Observational Study

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An observational study of health care provider collaboration networks and heterogenous hospital cost efficiency and quality outcomes

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Abstract

Provider network structure has been linked to hospital cost, utilization, and to a lesser degree quality, outcomes; however, it remains unknown whether these relationships are heterogeneous across different acute care hospital characteristics and US states. The objective of this study is to evaluate whether there are heterogeneous relationships between hospital provider network structure and hospital outcomes (cost efficiency and quality); and to assess the sources of measured heterogeneous effects. We use recent causal random forest techniques to estimate (hospital specific) heterogeneous treatment effects between hospitals' provider network structures and their performance (across cost efficiency and quality). Using Medicare cost report, hospital quality and provider patient sharing data, we study a population of 3061 acute care hospitals in 2016. Our results show that provider networks are significantly associated with costs efficiency ($P < .001$ for 7/8 network measures), patient rating of their care ($P < .1$ in 5/8 network measures), heart failure readmissions ($P < .01$ for 3/8 network measures), and mortality rates ($P < .02$ in 5/8 cases). We find that fragmented provider structures are associated with higher costs efficiency and patient satisfaction, but also with higher heart failure readmission and mortality rates. These effects are further found to vary systematically with hospital characteristics such as capacity, case mix, ownership, and teaching status. This study used an observational design. In summary, we find that hospital treatment responses to different network structures vary systematically with hospital characteristics..

Abbreviation: PTE = partial treatment effect.

Keywords: acute care hospitals, cost, heterogenous effects, provider networks, quality

1. Introduction

With health care cost per capita surpassing $11,500 in the United States in 2019, and with hospitals accounting for 31% of overall health care costs, understanding the inner workings of hospitals is critical to the objective of curbing rising costs without it coming at the expense of quality of care.[1] Prior work looking at the organizational structures of US hospitals has helped identify important relationships between provider network structures, inferred from patient sharing data, and hospital level costs and utilization patterns,[2,3] however, the link between network structure and hospital quality outcomes is less studied and existing studies have reported inconclusive findings.[4,5] The existence of any potential links between network structure and hospital cost-efficiency remains to our knowledge further unexplored.[4,5] Additionally, prior work focusing on US hospital networks have utilized a limited set of network measures within analyses and assumed a linear homogenous relationship between the network structure and hospital outcomes.[3,4,6–10]

In this study, we utilize Medicare patient sharing data in order to construct hospital-level provider networks across 3061 US acute care hospitals and explore the relationship between these network structures and the resulting cost efficiency and quality of care. Beyond our focus on the link between (hospital-level) network structure, quality and cost-efficiency, our study further differentiates itself from prior work in a number of important ways. Firstly, in contrast to prior studies looking at provider networks within the US acute care hospital setting, we utilize global network centralization measures, rather than averages of provider specific centrality measures (or ratios thereof). Second, we construct provider, rather than physician, networks. This allows our analysis to encompass all healthcare providers who are affiliated with, and therefore actively billing, Medicare for their services. Third, we draw on recent developments within the causal and interpretable machine learning literature in order to leverage highly flexible models that enable us to examine the heterogenous relationships between hospital network structure, cost efficiency and quality outcomes. These methods further enable us to probe the source of these heterogenous relationships by analyzing how they vary systematically with hospital characteristics such as: capacity, case mix, ownership status, teaching status, urban/rural status, bed size, disproportionate share patients, referral center and transfer center designation. Our approach

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The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

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Table 1

Summary statistics across 3 sets of variables.

Variable measure	Mean	Std. Dev.	N
Outcome variables			
log(Cost)	18.78	1.13	3061
Hospital rating high	70.76	8.21	3016
Heart failure readmission rate	21.99	1.62	274z
Heart failure mortality rate	12.06	1.49	2743
Network characteristics			
Number of nodes	359.41	311.35	3061
Number of links	15,035.40	18,953.88	3061
Global efficiency	0.60	0.08	3061
Betweenness centrality (×100)	0.01	0.10	3061
Transitivity	0.56	0.10	3061
Degree centrality	0.62	0.10	3061
Average clustering	0.77	0.06	3061
Closeness centrality	0.65	0.10	3061
Eigenvector centrality	0.13	0.06	3061
Node connectivity (/10)	0.08	0.08	3061
Cost controls			
log(Cost of labor)	11.37	0.29	3061
log(Cost of capital)	10.92	0.75	3061
log(Output Medicare)	9.15	1.46	3061
log(Output Medicaid)	7.29	1.92	2907
log(Output other)	9.43	1.66	3061
Case mix index	1.55	0.34	3061
Other hospital controls			
Capacity	0.48	0.19	3061
DSH percentage	0.29	0.17	3061
Number of beds	194.69	182.76	3061
Teaching hospital indicator	0.43	0.50	3061
Urban hospital indicator	0.62	0.49	3061
Nonprofit hospital indicator	0.60	0.49	3061
Government hospital indicator	0.15	0.36	3061
Referral center indicator	0.11	0.31	3061
Transfer center indicator	0.06	0.24	3061

At the top are the outcome variables, next the network characteristics, the cost controls, and lastly other hospital controls.
DSH = disproportionate share hospital.

also allows us to examine how these heterogenous relationships vary across US states. The focus on the heterogeneity of the relationships between hospital provider network structures and hospital outcomes present the most significant contribution of this study in relation to prior work.

