Using physicians' affiliations to build hospital networks: Local clustering and the COVID-19 pandemic

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Abstract

The paper studies hospital networks where edges represent physicians' affiliated with multiple hospitals. Using data from the universe of hospitals in the Brazilian healthcare system (n=7,837) and their corresponding physicians (n=623,680), we calculate local clustering using monthly variation from January 2016 to December 2023. We estimate network disruptions induced by the COVID-19 pandemic by comparing local clustering before and after the pandemic. The pandemic caused local connectivity disruptions in neighborhoods where triads are more likely formed under light physician flow. Heavy flow neighborhoods displayed resilience to the pandemic and connectivity was largely unaffected.

Keywords: local clustering, triads, weighted networks, physicians, COVID-19, Brazil.

1. Introduction

In health care, network structures arise in diverse contexts and can influence a variety of health outcomes. For example, social networks have been shown to influence the uptake of medical treatments (Sargent et al., 2024), the diffusion of vaccines (Hao and Shao, 2022) , healthy behaviors like physical activity (Prochnow and Patterson, 2022) , unhealthy behaviors like smoking (Christakis and Fowler, 2008; Sajjadi et al., 2018) or obesity-related habits (Serrano Fuentes et al., 2019), risky sexual behavior (Asrese and Mekonnen, 2018; Shushtari et al., 2018), mental health (Park et al., 2018; Turón et al., 2023), and drug use (Falade-Nwulia et al., 2022), to name a few. Networks contribute to our understanding of health care systems, and network data can be used to develop network interventions that may accelerate and enhance healthcare delivery (Valente, 2012).

One important area where networks play a key role is technology adoption and the spread of information and knowledge (Eckles et al., 2024). The literature has documented as early as in the 1960s that physicians' networks can influence the adoption of medical innovations (Coleman et al., 1966). Since then, network analysis has been increasingly contributing to the examination of drivers of the diffusion of innovations.

Physicians, and by extension their hospitals, are embedded in networks of relationships (Bravi et al., 2013; West et al., 1999). This connectivity in health care is crucial for several reasons. For example, research shows that physicians' knowledge can gradually deteriorate over time (Durning et al., 2010; Ramsey et al., 1991). Medical innovations are often not translated into practice in a timely manner (Westfall et al., 2007). Similarly, ineffective medical practices sometimes persist despite new scientific evidence supporting de-adoption (Selby and Barnes, 2018). Well-functioning networks disseminate information and therefore can mitigate these challenges.

Clustering is an important topological characteristic for network diffusion. In a hospital network, the local clustering coefficient of hospital i is defined as the probability that two randomly selected hospitals linked to i are linked to each other. As such, local clustering measures connectivity in the neighborhood of i. Networks with low local clustering have structural holes, i.e. missing links between hospitals connected to i (Burt, 1992). These structural holes may delay or even prevent diffusion (Newman, 2010). In fact, the classical work of Watts and Strogatz suggests that the dissemination of ideas is facilitated in ‘small-world’ networks, i.e. networks with short distances between nodes and a high degree of local clustering (Watts and Strogatz, 1998).

The literature has shown that local clustering has a positive impact on content propagation (Li et al., 2018) and adoption probability (Katona et al., 2011). Moreover, the flow of information is related to organizational relations (Malenko, 2024). These organizational structures are associated with local clustering. For instance, in the economics literature, Lahdelma uses employer–employee data and finds a positive relationship between local clustering and interorganizational mobility (Lahdelma, 2022). While research has shown that networks of medical knowledge and clinical practice exhibit small-world patterns (Tachimori et al., 2013), more needs to be learned about of the patterns of local clustering in health-related networks.

The literature above highlights the importance for health care professionals to maintain connectivity. However, it is possible, or even likely, that the COVID-19 pandemic disrupted medical networks. The pandemic triggered unprecedented policy response in healthcare systems around the world. Many system-wide impacts have been documented, including: sudden inflow of patients and high admission rates associated with new COVID-19 cases (Jeffery et al., 2020; Phua et al., 2024), the suspension of elective surgeries (Frio et al., 2022), and delays in diagnosis procedures (Maringe et al., 2020). Nevertheless, less in known about how the pandemic affected topological structures of networks in healthcare. Our paper focuses on clustering.

