda_0(t)$ is the baseline rate, assumed to have a non-parametric form, $s(t,i) \in \mathbb{R}^k$ is a vector of statistics, and $\theta \in \mathbb{R}^k$ is a vector of parameters.

The conditional probability modeling the mark distribution is defined as a conditional multinomial probability model

$$p_i(j|H_{t^-}) = \frac{\exp\left(\beta' s(t,i,j)\right)}{\sum\limits_{h \,\in\, \mathcal{R}_i(t)} \exp\left[\beta' s(t,i,h)\right]} \tag{3}$$

where $s(t,i,j) \in \mathbb{R}^k$ is a vector of statistics and $\beta \in \mathbb{R}^k$ is a vector of parameters. One intuitive interpretation of the probabilities in (3) derives from rational choice theory (Train, 2009) and random utility models (McFadden, 1973), which aim at explaining how decision makers choose among a set of alternatives. According to these approaches, the second step of the process can be interpreted as the decision of hospital i to choose the hospital j as the receiver of the referral event on the basis of the linear function $\beta' s(t,i,j)$. Therefore, when this interpretation is adopted, the considered model can also be regarded as an event-based actor-oriented model.

3.2.2 Statistics

Following a long-standing tradition in network modeling, the statistics for relational event models are defined as counts of local configurations representing the micro-mechanisms that might have operated in a certain network. Compared to the statistics used in other models for network sequencing (Butts, 2008; Stadtfeld, 2012; Stadtfeld and Block, 2017), the mathematical formulation of the statistics $s(t,i)$ and $s(t,i,j)$ allows accounting for temporal dependencies among all the past referral events. In the computation of the statics, a weight is indeed associated to each past event using a decay function $f\left(t, T^e_{ij}, \alpha\right)$, where t is the time at which the current event is taking place and T^e_{ij} is the time at which an event between hospitals i and j occurred.

In its simplest formulation, it is assumed that the temporal relevance of an event decreases according to a power law distribution $\left(\text{i.e., } f\left(t, T^e_{ij}, \alpha\right) = (t - T^e_{ij})^{-\alpha}\right)$, albeit other specifications might be used. The decay parameter $\alpha \geq 0$ is a free parameter that needs to be adjusted to make the model fit the data optimally. When α equals 0, all the past events contribute equally to the computation of the statistics. When $\alpha > 0$, past events close in time to the current event are more relevant. In general, the larger the value of α, the lower the contribution of past referral events to the value of the statistics. In the extreme case (e.g., $\alpha \geq 10$), the contribution of past events tend to 0 and only events happening a few days before contribute to the statistics. One of the consequences of this extreme situation is that only mechanisms completed in a short time interval would be significant and therefore a simpler model specification (based, for instance, on unweighted statistics, persistence and reciprocation) could be used. The procedure to find the optimal value of this parameter has been described in Vu et al. (2017). We briefly summarized this procedure in the supplementary material where we also illustrate how we determined the value of α for our empirical case.

In Section 2.1 we described micro-mechanisms associated with changes in interorganizational relations. In the following, we introduce the statistics by grouping them together by the micro-mechanisms they represent. Their graphical representation and mathematical formulation, as well as the role they play in the model specification (i.e., whether a statistic is used to specify the ground intensity function or the mark distribution) are shown in Table 3.

In the context of our sample, preferential attachment refers to the tendency of hospitals to establish relations with partners, or to be selected as partners. Several statistics have been considered to model this micro-mechanism: the *out-degree* and the *out-intensity* statistics, for modeling activity, and the *in-degree* and the *in-intensity* statistics for modeling popularity. The *out-degree* and the *out-intensity* statistics model the activity of hospitals in initiating a patient transfer and therefore are part of the specification of the ground intensity function. They are both defined as a function of the out-degree of a hospital i – i.e., the number of i's partner hospitals. While the out-degree is a simple sum of the receiving hospitals of the referral events initiated by i, the out-intensity is a weighted sum of the receiving hospitals, where the weights account for both the number of events between hospital i and any other receiving hospital j, and the temporal relevance of these events. A similar distinction is made between the *in-degree* and the *in-intensity* statistics, which are both functions of the in-degree of the partner hospitals of i. Since those statistics model the likelihood of hospital i to transfer patients to a hospital j receiving patients from many other hospitals or receiving many patients, they are used in the specification of the mark distribution.

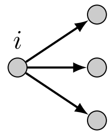
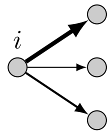
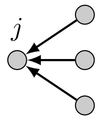
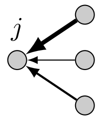
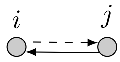
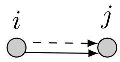
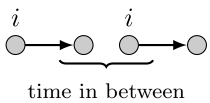
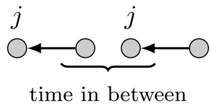
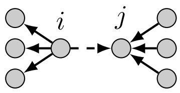
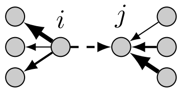
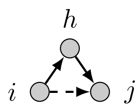
The second micro-mechanism we considered is reciprocation, the tendency of social relations towards symmetry. The corresponding statistic, hereafter referred to as *reciprocation*, is computed as a sum of the referral events from hospital j to hospital i weighted by their time-relevance. The reciprocation statistic explains the probability that a referral event from hospital i to hospital j occurs based on the existence of previous patient transfers from hospital j to hospital i. Therefore, this statistic concerns the specification of the mark distribution.

The third micro-mechanism we introduced is inertia which refers to the tendency of ties between partner organizations to persist, or relational events connecting a sender and a receiver organizations to be more likely if an event in the same direction occurred in the past. A set of dyadic statistics are considered in the model specification. The first statistic is named *persistence* and counts the number of events within the ordered pair of hospitals (i, j) weighted by their time-relevance. This statistic models the probability that a referral event from hospital i is received by hospital j given the presence of previous referral events in the same direction and thus appears in the specification of the mark distribution. Other two statistics that are used to model inertia are the *recent sending* and the *recent* *receiving* statistics, respectively used to specify the ground intensity function and the mark distribution. The *recent sending* statistic accounts for the time lag between the last referral event and the current referral event, both initiated by hospital i. Therefore, it is defined as the time elapsed between two consecutive patient transfers from hospital i to any other hospital j. The *recent receiving* statistic is similar to the recent sending statistic but refers to the receiving hospital j. It is defined as the time lag between two events from any hospital to the same receiving hospital j.

Assortativity, referring to the preferential tendency of hospitals to develop relations on the basis of similarity or dissimilarity in their degree, is modeled by the *assortativity by degree* and the *assortativity by intensity*. These statistics measure whether there is correlation between the out-degree of the sending hospital and the in-degree of the receiving hospital and between the out-intensity of the sending hospital and the in-intensity of the receiving hospital, respectively. Thus, those statistics are defined as interactions between out-degree and in-degree, and out-intensity and in-intensity. They are used in the specification of the mark distribution.

The last micro-mechanism we described is closure (or path-shortening) and relates to the tendency of hospitals separated by one or more intermediaries to become directly connected. Several statistics are defined and concern the specification of the mark distribution. The *transitive closure* statistic explains the likelihood of a referral event from hospital i to hospital j, which is also a receiving hospital of i's partner hospitals. This statistic is computed as a function of the number of two-paths, from i to h and from h to j, that are closed by the relation between i and j. To account for the amount and the temporal relevance of the ties in the two-path, the harmonic mean of the weights of the relational events between hospitals i and h and hospitals j and h is considered and aggregated over time. The *cyclic closure* statistics is defined in a similar way, but here the two-path is determined by the referral events from j to h and from h to i.

In the model we present in the empirical part of the paper, we also controlled for exogenous covariates depending on monadic and dyadic attributes of the hospitals. In particular, in the specification of the ground intensity function, we included the *complementarity* statistic modeling differences in referral rates depending on whether the sending hospital has the specialty required to treat the patient who is transferred to another hospital. For the mark distribution, we controlled for the size and the occupancy rate flows of the receiving hospitals by means of a *monadic attribute* statistic. This statistic models the likelihood of referral events to be directed to hospitals having a certain characteristic. We also controlled for homophily with respect to the local health unit a hospital belongs to by way of the *matching* statistic, a binary variable taking value 1 if the hospitals are located in the same LHU and 0 otherwise. Finally, we controlled for the geographical distance through the *dyadic attribute* statistic taking the value of the distance between two hospitals. These last two statistics model the likelihood of referral events to happen between hospitals in the same LHU and being close to each other, respectively.

