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Effect of hospital referral networks on patient readmissions

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ABSTRACT

Previous studies have shown that referral networks encompass important mechanisms of coordination and integration among hospitals, which enhance numerous organizational-level benefits, such as productivity, efficiency, and quality of care. The present study advances previous research by demonstrating how hospital referral networks influence patient readmissions. Data include 360,697 hospitalization events within a regional community of hospitals in the Italian National Health Service. Multilevel hierarchical regression analysis tests the impacts of referral networks' structural characteristics on patient hospital readmissions. The results demonstrate that organizational centrality in the overall referral network and ego-network density have opposing effects on the likelihood of readmission events within hospitals; greater centrality is negatively associated with readmissions, whereas greater ego-network density increases the likelihood of readmission events. Our findings support the (re)organization of healthcare systems and provide important indications for policymakers and practitioners.

1. Introduction

In the past two decades, considerable scholarly attention has been devoted to the organization of healthcare networks (Bazzoli et al., 1999; Shortell et al., 2000; Alexander et al., 2003; Dubbs et al., 2004; Wells and Weiner, 2007). In the market-driven US healthcare system, hospitals have long relied on interorganizational agreements as a viable strategy to attain greater market power over suppliers and customers, achieve operational efficiency, and, ultimately, improve strategic positioning vis-à-vis competitors (Shortell et al., 2000; Alexander et al., 2003; Dubbs et al., 2004). Collaboration networks improve hospitals' innovative capability (Goes and Park, 1997) and mitigate the downside of intense competition, thereby contributing to the development of a more sustainable market-based healthcare system (Peng and Bourne, 2009). In the US, recent reforms brought about by the Affordable Care Act have been intended to create a more unified, less fragmented healthcare system in which different actors (hospitals, specialty outpatient clinics, long-term care facilities, community services) further coordinate their activities to provide a comprehensive service for prevention and acute and chronic care. The roles and impacts of alliances and other interorganizational arrangements in healthcare have been of interest outside the US as well, and their exploration is a research priority in many European countries (e.g., Van Raak et al., 2005).

Whether and to what extent networks benefit healthcare organizations and patients have become increasingly compelling issues in healthcare management research (Bazzoli et al., 1999). Researchers have explored the impacts of such interorganizational models on several types of organizational outcome, including productivity, efficiency, and quality of care (Kaluzny et al., 1998). Other studies have investigated the ways in which interhospital collaboration enhances patient-centered goals, rather than organizational outcomes (Cuellar and Gertler, 2005; Chukmaitov et al., 2009). Vertical and horizontal collaboration have been associated with organizational advantages. Vertical collaboration comprises cooperation among actors along the care value chain and has been argued to reduce hospitals' opportunistic behavior and enhance continuity of care; horizontal collaboration involves cooperative agreements among competitors (Zuckerman et al., 1995; Buchner et al., 2015). In the healthcare domain, hospital cooperation reportedly spurs efficiency gains and cost reduction because of the

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advantages associated with shared resources, medical infrastructure, and care provision (Dranove and Shanley, 1995; Olden et al., 2002; Buchner et al., 2015). In some industries, horizontal collaboration has also been associated with detrimental price fixing and anti-competitive behaviors (e.g., Teece, 1994). However, price-fixing behaviors of networking hospitals have received little support in the US context (Burgess et al., 2005) and are even less likely to arise in European healthcare markets, which are mostly non-–price competitive (e.g., Cooper et al., 2011; Mascia et al., 2012).

Although abundant, previous research on this topic carries several limitations. First, most previous studies have examined formal collaborative agreements among hospitals, which may not reflect actual systems of care (Wells and Weiner, 2007). Moreover, such forms of health networks are largely confined to the US healthcare domain (Bazzoli et al., 1999), rendering the generalization of findings difficult. Lastly, even as collaborative healthcare networks diffuse and grow in importance in modern health systems around the world, little is known about their effects on one important indicator of care effectiveness: patient readmissions.

The present study addresses these limitations by investigating the extent to which hospital collaboration mechanisms are beneficial by reducing the likelihood of patient readmission events. Recent healthcare research has shown that hospital collaboration can often be examined through patient sharing or referral in US (Lee et al., 2011) and European (Lomi et al., 2014) settings. The literature on patient sharing highlights the strong and heterogeneous interconnectedness of hospitals through patient flows, suggesting that, "in many ways, hospitals are analogous to individual people within a social network. Just as people are connected by social ties and interactions, hospitals are often connected to each other through sharing patients, because patients discharged from one hospital may be admitted to other hospitals" (Lee et al., 2011; 707). Patient sharing involves the exchange of highly complex information and thus requires high levels of communication and coordination between receiving and sending hospitals (Gittell and Weiss, 2004). Hence, the practice of patient sharing embeds hospitals in collaborative networks in which not only patients, but also information and behavioral practices are exchanged (Iwashyna et al., 2009; Veinot et al., 2012). The investigation of patient-sharing dynamics allows researchers to move beyond a static and purely formal view of interhospital collaboration by taking into account actual clinical information sharing and relational coordination associated with care provision (Gittell and Weiss, 2004; Veinot et al., 2012).