The paper uses social network analysis to examine associations between the COVID-19 pandemic and hospitals’ local clustering using a large dataset from the Brazilian Unified Health System – SUS. SUS has a decentralized design where federal, state, and municipal governments work together to fund and manage health care delivery. While municipalities manage primary care, hospitals are typically managed by state governments. As such, we delimit hospital networks by state borders.

Our analysis is based on monthly data on physicians and their hospital affiliations. These type of data are sometimes referred to as affiliation data. We construct networks where hospitals are linked if they share physicians. This allows us to calculate hospitals' local clustering over time and make comparisons using data before and after the pandemic.

2. Methods

2.1 Data

The paper uses publicly available data from the Brazilian Unified Health System – SUS. The data is managed by the SUS's Information Technology Department – DATASUS. DATASUS divulges anonymous data available to the public in compliance with Article I of Resolution 510/2016 of the National Research Ethics Commission (Ministério da Saúde, 2016). Specifically, the data come from the National Registry of Health Establishments (in Portuguese, *Cadastro Nacional de Estabelecimentos de Saúde*) – CNES (https://cnes.datasus.gov.br/).

The CNES-PF database contains monthly information about all SUS hospitals and their corresponding physicians. The database tracks SUS physicians and how many hours they worked in each hospital. For each month, we drop physician-hospital observations where hours worked are reported to be zero.

The sampling period is from January 2016 to December 2023. In total, our sample contains 623,680 physicians and 7,837 hospitals in all Brazilian states (including the federal district). To the best of our knowledge, the paper represents the largest social network analysis of physicians' network clustering in Brazil.

2.2 Building the Hospital Network

In many health care systems, it is common for physicians to practice in multiple sites (Xierali, 2018). Physicians' connections can benefit healthcare delivery in different ways. Doctors with multiple hospital affiliations have greater service rates and procedure breadth (Linde and Beilfuss, 2021). Moreover, empirical work has shown that physicians with network affiliations are associated with higher quality of health care (Friedberg et al., 2007).

As discussed above, our data describes physician-hospital employment ties. These type of data are referred to as affiliation data as they describe which actors (physicians) are affiliated with which macro structures (hospitals). We use state-by-month affiliation data to construct undirected hospital networks where a link between two hospitals exist if at least one physician is active (i.e. works at least one hour) on both hospitals. That is, for each state and month, the hospital network is the one-model projection of the affiliation data onto hospitals.

State borders are used to define the set of hospitals in a network, which is in line with the state-level management of hospitals in SUS. As our sample includes all 26 Brazilian states and the federal district (indexed by $s = 1 \dots 27$), with monthly data from 2016 to 2023 (indexed by $t = 1 \dots 96$), our analysis involve 2592 (or 27 × 96) networks that can be indexed by st. The Appendix shows summary statistics of the hospital networks of all states, for selected periods (July of every year in the sample).

2.3 Hospital Clustering

It is reasonable to assume that the connection between two hospitals that share a large number of physicians is stronger than the connection between two hospitals that share one (or just a few) physician(s). To capture this, we develop our analysis based on weighted networks where the weight of the link between two hospitals is measured by the number of physicians the two hospitals have in common.

Our interest lies on measuring clustering on this weighted network. We employ the widely-used weighted clustering coefficient of Barrat et al. to calculate the hospital-level measure (Barrat et al., 2004):

$$C_i^w = (s_i(k_i - 1))^{-1} \sum_{jp} \frac{w_{ij} + w_{ip}}{2} a_{ij} a_{ip} a_{jp}$$

where a_{ij} is the entry $i - j$ of the adjacency matrix ($a_{ij} = 1$ if i is connected to j, 0 otherwise), and w_{ij} is the weight of the connection between hospitals i and j, s_i represents the strength of hospital i (the sum of the weights of all hospitals connected to i, $s_i = \sum_j a_{ij} w_{ij}$), k_i is the degree of hospital i (the number of hospitals connected to $i, k_i = \sum_j a_{ij}$). Barrat's weighted clustering returns its topological analog, i.e. classic (unweighted) clustering coefficient, when all nodes have the same weight.

The clustering coefficient of hospital i measures the fraction of possible interconnections between the neighbors of i. In other words, the clustering coefficient of i measures the probability that the neighbors of i are themselves interconnected. Local clustering captures whether a hospital is part of a larger highly connected group of hospitals and therefore can be viewed as a measure of the cohesiveness of the hospital's neighborhood.

