Return to sender

Published in:
Social Science and Medicine

Publication status and date:
Published: 01/01/2024

DOI (link to publisher):
10.1016/j.socscimed.2023.116351

Document Version
Publisher's PDF, also known as Version of record

Social Science & Medicine 340 (2024) 116351

Contents lists available at ScienceDirect

Social Science & Medicine

journal homepage: www.elsevier.com/locate/socscimed

Return to sender: Unraveling the role of structural and social network ties in patient sharing networks

Daan Westra [a,*], Peter Makai [b,c], Ron Kemp [b,c]

[a] Department of Health Services Research, Care and Public Health Research Institute (CAPHRI), Faculty of Health Medicine and Life Sciences, Maastricht University, Maastricht, the Netherlands
[b] Healthcare Department, Netherlands Authority for Consumers and Markets (ACM), The Hague, the Netherlands
[c] Erasmus School of Health Policy and Management, Erasmus University Rotterdam, Rotterdam, the Netherlands

ARTICLE INFO

Handling Editor: Prof. Winnie Yip

Keywords:
Patient sharing
Physician sharing
Integration
Hospital networks
Network analysis
Inter-organizational relations

ABSTRACT

Healthcare is increasingly delivered through networks of organizations. Well-structured patient sharing networks are known to have positive associations with the quality of delivered services. However, the drivers of patient sharing relations are rarely studied explicitly. In line with recent developments in network and integration theorizing, we hypothesize that structural and social network ties between organizations are uniquely associated with a higher number of shared patients. We test these hypotheses using a Bayesian zero-dispersed Poisson regression model within the Additive and Multiplicative Effects Framework based on administrative claims data from 732,122 dermatological patients from the Netherlands in 2017. Our results indicate that 2.6% of all dermatological patients are shared and that the amount of shared patients is significantly associated with structural (i.e. emergency contracts) and social (i.e. shared physicians) ties between organizations, confirming our hypotheses. We also find some evidence that patients are shared with more capable organizations. Our findings highlight the role of relational ties in the way health services are delivered. At the same time, they also raise some potential anti-trust concerns.

1. Introduction

Health and healthcare delivery are inherently relational (Luke and Harris, 2007) and require adequate coordination between providers within and across organizational boundaries (Gittell and Weiss, 2004). It is thus not surprising that policy spurs have sought to improve integration between providers (Burns et al., 2022) and that the structure of health networks have attracted considerable scholarly attention over the past several decades (Dubbs et al., 2004; Hearld and Westra, 2022). Patient sharing networks arguably constitute the network type that has been most actively studied in both the medical as well as health services research domains (cf. DuGoff et al., 2018). Patient sharing networks centralized around one (high-volume) 'hub' organization and with various 'spoke' organizations (Nobilio and Ugolini, 2003) have been associated with lower readmission rates (Mascia et al., 2015), higher quality care (Provan and Milward, 1995), and lower costs of care (Barnett et al., 2012a). However, patient sharing networks are not structured optimally by default (Iwashyna, 2012). In fact, Dudley et al. (2000) estimate that in 1997, over 600 deaths could have been avoided in California alone if patients had been referred to high-volume hospitals. It is thus imperative that we understand the drivers of effective patient sharing networks.

Theory on integration and coordination describes how organizational and social integration can contribute to improved patient care in distinct ways (Singer et al., 2020). In similar vein, Geissler et al. (2020) theorize that besides patient characteristics, patient sharing results from organizational factors (such as structure and affiliations) and physician factors (such as expertise and type of physicians). They empirically show that both matter for referrals between primary and specialized care providers. Mixed-method work by Veinot et al. (2012) shows that while physicians indeed typically decide whether or not to transfer (i.e. share) a patient, they are generally referred to one common referral partner. Qualitative work by Bertazzoni et al. (2008) even finds that a bit more than half of the transfers of these patients are unjustified. Most quantitative research of patient sharing, in acute as well as outpatient settings, identify distance between providers and colocation as main factors in the establishment of patient sharing relations (Landon et al., 2012; Lee et al., 2011). That is, patients are typically shared with organizations

* Corresponding author.
E-mail address: d.westra@maastrichtuniversity.nl (D. Westra).

https://doi.org/10.1016/j.socscimed.2023.116351
Received 24 October 2022; Received in revised form 22 September 2023; Accepted 22 October 2023
Available online 3 November 2023

that are not too far away and between physicians within the same organization. Several studies in this field also indicate that patients are directed towards more capable and higher quality hospitals (Iwashyna et al., 2009a). Existing evidence thus suggests that organizational (i.e. differences in quality and capabilities) as well as relational aspects both contribute to patient sharing ties between organizations. However, their relative importance remains unknown. As a result, it is unclear which levers can be used to effectively structure such networks.

The aim of this paper is to understand how organizational and relational factors influence patient sharing ties between organizations. We particularly seek to understand the degree to which structural (i.e. shared emergency services) and social (i.e. shared physicians) ties between organizations are associated with shared patients between those organizations. Given the salience of patient sharing networks for the value of care services (Song et al., 2014), it is imperative to develop a thorough understand of the antecedents of these collaborative networks. By shedding more light on the drivers of patient sharing ties between organizations, the findings of this study can thus make two important contributions. First, they advance the scientific understanding of these networks. More specifically, we study novel relational drivers of patient sharing ties in an outpatient empirical setting that has not been studied in earlier work. Second, they help health administrator to structure patient sharing networks in such a way that they generate optimal patient care and patient outcomes.

2. Theory

The attention for networks as relevant way of organizing health services, and thus as important precursors high quality service delivery, can be traced back to the work of Provan and Milward (1995). In their most rudimentary form, networks consist of a collection of nodes connected by a set of ties (Borgatti and Foster, 2003). Nodes can constitute anything from individuals to teams, organizations, or even concept, whereas ties represent a specific relation between the nodes (Borgatti and Foster, 2003). Recently, Nowell and Milward (2022) have identified three classes of networks, each of which has distinct features; purpose-oriented-, system-oriented, and structure-oriented networks. Structure-oriented networks emerge through patterns of dyadic tie formation between specific nodes and require social network analysis to 'reveal' the network (Nowell and Milward, 2022), which is the case for patient sharing networks (DuGoff et al., 2018). These ties furthermore occur within the boundaries of the health service delivery system.