In this study, we apply social network analysis techniques to investigate inter-hospital patient referrals, considered as relations constituting an interorganizational network amenable to direct empirical investigation. This social network perspective allows us to evaluate the relationship between healthcare networks and patient readmissions in a twofold manner. First, to conceptualize healthcare network variables, we identify networks as emerging from actual patient flows. Classifications and taxonomies routinely reported in the extant literature are based on formal agreements that simplify the actual patterns of collaboration between hospitals. Social network analysis of patient sharing instead captures and describes the complex characteristics of collaborative network structure as emerging from actual exchanges. In addition, this approach can be replicated across domains and geographic areas, overcoming the problematic use of formal classifications of healthcare networks (e.g., centralized vs decentralized networks) that may be highly context-specific. We thus propose a model that explores how hospitals' positions within referral networks influence the effectiveness of care delivered at the patient level, measured as patient readmissions.

2. Theoretical background

A hospital's patient referral – or sharing – network represents an important form of collaboration in the healthcare sector (Iwashyna et al., 2009; Lee et al., 2011). Patient referrals occur *via* direct interhospital transfers, whereby (in)patients discharged from one hospital are admitted to another hospital (Lee et al., 2011). For elective patients, initial admission is scheduled in advance and does not involve a medical emergency. Transferred patients are dispatched from a sender to a receiver hospital *via* ambulance service within 24 h of admission to the sender hospital, in line with Lee et al.'s (2011) classification of "uninterrupted patient sharing." Patient transfer requires deliberate adjustment between partnering hospitals because it takes place after the receiving organization has agreed to receive the patient. Thus, this type of patient sharing relies entirely on hospitals' decisions and is not influenced by patients' preferences (Lomi et al., 2014). In settings characterized by universal coverage and general access to services, such as European health systems or the US Medicare system, insurance schemes are also unlikely to influence transfer decisions.

Patient referrals may be driven by "asymmetries" in providers' clinical resources or competences (e.g., lack of necessary medical equipment, expertise, staffing, or supplies). For example, hospitals that provide only basic services may send patients with more complex clinical conditions to providers that offer comprehensive specialty care. Hospitals with medical school affiliations or advanced surgical capacity are more likely than other institutions to receive transferred patients (Iwashyna et al., 2009). Hospitals refer patients to more capable hospitals (Lomi et al., 2014).

Patient referral requires a high level of information sharing between hospitals, facilitated by close interorganizational coordination and shared routines. A transferred patient is accompanied by preliminary diagnostic analyses, clinical documentation, and reports, which the receiving hospital may use (Bosk et al., 2011). Veinot et al. (2012) documented wide reliance on a collective, repeated, and stable set of activities established by partner hospitals for patient sharing in the context of the US Medicare system. These interorganizational routines provide important learning opportunities, especially regarding patient care and appropriate ways of addressing clinical problems (Hilligoss and Cohen, 2011; Cohen et al., 2012).

Referral networks can thus provide opportunities for hospitals to improve the quality of care delivery. According to the relational view advanced by Lavie (2006), network resources can add to intrafirm knowledge and capabilities, enhancing financial and reputational returns. The complementarity of resources present in the network with respect to those possessed by the focal organization is crucial. In a patient referral event, the referring hospital confronts a shortage of knowledge, equipment, and/or capacity to treat the patient and requires a partner with complementary, non-shared resources. The provider partner with the best possible combination of capabilities, capacity, and reputation is identified and the patient is dispatched. This mechanism results in better, more specialized treatment for the patient, with important returns in terms of quality of care for the receiving and referring hospitals (Lomi et al., 2014). A patient referral event also enables the referring hospital to increase focus on its specialization(s) by avoiding resource investment for a patient requiring a different type of care (Dudley et al., 2000). At the same time, it allows the receiving hospital to refine its knowledge and capabilities related to selected treatments by increasing the number of patients treated.

3. Hypothesis development

The social network perspective focuses on how an organization's position within its interorganizational network shapes its ability to benefit from collaboration (Zaheer and Bell, 2005). Similarly, the way a hospital is embedded into its collaborative network may alter the quality of care delivered to patients.

The degree of centralization is strongly related to whether services are dispersed among network partners or concentrated among a few prominent hospitals (Bazzoli et al., 1999). Centrally organized systems have been shown to facilitate "effective coordination of key activities within and between hospitals, and between hospitals and other components of the system through multiple mechanisms" (Chukmaitov et al., 2009; 467). Centrally healthcare systems are often anchored to the presence of highly specialized hospitals serving as "hubs," as they are equipped with resources and facilities to treat patients who require advanced services and procedures.

In network terms, the "hubs" are associated with hospitals that gain a central network position through their own referrals or those of their partners. This recursive type of centrality – also known as Bonacich's eigenvector centrality or power (Bonacich, 1987) – assigns higher scores to nodes with more connections and/or those connected to highly connected nodes. Bonacich's centrality thus provides an indication of a node's power and status within a network (e.g., Benjamin and Podolny, 1999). Such central nodes benefit from visibility and prestige, and are in a privileged position to exert monitoring and control over network resources and information (Ahuja, 2000). Connectivity among highly specialized centers may be extremely beneficial for hospitals involved in patient referrals, as these relationships entail collaboration and knowledge sharing with more visible, highly reputed, and knowledgeable hospitals (Dudley et al., 2000). Hospitals with high degrees of centrality, or those who have collaborated with highly centralized hospitals, may be able to promote faster and more responsive patient transfers to trustworthy partners, which can increase the quality of care provided. Moreover, central hospitals may develop greater understanding of their network partners' capabilities and resources through numerous interactions with the most prestigious providers. This privileged knowledge associated with Bonacich's network centrality may facilitate better-informed decisions to guide patient transfers to hospitals that possess the necessary knowledge and equipment to treat specific conditions. In addition, a high degree of connectivity with other hospitals may increase a hospital's capacity to give the "correct" clinical response to individual hospitalization episodes. In sum, highly central hospitals, or hospitals connected to central actors, have vantage points from which to deepen their *know-how* – through the opportunity to treat and handle many patients – and their *know-who* – through their privileged overview of resources present in the network. Both of these mechanisms are argued to positively affect the quality of decisions and treatment delivered at the patient level. We thus advanced the following research hypothesis:

H1. Hospital centrality in interorganizational patient referral networks will be positively associated with the effectiveness of care delivered at the patient level.