The value of the (weighted or unweighted) clustering coefficient ranges between 0 and 1, where higher values indicate higher connectivity. To understand connectivity, consider the set of three hospitals (a triad) indexed by i, j, and p. A triad centered on i can have 0 links (hospitals do not share physicians), 1 link (i shares physicians with only one of the two other hospitals), 2 links (an open triangle, i is connected with both j and p, but j and p are not connected), or 3 links (a closed triangle, all three hospitals are connected – an interconnected, or transitive, triad). The higher the number of interconnected triads in the neighborhood of i, the higher is the neighborhood connectivity, and the higher is i's local clustering coefficient.

In networks where interconnected triads are more likely formed by the links with larger weights, the Barrat et al.'s weighted clustering coefficient will be larger than its topological analog ($C_i^w > C_i$). To the contrary, when the weighted clustering is less than the unweighted analog ($C_i^w < C_i$), the network structure is such that interconnected triads are generated by links with low weigh. Therefore, the comparison of C_i^w and C_i allows us to classify hospitals by the weight of links of transitive triads in their neighborhood. We refer to hospitals in neighborhoods with transitive triads of heavy physician flow as hospitals with 'High Flow Transitivity'. Conversely, if $C_i^w \leq C_i$, hospital type is of 'Low Flow Transitivity'.

The collection of all C_i^w represents the local clustering profile of a hospital network. The average C_i^w of a network summarizes its clustering profile and therefore represents a measure of cohesiveness (Barrat et al., 2004; Watts and Strogatz, 1998). Computing state and national clustering averages over time allows us to examine how the connectivity between hospitals evolve thus offering insights on system-wide trends.

2.4 Empirical Model

We estimate the following empirical model to test whether the pandemic disrupted clustering and whether the disruption varies by clustering patterns:

$$\ln(C^w)_{it} = \beta_0 + \beta_1 P_t + \beta_2 H_{it} + \beta_3 (P \times H)_{it} + f(t)_s + \rho_i + \varepsilon_{it}$$

The dependent variable $\ln(C^W)_{it}$ is the log of the clustering coefficient of hospital i in period t. P is a binary indicator for the onset of the pandemic. The first COVID-19 case recorded in Brazil was on February 25, 2020. As such, pre-pandemic baseline observations are assigned $P = 0$ while $P = 1$ from March 2020 onwards. H_{it} is a binary indicator that equals 1 for high flow transitivity, 0 otherwise. βs are parameters to be estimated. In the log-level model, the interpretation of an estimate is that a unit change in the independent variable leads to a 100β% change in the clustering coefficient. The term $f(t)_s$ represents state-specific restricted cubic splines to capture nonlinear time trends (Harrell, 2015). This term is important because the dynamics of health care systems may vary in a nonlinear fashion from state to state due to unobserved state-specific characteristics (Rocha et al., 2015). The term ρ_i is a hospital fixed effect that controls for unobserved and persistent hospital characteristics. Finally, ε_{it} is the error term that is clustered to allow for intragroup correlation.

The main interest lies on the coefficients β_1 and β_3. For each type of hospital, the model compares local clustering before and after the pandemic. β_1 indicates the percentage change in the local clustering coefficient of hospitals with low flow transitivity, where interconnected triads are more common among links with light physician flow. The impact of the pandemic on the local clustering of hospitals with high flow transitivity is given by $\beta_1 + \beta_3$.

The coefficient β_2 measures the average difference in local clustering between the two types of hospitals. A value $\beta_2 > 0$ suggests that, on average, the value of Barrat et al.'s weighted local clustering is higher in neighborhoods where closed triangles are more likely formed when hospitals share a large number of physicians. To the contrary, $\beta_2 < 0$ indicates that the local clustering coefficient is higher when closed triangles happen more frequently among light physician flow links.

The baseline (pre-pandemic) level of clustering is recovered with an exponential transformation. For hospitals with low flow transitivity, baseline local clustering is given by $\exp(\beta_0)$. For hospitals with high flow transitivity, pre-pandemic local clustering is recovered by $\exp(\beta_0 + \beta_2)$. The model is estimated using ordinary least squares.