In patient sharing networks, nodes can represent individual physicians or organizations, such as hospitals. A tie typically represents the fact that said physicians or organizations treated the same patient within a given timeframe (An et al., 2018; DuGoff et al., 2018). Patient sharing ties between organizations can either be physician-induced or patient-induced (Kesternich and Rank, 2022). The former is typical in acute care settings, in which physicians decide to transfer a patient to another hospital that is better equipped to treat the patient (Iwashyna, 2012). Lee et al. (2011) refer to such ties as direct patient-sharing ties and describe that there is typically no time in between the admission between the two providers. The latter occur in outpatient settings and can be driven by both physician and patient decisions (Kesternich and Rank, 2022). Lee et al. (2011) refers to this as total patient-sharing networks and describes that there can be a considerable amount of time (i.e. up to 365 days) in between the treatment at two organizations in such cases. Given the (implicit) exchange of information when patients are treated by multiple providers, patient sharing is typically conceptualized as a pattern of collaboration between the involved actors (DuGoff et al., 2018). However, patient sharing networks have also been used to study the diffusion of new treatments (Pollack et al., 2015) and spread of infections (e.g. Donker et al., 2010).

Patient sharing is relatively common but varies across patient populations and geographical regions. For intensive care patients for example, Bertazzoni et al. (2008) show that 1.1% of patients are transferred (i.e. shared), while Iwashyna et al. (2009b) find that 4.5% of all patients are shared and that hospitals share patients with 4.4 other hospitals on average. In related work on patients with Acute Myocardial Infarctions however, Iwashyna et al. (2010) show that 44.3% of all patients are shared. Within ambulatory care settings, Barnett et al. (2012c) find that the percentage of patients who are shared between physicians has risen over time to approximately 10% in 2009. The study of two hospitals by Bridewell and Das (2011) shows that approximately 20% of all oncology patients are shared between both organizations. Although patient sharing is thus common, the precise structure of these networks can vary greatly. In their study of referral networks across the United States, Landon et al. (2012) find that the mean adjusted degree centrality varies from 11.7 to 54.4, implying that a physician is connected to 11.7 others per 100 Medicare beneficiaries in one network as opposed to 54.4 in another.

Patient sharing ties have primarily been studied in the absence of an explicit theoretical perspective (DuGoff et al., 2018). Nevertheless, existing literature describes several drivers of patient sharing. These include patient preferences (i.e. a patient wanting to be treated by a specific provider), specialization (i.e. patients are shared to more specialized providers, typically for complex treatments), regionalization (i.e. specific providers are designated to treat specific patient populations in a region), and a lack of resources (e.g. time or beds) of a specific provider which warrants sharing patients to other providers (Iwashyna et al., 2009a; Song et al., 2014). Several studies have also shown that referrals are more likely between geographically proximate providers (Landon et al., 2012; Lee et al., 2011). Furthermore, referrals are more common between physicians with similar patient populations (Landon et al., 2012), between co-located physicians (Geissler et al., 2020), and between male physicians (Dossa et al., 2022).

Overall, the majority of the patient sharing literature has focused on understanding the structural characteristics of patient sharing networks and how these influence patient outcomes (e.g. Lomi et al., 2014; Mascia et al., 2015). Evidence increasingly points to the importance of social factors in patient sharing behavior however. The finding of Geissler et al. (2020) that co-located physicians are more likely to share patients could be explained by the fact that co-located physicians are more familiar with one another and thus more likely to work together. In fact, a third of all physicians indicate that being located in the same organization is a reason to refer patients to another physician (Barnett et al., 2012b). Such attention for social aspects of patient sharing is in line with recent theoretical developments in the field of integrated care (cf. Burns et al., 2022; Singer et al., 2020). This literature stipulates that organizational (i.e. structural and functional) and social (i.e. normative and inter-personal) factors drive integrated care delivery and patient outcomes (Singer et al., 2020). While it has emphasized structural aspects, the integrated care literature increasingly acknowledges the importance of social integration between providers for patient outcomes (Singer et al., 2020) and identifies networks as important vehicles to foster such social integration of providers (Burns et al., 2022). Based on this, we hypothesize:

Hypothesis 1. Organizations that have network ties with one another share more patients than organizations that do not have such ties.

We test the above hypothesis using two distinct network ties between organizations. The first is a structural agreement between organizations to redirect patients for emergency care services. That is, agreements between providers of elective care services and nearby hospitals that stipulate that if patients of the elective care provider require emergency treatment, they will be referred to said hospital. These agreements are made at the organizational level and thus harnesses relatively few opportunities to enable social and normative integration between both organizations. The second network tie is a novel form of operationalizing co-location of physicians across organizational boundaries. Similar to sharing patients, we refer to this as sharing physicians. Following the definition of Westra et al. (2016), two organizations share a physician when said physician treats patients in both organizations. For example a few days a week in organization A and a few days in organization B. Consequently, these physicians are co-located with physicians in both organizations and can thus foster social integration within and between both organizations. Similar to sharing patients, sharing physicians is driven by quality-goals as well as strategic motives of organizations, and typically occurs between geographically proximate organizations (Westra et al., 2016, 2017). Given the importance of physicians to the service delivery capacity of hospitals (Hitt et al., 2001), sharing them yields a network that Gulati et al. (2011) describe as 'rich' (i.e. a network containing highly valuable resources). Or, in integrated care terms, these inter-organizational ties enable the flow of information between both organizations, breeding familiarity and social (i.e. normative and inter-personal) integration. It is precisely this mechanism that has led some health economists to argue that networks of shared specialists could be collusive (Varkevisser et al., 2013). That is, sharing the organization's most important resource with competing organizations could counteract the market mechanisms on which some healthcare systems are based (Westra et al., 2016, 2017).

Based on the recent developments pertaining to the importance of social integration within the integrated care literature and the variance in the degree to which various network ties can enable such integration, we hypothesize that:

Hypothesis 2. The strength of the association between organizations' network ties and their patient sharing ties is contingent on the type of network tie.