Micro-mechanism	**Statistic**	**Representation**	**Mathematical formulation**	**Model specification**
Preferential attachment	Out-degree		$\sum_{j \neq i} \mathbb{I}[N_{ij}(t) > 0]$	Ground intensity function
	Out-intensity		$\frac{\sum_{j \neq i} \sum_{e=1}^{N_{ij}(t)} f\left(t, T^e_{ij}, \alpha\right)}{\sum_{j \neq i} \mathbb{I}[N_{ij}(t)>0]}$	Ground intensity function
	In-degree		$\sum_{k \neq j} \mathbb{I}[N_{kj}(t) > 0]$	Mark distribution
	In-intensity		$\frac{\sum_{k \neq j} \sum_{e=1}^{N_{kj}(t)} f\left(t, T^e_{kj}, \alpha\right)}{\sum_{k \neq j} \mathbb{I}[N_{kj}(t)>0]}$	Mark distribution
Reciprocity	Reciprocation		$\sum_{e=1}^{N_{ij}(t^-)} f\left(t, T^e_{ji}, \alpha\right)$	Mark distribution
Inertia	Percistence		$\sum_{e=1}^{N_{ij}(t^-)} f\left(t, T^e_{ij}, \alpha\right)$	Mark distribution
	Recent sending		$t - \max_{e \in E_i} t_e$	Ground intensity function
	Recent receiving		$t - \max_{e \in E_i} t_e$	Mark distribution
Assortativity	Assortativity by degree		out-degree $(t, i) \times$ in-degree (t, j)	Mark distribution
	Assortativity by intensity		out-intensity $(t, i) \times$ in-intensity (t, j)	Mark distribution
Closure	Transitive closure		$\sum_{h \neq i,j} g(w(t,i,h), w(t,h,j))$	Mark distribution

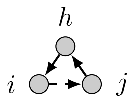
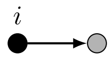
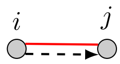
	Cyclic closure		$\sum_{h \neq i,j} g(w(t,h,i), w(t,j,h))$	Mark distribution
Controlling for exogenous covariates	Monadic attribute		$c(t,j)$	Mark distribution
	Complementarity		$\mathbb{I}_{\{c(t,i) \neq c(t,j)\}}$	Ground intensity function
	Matching		$\mathbb{I}_{\{(t,i)=c(t,j)\}}$	Mark distribution
	Dyadic attribute		$c(t,i,j)$	Mark distribution

Table 3: *Statistics for the model specification applied in the empirical part of the paper. In the formulas* $N_{ij}(t)$ *is the number of referral events from hospital* i *to hospital* j *by time* t*;* $f\left(t, T_{ij}^e, \alpha\right) = (t - T_{ij}^e)^{-\alpha}$ *is the decay function accounting for the temporal relevance of previous referral events;* c *is a covariate of the hospitals. The symbol* $\mathbb{I}$ *is an indicator function taking value 1 if the condition between brackets is satisfied, and 0 otherwise.*

3.2.3 Estimation and interpretation

Due to the separability property of the model and the non-parametric assumption on the baseline rate $\lambda_0(t)$ in (2), the parameters are estimated by maximizing the partial likelihood of the model (Jacobsen, 2006) defined as

$$PL(\theta, \beta) = PL(\theta) \times L(\beta) \tag{4}$$

where $PL(\theta)$ is the partial likelihood related to the ground intensity function and $L(\beta)$ is the likelihood related to the mark distribution. Since these two quantities depend either on θ or on β, the parameter estimates are computed separately by maximizing the two factors in (4).

In particular, the parameter θ in (2) is estimated by maximizing the partial likelihood

$$PL(\theta) = \prod_{e \in E} \frac{\exp[\theta' s(t_e, i_e)]}{\prod_{i \in \mathcal{R}_{ij}(t_e)} \exp[\theta' s(t_e, i_e)]} \tag{5}$$

where E is the sequence of events, and t_e and i_e are the time and the sending hospital of the event e, respectively. The form of the partial likelihood allows estimation of the model parameters and the corresponding standard errors using a logistic regression model conditional on the sequence of event E. This model is estimated on a data set where for each event the outcome variable "initiating an event" takes value 1 for the hospital which initiated that particular event and 0 for all the other hospitals, and the explanatory variables are the statistics $s(t,i)$ computed at the time of the considered event. The standard errors associated to the estimates are then obtained by computing the inverse of the Hessian matrix of the model. We remind to Perry and Wolfe (2013) and Vu et al. (2017) for the proof and the details.

The parameter β in (3) is the vector of parameters of a conditional multinomial logit model. Therefore, it can be estimated by maximizing the likelihood

$$L(\beta) = \prod_{e \in E} \frac{\exp[\beta' s(t_e, i_e, j_e)]}{\prod\limits_{h \in R_i(t_e)} \exp[\beta' s(t_e, i_e, h)]} \tag{6}$$

This is done by generating a case-control data set of network statistics nested in the event times – i.e., a data set containing the statistics $s(t_e, i_e, j_e)$ (cases) and $s(t_e, i_e, h), h \in R_i(t_e), h \neq j_e$ (controls). Then, the maximization is performed by using the same estimation algorithms that are adopted to estimate conditional multinomial logistic regression models and the standard errors associated to the estimates are obtained by computing the inverse of the Hessian matrix of the model.

Although the ground intensity function and the mark distribution are formulated as a conditional proportional hazard model and a conditional multinomial model, respectively, the interpretation of the parameters is not straightforward. Due to the correlation among the statistics, common measurements such as risk ratios and odds ratios have – at best – a heuristic value rather than an intrinsic meaning. Therefore, the interpretation is based on the significance and on the sign of the parameters: Positive values of a parameter indicate that the likelihood of a referral event increases with the value of the corresponding static, thereby providing evidence to the corresponding mechanism. For instance, a (significant and) positive value associated to the parameter of the out-degree statistic indicates that hospitals initiating more referral events are more prone to initiate a new referral event in the future. Similarly, a (significant and) positive value of the parameter of the indegree suggests that hospitals which have many sending hospitals partner are more likely to be the receivers of future referral events.

4 Results

4.1 Overall period

To describe the dynamics of the network of referral events we estimated two models: *i)* the null model (hereafter referred to as Model 0) including the recent sending and the recent receiving effects, besides the effects accounting for dyadic and monadic covariates, and *ii)* the full model (hereafter referred to as Model 1) including also the effects related to the endogenous mechanisms. The estimates of those models are reported in Table 4.

The two models were compared using the Akaike Information Criterion with a correction for finite sample size (Sugiura, 1978; Vu et al., 2017), shortly AICc, defined as

$$\mathrm{AICc} = -2 \cdot \log \mathrm{PL}(\hat{\theta}) + 2 \cdot \mathrm{p} + 2 \cdot \frac{(\mathrm{p}+1)(\mathrm{p}+2)}{|\mathrm{E}| \cdot \mathrm{p} - \mathrm{p} - 2}$$

where $PL(\hat{\theta})$ is the partial likelihood in (5) attained at the maximum likelihood estimate $\hat{\theta}$, $p(= 17)$ is the number of parameters and $|E|$ is the number of referral events. The AICc index indicates that Model 1 has a better fit than Model 0, thereby suggesting that the endogenous variables are important to explain the dynamics of the referral events.

The AICc was also used to determine the optimal value of the decay parameter α assigning importance weights to past events. For values of α ranging from 0 to 1, we computed the statistics and fitted the corresponding model. The optimal value of α was

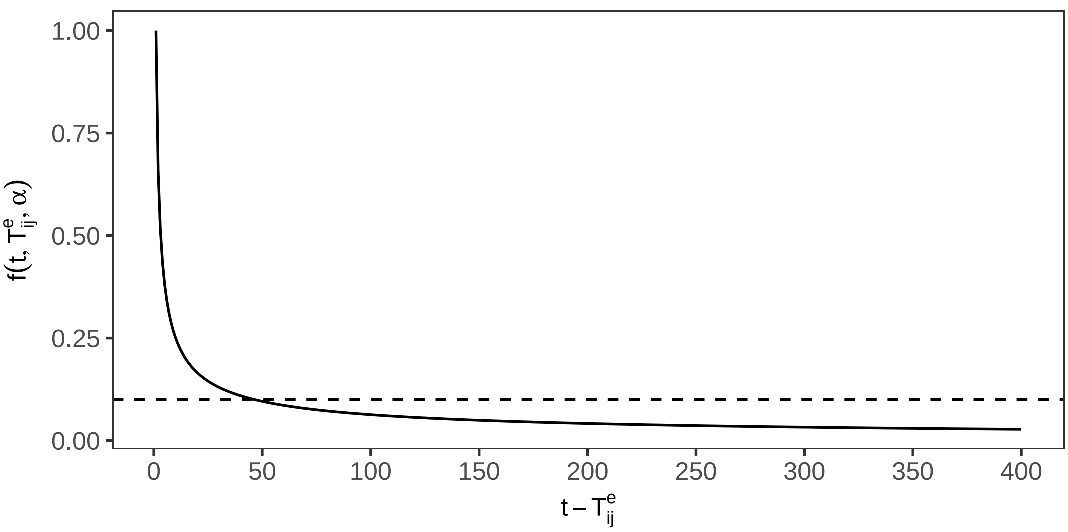


Figure 4: *Power law decay function for the optimal value $\alpha = 0.6$.*

selected as the value leading to the best fitting model, i.e., the model wit the lowest AICc. According to this procedure, the optimal value of α was fixed to 0.6 (see the supplementary material for details). Figure 4 shows the decay of the importance of events as a function of the time (in days) elapsed between a past event and the current event given $\alpha = 0.6$. The curve indicates that the weights decrease with time and, for instance, referral events happening six weeks before the current event have a weight lower than 0.1 in the computation of the statistics. Although these events play a minor role in determining the probability of observing a future referral event compared to more recent events, they are still relevant in the computation of the statistics. The computation of the statistics based only on events that happened within six weeks before the current event is not indeed a good approximation of the statistics computed on the entire sequence of past events.