3. Results

3.1 Descriptive Statistics

3.1.1 Hospital data

Figure 1 describes the spatial and temporal distributions of hospitals in our sample. Panel (A) distributes the 7,837 by states. We observe significant spatial heterogeneity. For example, São Paulo is the state with the largest number of hospital (1,188) while the northern state of Roraima (which borders Venezuela) has only 18 hospitals. Panel (B) shows the temporal dynamics of the number of hospitals in the entire national healthcare system. The national hospital infrastructure is relatively stable, with a small decrease in the number of hospitals around 2018-2020, followed by an increase in 2020-2022. The number of hospitals starts at 6106 in Jan 2016, drops to a minimum of 5914 in Jan 2020, and reaches 6328 in the last month of the sample (Dec 2023).

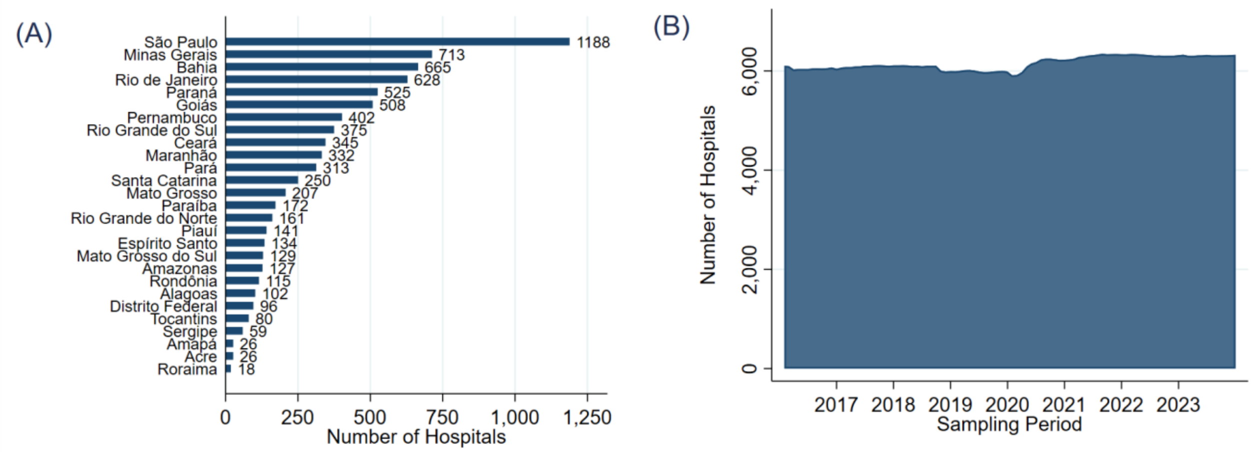

Figure 1: Number of hospitals in the study. (A) Distribution of hospitals, by state (N=7,837). (B) Number of hospitals in the sample, monthly counts from Jan 2016 to Dec 2023.

3.1.2 Physician data

Figure 2 describes the sample of physicians and their affiliations. Panel (A) distributes the 623,680 physicians in our sample by state. Again São Paulo leads the chart with 187,298 physicians, which accounts for approximately 30% of the physicians employed in SUS hospitals. Panel (B) shows the time path of the number of physicians in the national system. There is a relatively linear increase, with the number of physicians growing from 234,919 in Jan 2016 to 341,378 in Dec 2023.

To investigate the extent of practice in multiple sites, we use the physician level data to compute, for every month, the number of hospitals (employment ties or affiliations) of each physician.

Panels (C) of Figure 2 summarizes the physician-by-month data (N=27,403,641) with a focus on the number of employment ties (affiliations) for each observation. We find that approximately 14.2 million observations represent a physician-month dyad with a single hospital affiliation. More than 48% of the observations represent multiple affiliations. Panel (D) averages the count of affiliations for each month of the sample. The data show that, on average, Brazilian physicians in the hospital system are over time affiliated with an increasing number of hospitals, i.e. from an average of 1.680 (99% CI,[1.673-1.687]) in Jan 2016 to 1.976 (99% CI,[1.969-1.982]) in Dec 2023.