In summary, the primary objectives of this study are to evaluate whether there are heterogenous relationships between hospital provider network structure and hospital outcomes (cost efficiency and quality); and to assess the sources of measured heterogenous effects.

2. Methods

2.1. Study sample

We combine a number of data-sources for the purpose of our analysis. First, we draw on Medicare cost report data for all US acute care hospitals. Here, our inclusion criterion are hospitals that were paid by Centers for Medicare and Medicaid Services using a prospective payment system during the year of 2016, and that reported information on the following cost function variables: hospital costs, outputs across Medicare, Medicaid and other patient groups, as well as data on factor input prices related to labor and capital. The Medicare cost report data was next combined with data from the Medicare Impact File for inpatient prospective payment system hospitals in 2016. This additional file provided us with hospital specific case mix indices, which we use to control for differences in the intensity of conditions treated across hospitals, and with information on the average daily bed-occupancy census at a given hospital, which we use in order to construct our capacity variable (i.e., this measures the average percentage of beds occupied at a given hospital). Second, we supplement the hospital cost information with rich hospital-level quality data from the Medicare hospital compare database. This data contains information on hospital quality outcomes, which consist of both subjective patient ratings of their hospital experience, as well as more objective outcome measures pertaining to heart failure readmission and mortality rates. Table 1 provides descriptive on all of the hospital level variables under the headings "outcome variables," "cost controls," and "other hospital controls." Looking at this table we note that our observation counts range from 2743 to 3061 depending on the outcome variable. Observations with missing data were excluded form analyses.

Next, our provider and provider-network data is sourced from 2 additional sources. The first of these is the Medicare Physician Compare database which contains information on all providers that are affiliated with, and bill through, Medicare. This dataset contains information on providers' hospital affiliations, where an affiliation is defined by the providers' having billed Medicare for at least 3 different patents (at 3 different dates) from a given hospital (within a given year). In terms of the provider network data, this was constructed from Medicare claims by DocGraph.[11] In this data a link is present so long as 2 providers share at least 14 common patients. This definition is in line with the recommendation of prior work by Barnett et al (2011) who helped validate that 1 would want a minimum of at least 9 shared patients for a network link to be considered a shared patient tie.[12,13] Similar network and provider data has previously also been used by

Linde (2019), however, in differing from that application we allow for all Medicare providers (not just physicians) and explore providers across the whole of the United States (not just for the Chicago hospital referral region).[14] This network data was first linked with our physician compare dataset, and secondly, using the hospital affiliation identifiers, each provider was linked back to their hospital affiliations.[15] In cases where providers had more than 1 entry within the Physician Compare registry, we used the most complete entry for the purpose of our analysis. A set of 8 hospital specific network measures were constructed for each hospital, and these statistics were then linked back (using centers for Medicare and Medicaid services hospital identifiers) to the hospital-level data described above. This resulted in a dataset containing the variables outlined in Table 1. In terms of the analysis samples where all the control variables are included, these vary in size depending on the outcome variable, with: 2907 complete observations for the cost model (described below), 2873 observations for the patient rating model, 2659 observations for the heart failure readmission model, and 2657 for the heart failure mortality model.

2.1.1. Ethics statement. Ethical approval was not necessary for this study as it is based on publicly available deidentified data and does not constitute human subjects research as defined by 45 CFR §46.102. Additionally, no patients were part of this study, and it therefore did not involve any patient consent. This study follows the Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) reporting guidelines.

2.2. Outcome measures

We use 4 outcome measures: (i) log total hospital expenditures; (ii) the percentage of patients rating the hospital with a 4 or 5 on a 5-point quality scale (1 = worst; 5 = best); (iii) the heart failure readmission rate; and (iv) the heart failure mortality rate.