The ego-network structures of individual hospitals in interorganizational patient referral networks may also be important for providers' hospitalization decisions (Lee et al., 2011). Study of the ego network requires definition of the reference player (ego) and other actors (alters) with which the ego is connected (Burt, 1992). The objects under examination are, in this case, ego–alter relationships and existing ties among alters.

The density of each hospital's ego network may be particularly relevant in this perspective. In general, density is defined as the total number of ties divided by the total number of possible ties. An ego network with few partner relationships is sparse, whereas a network with many connections is dense. Ego-network density is a general measure of cohesion that can be correlated with the degree of behavioral similarity within a group (Coleman, 1988). Research guided by management theories has found that organizations with sparse networks may access more diverse resources (Burt, 1992; Zaheer and Bell, 2005). However, prior research has shown that low density networks are not likely to develop anti-opportunistic, trust-based coordination mechanisms as more dense networks are (e.g., Ahuja, 2000).

Within healthcare systems, we argue that hospitals' ego-network density is detrimental to effectiveness of care. Organizations in dense networks tend to be highly interconnected, with many ties established between each hospital's partners. If hospital A refers/receives to/from hospital B and hospital B refers/receives to/from hospital C, then hospital C is likely to refer/receive to/from hospital A. Such a configuration, in which any hospital can refer/receive to/from any other, reveals that clear specialization in terms of network-level division of labor has not been achieved. Such unstructured referral pathways are likely to result from a temporary lack of capacity, rather than from a specific intention to direct patients to hospitals with better resources. Indeed, dense networks denote a situation in which partners have a homogenous set of capabilities that become even more similar over time (Lomi et al., 2014). In contrast, sparse relationships indicate that hospitals are more selective in patient referrals because of greater heterogeneity of capabilities in the network.

A dense network also entails the handling of many referrals to and from all, or nearly all, network partners, which may be relationally taxing. Transfer of a patient transfer requires procedural routines, waiting times, and paperwork, which are often specific to the partner organization (Hilligoss and Cohen, 2011). Patient referral/receipt to/from many partners with diverse working procedures substantially increases the operational burden related to patient referrals and the risks of diagnostic mistakes, imperfect treatment, and suboptimal referral decisions (Cohen et al., 2012). Limited variety of referral partners' capabilities, poorly specialized coordination dynamics, and lack of fruitful learning opportunities associated with dense relationships may negatively affect the effectiveness of care delivered to patients. We thus hypothesized that:

H2. Hospital ego-network density in interorganizational patient referral networks will be negatively associated with the effectiveness of care delivered at the patient level.

4. Research methodology

4.1. Study setting

Our study sample included the entire hospital network providing services to patients in Abruzzo, a region in central Italy with a population of approximately 1,300,000 residents distributed over approximately 4200 square miles. Abruzzo is partitioned into four provinces (Chieti, L'Aquila, Pescara, and Teramo) containing 305 municipalities, none of which is a major urban center. Only 10% of municipalities had more than 10,000 residents, 30% had fewer than 1000 residents, and the largest city (Pescara) had fewer than 120,000 residents during the study period. The Abruzzo health system is part of the tax-funded Italian National Health System (I-NHS), which provides universal coverage through a single government payer (Fattore, 1999; Lo Scalzo et al., 2009).

The I-NHS allocates resources to 21 regions in Italy that are responsible for providing community healthcare services to their target populations. At the national level, the government bears the responsibility for defining core benefit packages and ensuring that basic coverage is provided to the entire population; organizational responsibility and health service implementation are primarily devolved to regions. Regional governments, responsible for healthcare service delivery to their residents, have wide-scale autonomy in strategic planning, financial resource allocation, and service organization at the regional level.

The healthcare system in Abruzzo is characterized by a "quasi-market" institutional framework, designed to sustain the equity benefits of traditional public healthcare management and financing systems while reaping potential efficiency gains allowed by market competition (Lo Scalzo et al., 2009; Mascia et al., 2012). This framework is the result of institutional reforms enacted in the 1990s to improve the performance of single hospitals and the whole system. Rules regulating the decisions, behaviors, and outcomes of regional hospitals in Abruzzo exhibit features of "managed competition," including the split between purchasers and providers of hospital services, freedom of patients to choose where to receive care, and use of diagnosis-related groups and price mechanisms for hospital service reimbursement.

The Abruzzo regional health system is entrusted to six Local Health Authorities (LHAs), and 31 hospital organizations (21 public, 10 private) provide healthcare. Two of the 21 public providers are teaching hospitals. Public hospitals provide highly specialized hospital care and are characterized by technical, economic, and financial autonomy. Teaching hospitals are regional hospitals linked to universities and provide education, research, and tertiary care. Private hospitals are investor-owned organizations that provide ambulatory assistance, hospital care, and diagnostic services that are partially financed by the regional healthcare service.