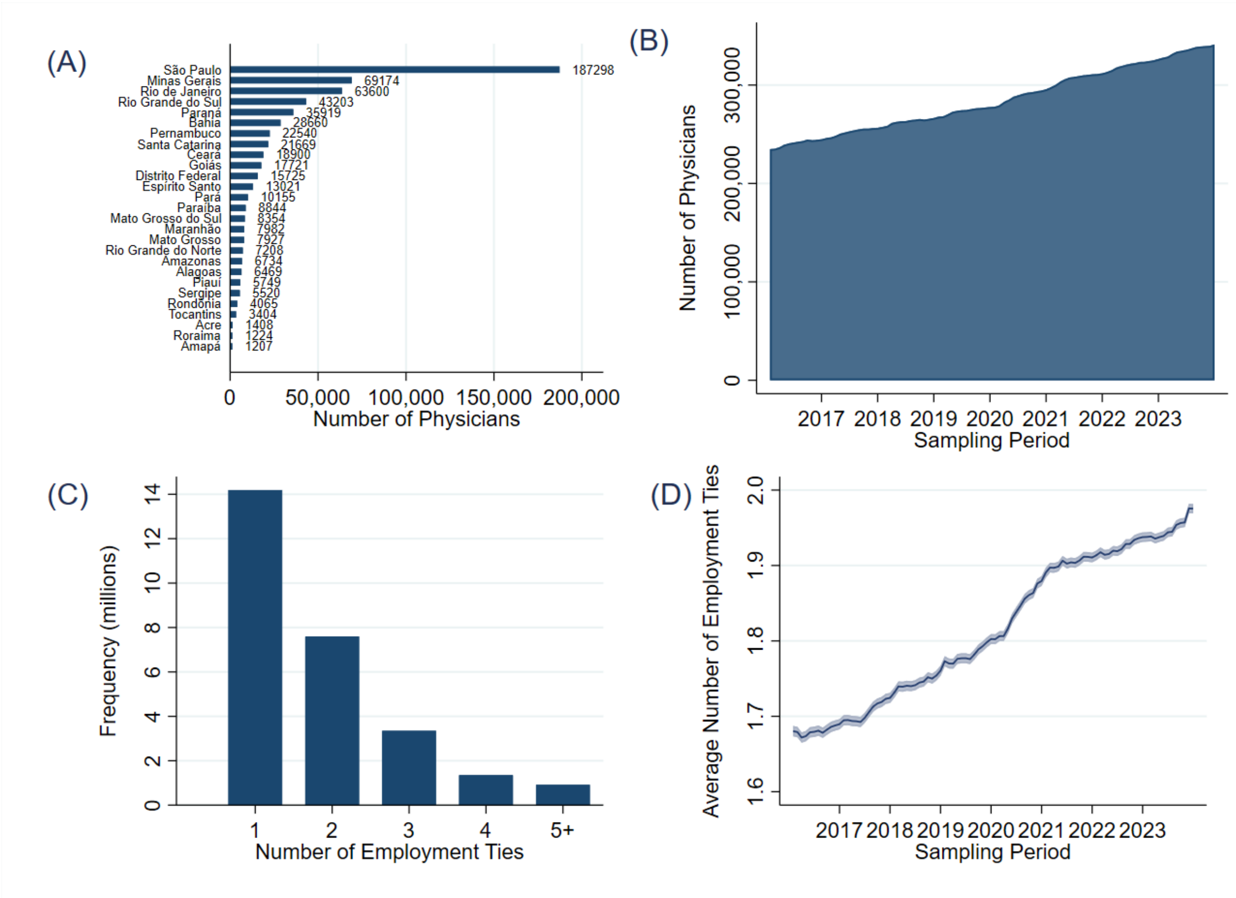

Figure 2: Description of physicians' data. (A) Distribution of physicians, by state (N=623,680). (B) Number of active physicians in the sample, monthly counts from Jan 2016 to Dec 2023. (C) Distribution of physician-month observations, by number of employment ties (N= 27,403,641). (D) Number of employment ties averaged each month over all active physicians. The shaded area represents the 99% confidence interval for the mean of the count data.

3.1.3 Model Variables

Table 1 shows summary statistics of the variables of the empirical model. As discussed above, an observation (indexed by it) represents a hospital in a month. On average, weighted local clustering is larger than its unweighted analog. This suggests that transitive triads are more common in neighborhoods with heavy (as opposed to light) flow of physicians. In fact, the last row of the table shows that $C^w > C$ for 73.4% of the observations. Both local clustering coefficients have similar interquartile range of approximately 0.3. Finally, half of the observations represent hospitals operating after the start of the COVID-19 pandemic.