2.3. Network measures

We use a total of 8 network measures to capture the organizational (hospital-level) network structure – degree centralization, betweenness centralization, eigenvector centrality, global efficiency, transitivity, node-connectivity, and average-clustering. Starting with the centrality measures, these are based on 3 different centrality measures. First, we define the provider i specific degree centrality in network g as: $C_i^{degree}(g) = \eta_i(g)$, where $\eta_i(g)$ is the degree of provider i in network g.[16] Betweenness centrality is also defined at the provider level, and it is given by: $C_i^{betwe}(g) = \frac{P_i(kj)/P(kj)}{(n-1)(n-2)/2}$, where $P_i(kj)$ is the number of shortest paths between the two providers k and j (within network g) that provider i is on, and $P(kj)$ is the total number of paths between providers k and j. The eigenvector centrality is expressed by: $\lambda c_i^{eigen}(g) = \sum g_{ij} c_j^{eigen}(g)$, where λ is a proportionality factor, $c_j^{Eigen}(g)$ is the eigenvector centrality of provider j and $g_{ij} = 1$ if providers i and j are connected, and $g_{ij} = 0$ if there is no connection between providers i and j within network g. Given these provider level centrality measures we are able to define our hospital (network) level centralization measure. For each of our centrality measures ($X \in \{Degree, Betweenness, Eigenvector\}$) the centralization of hospital g is given by: $C^X(g) = \frac{\sum_{i=1}^{n}(C_{i*}^X(g) - C_i^X(g))}{max_{g' \in G}[\sum_{i=1}^{n}(C_{i*}^X(g') - C_i^X(g'))]}$, where i^* denotes the provider with the highest X centrality within hospital (network) g.[16,17] This measure will be zero for networks where all providers occupy identical positions within the network, and it will increase with the level of overall inequality within the specified network measure.

Next, we utilize a number of additional measures pertaining to overall network connectivity and clustering. First, we have the measure of global efficiency, which gives us the average of the inverse across all shortest paths between all pairs of providers within the data. If these distances are small, meaning that providers are overall closely connected to each other within the hospital, then the global efficiency measure will be larger. As such, larger global efficiency measures indicate a more densely connected network structure with higher capacity for parallel information transfer and integrated collaboration among providers.[18] Conversely, if the average shortest path distance between pairs of nodes is large, then this metric will decrease, suggesting a sparser and/or regular overall hospital connectivity.

Other measures capturing network connectivity are those of: transitivity, average clustering, and node connectivity. A hospital's (network) transitivity is given by: $Transivity = \frac{NumberOfTriangles}{NumberOfPossibleTriads}$, which captures the fraction of triangles that exists within a network relative to the total number that are possible within that network. The clustering coefficient of a given provider is given by the fraction of a provider's direct colleagues that also have a link with one-another (out of all the possible such connections). The average hospital level clustering coefficient is obtained by simply averaging across all the provider clustering coefficients.[16] Lastly, the node connectivity of a hospital is given by the number of providers that would need to be removed in order to separate the hospital network into isolated sub-components. Hence higher node-connectivity implies less fragmentation, and greater interconnectivity of providers within the network at large.

2.4. Interpretation of key network measures

Within our application, we interpret patient sharing networks to represent latent collaboration/information sharing networks across providers. As such, our various network measures help capture the structure of these collaborations/information-transmission flows. First, pertaining to our centralization measures (across our degree, betweenness and eigenvector measures), these capture the degree to which all providers inhabit similar positions relative to the provider with the highest centrality importance (within a given hospital). As such, these measures help distinguish hospitals with more symmetric informational access flows from those with greater structural inequities pertaining to the flow of information. Second, our global efficiency measure helps capture overall hospital connectivity, and with that, the closeness of providers within the hospital. As such, the global efficiency measure can help distinguish hospitals that have high capacity for the diffusion of information/ideas from those that have a lower capacity for such diffusion. Third, our measures of transitivity and average clustering capture hospital network features pertaining to the level at which providers are connected to the collaborators of their own collaborators. Thus, these measures distinguish hospitals that have structures indicative of closely-knit teams, from those that do not. Lastly, the node connectivity measure similarly helps distinguish hospitals that are primarily organized around the work of several different groups, from those that have more uniform interconnectedness among all providers/teams. In summary, these measures help describe the structure of hospital provider's patient sharing relationships, and with that, they may reveal indirect information on latent organizational structures, cultures and policies that vary across hospitals.

2.5. Other control variables

In choosing our control variables we draw on the literature on cost and cost-frontier estimation by including: hospital outputs based on discharges (by Medicare, Medicaid and other payor segments); input prices for hospital full time equivalent labor units and capital expenditures; and other hospital level features such as: case-mix-index, capacity, disproportionate share percentage, bed