3. Methods

We conducted a population-based retrospective study using all-payer claims data from the Netherlands. The study was approved by the Medical Ethics Review Committee of the lead author's university *(details omitted for blind peer review).*

3.1. Setting

We conducted our study in the Dutch specialized care sector. Specialized care in the country is delivered by 57 general hospitals, 8 academic (university) hospitals, 65 specialized hospitals (e.g. cancer hospitals, eye hospitals, rehabilitation centers), 268 independent treatment centers (ITCs), 28 top clinical centers (providing general hospital care and complex care), and 11 trauma centers (Kroneman et al., 2016). All specialized care organizations are independent (i.e. non state-owned), non-profit organizations, which are selectively contracted by private health insurers (Kroneman et al., 2016). Patients can only access the services of specialized care organizations with a referral form their general practitioner (Kroneman et al., 2016). All inhabitants in the Netherlands are obliged to take out a basic insurance package, which covers the costs for specialized care services (Kroneman et al., 2016). Specialized care organizations are paid by insurers based on a Diagnosis Related Group (DRG)-like system developed specifically for the Dutch context called 'Diagnosis Treatment Combinations' (Kroneman et al., 2016). Under this system, specialized care organizations receive a reimbursement for their services depending on a patient's diagnosis and the associated treatment (see Kroneman et al., 2016 for more details on the Dutch DRG system).

3.2. Data

We used two main data sources in this study. Similar to previous studies in this context (van Dijk et al., 2016; Westra et al., 2016), both were supplied by the center for information for Dutch health insurers (Vektis). The first dataset is the national all-payer claims dataset, consisting of all DRGs claimed to Dutch health insurers. Claims data are a commonly used source of data to map referral networks in various countries (DuGoff et al., 2018). The second is a national dataset of physician-to-hospital affiliations, which is used to validate incoming claims from organizations. That is, insurers will only reimburse a claim in case the physician-organization combination that submits the claim has an active record in the affiliation database. As such, both organizations and physicians have a financial incentive to keep the affiliation data up to date and the data has previously been used to map networks of shared physicians between hospitals (Westra et al., 2016).

3.3. Sample

We focused our analysis on dermatological conditions. We did so for three reasons. First, dermatology patients can be treated in ambulatory as well as inpatient settings. This allows us to capture direct patient-sharing ties as well as total patient sharing ties (Lee et al., 2011). Second, sharing physicians is relatively common in this specialty (Westra et al., 2016). Third, dermatology is a specialty that is offered by all types of specialized care providers. Our sample consisted of patients for whom a DRG related to the treatment of a dermatological condition was claimed in 2017. Confining the sample to patients treated in 2017 ensures that all claims have been processed and that we thus have a dataset of all dermatological care delivered in the country. To ensure a degree of homogeneity within the patient population, we selected DRGs pertaining to the two largest patient groups within dermatological care (i.e. skin cancer and eczema). This resulted in a final sample (at patient level) of 732,122 patients, for whom 1,123,669 DRGs were claimed across 790.890 'care episodes' (i.e. DRGs associated with the same medical condition within an organization). These patients were treated by a total of 653 physicians, across 170 specialized care organizations. Table 1 includes details regarding the sample at the patient, physician, and organizational level.

Table 1
Descriptive statistics.

	Mean/ Proportion	SD	Range (95% CI, percentiles)
Patients (n = 732,122)			
Age (years)	56.7	23.31	[5.0–86.0]
Female (percentage)	55.0%		
Shared patients (percentage)	2.6%		
Cancer patients (percentage)	82.7%		
Eczema patients (percentage)	27.0%		
Additional distance to second-closest provider (in km) versus closest provider	32.3	43.46	[1.7–129.7]
Physicians (i.e. medical specialists) (n = 653)			
Female (percentage)	49.3%		
Professional experience (yeas)	13.6%	10.66	[0.0–34.0]
Salaried physicians (percentage)	48.9%		
Non-salaried physicians (percentage)	70.6%		
Shared physicians (percentage)	56.5%		
Organizations (n = 170)			
Academic/specialized (percentage)	5.9%		
General/teaching (percentage)	43.0%		
Independent Treatment Center (percentage)	51.0%		
Quality	0	0.99	[−1.12–1.31]
Revenue from included patient groups	€ 289,334	€ 800,157	[€ 349–€ 1,244,590]
Number of patients treated	209.70	307.73	[1.0–682.0]
Revenue from cancer patients	€ 274,074	€ 783,501	[€ 349–€ 1,083,539]
Number of patients cancer	169.05	254.22	[1–477]
Revenue from eczema patients	€ 26,795	€ 50,986	[€ 678–€76,521]
Number of patients eczema	59.49	82.62	[2–228]

3.4. Variables

3.4.1. Dependent variable

Our dependent variable is a directed dyadic variable representing the total number of patients shared from one organization to another. To construct this variable, we sorted the claims for patients treated in 2017 by patients and starting date of the DRG. We subsequently identified which organization claimed each DRG. In case two or more organizations claimed a DRG for the same condition for the same patient, within a 365 day window, the patient was considered shared between both organizations. The organization that claimed the DRG with the earliest starting date was considered the sending organization and the organization that claimed the DRG with the subsequent starting date was considered the receiving organization. We used DRGs claimed in 2016 (1,129,466 DRGs) and 2018 (1,150,623 DRGs) to allow us to construct the total patient sharing network, which has a maximum interval of 365 days between DRG starting dates, as specified by Lee et al. (2011). The 2016 data enables us to identify whether a patients in our sample (i.e. patients treated in 2017) had already been treated for the same condition by another organization in the 365 days *prior* to the treatment in 2017. Similarly, the 2018 data enables us to identify whether patients treated in 2017 were treated in another organization for the same condition within 365 days *after* the treatment in 2017.