4.2. Data

Data were provided by the Agency of Public Health, whose institutional mandate is to collect and manage administrative discharge data for the purpose of assessing regional hospitals' activities and performance. Patient information was anonymized using unique identification codes assigned to admitted patients by the regional agency. The codes, together with information about the dates and nature of discharges/admissions, were used to identify collaborative interhospital patient referrals. Administrative data were matched to identify patient transfers between hospitals, defined as discharge of a given patient and his/her admission by a different referral provider within 24 h after admission to the sender hospital (Lee et al., 2011). No ethical approval was necessary for this study since no experimental research was performed and patient information consisted of secondary data routinely collected and released by a regional agency of public health.

Using data available for admissions to the 31 hospitals recorded over the period of January to December 2005, a square socio-matrix representing the patterns of referral network ties between each pair of regional hospitals was built (Lee et al., 2011). Rows and columns represented hospitals sending and receiving patients, respectively, and cells contained information on the number of patients transferred between partner providers. The matrix included two transfer types – patient referrals "within" a specialty and those "between" specialties – to enable identification and joint examination of two potentially different networks of interhospital collaborative relations (Lomi et al., 2014).

The total number of patients transferred between hospitals is 766. Network density (i.e., ratio between the number of collaborative relationships observed and total number of possible relationships in the network) and average network degree (i.e., average number of referral ties) were computed on the dichotomized matrix. Because we were interested in the act of patient sharing between hospitals, matrix entries were coded as "1," representing the transfer of a patient from hospital i to hospital j, and "0" otherwise. Fig. 1 provides an illustration of the overall network structure of patient referrals between regional hospitals.

The Abruzzo Agency of Public Health also provided information for the year 2006 on hospital-specific covariates and activities for all regional hospitals included in our analysis.

4.3. Measures

4.3.1. Dependent variable

Hospital readmission is generically considered to be an indicator of the quality of care delivered to patients (Ashton and Wray, 1996; Wong et al., 2011). A high readmission rate is generally considered to be a possible consequence of inadequate care during initial admission, premature discharge, and/or absence of planning for transition to community care (Kiefe et al., 2013). The dependent variable in the present study was a patient-level measure of readmission (year 2006), operationalized as a binary indicator: "1" if a hospitalized patient had been treated previously with a similar primary diagnosis (according to the International Classification of Diseases, Ninth Revision, Clinical Modification codes) in any regional hospital in the 45-day period before the admission date, and "0" otherwise (Coffey et al., 2012). Readmission was defined as a patient's self-reported admission at a regional hospital 1–45 days after initial admission. Although a 30-day period is more conventional, regional health authorities with exclusive jurisdiction over community healthcare services established and enforced the 45-day measure. A payment penalty program has been launched in the region to reduce the number of hospital readmissions (Pizer, 2013).

4.3.2. Independent variables

The main explanatory variables in the present study are two network measures derived from the patient transfer matrix. The first variable is *hospital centrality*, measured in this study using the concept of Bonacich power (Bonacich, 1987), which holds that a node's centrality is based on that of its neighbors (i.e., nodes to which it is directly connected). This measure suggests that a hospital is central to the extent to which it sends patients to and receives patients from many other central hospitals. Using the square socio-matrix representing the network of interhospital patient referrals, we calculated the Bonacich centrality measure for each hospital using the following formula (Bonacich, 1987):

$$c(\alpha,\beta) = \alpha \sum_{K=1}^{\infty} \beta^k R^{k+1} 1,$$

where $c(\alpha,\beta)$ is a vector of hospital centrality scores, α is an arbitrary scaling factor, β is a weight, R is the square socio-matrix, k is the number of actors in the network, and 1 denotes a column-vector of ones. In a communication network, for example, a positive β value indicates that the amounts of information available to a given network actor and those with whom it has contacts are positively related. Whenever actor centrality is increased positively by connections to high-status others, a positive β value is called for (Bonacich, 1987). In our case, hospitals involved in patient referrals (incoming and outgoing) with other providers that, in turn, handled many referrals to/from other regional hospitals were