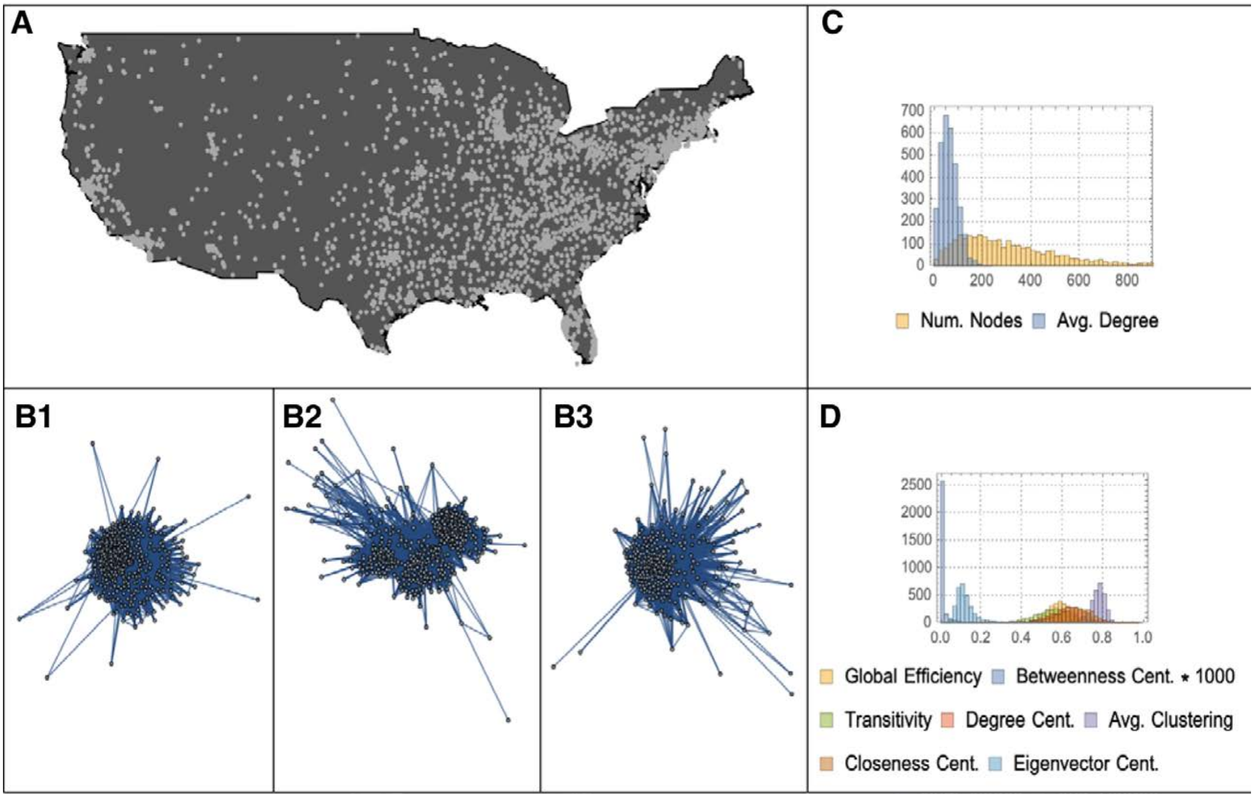

Figure 1. Hospital network statistics. (A) The acute care hospitals within our sample; (B) 3 of these networks; (C and D) the distributions for the hospital-level network features.

count, teaching status, urban location indicator, ownership status, referral center status, transplant center status, and state-level indicators.[19–25] Additional variable definition details can be found within the Online Supplementary Appendix B, Supplemental Digital Content 1, http://links.lww.com/MD/H354.

2.6. Cost and quality function specification

The output measures of hospital i is given by:

$$Y_i = f(g_i, q_i, w_i, x_i, \gamma_s) + \epsilon_i$$

where g_i captures hospital i's network feature, q_i stands for hospital outputs, w_i are input prices, and x_i includes other hospital specific controls. Lastly, γ_s denotes state level indicators. This specification draws on a rich literature on cost and cost-frontier estimation within the US hospital industry, and adds to this literature by incorporating hospital-level network features something that has not previously been modeled within this literature.[19–25]

2.7. Causal analysis: causal forest

In following with the potential outcomes framework of Neyman (1923) and Rubin (1974), we have $Y_{it}(W_{it})$ denote one of our outcome measure (defined across our cost and quality measures) for hospital i in time period t, have X_{it} capture the hospital level feature vector, and let W_{it} denote a continuous treatment variable represented by our network structure measures.[26–28] Here, our identification strategy rests on the assumption that the treatment (network) exposure W_{it} is independent of the potential outcomes $Y_i(W_i)$ conditional on X_i (a la Rosenbaum and Rubin (1983)).[29]