All the parameter estimates are significant. With the partial exception of cyclic closure (which is positive) and transitive closure (which is negative) all the estimates of the network effects are consistent with results of prior studies of interorganizational networks. We start by commenting on the results for the parameter estimates related to the statistics modeling preferential attachment. The estimates of the out-degree and out-intensity parameters are positive suggesting that hospitals initiating more referral events are more likely to initiate a new referral event. Therefore, there is evidence for preferential attachment in terms of the activity of the hospitals. Similarly, there is evidence for preferential attachment based on popularity. In fact, both the parameters of the in-degree and the in-intensity statistics are positive indicating that referral events are more likely to flow in the direction of hospitals that are the receivers of referral events initiated by many other hospitals or the receiver of many referral events.

We also found evidence for reciprocation. The positive value of the reciprocation parameter suggests that referral events reciprocating past referral events are more likely to be observed than events that are not part of sequences of reciprocated events.

Evidence of relational inertia is also suggested by the parameter estimates of the corresponding statistics. The persistence parameter is positive indicating that referral events within an ordered pair of hospitals are more likely when previous referral events in the same direction took place before the current referral event. The negative value of the parameter of the last sending statistic shows that it is more likely that hospitals will initiate a new referral event, given the recent initiation of a past event. In a similar way, the negative value associated to the parameter of the recent receiving statistic indicates that referral events are more likely to flow to recently receiving hospitals.

Concerning the assortativity mechanisms, we found that, on the one hand, there is evidence against the assortativity by degree, and on the other hand, evidence for the assortativity by intensity. Thus, referral events between hospitals with many receiving partners and those with few sending partners are more likely, but referral events between hospitals (recently) sending many patients and those (recently) receiving many patients are more likely. This result suggests that out-degree and in-degree of the sending and receiving hospitals correlate positively when the number and the temporal relevance of previous events are considered and correlate negatively when they are ignored. The ability of the model to distinguish between degree-based and volume-based effects reveals complex mixing patterns that – to the best of our knowledge – have rarely been been examined together in studies of interorganizational relations. This happens because statistical models developed for the analysis of tie variables are generally unable to incorporate information about the weight of the edges. More conventional statistical models typically adopted in the analysis of flows are unable to represent network dependencies.

Finally, the estimates related to the parameters of the closure statistics provide evidence for cyclic closure, and against transitive closure. Jointly interpreted, the positive parameter of the cyclic closure and the negative parameter of the transitive closure – together with strong tendencies toward reciprocity – suggest that there is no hierarchical ordering among the hospitals endogenously arising from exchange relations (Chase, 1974, 1980). Apparently, the collaborative nature of the relation that we have observed, and the self-containment and limited size of the regional health care system that we have examined provided favorable conditions for the emergence of generalized exchange, and discouraged the formation of interorganizational hierarchies.

Focusing now on the control variables included in the model, we found that hospitals with complementary clinical activities (or knowledge) are more likely to be connected by referral events, as suggested by the positive value of the complementarity parameter. Furthermore, referral events are more likely to be geographically bounded and to occur between hospitals belonging to the same LHU as shown by the negative parameter of the geographical distance and the positive parameter of the LHU membership, respectively. The estimates for the hospital size and the occupancy rate parameters suggest that referral events are more likely to flow to large and better-performing hospitals.

4.2 Daily variation

To investigate how the relevant network mechanisms might operate differently in different days of the week two traditional statistical approaches may be used.

The first method consists in estimating separate models for the event and non-events related to each day of the week, and then compare the estimated coefficients across the models. This contrast is usually based on the magnitude (as well as odds ratios or risk ratios) of the estimated coefficients and their confidence intervals, and, ideally, also on a statistical test revealing which coefficients are significantly different. The second method consists in estimating a model including interactions between the statistics and a set of dummy variables for the days of the week (i.e., a set of binary variables taking value one for a certain day of the week and 0 for all the others). Given this approach, significant

	Model 0		Model 1	
	Est.	s.e.	Est.	s.e.
Preferential attachment				
Out-degree			0.582^{***}	0.013
Out-intensity			0.518^{***}	0.010
In-degree			0.771^{***}	0.061
In-intensity			0.220^{***}	0.035
Reciprocity				
Reciprocation			0.080^{***}	0.014
Inertia				
Persistence			0.273^{***}	0.016
Last sending	-7.802^{***}	0.198	-2.042^{***}	0.129
Recent receiving	-4.888^{***}	0.200	-2.460^{***}	0.162
Assortativity				
Assortativity by degree			-0.718^{***}	0.055
Assortativity by intensity			0.334^{***}	0.040
Closure				
Transitive closure			-0.043^{***}	0.017
Cyclic closure			0.097^{***}	0.027
Exogenous attributes				
Complementarity	0.015	0.013	0.196^{***}	0.015
Number of beds	0.005^{***}	0.000	0.001^{***}	0.000
Occupancy rate flow	0.024	0.021	0.294^{***}	0.027
Geographical distance	-0.917^{***}	0.025	-0.805^{***}	0.028
LHU membership	0.893^{***}	0.015	0.670^{***}	0.017
AICc	51626.498		45536.459	

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table 4: *Model estimation for the referral events observed over the period 01.01.2005-31.12.2011.*

interactions indicate significant differences across groups. In general, those two methods are equivalent when all the interactions between every statistic and the set of dummy variables are included in the model.

An issue related to either approach and explored in the context of generalized linear models, and in particular logit and probit models (Allison, 1999; Mood, 2010), concerns the presence of unobserved heterogeneity varying across groups. This concerns stems from the possibility that models across groups might not predict the response variable equally well even if they are specified in terms of the same set of explanatory variables. If that is the case, differences in the coefficients might suggest evidence of differences in the effects of the explanatory variables, and differences in unobserved heterogeneity. Thus, comparing the magnitude (as well as odds ratios or risk ratios) of the parameters and confidence intervals might lead to the wrong conclusions.

Several methods are available for comparing parameters of generalized linear models across groups correcting for unobserved heterogeneity, but there is no consensus on which one is the most appropriate approach (Mood, 2010). Furthermore, the validity of available techniques might also be affected by the correlation among the statistics, which can be quite high in the case of network statistics. For these reasons, in the following, we draw conclusions only on the significance of the parameters.

Given the sequence of referral events observed between 2005 and 2011, we define the sets of events and non-events related to each day of the week. Then, we estimate the full model (Model 1 in Table 4) for each set and compare the estimated coefficients based on their significance. It must be noted that the statistics are computed on the complete sequence of events to account for the entire history of the process and the decay parameter α was set to 0.6, since this was also the optimal value for all the daily models, but the Sunday model, for which the optimal value was 0.7 (see the supplementary material).

Table 5 reports the models estimated on the stream of events for each day of the week. This means that the statistics are computed for the entire sequence of events, whereas the dependent variable is stratified according to the weekday. The estimated coefficients of these models together with their 95% confidence intervals are depicted in Figure 5 and Figure 6. In the figures, black bars suggest that the corresponding parameters are significantly different from 0, red bars refers to parameters that are not significantly different from 0. We can observe that the confidence intervals for the estimated coefficients of the weekend models are usually larger than those of the models of the regular days. This is due to the fact that, while the number of events happening during regular days has more or less the same magnitude, a lower number of events took place during the weekend, and especially on Sunday (see Table 1). For this reason, and since we know that the dynamics of referral events operate differently during the weekend, we focus only on differences in significance of the parameters during the regular days of the week.

Figure 5 reports the results for the parameters related to the network statistics. The first row of the bar plot matrix refers to the estimated coefficients of the statistics modeling preferential attachment. While there is not daily variation of the preferential attachment mechanisms in terms of the activity of the hospitals, daily variation is observed for the popularity, and more specifically, for the in-intensity parameter. The red bars indicate that, on Monday and Wednesday, referral events are more likely to flow in the direction of hospitals that are characterized by having a high number of sending partners rather than having a high weighted number of events from sending partners.

The second row of the bar plot matrix shows the graphs for the reciprocity and the inertia mechanisms. Reciprocity plays a role in the dynamic of the referral events taking place on every regular day but Thursday. Thus, referral events reciprocating past referral events are less likely to be observed on Thursday. We do not observe daily variation for inertia mechanisms, both in terms of the tendency of ties between partner organizations to persist, or relational events connecting a sender and a receiver organizations to be more likely if an event in the same direction occurred in the past. Similarly, we did not observe daily variation for the assortativity mechanisms as suggested by the first two graphs in the last row of the bar plot matrix.