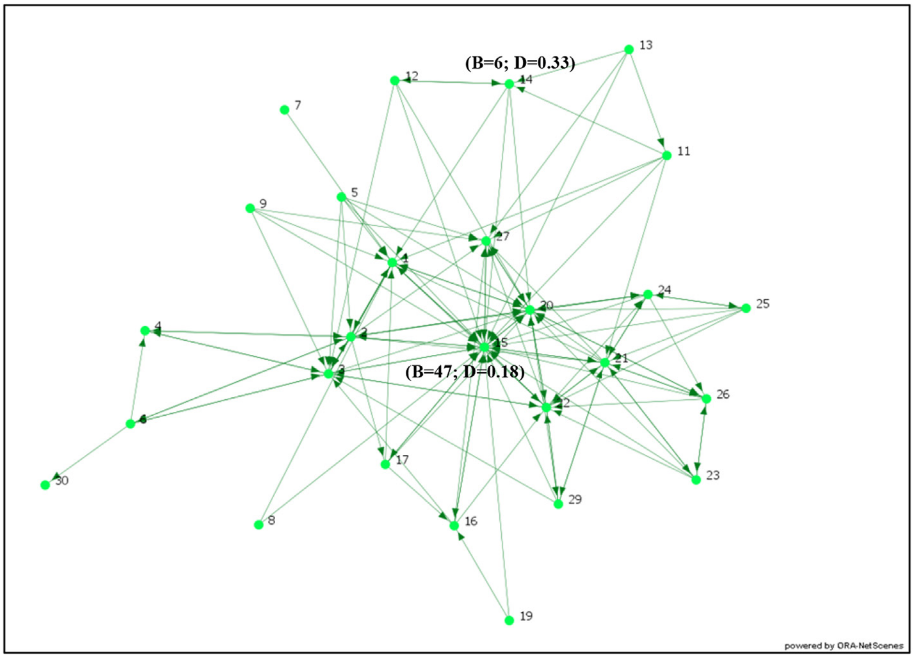

Fig. 1. Visualization of the patient sharing network in the Abruzzo region. Note: Each node represents one hospital and each link represents an act of patient sharing between node pairs. *B* indicates Bonacich centrality; *D* indicates ego-network density. Nodes' locations are determined using a spring-embedding heuristic, multidimensional scaling algorithm, with proximity indicating the extent to which two hospitals are connected directly and indirectly through mutual partners. Isolates are not included in the illustration.

defined as central.

The second variable is *ego-network density*, which measures a focal hospital's existing connections with other partners and connectivity among the ego's partners (Coleman, 1988). In our case, ego-network density represented the extent to which all hospitals that shared patients with a focal provider also shared patients among themselves.

Network measures were computed using the ORA social-network analysis software package (version 3.0.0.2; Carley et al., 2012), which also performed the graphical analysis reported in Fig. 1.

In Fig. 1, we report the value of Bonacich centrality and Ego-network density for two hospitals that exhibit very different network characteristics. Hospital (node) 15 is characterized by high Bonacich centrality and low Ego-network density. This indicates that this hospital has many direct ties (direct relationships with other hospitals, i.e., neighbors), many indirect ties (relationships that neighbors have in turn with others in the region), and low ego-network density (there are relatively few connections compared to all possible connections in the hospital ego-network). In line with our hypotheses, we expect that hospital 15 would have a low likelihood of patient readmission. Low Bonacich centrality and a relatively high Ego-network density instead characterize hospital (node) 14, for which we hypothesize a higher likelihood to observe patient readmissions.

4.3.3. Control variables

We controlled for several variables at the patient and organizational levels that may influence readmission events. Following previous research (Chukmaitov et al., 2009), patient-level control variables are *gender*, *age*, and *Charlson comorbidity index*; the latter variable is commonly used in the medical literature (Charlson et al., 1987; Deyo et al., 1992). Organizational-level control variables are based on hospital demographic characteristics such as organization size and ownership status, which are considered to be predictors of patient outcomes and thus readmissions. Hospital size is measured using the total number of *staffed beds.* We distinguish *public* and *private* hospitals using a binary variable. Because hospitals with medical school affiliations or advanced surgical capacity are more likely to receive transferred patients, which may influence hospital admissions (Iwashyna et al., 2009), we defined the binary variable of *institutional profile – teaching* (1 = teaching hospital, 0 = non-teaching provider). Finally, the average percentage of beds occupied (*occupancy rate*) was taken into account to control for the impact of hospital capacity management on patient readmissions.

Location-specific factors may also affect hospital readmissions. Membership in a particular LHA was operationalized as a categorical variable by which hospitals were assigned to reference geographical areas. We used six binary variables (one of which, LHA 4, was adopted as a baseline category in our statistical analysis) to identify each hospital's membership in one of the six LHAs. As several studies have shown that market characteristics may affect patient readmission and healthcare quality, we controlled for *niche crowding*, which represents the competitive pressure that a hospital faces (Mascia and Di Vincenzo, 2011; Lomi and Pallotti, 2012). Finally, we considered the network size of an ego hospital by determining the number of partnering hospitals that send patients to the ego (*N of hospitals sending to ego*) as well as the number of hospitals to which the ego is referring patients to (*N of hospitals receiving from ego*). These variables are operationalized through the normalized scores of network indegree and outdegree (Wasserman and Faust, 1994), respectively.

4.4. Statistical analyses

To explain hospital readmissions through organizational attributes, such as network position, the model accounts for patient-level and hospital-level variables. Due to the nested nature of data, and because the dependent variable is dichotomous, we conducted logistic regression analyses using hierarchical generalized linear modeling (Raudenbush and Bryk, 2001; Snijders and Bosker, 2011). Multilevel estimates are necessary to analyze these data because ordinary-least-square regression produces inaccurate results when individual observations are inherently non-independent (Raudenbush and Bryk, 2001). Multilevel models provided robust estimates of the standard errors of coefficients and the portion of variance in the dependent variable accounted for by each level of analysis. Analyses were performed through SSI HLM 7 software package.