In order to estimate the treatment function ($\tau(x)$) of network structure upon our outcome, we adopt a causal forest methodology.[30,31] For a given tree, this approach starts by recursively splitting the feature space (X_{it}) into a set of leaves L, each containing a number of observations. Next, within each leaf of the tree, we are able to estimate the treatment effect as:

$$\tau\ (x) = \frac{Cov\,(Y_i, W_iX_i = x)}{Var\,(W_iX_i = x)}.$$

Finally, to obtain our causal forest treatment effect estimates we construct an ensemble of B trees, each with an estimated $\tau_b(x)$ (from Equation (2)). As such, the forest prediction of the network measure effect on our outcome is given by taking the average over all the predictions by the individual trees, that is:

$$\tau\,(x) = \frac{1}{B}\sum_{b=1}^{B} \tau_b(x).$$

With the individual treatment effects estimated, we examine the effect that network structure has on our hospital outcomes, and further examine how these treatment effects vary with hospital specific characteristics by means of regressing out hospital specific treatment effects on hospital characteristics (X) and state indicators (γ_s) (as described in Equation (4)):

$$\tau_i(x) = \alpha + \beta X + \gamma_s + \epsilon_{it}$$

Lastly, we also perform additional heterogeneity, and relative network variable importance, analyses using a Shapley additive explanations approach. The methodological details, and analyses result, of this approach can be found within the Online Supplementary Appendix A, Supplemental Digital Content 2, http://links.lww.com/MD/H355 and Online Supplementary

Table 2

Causal forest estimates based on an ensemble of 2000 trees.

Network measures	ATE	95% CI	*P* value
log(Cost)			
Global efficiency	–1.55	(–1.75, –1.35)	.00
Betweenness centrality (×1000)	–2.85	(–4.24, –1.47)	.00
Transitivity	–0.97	(–1.1, –0.82)	.00
Degree centrality	0.31	(0.16, 0.46)	.00
Average clustering	–0.49	(–0.80, –0.19)	.00
Closeness centrality	–0.00	(–0.14, 0.14)	.99
Eigenvector centrality	1.03	(0.72, 1.34)	.00
` Node connectivity (/10)	–0.58	(–0.81, –0.35)	.00
High patient rating			
Global efficiency	–1.26	(–5.72, 03.20)	.58
Betweenness centrality (×1000)	–18.90	(–41.03, 3.23)	.09
Transitivity	–7.39	(–10.64, –4.15)	.00
Degree centrality	5.02	(1.68, 8.36)	.00
Average clustering	5.63	(–0.41, 11.67)	.07
Closeness centrality	4.09	(1.04, 7.14)	.01
Eigenvector centrality	–3.78	(–10.64, 3.08)	.28
Node connectivity (/10)	–2.08	(–6.20, 2.04)	.32
Heart failure readmission rate			
Global efficiency	2.01	(0.85, 3.16)	.00
Betweenness centrality (×1000)	7.04	(–6.40, 20.48)	.30
Transitivity	1.36	(0.56, 2.15)	.00
Degree centrality	–0.19	(–0.97, 0.59)	.63
Average clustering	0.21	(–1.45, 1.86)	.81
Closeness centrality	0.33	(–0.39, 1.05)	.37
Eigenvector centrality	–0.62	(–2.58, 1.34)	.54
Node connectivity(/10)	1.38	(0.29, 2.46)	.01
Heart failure mortality rate			
Global efficiency	1.12	(0.06, 2.19)	.04
Betweenness centrality (×1000)	14.71	(–1.00, 30.42)	.07
Transitivity	–0.24	(–0.99, 0.51)	.53
Degree centrality	0.85	(0.11, 1.58)	.02
Average clustering	2.71	(1.18, 4.23)	.00
Closeness centrality	0.78	(0.11, 1.45)	.02
Eigenvector centrality	–0.85	(–2.66, 0.96)	.36
Node connectivity (/10)	0.82	(–0.13, 1.77)	.09

Each row represents a separate model where the stated Network Measure is used as the treatment variable. Standard errors used to construct the 95% confidence interval were clustered at the state level are reported in parentheses. Each model included additional covariates for: cost controls, other hospital controls, and state fixed effects.
CI = confidence interval.

Figure 4, Supplemental Digital Content 3, http://links.lww.com/MD/H356.

3. Results

3.1. Sample and descriptive statistics

Our results are based on a sample of 3061 acute inpatient care hospitals across the United States in 2016. These hospitals are visually displayed within Figure 1A. where each gray dot represents the geographic location of a given hospital facility. To analyze the internal collaborative structure of each hospital, we construct provider networks based on the providers' patient sharing ties related to Medicare patients. A sample of 3 such collaboration networks (representing 3 different hospitals) are visualized within Figure 1B1–1B3.