Finally, for the closure mechanisms we observed that, while there is no variation in the transitive closure, the cyclic closure operates only on Thursday and Friday and it does not play a role in the first three days of the week.

Figure 6 reports the comparison for the mechanisms related to the exogenous network effects. Only the number of beds is affected by daily variation. In particular, the number of beds of the receiving hospitals does not affect the likelihood of referral events to larger hospitals on Monday and Friday.

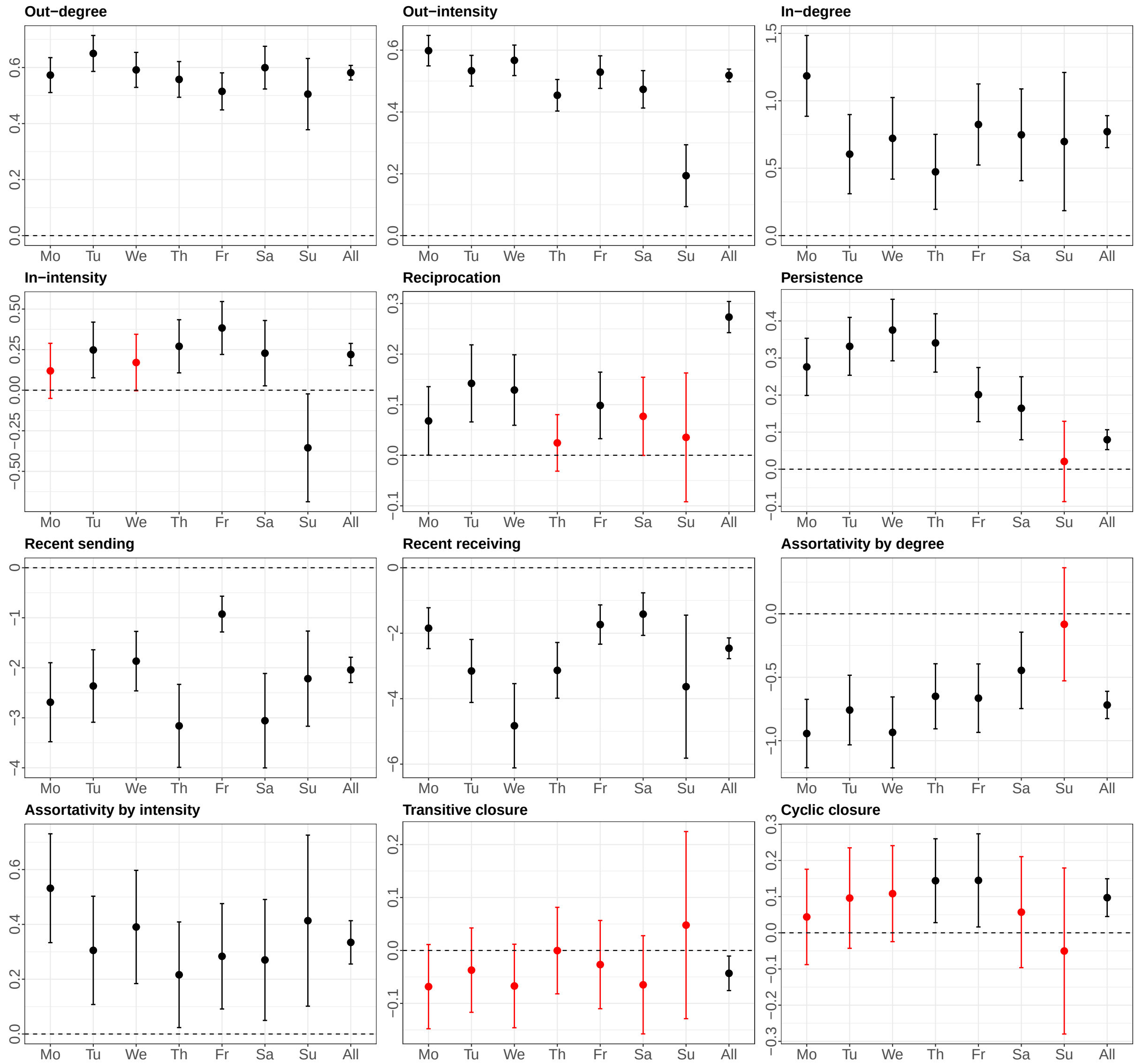


Figure 5: *Parameter values and corresponding 95% confidence interval by day of the week for the network endogenous effects. Black bars indicate that the corresponding parameters are significantly different from 0, and vice versa, red bars indicate that the corresponding parameters are not significantly different from 0.*

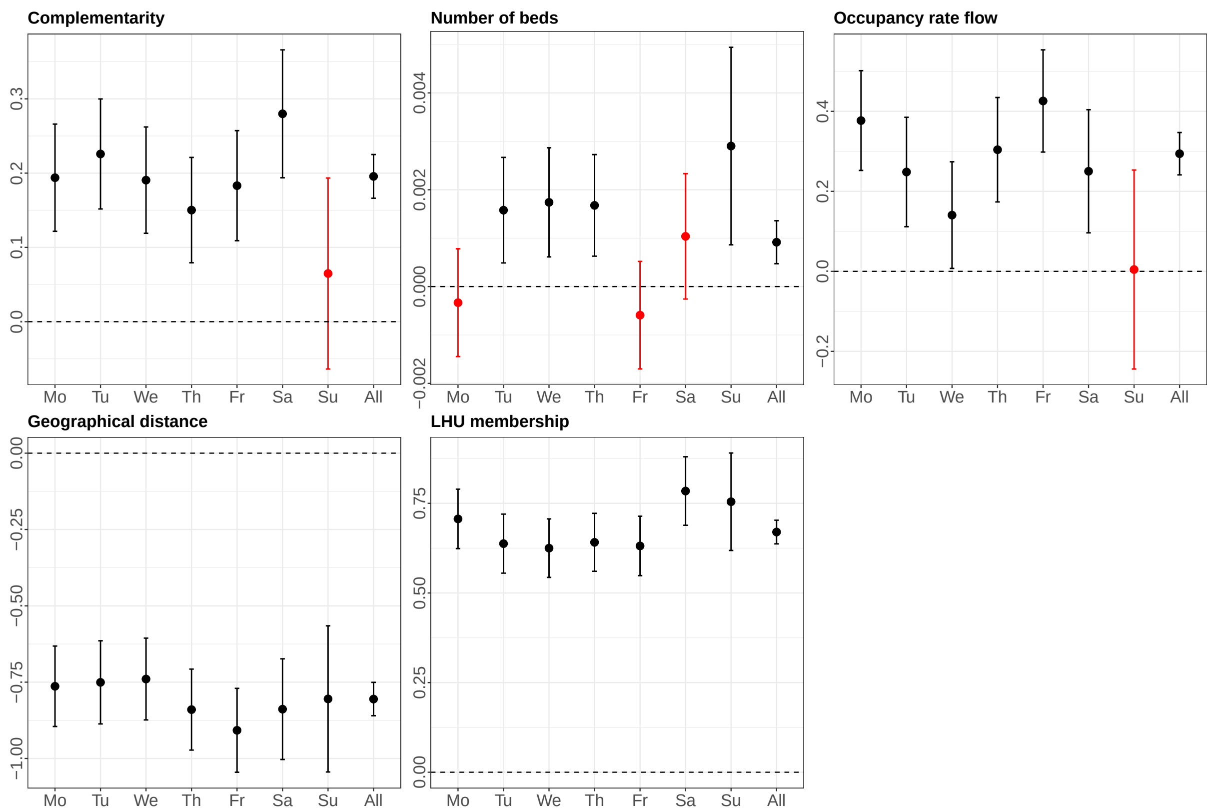


Figure 6: *Parameter values and corresponding 95% confidence interval by day of the week for the network exogenous effects. Black bars indicate that the corresponding parameters are significantly different from 0, and vice versa, red bars indicate that the corresponding parameters are not significantly different from 0.*