The two-level hierarchical logistic regression analysis used a restricted maximum likelihood estimation method. The first regression equation estimated the effects of patient-level variables (age, gender, and comorbidity) on the probability that patient *i* treated in hospital *j* would be readmitted within 45 days. Second-level regression equations included the first-level coefficients and intercept as the dependent variables. We modeled the first-level intercept as a function of organizational attributes (hospital characteristics and network variables), which entered the model after being centered on their grand mean. This statistical approach enables estimation of the influence of predictors at the organizational level less the influence of level-1 variables (Hofmann and Gavin, 1998). As we did not expect relations between level-1 and dependent variables to vary randomly across units, we modeled level-1 coefficients as fixed effects. The final model was a random-intercept model, as detailed below:

$$Level - 1\ Model$$

$$Prob(READMISSION_{ij} = 1/\beta_j) = \phi_{ij}; \log[\psi_{ij}/(1-\psi_{ij})] = \eta_{ij}$$

$$\eta_{ij} = \beta_{0j} + \beta_{1j}(GENDER_{ij}) + \beta_{2j}(AGE_{ij}) + \beta_{3j}(COMORBIDITY_{ij}),$$

$$Level - 2\ Model$$

$$\begin{aligned}\beta_{0j} = {} & \gamma_{00} + \gamma_{01}(PRIVATE_j) + \gamma_{02}(TEACHING_j) + \gamma_{03}(BEDS_{ij}) \\ & + \gamma_{04}(OCCUPANCYRATE_j) + \gamma_{05}(LHA1_j) + \gamma_{06}(LHA2_j) \\ & + \gamma_{07}(LHA3_j) + \gamma_{08}(LHA5_j) + \gamma_{09}(LHA6_j) \\ & + \gamma_{010}(NICHECROWDING_j) \\ & + \gamma_{011}(NHOSPITALSSENDINGTOEGO_j) \\ & + \gamma_{012}(NHOSPITALSRECEIVINGFROMEGO_j) \\ & + \gamma_{013}(EGONETDENSITY_j) \\ & + \gamma_{014}(BONACICHCENTRALITY_j) + \mu_{0J}\end{aligned}$$

Although cross-sectional, the model introduced a 1-year time lag between the measurement points of dependent and independent variables. Dependent variable, individual-level predictors (age, gender, and comorbidity) and organizational-level attributes (institutional type, ownership status, LHA membership, staffed beds, and occupancy rate) were measured in 2006, whereas explanatory network variables were measured in 2005.

To understand the effects of patient traits, hospital attributes, and network measures on patient readmissions, we conducted subsequent hierarchical logistic regression analyses with different blocks of predictors. Model 1 included patient (age, gender, and comorbidity) and organizational (type of institution, number of staffed beds, occupancy rate, and local health area) attributes. Model 2 additionally contained the 'number of hospitals receiving from ego' and 'number of hospitals sending to ego' variables. Model 3 tested the effects of ego-network density and Model 4 was used to examine the effects of centrality. Model 5, the full model, contained individual-level and organization-level predictors, including hospital attributes and network variables.

5. Results

During the study period, 766 patients were transferred between

Table 1
Descriptives and correlations.

	First-level descriptive statistics and correlation matrix − N = 360,697					
		Mean	S.D.	Min	Max	1	2
1	Gender (Female = 1; Male = 0)	52%	–	0	1	–	
2	Age	53.14	24.79	0	106	−0.03	–
3	Comorbidity index	0.41	0.72	0	2	−0.10	0.37

	Second-level descriptive statistics and correlation matrix − N = 31																	
	Variable	Mean	S.D.	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	Private hospital (1 = private; 0 = otherwise)	32.25%	–	0	1	–													
2	Teaching hospital (1 = teaching; 0 = otherwise)	6.45%	–	0	1	−0.18	–												
3	Staffed beds	186.26	146.00	41	661	−0.29	0.47	–											
4	Occupancy rate	62.35	15.46	15.13	86.1	−0.26	0.23	0.48	–										
5	LHA1	29.03%	–	0	1	0.17	−0.17	−0.37	−0.10	–									
6	LHA2	16.13%	–	0	1	0.07	0.24	0.09	0.21	−0.28	–								
7	LHA3	16.13%	–	0	1	−0.30	−0.12	−0.09	−0.17	−0.28	−0.19	–							
8	LHA4	9.68%	–	0	1	−0.18	−0.01	0.39	0.16	−0.74	−0.26	−0.02	–						
9	LHA5	16.13%	–	0	1	0.07	−0.12	0.32	0.14	−0.28	−0.19	−0.19	0.47	–					
10	LHA6	12.90%	–	0	1	−0.27	−0.10	0.17	0.29	−0.25	−0.17	−0.17	0.63	−0.17	–				
11	Niche crowding	44.90	34.74	6.99	124.61	0.75	−0.24	−0.54	−0.40	0.31	−0.12	−0.16	−0.28	−0.13	−0.28	–			
12	#Hospitals receiving from ego	0.15	0.09	0	10	−0.73	0.12	0.51	0.19	−0.06	−0.06	0.37	−0.01	−0.02	0.01	−0.62	–		
13	#Hospitals sending to ego	0.15	0.17	0	23	−0.39	0.49	0.77	0.31	−0.17	0.17	0.08	−0.01	0.14	−0.21	−0.52	0.65	–	
14	Ego-network density	0.35	0.23	0	0.68	−0.41	−0.15	−0.35	−0.12	−0.05	0.14	0.34	−0.19	−0.06	−0.23	−0.18	0.09	−0.17	–
15	Bonacich centrality	23.71	29.56	0	143	−0.51	0.47	0.44	0.28	−0.10	0.29	0.19	−0.15	0.00	−0.19	−0.49	0.66	0.64	0.05

Table 2
Hierarchical logistic regressions predicting the likelihood of patient readmission. Level-2 predictors include organizational attributes and network measures. Level-1 predictors include patient characteristics.