The average number of providers (or nodes) for a given hospital (network) within our data is 359 (standard deviation [SD] = 311), with a mean hospital-level average degree of 65 (SD = 35). Population level distributions for these metrics are further depicted within Figure 1C. where we note considerable heterogeneity across hospitals. This heterogeneity is also seen when we consider efficiency, transitivity, clustering and centralization measures across these hospitals (Note: these measures are defined within Section 2). Looking at Figure 1D. we see the distributions of these network statistics across our sample. Here we observe a mean global efficiency of 0.595 (SD = 0.076), mean betweenness centralization (when scaled by 100) of 0.008 (SD = 0.100), mean transitivity of 0.561 (SD = 0.103), mean degree centralization 0.621 (SD = 0.101), mean average clustering of 0.771 (SD = 0.060), mean closeness centralization of 0.652 (SD = .098), and mean eigenvector centralization of 0.129 (SD = 0.064).

3.2. Causal forest estimation results: average partial treatment effects

Table 2 reports the average partial treatment effect (PTE) estimates for all of our models across our 4 different outcomes – cost (measured using log total cost), patient rating, heart failure readmission rate and the heart failure mortality rate – and 1 of our 8 network measures. For each of these models we also include all the cost controls and other hospital controls (that are listed within the second half of Table 1), as well as state fixed effects in order to account for unobserved regional differences that may influence our outcome and treatment effects. In looking across our outcomes, we for example see that a 1 SD increase of the hospital level provider network's Global Efficiency is on average associated with a 12.4 percent reduction in cost ($P < .01$), a 0.73% increase in the heart failure readmission rate ($P < .01$), and a 0.74% increase in heart failure mortality rate. Important to note here is that the readmission and mortality rate marginal effects are sizable, with the noted change in the readmission rate representing 10.05% of the SD within the readmission rate, and similarly 6.01% of the SD within the mortality rates. What we

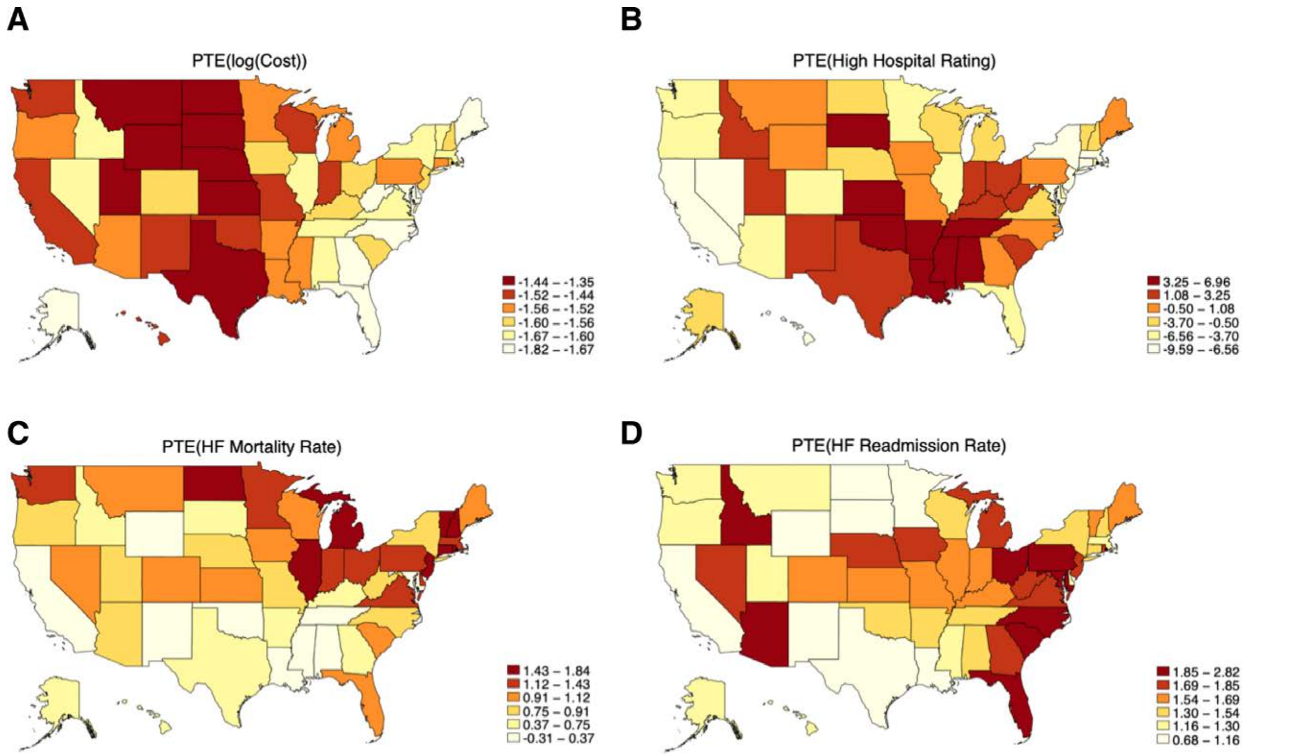

Figure 2. Hospital specific heterogenous partial treatment effects (PTEs) from global efficiency of provider network. (A) The state level variation in the average hospital partial treatment effect that the provider network's global efficiency has on log(Cost). (B–D) Report on the same variation across patient quality ratings, heart failure readmission rates, and heart failure mortality rates. HF = heart failure, PTE = partial treatment effect.