	Monday		Tuesday		Wednesday		Thursday		Friday		Saturday		Sunday	
	Est.	s.e.	Est.	s.e.	Est.	s.e.	Est.	s.e.	Est.	s.e.	Est.	s.e.	Est.	s.e.
Preferential attachment														
Out-degree	0.573***	0.032	0.650***	0.033	0.592***	0.032	0.558***	0.033	0.515***	0.034	0.600***	0.039	0.505***	0.065
Out-intensity	0.598***	0.025	0.533***	0.025	0.567***	0.025	0.454***	0.026	0.529***	0.027	0.473***	0.031	0.194***	0.051
In-degree	1.185***	0.153	0.604***	0.150	0.721***	0.154	0.473***	0.142	0.824***	0.153	0.748***	0.174	0.698**	0.262
In-intensity	0.119	0.087	0.248**	0.088	0.171	0.089	0.271**	0.084	0.383***	0.083	0.228*	0.103	−0.355*	0.170
Reciprocity														
Reciprocation	0.068*	0.035	0.142***	0.039	0.129***	0.036	0.024	0.029	0.099**	0.034	0.077	0.039	0.035	0.065
Inertia														
Persistence	0.276***	0.039	0.332***	0.040	0.375***	0.042	0.341***	0.040	0.201***	0.037	0.164***	0.043	0.021	0.055
Last sending	−2.689***	0.403	−2.364***	0.370	−1.867***	0.303	−3.161***	0.423	−0.926***	0.182	−3.058***	0.481	−2.217***	0.485
Recent receiving	−1.847***	0.318	−3.154***	0.491	−4.828***	0.657	−3.135***	0.434	−1.736***	0.306	−1.417***	0.332	−3.633**	1.115
Assortativity														
Assortativity by degree	−0.944***	0.138	−0.759***	0.140	−0.935***	0.143	−0.650***	0.131	−0.665***	0.138	−0.446**	0.154	−0.082	0.227
Assortativity by intensity	0.532***	0.101	0.305**	0.101	0.391***	0.105	0.216*	0.098	0.284**	0.098	0.270*	0.113	0.414**	0.159
Closure														
Transitive closure	−0.068	0.041	−0.037	0.041	−0.067	0.040	−0.000	0.042	−0.027	0.043	−0.065	0.047	0.048	0.090
Cyclic closure	0.044	0.067	0.096	0.071	0.108	0.068	0.144*	0.059	0.145*	0.066	0.057	0.078	−0.050	0.117
Exogenous attributes														
Complementarity	0.194***	0.037	0.226***	0.038	0.191***	0.037	0.150***	0.036	0.183***	0.038	0.280***	0.044	0.065	0.066
Number of beds	−0.000	0.001	0.002**	0.001	0.002**	0.001	0.002**	0.001	−0.001	0.001	0.001	0.001	0.003**	0.001
Occupancy rate flow	0.377***	0.064	0.248***	0.070	0.141*	0.068	0.304***	0.067	0.426***	0.065	0.250**	0.079	0.005	0.127
Geographical distance	−0.763***	0.067	−0.751***	0.069	−0.740***	0.068	−0.840***	0.068	−0.908***	0.070	−0.838***	0.084	−0.805***	0.122
LHU membership	0.707***	0.042	0.638***	0.042	0.625***	0.042	0.641***	0.041	0.631***	0.042	0.784***	0.049	0.754***	0.069

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table 5: *Model estimates and risk ratio across days of the week*

4.3 Qualitative interpretation

The data collection was accompanied by a number of unstructured interviews and discussion with key informants working in some of the organizations included in our sample, and with health care professionals involved in clinical care in other hospitals as well. During the last five years we have had the opportunity to interview several physicians and clinician-managers, i.e., hospital physicians with managerial responsibilities, medical doctors responsible for managing clinical units, hospital executives and policy makers.

As it is the case for airports, railways, and utility companies, hospitals are expected to provide their services continuously (without interruption) and consistently (with no variation in quality). In systems of public health care (like the one under discussion) hospitals are also expected to provide health care services to any citizen in the same way and at any time in line with basic principles of non-discrimination and universal care. Time-specific variations in the supply of health care services are typically considered both inevitable, as well as surprising. As the medical director of one of the hospitals in our sample observed[2]:

> "We typically look at hospitals as organizations that must be able to provide 24 hour services. Since we do not know when patients need help and require care, hospitals must be in the conditions to deliver services continuously and resources have to be allocated without any significant daily, weekly or seasonal variation. Despite this common view, there are several constraints which affect the temporal allocation of resources in hospitals."

Despite agreement on the view of hospitals as organizations permanently "on call," informants generally acknowledged that temporal variations of treatment and organizational routines are common in their organizations. They identified several reasons for such variation. Some of the reasons presented are exogenous, mainly related to constraints on economic, technical, and human resources. One of the perceived causes was reduced hospital staffing during weekends, resulting in lower levels of activity. For example, because of the lack of administrative and logistic support, patients are not normally discharged or transferred during the weekends. These resource-constraints provide a simple explanation for time-specific variations in service during the weekend.

Informants and medical doctors we have interviewed agreed that resource constraints clearly affect the decision of administrators to allocate human and operational resources also over different days of the week. Because the bulk of activity occurs in weekdays, capacity and resources are allocated to weekdays. However, decisions about resource allocation are also affected by the legislative regulation of hospital shifts and workloads, hence constraining staffing during the weekend. Several organizational practices and routines may also explain temporal variations. For example, surgery rooms are typically used in weekdays and only residual capacity can be allocated to weekends. Other clinical routines and behaviors seem to be affected by the weekend effect. In the words of one of our informants – a senior clinician in one of the largest hospitals in our sample:

> "The joint effect of budget constraints and fixed labor contracts is that hospital day-by-day activities are not constant and unmodifiable, but are rather subject to weekly and seasonal variations. Resource allocation waxes and

[2]All the excerpts from interviews reported in the text have been translated by the authors from Italian

> wanes over the week. Overcapacity typically occurs on Saturdays and Sundays. Saturation is instead observed typically on the two weekdays mostly affected by the interruption of hospital activities during the weekends, i.e. Mondays and Fridays. Such variations unfortunately reverberate their effects on the normal sequence of hospitals activities and routines, such as coordination and integration across physicians. An intense activity of communication and integration is required to ensure continuity of care among providers in the context of patient sharing, for example. The exchange of information pertinent to patient care seems to be differently exchanged when "on call" doctors are involved in patient sharing with other physicians. We often observe more conflicts, duplication of tests along with several unnecessary exams prescribed. But probably the major problem we all see is related to the continuity of care, which is somehow compromised by the less active participation that we observe in knowledge sharing efforts involving "on call" doctor and the physician who will then take responsibility of shared clinical cases."

Our fieldwork also suggests that during weekends the reduced availability of personnel in biological testing services and radiology units is likely to affect clinical activities, causing delays in the implementation of care, and reducing treatment possibilities normally available to physicians during regular days of the week. These problems become even more important in the case of patient referrals, when physicians working in different hospitals have to exchange complex information about patients across organizational boundaries – i.e, under conditions of partial information about what partners might consider feasible. In other words, there is reason to believe that the time variability of clinical activities within hospitals likely extends to other coordination processes regulating inter-hospital patient transfers. Our informants observed that time-specific variations in outcomes and practices also affect hospital operations in other "special dates" like, for example, official holiday periods or local festivities. Unfortunately, no formal recognition of time variability is incorporated in clinical protocols and guidelines, despite informants acknowledging that for hospital patients some days may indeed be better than others.

5 Discussion and conclusions

5.1 Discussion

The estimates reported in the prior section clearly reveal the presence of daily variation in the effects of relational mechanisms on the the probability of observing patient referral events between hospitals. This statistical regularity begets three main questions: Is this result believable given the empirical context of the study? Why does this happen? And, finally, how does it matter? Our extensive fieldwork experience suggests potential answers to these questions that statistical estimates help to frame, but cannot fully address.

Are the statistical results of the study believable? As we have discussed, calendar effects in health care have been extensively documented. Empirical studies have concentrated almost exclusively on time-specific variations in clinical outcomes (Kostis et al., 2007), and only occasionally in organizational processes (Hilligoss and Cohen, 2013). Extant research has focused mainly on the well-documented, and easily predictable "weekend effect" (Sharp et al., 2013). To the best of our knowledge, this is the first study that reveals the presence of a general time-specific variation in patterns of relational coordination in the delivery of health-care services involving multiple providers. While the subjects we interviewed were not surprised to learn about time specific-variation – and in fact winked at the notion of "weekend effect" – they were also at a loss when asked to provide a general explanation for day-to-day variations. While this is not an objective of our study, we suspect that future research on time-specific variation in relational mechanisms will develop hypotheses about the factors that may affect synchronization of work processes across the boundaries of potentially competing organizations (Brailly, 2016; Lomi and Pallotti, 2012). We think our study could inspire a variety of hypotheses about how institutional, organizational and geographical contingencies intersect to affect time-specific variations in patterns of relational coordination within spatially bounded organizational communities (Bathelt and Glückler, 2003). Hypotheses could be derived about the kind of network effects that may be more or less sensitive to time-specific variation under conditions of uncertainty in the selection of partners. A recent study by Bianchi (2017) illustrates how such hypotheses could be developed and tested given appropriate relational event data.