Fixed effects	Model 0		Model 1		Model 2		Model 3		Model 4		Model 5	
	Coefficient (S.E.)	Odds ratio	Coefficient (S.E.)	Odds ratio	Coefficient (S.E.)	Odds ratio	Coefficient (S.E.)	Odds ratio	Coefficient (S.E.)	Odds ratio	Coefficient (S.E.)	Odds ratio
For INTRCPT1, β_0												
INTRCPT2, γ_{00}	−3.551*** (0.084)	0.029	−3.595*** (0.070)	0.028	−3.606*** (0.066)	0.027	−3.612*** (0.078)	0.027	−3.611*** (0.063)	0.027	−3.615*** (0.061)	0.027
PRIVATE. γ_{01}			0.319 (0.274)	1.376	0.670* (0.328)	1.955	0.628* (0.301)	1.875	1.078*** (0.312)	2.94	0.983*** (0.267)	2.673
TEACHING. γ_{02}			0.579* (0.315)	1.784	0.825** (0.391)	2.282	1.175*** (0.363)	3.24	0.975** (0.375)	2.651	1.257*** (0.346)	3.515
BEDS. γ_{03}			−0.001 (0.001)	0.997	−0.003 (0.001)	0.997	−0.004** (0.001)	0.996	−0.003** (0.001)	0.997	−0.004** (0.001)	0.996
Occupancy rate. γ_{04}			−0.003 (0.004)	0.999	−0.002** (0.004)	0.998	−0.001 (0.004)	0.998	−0.001 (0.004)	0.999	−0.001 (0.003)	0.999
LHA1. γ_{05}			0.712*** (0.238)	2.038	0.554*** (0.176)	1.74	0.705*** (0.166)	2.024	0.528*** (0.163)	1.695	0.664*** (0.142)	1.942
LHA2. γ_{06}			0.787*** (0.215)	2.196	0.729*** (0.229)	2.072	1.001*** (0.209)	2.72	0.584** (0.212)	1.793	0.844*** (0.176)	2.326
LHA3. γ_{07}			1.187*** (0.301)	3.277	1.060*** (0.294)	2.886	1.249*** (0.306)	3.487	0.971*** (0.277)	2.64	1.148*** (0.273)	3.145
LHA5. γ_{08}			1.132** (0.427)	3.102	1.263*** (0.406)	3.535	1.494*** (0.406)	4.454	1.237*** (0.404)	3.445	1.445*** (0.402)	4.241
LHA6. γ_{09}			0.975*** (0.269)	2.652	1.375*** (0.337)	3.954	1.520*** (0.320)	4.571	1.640*** (0.342)	5.153	1.727*** (0.309)	5.624
NICHECRO. γ_{10}			−0.004 (0.004)	0.996	−0.005 (0.003)	0.996	−0.004 (0.003)	0.996	−0.005 (0.003)	0.995	−0.004 (0.002)	0.996
#Hospitals receiving from ego. γ_{012}					0.024 (0.016)	1.024	0.036** (0.016)	1.037	0.033** (0.013)	1.034	0.043*** (0.013)	1.044
#Hospitals sending to ego. γ_{011}					0.014 (0.010)	1.014	0.017* (0.010)	1.017	0.018* (0.002)	1.019	0.020** (0.009)	1.020
Bonacich centrality. γ_{014}							−0.007*** (0.002)	0.993			−0.006*** (0.002)	0.994
Ego-network density. γ_{013}									0.407** (0.147)	1.502	0.341** (0.137)	1.407
For gender slope. β_1												
Intrcpt2. γ_{10}			−0.047 (0.032)	0.954	−0.047 (0.031)	0.954	−0.047 (0.031)	0.954	−0.047 (0.031)	0.954	−0.047 (0.031)	0.954
For age slope. β_2												
Intrcpt2. γ_{20}			0.003 (0.002)	1.003	0.003 (0.002)	1.003	0.003 (0.002)	1.003	0.003 (0.002)	1.003	0.003 (0.002)	1.003
For comorbidity slope. β_3												
Intrcpt2. γ_{30}			0.139*** (0.040)	1.149	0.139*** (0.039)	1.149	0.139*** (0.039)	1.149	0.139*** (0.039)	1.149	0.139*** (0.039)	1.149
Random effects	Variance Component (τ)	$\chi 2$	Variance Component (τ)	$\chi 2$	Variance Component (τ)	$\chi 2$	Variance Component (τ)	$\chi 2$	Variance Component (τ)	$\chi 2$	Variance Component (τ)	$\chi 2$
Intrcpt1. *u0*	0.225	2096.654***	0.214	1416.462***	0.197	1267.540***	0.187	1023.781***	0.192	1200.125***	0.188	1010.194***

Note: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

hospitals (range per hospital pair, 0–128). Network density and the average network degree were 11.8% and 3.8, respectively. Four hospitals in the region were isolated because they transferred no patient during 2005. Hospitals readmitted an average of 6.6% (range, 1.7%–12%) of all discharged patients. Table 1 provides descriptive statistics for and pairwise correlations among patient- and organizational-level variables.

Table 2 shows hierarchical logistic model regression results. By applying the inter-class correlation coefficient formula (Snijders and Bosker, 2011) to the baseline model it was found that 18% of variance was among hospitals and 82% was at the patient level. Explanatory power increased consistently across regression models, as shown by decreasing and highly significant χ^2 statistics. Comparison of level-2 variance characterized by the fully specified model (0.188) and the empty model (0.225) reveals that model 5 explained approximately 16% of outcome variance across hospitals.