The following example illustrates how we constructed our dependent variable. Suppose three DRGs pertaining to the treatment of skin cancer were claimed for patient Z in the following order; On August 1st of 2016 by organization A, on March 1st of 2017 by organization B, and on February 1st of 2018 by organization C. The patient was included in our sample because a DRG was claimed for them in 2017. The DRG claimed in 2016 and 2018 were subsequently identified as belonging to the same patient for the same condition within a 365 day time window of the 2017 DRG. Based on these DRGs, there are two patient sharing dyads; organization A had claimed the DRG with the earliest starting date. It thus has an outgoing patient sharing tie to organization B. Similarly, organization B has an outgoing tie to organization C. Represented in network terms A→B→C. Following the above approach resulted in a network of directed patient sharing ties between organizations. Because the ties in this network are directed, the number of patients shared from organization A to organization B does not have to equal those shared from B to A.

3.4.2. Independent variables

Our main independent variables of interest are two directed dyadic variables. First, we included a directed dyadic variable indicating whether organizations share physicians. Following the operationalization of (Westra et al., 2016, 2017), organizations shared a physician when one physician had an active affiliation with both organizations at the same time. Similar to the directionality of the patient transfer network, we used the date of registration to compute the direction of the tie. That is, we sorted the physician-organization affiliation data by physician and starting date of the affiliation. We removed all inactive affiliations between physicians and organizations from the list. To ensure temporal precedence, physician-organization affiliations that commenced after December 31st' 2016 were also disregarded. For those physicians with multiple active affiliations, we considered the organization to share physicians sequentially. The following example illustrates our approach. Suppose a physician holds four active affiliations; one to organization A since January 1st, 2000, one to organization B since June 1st, 2010, one to organization C since November 1st, 2016, and one to organization D since May 1st' 2017. The physician's initial affiliation was to Organization A. Therefore, Organization A was considered to share said physician to organization B (A→B). Subsequently, organization B (i.e. the second affiliation of the physician) was considered to share the physician to organization C (i.e. the physician's third affiliation) (B→C). The affiliation to organization D was disregarded because it started after December 31st' 2016. Because organizations typically do not share a high number of physicians, we used a binary variable to indicate whether organizations shared at least one physician between them.

Our second independent variable was a directed binary variable indicating whether independent treatment centers had a contract for emergency care with a (nearby) hospital. These contracts constitute agreements to ensure access to urgent care in hospitals for patients of independent treatment centers. We retrieved the existing emergency contracts in 2016 from the Dutch Health Care Inspectorate, which registers these for all independent treatment centers and makes the data publicly available.

3.4.3. Control variables

Following existing patient sharing literature, we included the type of organization, average travel time for patients to the organization, quality of the care delivered at the organization, percentage of salaried specialists, and percentage of skin cancer patients as control variables. The type of organization was a categorical variable with three categories; academic/specialized hospital, general/top clinical hospital (reference category), and independent treatment center. The average travel time to the organization was calculated as the average additional distance that patients need to travel to the organization, when they bypass their nearest organization (Iwashyna et al., 2010). The quality of care provided by the organization was based on data from the Dutch healthcare inspectorate and collected by the National HealthCare Institute. These contain 40 indicators of quality of dermatological care for all providers, most of which are binary. For parsimony, we collapsed these into a single factor using principal component analysis (Jolliffe and Cadima, 2016). The percentage of salaried specialists within an organization was based on the specialist to hospital affiliation data and was included to account for the fact that non-salaried (i.e. self employed) specialists have a financial incentive not to refer patients to other organizations. Lastly, the percentage of skin cancer patients in the organization was based on the proportion of DRGs claimed for skin cancer versus eczema (the two groups included in the study) within an organization, in order to account for potential differences in patient mix between providers.

3.5. Analyses

We first conducted visual analyses of the networks (see supplementary material) and computed descriptive network measures, including; network density, reciprocity of nodes, and indegree and outdegree centralization (Freeman, 1979; Wasserman et al., 2014). Density is the proportion of potential connections that are actual connections. Reciprocity measures the probability of a directed network to be mutually linked (A→B and B→A). Indegree and outdegree centralization measure the extent to which a network is centralized around specific nodes, or the 'compactness' of a network (Freeman, 1979). Subsequently, we tested our hypotheses using a Bayesian, zero-dispersed Poisson regression approach. This approach is a specific form of the Additive and Multiplicative Effects (AME) framework. The AME framework is specifically designed to analyze network data (Hoff, 2021). The ease of fitting is a main strength of the AME framework compared to other network analytical approaches (e.g. ERGM) and the approach has been used in previous patient sharing studies (Paul et al., 2014). The AME framework is capable of accounting for various network characteristics by accounting for first, second and third order dependencies between nodes. First order dependencies are captured by explicitly modelling node-specific heterogeneity (for example type of organization). Second order effects, such as reciprocity, are modeled by the correlation structure given by the edges. Third order dependencies, for example triadic structures, are captured through a multiplicative error term. The estimated equation has the following form (Hoff, 2015; Minhas et al., 2019):

$$y_{i,j} = \beta_{d,i,j}^T X_{d,i,j} + \beta_r^T X_{r,i} + \beta_c^T X_{c,j} + a_i + b_j + u_i^T D v_j + \epsilon_{i,j}$$

where $y_{i,j}$ is the outcome (i.e. a patient sharing tie between organization i and j), $\beta_{d,i,j}^{T}X_{d,i,j}$ are the dyadic covariates, $\beta_r^T X_{r,i}$ the row covariates and $\beta_c^T X_{c,j}$ the column covariates (i.e. our main independent variables). $a_i + b_j$ are sender and receiver effects respectively (i.e. our control variables), and $\epsilon_{i,j}$ is the within dyad effect. In case of directed networks like the one we specify, the multiplicative effects are given by $u_i^T D v_j$.

The first order dependencies are captured by the following additive terms:

$$\beta_{d,i,j}^{T}X_{d,i,j} + \beta_r^T X_{r,i} + \beta_c^T X_{c,j} + a_i + b_j$$

The second order dyadic dependencies are captured in the following part of the error term:

$$\epsilon_{i,j}$$

and the third order terms are:

$$u_i^T D v_j$$

where u and v are a vectors of latent characteristics (random effects) of the senders (u) and the receivers (v). D is a diagonal matrix.