Which brings us to the second question orienting our discussion. What are the likely causes of time-specific variation in the effect of relational mechanisms on interorganizational collaboration? Our fieldwork suggests the general hypothesis that the time-specific variations in relational mechanisms revealed by statistical analysis may be one outcome of temporal variation in patterns of resource availability within and between organizations. Consistent with results of extant research (Schilling et al., 2010), our informants indicated variable resource constraints as the main cause of time-dependent variation not only in quality of clinical outcomes, but also in the capacity of hospitals to maintain a constant level of service. Commonly cited factors included the reduced availability of operating rooms, biological testing laboratories, radiology units, and – to some extent – medical doctors and support staff during holidays and weekends (Needleman et al., 2002). Obviously, our informants tended to provide explanations based on their own experience which was typically specific to their own organization. At the community level, these individual arguments suggest that time-specific variations in mechanisms of organizational bonding may be due to difficulties that individual organizations experience in their attempt to control and stabilize the allocation of their internal resources – a conclusion that invites hypotheses on the active role of management in organizational resource allocation decisions.

A second, and equally credible set of conjectures about the possible causes of time-specific variation in the effect of relational mechanisms on collaboration across organizational boundaries concerns the presence of information asymmetry between the partners. As Hilligoss and Cohen (2013, p. 58) observed in the case of between-unit (within hospital) patient handoffs: "because routines, workloads, capacities, shift schedules, and temporal rhythms can differ significantly from one unit to the next, staff in one unit may be unaware of the current state of another unit." Difficulties in synchronizing work processes between teams within the same organization may be amplified when patient referral relations have to cross the organizational boundaries of partners that may also compete for patients, or have other reasons for limiting disclosure of information about the details of their internal organizational processes. One general hypothesis inspired by this argument is that time-specific variations in relational mechanisms are amplified by information asymmetries between the partners, and reduced by attempts of partners to share knowledge about their internal procedures across organizational boundaries.

How should time-specific variation in network effect matter? Clearly, continuity of care matters greatly for the welfare of patients, and for the level of effectiveness (and efficiency) of treatment of health care services that hospitals are able to provide (Pham et al., 2007). This is particularly the case when treatment has to be provided by more than one provider – potentially leading to fragmented health care provision (Cebul et al., 2008). One way to frame the network effects that our models documented is as ways in which hospitals try to alleviate problems of fragmentation when care must be coordinated across providers. Time variations in patterns of relational coordination across hospitals obviously matter greatly as they affect directly the quality of care that patients receive when services are rendered by multiple providers (Stange, 2009). One hypothesis that future studies could entertain is that variation in patterns of relational coordination are associated to variations in the quality of care or in clinical outcomes. Healthcare provides a useful setting to test this hypothesis, but institutional sectors where consumers experience depends equally strongly on coordination between producers (or service providers) would be similarly appropriate.

5.2 Conclusions

To conclude our discussion, we present a brief outline of some of major methodological, empirical and theoretical implications of our study for future research on interorganizational relations – and social relations more generally. From a methodological standpoint, our study demonstrates the unique value of event-oriented research designs, data, and analytical frameworks for addressing issues of high-frequency time-specific variation in the effect of relational mechanisms on relational outcomes of interest. Obviously, what frequencies are "high" or "low" depend entirely on the setting, and on assumptions about the meaningful time frames for action. Variation in relational mechanisms may be observed over minutes at mixer parties (Ingram and Morris, 2007), hours in emergency response situations (Butts, 2008), days in case of complex decisions (Gibson, 2011), or even over months in case of interorganizational collaborations (Kitts et al., 2017). Building directly on the argument proposed by Butts (2008), the relational event models we have implemented facilitate the analysis of interorganizational relations unfolding simultaneously across different time scales by avoiding aggregation and successive transformation of time-specific events into binary network ties. Network ties have a duration that may be of substantive interest, and that event-oriented/point-process models cannot capture. Building on Vu et al. (2017) we defined a decay parameter that controls the duration of the effect that events have on successive events. We have shown how the numerical value of this parameter may be estimated directly from data, and substantively interpreted. We suspect that interest in the "time drag" (or "inertia") of relational events will increase as a general consensus diffuses on the contingent, time-specific value of social relations for a wide variety of behavioral outcomes considered of theoretical interest (Burt, 2002).

Our study also carries clear empirical implications. Future studies of interorganizational relations interested in representing explicitly network-like dependencies, might benefit from considering the possibility that estimates of models fitted to aggregate network data mask significant time-specific variations in relational mechanisms that have generated the observations (Stadtfeld et al., 2016). Understanding the contingent factors underlying patterns of time-specific variation in relational mechanism may contribute to a more detailed understanding of how interorganizational networks stabilize or change over time. We believe that the empirical implications of our study are not limited to research on interorganizational relations. The results we have reported clearly resonate with recent studies on intra and inter-day variations in individual moods and attitudes as expressed through interpersonal (i.e., relational) communication activities produced by participation in on line social media (Dodds et al., 2011; Golder and Macy, 2011; Golder et al., 2007). Like ours, these studies suggest that connective behavior is affected by detectable time-specific variations in the underlying mechanisms that shape, and at the same time emerge from social interaction.

According to Padgett (2018, p.2): "Seen dynamically, "social structure" is a set of trajectories and movements through space-time. That is, it is synonymous with "history." But the starting problem for all analysts (and observers) is that "history" in the singular does not exist – just as unitary "social structure" is a fantasy." Until very recently, we lacked a principled analytical framework to represent a notion of "social structure" as a set of interwoven trajectories of change, rather that as a unitary construction represented as a static configuration of network ties. The main theoretical implication of our work is that it invites further development of the connection between this theoretical position and research designs that go beyond the antimony of "structure" and "change" to recognize change as a core feature of social and network structure.

References

Abbott, A. (1990). A primer on sequence methods. *Organization science*, 1(4):375–392.

Abbott, A. (1995). Sequence analysis: new methods for old ideas. *Annual review of sociology*, 21(1):93–113.

Allison, P. D. (1999). Comparing logit and probit coefficients across groups. *Sociological methods & research*, 28(2):186–208.

An, C., O'Malley, A. J., Rockmore, D. N., and Stock, C. D. (2018). Analysis of the US patient referral network. *Statistics in medicine*, 37(5):847–866.

Ananthakrishnan, A. N., McGinley, E. L., and Saeian, K. (2009). Outcomes of weekend admissions for upper gastrointestinal hemorrhage: a nationwide analysis. *Clinical Gastroenterology and Hepatology*, 7(3):296–302.

Baker, W. E. and Faulkner, R. R. (2002). Interorganizational networks. *The Blackwell companion to organizations*, pages 520–540.

Barnett, M. J., Kaboli, P. J., Sirio, C. A., and Rosenthal, G. E. (2002). Day of the week of intensive care admission and patient outcomes: a multisite regional evaluation. *Medical care*, 40(6):530–539.

Bathelt, H. and Glückler, J. (2003). Toward a relational economic geography. *Journal of economic geography*, 3(2):117–144.

Baum, J. A., Shipilov, A. V., and Rowley, T. J. (2003). Where do small worlds come from? *Industrial and Corporate change*, 12(4):697–725.

Becker, D. J. (2007). Do hospitals provide lower quality care on weekends? *Health services research*, 42(4):1589–1612.

Bell, C. M. and Redelmeier, D. A. (2001). Mortality among patients admitted to hospitals on weekends as compared with weekdays. *New England Journal of Medicine*, 345(9):663–668.

Berger, A., Stauffer, J.-C., Radovanovic, D., Urban, P., Bertel, O., Erne, P., Investigators, A. P., et al. (2008). Comparison of in-hospital mortality for acute myocardial infarction in switzerland with admission during routine duty hours versus admission during out of hours (insight into the amis plus registry). *The American journal of cardiology*, 101(4):422–427.

Bianchi, F. (2017). Market uncertainty and the network structure of transaction sequences in the EU interbank money market. Paper presented at the XXXVII Sunbelt Conference of the International Network for Social Network Analysis.

Block, P. (2015). Reciprocity, transitivity, and the mysterious three-cycle. *Social Networks*, 40:163–173.

Block, P., Koskinen, J., Hollway, J., Steglich, C., and Stadtfeld, C. (2018). Change we can believe in: comparing longitudinal network models on consistency, interpretability and predictive power. *Social Networks*, 52:180–191.

Block, P., Stadtfeld, C., and Snijders, T. A. (2016). Forms of dependence: Comparing saoms and ergms from basic principles. *Sociological Methods & Research*, page 0049124116672680.

Borgatti, S. P. and Halgin, D. S. (2011). On network theory. *Organization science*, 22(5):1168–1181.

Brailly, J. (2016). Dynamics of networks in trade fairs—a multilevel relational approach to the cooperation among competitors. *Journal of Economic Geography*, 16(6):1279–1301.

Brandes, U., Lerner, J., and Snijders, T. A. (2009). Networks evolving step by step: Statistical analysis of dyadic event data. In *Social Network Analysis and Mining, 2009. ASONAM'09. International Conference on Advances in*, pages 200–205. IEEE.

Burt, R. S. (2002). Bridge decay. *Social networks*, 24(4):333–363.

Butts, C. T. (2008). A relational event framework for social action. *Sociological Methodology*, 38(1):155–200.

Butts, C. T. (2009). Revisiting the foundations of network analysis. *Science*, 325(5939):414–416.