Table 1: Summary Statistics

	Mean	Median	Std. Dev.	25th Quantile	75th Quantile
C^w	0.628	0.620	0.216	0.470	0.779
C	0.555	0.509	0.225	0.381	0.686
P	0.500	0	0.500	0	1
H	0.734	1	0.442	0	1

Notes: N=506,350.

Figure 3 (A) shows the distribution of Barrat et al.'s local clustering measure for all observations in our sample (N=506,350). The value of C^w is zero for only 3% of the observations. For these hospitals, none of the possible connections among the neighbors are materialized. For 10% of the observations, the neighborhood of hospitals represent a clique (all possible links are materialized, thus C^w=1). Next, we compute C^w state averages of all hospital-month observations. Figure 3 (B) displays these results in a map of Brazil. No clear spatial pattern emerges. In fact, we tested for the correlation between C^w and the state's area using a linear regression (with clustering as the dependent variable). We cannot reject the null hypothesis of no correlation between the two variables (the p-value of the slope is 0.192).

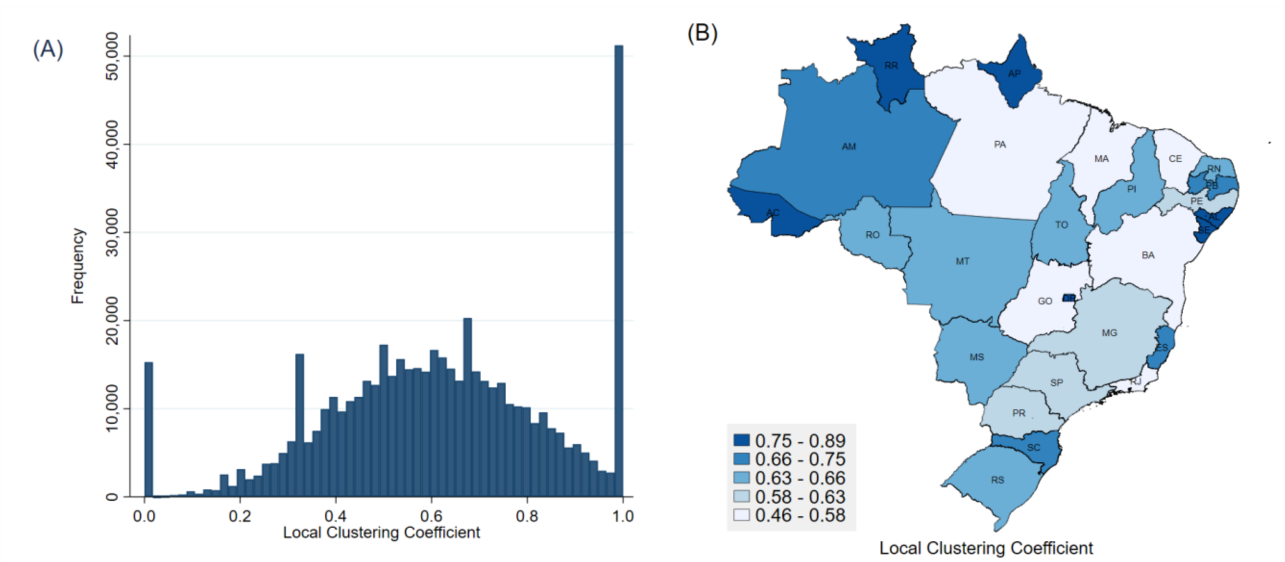

Figure 3: Local clustering coefficient. (A) The local clustering coefficient distribution using hospital-month data employed in the empirical model (N=506,350). (B) Local clustering map based on state averages of the model's data.

Figure 4 displays the national clustering dynamics in the sampling period (2016-2023). Specifically, the figure shows the monthly average of Barrat et al.'s local clustering coefficient, and its 95% confidence interval, by hospital type. In general, the local clustering coefficients of both types of hospitals are increasing over time suggesting that Brazilian hospital networks are become more interconnected. This result sheds some light on the hospitals and physicians time paths discussed above. Figure 1 (B) shows that, between 2016 and 2023, the number of hospitals is relatively stable while Figure 2 (B) shows that, in the same period, the number of physicians grew by about 45%. The data in Figure 4 suggests that the faster rate of expansion of physicians (relative to hospital infrastructure) is contributing to an increase in hospital connectivity. Figure 4 also shows that month-to-month variation of the clustering of hospitals with low flow transitivity is less smooth and noisier (with wider confidence intervals) than that of high flow transitivity.