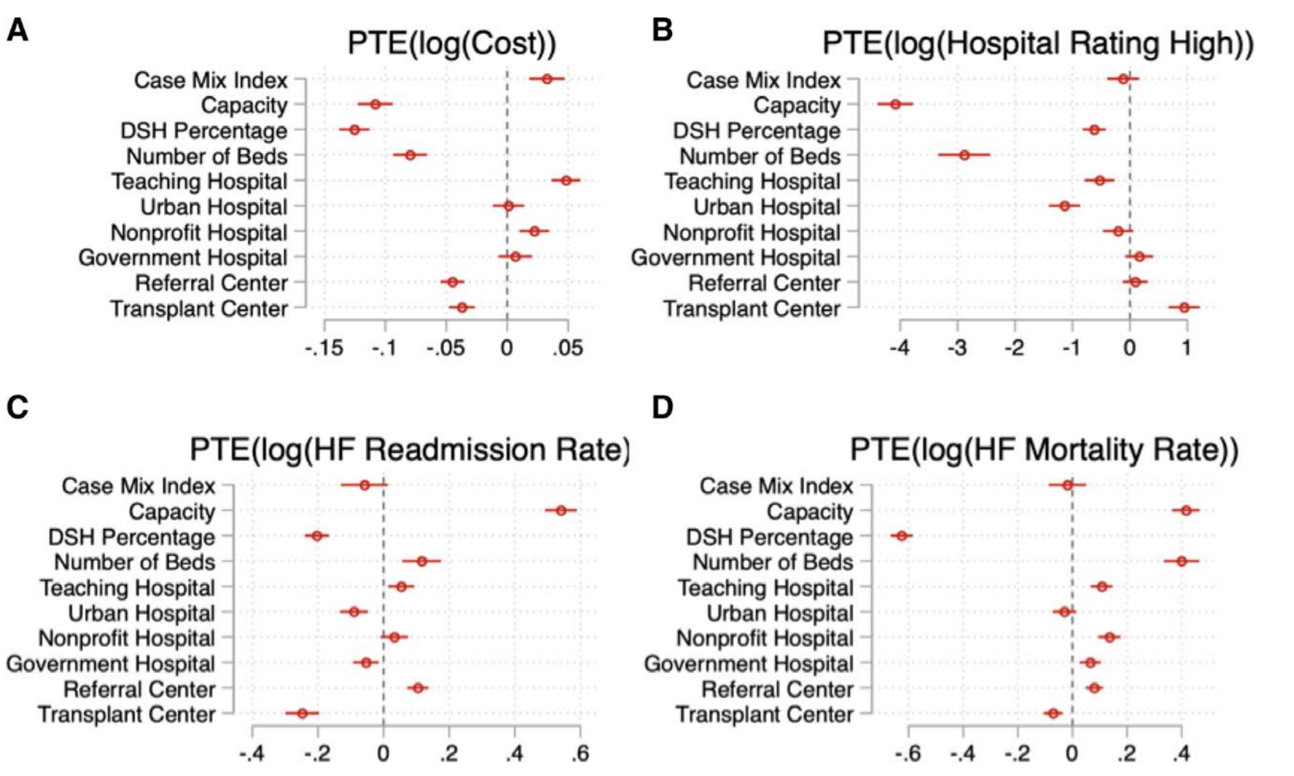

Figure 3. Hospital specific heterogeneous partial treatment effects (PTEs) from global efficiency of provider network. (A–D) Report on the coefficient plots (along with the 95% confidence bars) from regressing the estimated hospital-level partial treatment effects on the reported (standardized) hospital characteristics and state fixed-effects (not reported here). HF = heart failure, PTE = partial treatment effect.

note here, and also across our other network measures, is a broad inverse relationship between the effect that the network measures have on log total cost and the effect that they have on the quality outcomes given by the hospitals' readmission rates and mortality rates associated with heart failure. Taking the network measure of global efficiency as an example, we note that increases in global efficiency – which indicates higher global connectivity within the network – is associated with lower costs, but also with increased heart failure readmission and mortality rates. These results highlight important trade-offs between cost and quality that need to be considered in seeking to design said provider networks. Moreover, it is plausible that these effects may furthermore depend on, and interact with, institutional features that may be hospital specific.