Butts, C. T., Petrescu-Prahova, M., and Remy Cross, B. (2007). Responder communication networks in the world trade center disaster: Implications for modeling of communication within emergency settings. *Mathematical Sociology*, 31(2):121–147.

Cebul, R. D., Rebitzer, J. B., Taylor, L. J., and Votruba, M. E. (2008). Organizational fragmentation and care quality in the us healthcare system. *Journal of Economic Perspectives*, 22(4):93–113.

Chase, I. D. (1974). Models of hierarchy formation in animal societies. *Behavioral Science*, 19(6):374–382.

Chase, I. D. (1980). Social process and hierarchy formation in small groups: a comparative perspective. *American Sociological Review*, pages 905–924.

Chase, I. D. (1982). Behavioral sequences during dominance hierarchy formation in chickens. *Science*, 216(4544):439–440.

Cohen, M. D. and Hilligoss, P. B. (2010). The published literature on handoffs in hospitals: deficiencies identified in an extensive review. *Quality and Safety in Health Care*, 19(6):493–497.

Cohen, M. D., March, J. G., and Olsen, J. P. (1972). A garbage can model of organizational choice. *Administrative science quarterly*, pages 1–25.

Coleman, J. S. (1988). Social capital in the creation of human capital. *American journal of sociology*, 94:S95–S120.

Cooke, C. R., Nallamothu, B., Kahn, J. M., Birkmeyer, J. D., and Iwashyna, T. J. (2011). Race and timeliness of transfer for revascularization in patients with acute myocardial infarction. *Medical care*, 49(7):662.

Corbo, L., Corrado, R., and Ferriani, S. (2016). A new order of things: Network mechanisms of field evolution in the aftermath of an exogenous shock. *Organization Studies*, 37(3):323–348.

Cram, P., Hillis, S. L., Barnett, M., and Rosenthal, G. E. (2004). Effects of weekend admission and hospital teaching status on in-hospital mortality. *The American journal of medicine*, 117(3):151–157.

Davis, G. F., Yoo, M., and Baker, W. E. (2003). The small world of the american corporate elite, 1982-2001. *Strategic organization*, 1(3):301–326.

DiMaggio, P. J. (1991). Constructing an organizational field as a professional project: Us art museums, 1920-1940. In Powell, W. W. and DiMaggio, P. J., editors, *The new institutionalism in organizational analysis*, pages 267–292. Chicago: The University of Chicago Press.

Dodds, P. S., Harris, K. D., Kloumann, I. M., Bliss, C. A., and Danforth, C. M. (2011). Temporal patterns of happiness and information in a global social network: Hedonometrics and twitter. *PloS O ne*, 6(12):e26752.

DuBois, C., Butts, C. T., McFarland, D., and Smyth, P. (2013). Hierarchical models for relational event sequences. *Journal of Mathematical Psychology*, 57(6):297–309.

Freeman, L. C., Romney, A. K., and Freeman, S. C. (1987). Cognitive structure and informant accuracy. *American anthropologist*, 89(2):310–325.

Galaskiewicz, J. (1985). Interorganizational relations. *Annual review of sociology*, 11(1):281–304.

Gibson, D. R. (2011). Avoiding catastrophe: The interactional production of possibility during the cuban missile crisis. *American Journal of Sociology*, 117(2):361–419.

Golder, S. A. and Macy, M. W. (2011). Diurnal and seasonal mood vary with work, sleep, and daylength across diverse cultures. *Science*, 333(6051):1878–1881.

Golder, S. A., Wilkinson, D. M., and Huberman, B. A. (2007). Rhythms of social interaction: Messaging within a massive online network. In *Communities and technologies 2007*, pages 41–66. Springer.

Gulati, R. and Gargiulo, M. (1999). Where do interorganizational networks come from? *American journal of sociology*, 104(5):1439–1493.

Gulati, R. and Nickerson, J. A. (2008). Interorganizational trust, governance choice, and exchange performance. *Organization Science*, 19(5):688–708.

Hilligoss, B. and Cohen, M. D. (2013). The unappreciated challenges of between-unit handoffs: negotiating and coordinating across boundaries. *Annals of emergency medicine*, 61(2):155–160.

Hoh, B. L., Chi, Y.-Y., Waters, M. F., Mocco, J., and Barker, F. G. (2010). Effect of weekend compared with weekday stroke admission on thrombolytic use, in-hospital mortality, discharge disposition, hospital charges, and length of stay in the nationwide inpatient sample database, 2002 to 2007. *Stroke*, 41(10):2323–2328.

Hollway, J., Lomi, A., Pallotti, F., and Stadtfeld, C. (2017). Multilevel social spaces: The network dynamics of organizational fields. *Network Science*, 5(2):187–212.

Ingram, P. and Morris, M. W. (2007). Do people mix at mixers? structure, homophily, and the "life of the party". *Administrative Science Quarterly*, 52(4):558–585.

Iwashyna, T. J. (2012). The incomplete infrastructure for interhospital patient transfer. *Critical care medicine*, 40(8):2470–2478.

Iwashyna, T. J., Christie, J. D., Moody, J., Kahn, J. M., and Asch, D. A. (2009). The structure of critical care transfer networks. *Medical care*, 47(7):787.

Iwashyna, T. J. and Courey, A. J. (2011). Guided transfer of critically ill patients: where patients are transferred can be an informed choice. *Current opinion in critical care*, 17(6):641–647.

Jacobsen, M. (2006). *Point process theory and applications: marked point and piecewise deterministic processes*. Springer Science & Business Media.

Jneid, H., Fonarow, G. C., Cannon, C. P., Palacios, I. F., Kilic, T., Moukarbel, G. V., Maree, A. O., LaBresh, K. A., Liang, L., Newby, L. K., et al. (2008). Impact of time of presentation on the care and outcomes of acute myocardial infarction. *Circulation*, 117(19):2502–2509.

Kitts, J. A., Lomi, A., Mascia, D., Pallotti, F., and Quintane, E. (2017). Investigating the temporal dynamics of interorganizational reciprocity: Patient exchange among italian hospitals. *American Journal of Sociology*, 123(3):850–910.

Kogut, B. and Walker, G. (2001). The small world of germany and the durability of national networks. *American sociological review*, pages 317–335.

Koskinen, J. and Lomi, A. (2013). The local structure of globalization. *Journal of statistical physics*, 151(3-4):523–548.

Kostis, W. J., Demissie, K., Marcella, S. W., Shao, Y.-H., Wilson, A. C., and Moreyra, A. E. (2007). Weekend versus weekday admission and mortality from myocardial infarction. *New England Journal of Medicine*, 356(11):1099–1109.

Laumann, E. O., Galaskiewicz, J., and Marsden, P. V. (1978). Community structure as interorganizational linkages. *Annual review of sociology*, 4(1):455–484.

Laumann, E. O. and Marsden, P. V. (1982). Microstructural analysis in interorganizational systems. *Social networks*, 4(4):329–348.

Lee, B. Y., McGlone, S. M., Song, Y., Avery, T. R., Eubank, S., Chang, C.-C., Bailey, R. R., Wagener, D. K., Burke, D. S., Platt, R., et al. (2011). Social network analysis of patient sharing among hospitals in orange county, california. *American journal of public health*, 101(4):707–713.

Lerner, J. and Lomi, A. (2017). The third man: hierarchy formation in wikipedia. *Applied Network Science*, 2(1):24.

Lomi, A., Mascia, D., Vu, D. Q., Pallotti, F., Conaldi, G., and Iwashyna, T. J. (2014). Quality of care and interhospital collaboration: a study of patient transfers in italy. *Medical care*, 52(5):407.

Lomi, A., Negro, G., and Fonti, F. (2008). Evolutionary perspectives on inter-organizational relations. In Cropper, S., Huxham, C., Ebers, M., and Smith Ring, P., editors, *The Oxford Handbook of Inter-Organizational Relations*. Oxford University Press on Demand.

Lomi, A. and Pallotti, F. (2012). Relational collaboration among spatial multipoint competitors. *Social networks*, 34(1):101–111.

Lomi, A. and Pallotti, F. (2013). How to close a hole: Exploring alternative closure mechanisms in interorganizational networks. In Lusher, D., Koskinen, J., and Robins, G., editors, *Exponential random graph models for social networks: theory, methods, and applications*, pages 202–212.

Lomi, A. and Pattison, P. (2006). Manufacturing relations: An empirical study of the organization of production across multiple networks. *Organization science*, 17(3):313–332.

Lospinoso, J. A., Schweinberger, M., Snijders, T. A., and Ripley, R. M. (2011). Assessing and accounting for time heterogeneity in stochastic actor oriented models. *Advances in data analysis and classification*, 5(2):147–176.

Marcum, C. S., Bevc, C. A., and Butts, C. T. (2012). Mechanisms of control in emergent interorganizational networks. *Policy Studies Journal*, 40(3):516–546.