The variance terms are

$$a_i + b_j \sim N(0, \Sigma_{ab})$$

$$\epsilon_{i,j} \sim N(0, \Sigma_\epsilon)$$

$$\Sigma_{ab} = \begin{pmatrix} \sigma_a^2 & \sigma_{ab} \\ \sigma_{ab} & \sigma_b^2 \end{pmatrix}$$

$$\Sigma_\epsilon = \sigma_\epsilon^2 \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix}$$

The variance terms are as follows: σ_a^2 sending covariance, σ_b^2 recieving covariance, σ_{ab} row-column covariance, ρ reciprocity, σ_ϵ^2 dispersion.

The AME approach allows us to include three types of independent variables: dyadic variables (a relation between a sending and a receiving hospital), characteristics of the sending organizations, and characteristics of the receiving organization, thus decomposing these various effects. See Hoff (2005, 2021) for more detailed information on the approach. During estimation, we specified a burn-in period of 2000 iterations followed by 10,000 iterations of the Markov-Chain Monte Carlo (MCMC) algorithm. Every 25-th sample was saved. Regression models were performed using the amen package (Hoff, 2015). All analyses were conducted in R version 4.0.4.

4. Results

Table 1 contains the descriptive statistics of the patients, physicians (i.e. specialist), and organizations in our sample. It shows that 19,278 of the 732,122 patients (i.e. 2.63%) in our sample were treated by more than one organization for the same condition within a year (i.e. were shared). In total, 369 of the 653 specialists (56.5%) had affiliations to multiple organizations (i.e. were shared), with a few being shared between as many as four organizations.

Table 2 contains the descriptive network measures of the dyadic variables (i.e. shared patients, shared specialists, and emergency contracts). As the table indicates, approximately nine, two, and one-half a percent of the possible ties are formed within these networks respectively, as indicated by the density variable. Using these density values and the number of possible directed dyads that can be formed in the network (i.e. 170*169), we can deduce that across the dyads in which organizations indeed share patients (i.e. the dyads that were actually formed), the average amount of shared patients is 6.05. Similarly, the dyads of organizations that share physicians, share 0.78 physicians on average. The latter is below one due to the fact that some specialists are shared in more than one dyad.

Table 2
Network characteristics.

	Patient transfer network	Shared specialist network	Emergency contract network
Density	0.09380439	0.01610018	0.006991261
Reciprocity	0.6345083	0.2074074	0
Standardized indegree centralization (unstandardized)	0.4472883 (12,775)	0.04627126 (770)	0.004292387 (34)
Standardized outdegree centralization (unstandardized)	0.4056231 (11,585)	0.06970735 (1160)	0.04974119 (349)

As the reciprocity variable indicates, 63% of the patient sharing ties that go from organization A to organization B, also go from organization B to organization A. In other words, in 63% of the cases where there is at least one patient who was treated for the same condition in organization A first and in organization B subsequently, there is also at least one patient who was treated for the same condition in the reverse order. Such reciprocity could occur in case a patient is seen for the same condition sequentially in organization A, then in B within 365, and then in A again within 365 of being seen in organization B. It could also occur when one patient is seen for the same condition in organization A and subsequently in organization B within 365 days and another patient is seen in organization B and subsequently in organization A within 365 days. The reciprocity value in the network of shared professionals is lower than in the network of shared patients (i.e. 20%). This implies that in one fifth of the cases where there is at least one specialist who worked in organization X and subsequently also started working in organization Y, there is also at least one specialist who worked in organization Y and also started working in organization X.

The centralization measures are roughly 10 times as high in the patient sharing network than in the networks of shared specialists and emergency contracts. This indicates that the patient sharing networks tend are more centralized around specific organizations than the networks of shared specialist and of emergency contracts. For each network, Hive plots showing the relation between organizations of different types (i.e. independent treatment centers, non-academic hospitals, and academic hospitals) and visualizations for the relation between organizations of the same type are included in the supplementary material to aid visual interpretation of the data.

Table 3 contains the results of the bivariate analyses and multivariate regression models. It indicates that both relational variables (i.e. shared physicians and emergency contracts) are associated with a significantly higher number of shared patients between two organizations, confirming our first hypothesis. The bivariate results show that organizations that share physicians, also share approximately seven patients more than those organizations that do not share any physicians. The effect size is similar (i.e. 7.109 additional shared patients) when controlled for other factors in the multivariate analyses and it is statistically significant at the $p < 0.001$ level and is greater than the average amount of patients shared between organizations. In other words, ceteris paribus, organizations that share physicians, share more than twice as many patients than organizations that do not share physicians. The number of emergency contracts between providers, the other dyadic independent variable, is also positively and significantly associated with the number of shared patients between organizations. Organizations that have an emergency contract between them, share 0.410 patients more than organizations that do not have an emergency contract between them. This constitutes 6.3% of the average amount of patients shared between organizations. The different effect sizes of these two variables also confirm our second hypothesis.

Of the node-level variables, the distance of the sending organization

Table 3
Bayesion zero dispersed POISSON bivariate and multivariate results.

Bivariate analysis	Dyad		From		To	
	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
Shared physicians	7.042**	0.000				
Intercept	−6.457**	0.000				
Variance parameters:						
σ_a^2 sending covariance	0.090					
σ_{ab} row-column covariance	0.037					
σ_b^2 recieving covariance	0.151					
ρ reciprocity	0.969					
σ_ϵ^2 dispersion	0.847					
Multivariate analysis	**Dyad**		**From**		**To**	
	Coefficient	**p-value**	**Coefficient**	**p-value**	**Coefficient**	**p-value**
Shared physicians	7.109***	0.000				
Emergency contracts	0.410**	0.003				
Extra distance			0.000*	0.015	0.000	0.079
Percentage salaried			0.003	0.050	0.002	0.124
Academic/specialized hospital[a]			0.024	0.871	0.580***	0.000
Independent treatment center[a]			−0.285*	0.010	−0.135	0.347
Percentage skin cancer patients			0.004	0.061	0.006**	0.003
Quality			−0.042	0.329	0.016	0.752
Centrality			−0.004	0.912	0.073	0.645
Constant	−7.378***	0.000				
Variance parameters						
σ_a^2 sending covariance	0.082					
σ_{ab} row-column covariance	0.015					
σ_b^2 recieving covariance	0.099					
ρ reciprocity	0.960					
σ_ϵ^2 dispersion	0.871					

Dependent variable is the number of shared patients between two organizations.
* p-value <0.05.
** p-value <0.01.
*** p-value <0.001.
[a] Dummy variable, general/teaching hospital is the reference category.