Among patient-level control variables, the Charlson comorbidity index was consistently associated with readmission in all models [odds ratio (OR), 1.149; $p < 0.001$]. Patients with co-morbidities were thus more likely to be readmitted. At the organizational level, ORs for all LHAs in the model exceeded 1, indicating that patient readmission to hospitals located in these areas was more likely than patient readmission to hospitals in the baseline area (LHA 4). Private and teaching hospitals were also more prone than public hospitals to readmission events. Hospital size (number of staffed beds) reduced the odds of patient readmission.

Variables concerning the hospital ego-network size in terms of number of hospitals sending to and receiving from ego had complex effects on readmission. No significant association was observed in Model 2, but both variables significantly increased the odds of hospital readmission in Models 3–5. Thus, the odds of readmission increased with the number of partners dispatching or receiving transfers to or from a focal hospital in models accounting for hospital position within the referral network.

Models 4 and 5 showed that network centrality decreased the odds of readmission (OR, 0.993; $p < 0.01$). Thus, the odds of readmission were negatively related to the number of patient sharing links to and from more central hospitals. These results support H1. In contrast, Models 3 and 5 indicated that ego-network density increased the odds of readmission (OR, 1.502; $p < 0.05$). Thus, the odds of readmission were positively associated to the number of mutual exchanges between the same partners in a hospital network, supporting H2.

6. Discussion

6.1. Scientific contributions

This research provides the first empirical evidence of how patient referral networks between hospitals affect patient outcomes. The focus on patient referral networks allowed us to move beyond formal collaborative interorganizational arrangements, in which underlying interaction behavior is often taken for granted (Gittell and Weiss, 2004; Wells and Weiner, 2007). In the present study, we explored the structure of directly observed, emerging collaborative interactions between hospitals (Iwashyna et al., 2009; Veinot et al., 2012). Social network analysis techniques enabled examination of the effects of hospitals' structural positions within referral networks on the likelihood of patient readmission (Lee et al., 2011). Hierarchical linear modeling enabled observation of the effects of hospital-level attributes and network positions on individual patients' readmission events while accounting for hospital attributes and individual demographic characteristics.

Our analyses highlight two important findings. First, hospitals that display high degrees of centrality (those participating in many referrals or connected to other hospitals with many referral ties) are less likely to readmit patients, perhaps suggesting a better capacity of these hospitals to handle hospitalizations. Such evidence is particularly striking and novel when compared with the effects of two related variables: the number of receiving and sending hospitals. Although a hospital's central position or connection to central actors has advantages, having many referral partners – whether sending or receiving – proves to be detrimental. Importantly, this finding suggests that the quality, rather than quantity, of partners matters. A network in which referrals present clear and structured transfer patterns, which direct patients from peripheral nodes to central hubs (including hospitals with better knowledge, infrastructure, prestige, and visibility), is beneficial.

Second, our results suggest that a dense network of patient referrals increases the likelihood of a readmission event. Although this finding is at first counterintuitive, it appears upon closer examination to be in line with the centrality argument, according to which a network structure of patient transfers characterized by the presence of "hub" hospitals with large numbers of connections or connections to few central actors is most beneficial. In contrast, hospitals with dense networks transfer patients to other hospitals that are also transferring patients amongst themselves, which denotes a somewhat less structured and less directed network configuration. As dense networks tend to homogenize actors' capabilities and resources (Lomi et al., 2014), unstructured referral pathways associated with such networks may reveal lack of specialization among hospitals.

6.2. Implications for policymakers and practitioners

Our findings yield several implications for the healthcare system. For practitioners, a hospital's clear identification of a role within the larger regional network of providers is crucial, as this process may drive strategic decisions in terms of bed capacity, medical equipment, clinical expertise, and treatment specialization of the focal provider. Once the hospital's position on the patient transfer path is established, the direction of patient transfer can be clearly identified, leading to better-informed and possibly more rapid hospitalization decisions.

Policymakers can benefit from the use of these findings to develop new regulations and plan health system restructuring. First, patient referral networks can be used as a valid coordination mechanism for policymakers to adjust/optimize collaborative patterns in healthcare delivery. Second, regulation should promote network-level specialization and differentiation to favor hub formation in view of collective benefits. Finally, our data show that regional effects should not be underestimated. LHA membership was a significant predictor of the likelihood of readmissions, indicating the relevant effects of differences in LHA's managerial and clinical capabilities.

6.3. Directions for future research

Our findings should be interpreted in light of several limitations, each indicating clear directions for future research. First, this study was cross sectional, considering patient- and organizational-level data from a single specific timepoint. We included a time lag by considering the impact of network variables calculated in 2005 on patient readmissions of 2006. Nevertheless, future studies should examine a period of several years to produce more robust results. Second, the hospital readmission rate captures only a selected aspect of quality, which may be correlated with other factors not observed directly in our study. Further research is needed to assess the extent to which patient referral networks affect better care through the consideration of different indicators of quality. Finally, although we are aware that our sample is characterized by several institutional peculiarities – such as the mainly public, tax funded, and non–price competitive nature of the I-NHS – we believe that the problem addressed remains of general interest and relevance for health policy. Future studies should explore whether our results remain robust outside of the Italian context, with its known universalistic-based idiosyncrasies. Despite these limitations, our research provided novel insights into hospital referral networks and patient readmissions, and highlighted a nascent research avenue with diverse further development opportunities.

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