3.3. Factors explaining heterogenous responses by hospitals to network structure

Given the preceding findings, Figure 2 presents evidence suggesting considerable heterogeneities in the partial treatment effects from provider structure on cost efficiency and quality outcomes across both geography and institutional features. Looking at Figure 2A, we see significant regional variation in the recorded average partial treatment effects across the United States, where lighter colors indicate larger (negative) PTEs for global efficiency on log total cost, and darker-red colors indicating smaller-magnitude PTEs. Figure 2B–D. similarly indicates considerable geographic heterogeneity when it comes to the PTEs of global efficiency on patient ratings, heart failure readmission and mortality. In addition, we note that the inverse relationships between the effect that network structure has on cost and quality can be seen by comparing Figure 2A with the figures on readmission (Figure 2C) and mortality.

Next, Figure 3A–D reports the coefficient plots from regressing the PTE estimates (of the hospital networks' global efficiency) on a set of hospital specific characteristics (which have here been normalized to have a unit SD for ease of interpretation). These include: patient descriptive with regards to the case mix index, and percentage of patient classified as disproportionate-share patients; operational capacity (based on the percentage of beds occupied); institutional bed size; location in terms of being urban or rural; and organizational features such as ownership and teaching status, as well as whether the organization is classified as a referral center and/or transplant center. In looking at teaching status (across Fig. 3A–D), we find that teaching hospitals tend to have a higher average PTE (due to global efficiency) when it comes to its effect on log total cost, heart failure readmission and mortality rate, but a lower effect upon patient ratings (when compared to non-teaching hospitals). These effects appear to further be mirrored when it comes to the PTE due to a nonprofit ownership status when compared to a for profit ownership classification. Perhaps most interesting are the effects noted pertaining to hospitals' operational capacity and the patient share classified as disproportionate share (i.e., share of at need low income patient population). Looking at Figure 3A–D, we see that hospitals operating at a higher level of capacity have larger cost reduction PTE gains associated with the increased global efficiency of their provider structure (a 1 SD increase in capacity corresponds to a 10.84% lower PTE on cost, $P < .001$), but we also see higher adverse effects in terms of lower PTEs pertaining to hospital rating, and higher readmission (a 1 SD increase corresponds to a 54.07% higher PTE on readmissions, $P < .001$) and mortality (a 1 SD increase corresponds to a 41.60% higher PTE on the mortality rate, $P < .001$). Considering hospitals with a larger share of patients classified as disproportionate share, however, we see that the PTE of increased global efficiency has a more cost reducing effect on hospitals, while also having lower spill-through effects onto increased readmission and mortality rates. In summary, these results highlight considerable treatment effect heterogeneity across hospitals.

4. Limitations

There are 2 important study limitations that need to be noted. First, given the observational study design, our estimates may be susceptible to omitted variable bias from unobserved confounders. Second, our results focus on acute care hospitals in the US, and may not be generalizable beyond the US, nor beyond the noted hospital types.

5. Discussion

Our results show that provider networks are significantly associated with costs efficiency ($P < .001$ for 7/8 network measures), patient rating ($P < .1$ in 5/8 network measures), heart failure readmissions ($P < .01$ for 3/8 network measures) and mortality rates ($P < .02$ in 5/8 network measures). The network measures indicate that fragmented provider structures are associated with higher costs efficiency and patient satisfaction, but also with higher heart failure readmission and mortality rates. We further find that network specific treatment responses by hospitals vary systematically with hospital characteristics such as capacity, case mix, ownership and teaching status.

The results indicate that there exists an inverse relationship between hospital level cost efficiency and heart-failure quality outcomes (across patient readmissions and mortality) related to the organizational design of provider networks. These findings suggest that any discussion concerning optimal organizational structures needs to account for the noted trade-off between cost efficiency and quality that stems from how hospital provider networks are structured. Furthermore, our analysis indicates that there exists considerable heterogeneity in the responses that different hospitals have to a given provider network structure. These findings suggest that in addition to the inverse relationship just noted (between the effect that network structure has on cost and quality outcomes), researchers have to in addition consider how the organizational features of a given hospital may act to mediate the effect that provider network structure has on that hospital's cost efficiency and quality outcomes. The observation that health outcomes across readmissions and mortality may be particularly sensitive to the structural organization of provider networks when hospitals are operating at low levels of capacity suggests that ensuring optimal provider structures may be particularly important during times of crisis and pandemics during which hospitals are pushed to work at levels that may exhaust most, if not all available capacity.

Author contributions

Conceptualization: Sebastian Linde, Hajime Shimao.
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Formal analysis: Sebastian Linde, Hajime Shimao.
Methodology: Sebastian Linde, Hajime Shimao.
Visualization: Sebastian Linde, Hajime Shimao.
Writing – original draft: Sebastian Linde.
Writing – review & editing: Sebastian Linde, Hajime Shimao.

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