(albeit with a small effect size), the type of the sending and receiving organization, and the percentage skin cancer patients treated in the receiving organization are significantly associated with the number of shared patients. Dyads in which the sending hospital is an independent treatment center share 0.285 fewer patients (4.7% of the average amount of shared patients between two sharing organizations) than dyads in which the sending hospital is a general or teaching hospital (i.e. the reference category for the type variable). On the other hand, dyads in which the receiving hospital is an academic center share 0.580 more patients (9.6% of the average amount of shared patients between two sharing organizations) than dyads in which the receiving organization is a general or teaching hospital. Every additional percentage point of skin cancer patients in the receiving organization of a dyad is associated with a 0.006 higher amount of shared patients (i.e. 0.3% of the average amount of shared patients between two sharing organizations). The other node-level variables, including quality of care of the sending and receiving organization, are not significantly associated with the number of shared patients. The variance parameters furthermore indicate low covarience of hospitals having a common sender (σ_a^2) and of hospitals having a common receiver (σ_b^2), as well as a low covariance (σ_{ab}) within common sender and receiving hospitals.

5. Discussion

The aim of this paper was to further unravel the drivers of patient sharing ties between organizations. More specifically, we sought to test the association that two distinct relational ties had with patient sharing ties. Our results reveal that 2,6% of patients are shared between organizations, which is on the lower end of previous estimates (e.g. Bertazzoni et al., 2008; Iwashyna et al., 2009b). This is most likely a result of our focus on two common dermatological conditions, for which visiting additional providers might be less necessary than for other conditions. The finding that the percentage of skin cancer (i.e. complex) patients in the receiving organization is associated with a higher number of shared patients is in line with previous work (Lee et al., 2011) and provides additional support for this explanation. Our results furthermore confirm our hypothesis that relational ties between organizations are associated with a higher number of shared patients, albeit in unequal degrees. In what follows, we reflect on these findings.

First, existing literature has suggested specialization, regionalization, a lack of resources, and patient preferences as possible drivers of decisions to refer patients (Iwashyna et al., 2009a; Song et al., 2014). In each of these cases, transferring patients is ultimately considered beneficial to patients. In the case of specialization and regionalization, a specific provider (in a region) specializes in, amongst others by increasing the treatment volume of, a specific procedure in the pursuit of improved outcomes such as lower mortality rates or readmission rates (Birkmeyer et al., 2002; Dudley et al., 2000; Finks et al., 2011). Mascia et al. (2015) show that this can lead to lower readmission rates and Dudley et al. (2000) argue that it can avoid unnecessary deaths. Our results provide partial support for this notion. That is, we find no relation between the number of shared patients and quality of care of the sending nor the receiving organization. This suggests that quality differences between providers is not a main driver of patient sharing. A possible explanation is that the patient-induced sharing ties we study (Kesternich and Rank, 2022) are less sensitive to quality difference but instead driven by other patient preferences. Alternatively, the finding might be due to the fact that our quality indicator consists of a composite score of publicly available quality indicators, whereas previous research has used more specific quality indicators such as readmission rates. Transfer decisions might be based on such more easily observable indicators. This explanation is supported by the finding that dyads in which the receiving organization is an academic hospital (i.e. which constitutes an easily observable organizational indicator) consist of a higher number of shared patients than dyads in which the receiving organization is a general hospital. This latter finding, does support the notion that patients are shared with more capable providers (Lomi et al., 2014).

Second, in line with our first hypothesis, the results clearly indicate that relational ties between organizations are associated with a higher number of shared patients between those same providers. Organizations that share physicians share more than double the average amount of patients and organizations that have emergency contracts share approximately 6% more patients than average, after controlling for quality and specialization effects. In line with our second hypothesis, the association between shared physicians and shared patients is particularly strong. These findings are in line with prior work regarding the role of co-location of physicians (Landon et al., 2012; Lee et al., 2011). They furthermore provide evidence for the theorized role of structural and social integration in health care (Singer et al., 2020). This body of literature suggests that inter-personal familiarity between providers breeds the trust required to cooperate effectively (Kerrissey et al., 2022). When organizations share physicians, the teams in both organizations become more familiar with one another, facilitating said familiarity (Westra et al., 2016). As a result, the threshold to share patients to the other organization could lower, because physicians know what they can expect from the receiving organization in handling the incoming referral, increasing trust that the outcome will be satisfactory.

While our findings shed new light on the drivers of patient sharing networks, they also harness several practical implications. First, they signal to health administrators that patient sharing networks might be amendable through improving the relational ties between organizations. As such, administrators could be able to direct the flow of patients in a way that is conducive for improved patient outcomes. However, from an antitrust perspective, the strong association between shared specialist and shared patients could raise questions. Westra et al. (2016) show that sharing physicians is partly driven by providers' pursuit to increase the volume of incoming referrals from other organizations. Our findings suggest that sharing specialists is indeed associated with patient sharing ties between organizations, providing support for the notion of Varkevisser et al. (2013) that sharing physicians between organizations can have a collusive effect. Particularly in market-based systems, anti-trust agencies might thus consider scrutinizing those patient and physician sharing ties that do not flow in the direction of higher quality of more capable providers.

5.1. Limitations

Our study is subject to several limitations. First, the nature of our data (i.e. administrative claims data) does not allow us to identify whether a patient was actively referred to another provider by their specialist or whether it was the patients' own choice to visit another provider. Recent work by Kesternich and Rank (2022) reveals that patient sharing relations in outpatient settings are indeed partly induced by patients themselves. However, the magnitude of the effect size of shared physicians suggests that seeing the same physician in another organization could constitute a main driver of patients' destination decision when seeking out another organization. Second, we have limited our analysis to two groups of dermatological services and specific relational ties between organizations. Therefore, our results cannot be generalized to other relational ties and other specialties without caution. In other treatment groups and/or other specialties, patient sharing ties might be more or less common. Similarly, other relations between organizations could have distinct effect, as our results already indicate. Future research could thus unravel this in more detail. Studying the role of informal ties between physicians seems particularly salient in this regard.