Martin, G. P., Kinnaird, T., Sperrin, M., Anderson, R., Gamal, A., Jabbar, A., Kwok, C. S., Barker, D., Heatlie, G., Zaman, A. G., et al. (2017). Effect of weekend admission on process of care and clinical outcomes for the management of acute coronary syndromes: a retrospective analysis of three uk centres. *BMJ open*, 7(9):e016866.

Mascia, D., Angeli, F., and Di Vincenzo, F. (2015). Effect of hospital referral networks on patient readmissions. *Social Science & Medicine*, 132:113–121.

Mascia, D. and Di Vincenzo, F. (2011). Understanding hospital performance: The role of network ties and patterns of competition. *Health Care Management Review*, 36(4):327–337.

Mascia, D., Pallotti, F., and Angeli, F. (2017). Don't stand so close to me: competitive pressures, proximity and inter-organizational collaboration. *Regional Studies*, 51(9):1348–1361.

McFadden, D. (1973). *Conditional logit analysis of qualitative choice behavior*. Institute of Urban and Regional Development, University of California.

Mood, C. (2010). Logistic regression: Why we cannot do what we think we can do, and what we can do about it. *European sociological review*, 26(1):67–82.

Needleman, J., Buerhaus, P., Mattke, S., Stewart, M., and Zelevinsky, K. (2002). Nurse-staffing levels and the quality of care in hospitals. *New England Journal of Medicine*, 346(22):1715–1722.

Newman, M. E. (2001). Clustering and preferential attachment in growing networks. *Physical review E*, 64(2):025102.

Newman, M. E. (2002). Assortative mixing in networks. *Physical review letters*, 89(20):208701.

Padgett, J. (in press' 2018). Faulkner's assembly of memories into history: Narrative networks in multiple times. *American Journal of Sociology*.

Padgett, J. F. and Powell, W. W. (2012). *The emergence of organizations and markets*. Princeton University Press.

Palmer, W. L., Bottle, A., Davie, C., Vincent, C. A., and Aylin, P. (2012). Dying for the weekend: a retrospective cohort study on the association between day of hospital presentation and the quality and safety of stroke care. *Archives of neurology*, 69(10):1296–1302.

Perry, P. O. and Wolfe, P. J. (2013). Point process modelling for directed interaction networks. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, 75(5):821–849.

Pescosolido, B. A. and Rubin, B. A. (2000). The web of group affiliations revisited: Social life, postmodernism, and sociology. *American Sociological Review*, pages 52–76.

Pham, H. H., Schrag, D., O'malley, A. S., Wu, B., and Bach, P. B. (2007). Care patterns in medicare and their implications for pay for performance. *New England Journal of Medicine*, 356(11):1130–1139.

Podolny, J. M. (1994). Market uncertainty and the social character of economic exchange. *Administrative science quarterly*, pages 458–483.

Powell, W. W., White, D. R., Koput, K. W., and Owen-Smith, J. (2005). Network dynamics and field evolution: The growth of interorganizational collaboration in the life sciences. *American journal of sociology*, 110(4):1132–1205.

Pronovost, P. J., Angus, D. C., Dorman, T., Robinson, K. A., Dremsizov, T. T., and Young, T. L. (2002). Physician staffing patterns and clinical outcomes in critically ill patients: a systematic review. *Jama*, 288(17):2151–2162.

Redelmeier, D. A. and Bell, C. M. (2007). Weekend worriers. *The New England Journal of Medicine*, 356:1164–1165.

Rivera, M. T., Soderstrom, S. B., and Uzzi, B. (2010). Dynamics of dyads in social networks: Assortative, relational, and proximity mechanisms. *Annual Review of Sociology*, 36:91–115.

Robins, G., Pattison, P., and Wang, P. (2009). Closure, connectivity and degree distributions: Exponential random graph (p*) models for directed social networks. *Social Networks*, 31(2):105–117.

Rosenkopf, L. and Padula, G. (2008). Investigating the microstructure of network evolution: Alliance formation in the mobile communications industry. *Organization Science*, 19(5):669–687.

Saposnik, G., Baibergenova, A., Bayer, N., and Hachinski, V. (2007). Weekends: a dangerous time for having a stroke? *Stroke*, 38(4):1211–1215.

Schilling, P. L., Campbell, D. A., Englesbe, M. J., and Davis, M. M. (2010). A comparison of in-hospital mortality risk conferred by high hospital occupancy, differences in nurse staffing levels, weekend admission, and seasonal influenza. *Medical care*, pages 224–232.

Schmid, M., Ghani, K. R., Choueiri, T. K., Sood, A., Kapoor, V., Abdollah, F., Chun, F. K., Leow, J. J., Olugbade, K., Sammon, J. D., et al. (2015). An evaluation of the 'weekend effect'in patients admitted with metastatic prostate cancer. *BJU international*, 116(6):911–919.

Sharp, A. L., Choi, H., and Hayward, R. A. (2013). Don't get sick on the weekend: an evaluation of the weekend effect on mortality for patients visiting us eds. *The American journal of emergency medicine*, 31(5):835–837.

Snijders, T. A., Van de Bunt, G. G., and Steglich, C. E. (2010). Introduction to stochastic actor-based models for network dynamics. *Social Networks*, 32(1):44–60.

Sorenson, O. and Stuart, T. E. (2008). Bringing the context back in: Settings and the search for syndicate partners in venture capital investment networks. *Administrative Science Quarterly*, 53(2):266–294.

Stadtfeld, C. (2012). *Events in social networks: A stochastic actor-oriented framework for dynamic event processes in social networks*. KIT Scientific Publishing.

Stadtfeld, C. and Block, P. (2017). Interactions, actors, and time: Dynamic network actor models for relational events. *Sociological Science*, 4:318–352.

Stadtfeld, C., Mascia, D., Pallotti, F., and Lomi, A. (2016). Assimilation and differentiation: A multilevel perspective on organizational and network change. *Social Networks*, 44:363–374.

Stange, K. C. (2009). The problem of fragmentation and the need for integrative solutions. *The Annals of Family Medicine*, 7(2):100–103.

Stark, D. and Vedres, B. (2006). Social times of network spaces: Network sequences and foreign investment in hungary1. *American journal of sociology*, 111(5):1367–1411.

Stuart, T. E. (1998). Network positions and propensities to collaborate: An investigation of strategic alliance formation in a high-technology industry. *Administrative science quarterly*, pages 668–698.

Stuart, T. E. and Yim, S. (2010). Board interlocks and the propensity to be targeted in private equity transactions. *Journal of Financial Economics*, 97(1):174–189.

Sugiura, N. (1978). Further analysts of the data by akaike's information criterion and the finite corrections: Further analysts of the data by akaike's. *Communications in Statistics-Theory and Methods*, 7(1):13–26.

Thaler, R. (1987a). Anomalies: seasonal movements in security prices ii: weekend, holiday, turn of the month, and intraday effects. *The Journal of Economic Perspectives*, 1(2):169–177.

Thaler, R. H. (1987b). Amomalies: The january effect. *The Journal of Economic Perspectives*, 1(1):197–201.

Train, K. E. (2009). *Discrete Choice Methods with Simulation*. Cambridge university press.

Uzzi, B. (1997). Social structure and competition in interfirm networks: The paradox of embeddedness. *Administrative science quarterly*, pages 35–67.

Uzzi, B. (2008). A social network's changing statistical properties and the quality of human innovation. *Journal of Physics A: Mathematical and Theoretical*, 41(22):224023.

Veinot, T. C., Bosk, E. A., Unnikrishnan, K., and Iwashyna, T. J. (2012). Revenue, relationships and routines: The social organization of acute myocardial infarction patient transfers in the united states. *Social science & medicine*, 75(10):1800–1810.

Vu, D. (2012). *Statistical models and algorithms for large network analysis*. PhD thesis, The Pennsylvania State University.

Vu, D., Lomi, A., Mascia, D., and Pallotti, F. (2017). Relational event models for longitudinal network data with an application to interhospital patient transfers. *Statistics in Medicine*, 36(14):2265–2287.

Vu, D., Pattison, P., and Robins, G. (2015). Relational event models for social learning in moocs. *Social Networks*, 43:121–135.

Vu, D. Q., Hunter, D., Smyth, P., and Asuncion, A. U. (2011). Continuous-time regression models for longitudinal networks. In *Advances in neural information processing systems*, pages 2492–2500.

White, H. C. (1970). *Chains of opportunity*. Cambridge, Mass., Harvard University Press.

Zare, M. M., Itani, K. M., Schifftner, T. L., Henderson, W. G., and Khuri, S. F. (2007). Mortality after nonemergent major surgery performed on friday versus monday through wednesday. *Annals of surgery*, 246(5):866–874.

Zerubavel, E. (1979). *Patterns of Time in Hospital Life. A Sociological Perspective*. University of Chicago Press.

Zhao, K., Ngamassi, L.-M., Yen, J., Maitland, C., and Tapia, A. (2010). Assortativity patterns in multi-dimensional inter-organizational networks: a case study of the humanitarian relief sector. In *International Conference on Social Computing, Behavioral Modeling, and Prediction*, pages 265–272. Springer.