6. Conclusion

Networks are increasingly common in health service delivery. Patient sharing networks constitutes a prime example and have shown to be associated with improved quality of care. Within the two most common dermatological conditions, approximately 2.6% of all patients are shared. The amount of patients shared between providers has a strong association with other relational ties between those organizations, in particular sharing physicians. These relational aspects outweigh organizational characteristics of the sending and receiving organization such as specialization and quality, which previous research had identified as important drivers of patient sharing relations. These findings confirm recent theoretical developments around integration of care services. In case these ties do not flow towards more capable providers, they could raise anti-trust concerns. Overall, our findings confirm the importance of relational and social integration in the healthcare sector and call for further empirical research into the effect size of these mechanisms.

Data availability

The data that has been used is confidential.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.socscimed.2023.116351.

References

An, C., O'Malley, A.J., Rockmore, D.N., Stock, C.D., 2018. Analysis of the US patient referral network. Stat. Med. 37 (5), 847–866.

Barnett, M.L., Christakis, N.A., O'Malley, A.J., Onnela, J.-P., Keating, N.L., Landon, B.E., 2012a. Physician patient-sharing networks and the cost and intensity of care in US hospitals. Med. Care 50 (2), 152.

Barnett, M.L., Keating, N.L., Christakis, N.A., O'malley, A.J., Landon, B.E., 2012b. Reasons for choice of referral physician among primary care and specialist physicians. J. Gen. Intern. Med. 27, 506–512.

Barnett, M.L., Song, Z., Landon, B.E., 2012c. Trends in physician referrals in the United States, 1999-2009. Arch. Intern. Med. 172 (2), 163–170.

Bertazzoni, G., Cristofani, M., Ponzanetti, A., Trabalzini, A., Attalla, H., De Vito, C., Villari, P., 2008. Scant justification for interhospital transfers: a cause of reduced efficiency in the emergency department. Emerg. Med. J. 25 (9), 558–561.

Birkmeyer, J.D., Siewers, A.E., Finlayson, E.V., Stukel, T.A., Lucas, F.L., Batista, I., Welch, H.G., Wennberg, D.E., 2002. Hospital volume and surgical mortality in the United States. N. Engl. J. Med. 346 (15), 1128–1137.

Borgatti, S.P., Foster, P.C., 2003. The network paradigm in organizational research: a review and typology. J. Manag. 29 (6), 991–1013. http://ac.els-cdn.com/S0149206303000874/1-s2.0-S0149206303000874-main.pdf?_tid=2861e1ba-4df4-11e6-b531-00000aacb35f&acdnat=1468962352_d2baf6a917b038db904ed6c40cc157e5.

Bridewell, W., Das, A.K., 2011. Social network analysis of physician interactions: the effect of institutional boundaries on breast cancer care. In: AMIA Annual Symposium Proceedings.

Burns, L.R., Nembhard, I.M., Shortell, S.M., 2022. Integrating network theory into the study of integrated healthcare. Soc. Sci. Med. 296, 114664.

Donker, T., Wallinga, J., Grundmann, H., 2010. Patient referral patterns and the spread of hospital-acquired infections through national health care networks. PLoS Comput. Biol. 6 (3), e1000715.

Dossa, F., Zeltzer, D., Sutradhar, R., Simpson, A.N., Baxter, N.N., 2022. Sex differences in the pattern of patient referrals to male and female surgeons. JAMA Surg. 157 (2), 95–103.

Dubbs, N.L., Bazzoli, G.J., Shortell, S.M., Kralovec, P.D., 2004. Reexamining organizational configurations: an update, validation, and expansion of the taxonomy of health networks and systems. Health Serv. Res. 39 (1), 207–220.

Dudley, R.A., Johansen, K.L., Brand, R., Rennie, D.J., Milstein, A., 2000. Selective referral to high-volume hospitals: estimating potentially avoidable deaths. JAMA 283 (9), 1159–1166.

DuGoff, E.H., Fernandes-Taylor, S., Weissman, G.E., Huntley, J.H., Pollack, C.E., 2018. A scoping review of patient-sharing network studies using administrative data. Trans. Behav. Med. 8 (4), 598–625.

Finks, J.F., Osborne, N.H., Birkmeyer, J.D., 2011. Trends in hospital volume and operative mortality for high-risk surgery. N. Engl. J. Med. 364 (22), 2128–2137.

Freeman, L.C., 1979. Centrality in social networks: conceptual clarification. Soc. Network. 215–239.

Geissler, K.H., Lubin, B., Ericson, K.M.M., 2020. The role of organizational affiliations in physician patient-sharing relationships. Med. Care Res. Rev. 77 (2), 165–175.

Gittell, J.H., Weiss, L., 2004. Coordination networks within and across organizations: a multi-level framework. J. Manag. Stud. 41 (1), 127–153.

Gulati, R., Lavie, D., Madhavan, R.R., 2011. How do networks matter? The performance effects of interorganizational networks. Res. Organ. Behav. 31, 207–224.

Hearld, L.R., Westra, D., 2022. Charting a course: a research agenda for studying the governance of health care networks. In: Shortell, S.M., Burns, L.R. (Eds.), Responding to the Grand Challenges in Healthcare via Organizational Innovation: Needed Advances in Management Research, vol. 21. Emerald.

Hitt, M.A., Bierman, L., Shimizu, K., Kochhar, R., 2001. Direct and moderating effects of human capital on strategy and performance in professional service firms: a resource-based perspective. Acad. Manag. J. 44 (1), 13–28.

Hoff, P., 2021. Additive and multiplicative effects network models. Stat. Sci. 36 (1), 34–50.

Hoff, P.D., 2005. Bilinear mixed-effects models for dyadic data. J. Am. Stat. Assoc. 100 (469), 286–295.

Hoff, P.D., 2015. Dyadic data analysis with amen. arXiv preprint arXiv:1506.08237.

Iwashyna, T.J., 2012. The incomplete infrastructure for interhospital patient transfer. Crit. Care Med. 40 (8), 2470–2478.

Iwashyna, T.J., Christie, J.D., Kahn, J.M., Asch, D.A., 2009a. Uncharted paths: hospital networks in critical care. Chest J. 135 (3), 827–833. http://ac.els-cdn.com/S0012369209602105/1-s2.0-S0012369209602105-main.pdf?_tid=89d69a3a-4df4-11e6-b531-00000aacb35f&acdnat=1468962516_6e31b72466d208bb39e637ad59ecb837.

Iwashyna, T.J., Christie, J.D., Moody, J., Kahn, J.M., Asch, D.A., 2009b. The structure of critical care transfer networks. Med. Care 47 (7), 787.

Iwashyna, T.J., Kahn, J.M., Hayward, R.A., Nallamothu, B.K., 2010. Interhospital transfers among Medicare beneficiaries admitted for acute myocardial infarction at nonrevascularization hospitals. Circ.: Cardiovsc. Qual. Outcome 3 (5), 468–475.

Jolliffe, I.T., Cadima, J., 2016. Principal component analysis: a review and recent developments. Phil. Trans. Math. Phys. Eng. Sci. 374 (2065), 20150202.

Kerrissey, M., Tietschert, M., Novikov, Z., Bahadurzada, H., Sinaiko, A.D., Martin, V., Singer, S.J., 2022. Social features of integration in health systems and their relationship to provider experience, care quality and clinical integration. Med. Care Res. Rev. 79 (3), 359–370.

Kesternich, E., Rank, O., 2022. Beyond patient-sharing: comparing physician-and patient-induced networks. Health Care Manag. Sci. 1–17.

Kroneman, M., Boerma, W., van den Berg, M., Groenewegen, P.P., De Jong, J., van Ginneken, E., 2016. Health systems in transition: the Netherlands (Health Systems in Transition, Issue. http://www.euro.who.int/_data/assets/pdf_file/0016/314404/HIT_Netherlands.pdf.

Landon, B.E., Keating, N.L., Barnett, M.L., Onnela, J.-P., Paul, S., O'Malley, A.J., Keegan, T., Christakis, N.A., 2012. Variation in patient-sharing networks of physicians across the United States. JAMA 308 (2), 265–273.

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., 2011. Social network analysis of patient sharing among hospitals in Orange County, California. Am. J. Publ. Health 101 (4), 707–713.

Lomi, A., Mascia, D., Vu, D.Q., Pallotti, F., Conaldi, G., Iwashyna, T.J., 2014. Quality of care and interhospital collaboration: a study of patient transfers in Italy. Med. Care 52 (5), 407–414.

Luke, D.A., Harris, J.K., 2007. Network analysis in public health: history, methods, and applications. Annu. Rev. Publ. Health 28, 69–93.

Mascia, D., Angeli, F., Di Vincenzo, F., 2015. Effect of hospital referral networks on patient readmissions. Soc. Sci. Med. 132, 113–121.

Minhas, S., Hoff, P.D., Ward, M.D., 2019. Inferential approaches for network analysis: AMEN for latent factor models. Polit. Anal. 27 (2), 208–222.

Nobilio, L., Ugolini, C., 2003. Selective referrals in a 'hub and spoke'institutional setting: the case of coronary angioplasty procedures. Health Pol. 63 (1), 95–107. http://ac.els-cdn.com/S0168851002000805/1-s2.0-S0168851002000805-main.pdf?_tid=c50c101c-4df4-11e6-991f-00000aacb35f&acdnat=1468962615_8c77d95b7e692830dc53dd0314b7f721.

Nowell, B., Milward, H.B., 2022. Apples to Apples: A Taxonomy of Networks in Public Management and Policy. Cambridge University Press.

Paul, S., Keating, N.L., Landon, B.E., O'Malley, A.J., 2014. Results from using a new dyadic-dependence model to analyze sociocentric physician networks. Soc. Sci. Med. 117, 67–75.

Pollack, C.E., Soulos, P.R., Gross, C.P., 2015. Physician's peer exposure and the adoption of a new cancer treatment modality. Cancer 121 (16), 2799–2807.

Provan, K.G., Milward, H.B., 1995. A preliminary theory of network effectiveness: a comparative study of four community mental health systems. Adm. Sci. Q. 40 (1), 1–33.

Singer, S.J., Kerrissey, M., Friedberg, M., Phillips, R., 2020. A comprehensive theory of integration. Med. Care Res. Rev. 77 (2), 1077558718767000.

Song, Z., Sequist, T.D., Barnett, M.L., 2014. Patient referrals: a linchpin for increasing the value of care. JAMA 312 (6), 597–598.

van Dijk, C.E., de Jong, J.D., Verheij, R.A., Jansen, T., Korevaar, J.C., de Bakker, D.H., 2016. Compliance with referrals to medical specialist care: patient and general practice determinants: a cross-sectional study. BMC Fam. Pract. 17 (1), 1–7.

Varkevisser, M., van der Geest, S.A., Loozen, E.M.H., Mosca, I., Schut, F.T., 2013. Instellingsoverstijgende Maatschappen: Huidige Ontwikkelingen, Mogelijke Gevolgen en de Aanpak van Eventuele Mededingingsproblemen.

Veinot, T.C., Bosk, E.A., Unnikrishnan, K., Iwashyna, T.J., 2012. Revenue, relationships and routines: the social organization of acute myocardial infarction patient transfers in the United States. Soc. Sci. Med. 75 (10), 1800–1810.

Wasserman, S., Pattison, P., Steinley, D., 2014. Social Networks. Wiley StatsRef: Statistics Reference Online.

Westra, D., Angeli, F., Carree, M., Ruwaard, D., 2017. Coopetition in health care: a multi-level analysis of its individual and organizational determinants. Soc. Sci. Med. 186, 43–51. https://doi.org/10.1016/j.socscimed.2017.05.051.

Westra, D., Angeli, F., Jatautaitė, E., Carree, M., Ruwaard, D., 2016. Understanding specialist sharing: a mixed-method exploration in an increasingly price-competitive hospital market. Soc. Sci. Med. 162, 133–142. https://doi.org/10.1016/j.socscimed.2016.06.019.