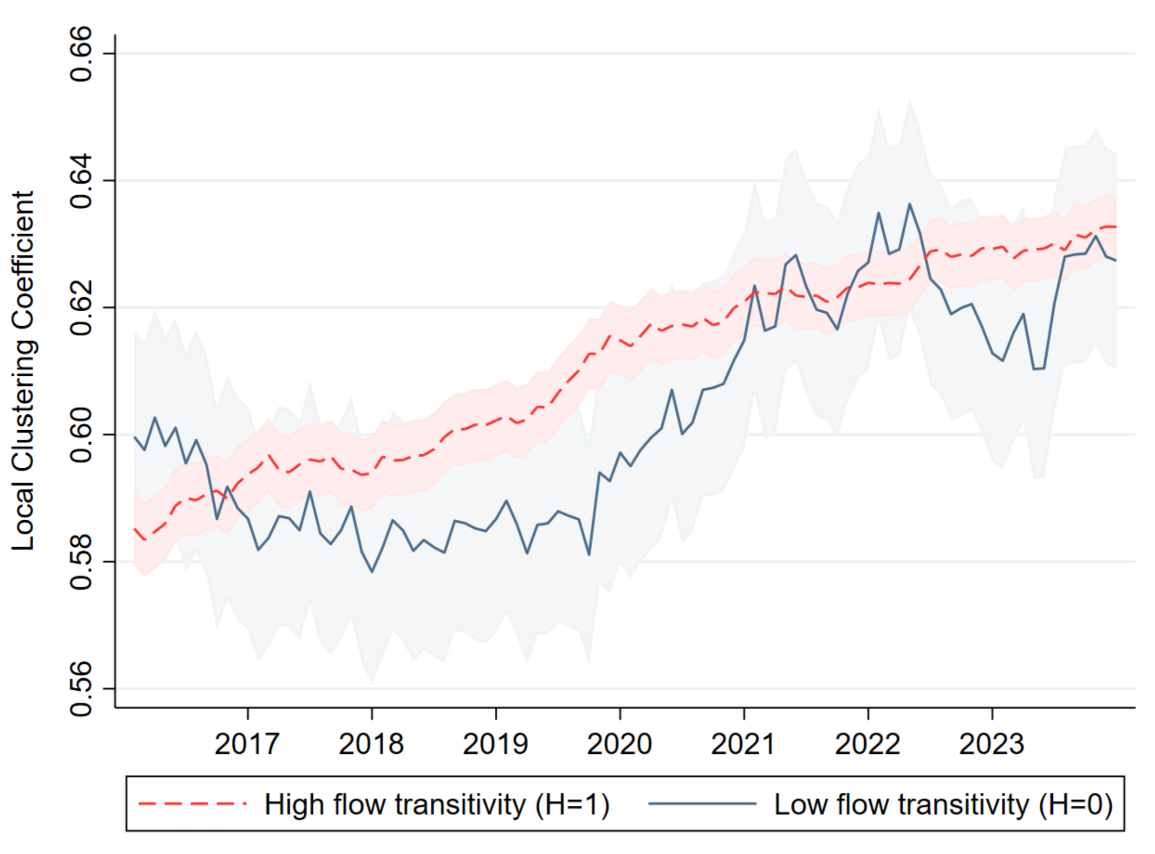

Figure 4: The system-wide dynamics of the local clustering coefficient, by hospital type. The 371,428 hospital-month observations of high flow hospitals are averaged for each month from Jan 2016 to Dec 2023. The same procedure is repeated for the 150,192 low flow observations. Shaded areas represent 95% confidence intervals for the mean.

3.2 Model estimates

Table 2 shows the estimates of the empirical model. We find that the baseline coefficient β_0 for low type hospitals is equal to -0.560 (p-value<0.01). This means that, abstracting away from state-specific nonlinear time trends and unobserved fixed hospital characteristics, the average pre-pandemic local clustering of Brazilian hospitals with low flow transitivity is $\exp(\beta_0)$=0.571. The hospital type coefficient β_2 is equal to -0.019 (p-value<0.01), i.e. hospitals with high flow transitivity have pre-pandemic levels of local clustering that are 1.9% lower than that of hospitals with low flow transitivity. On average, the pre-pandemic local clustering of high type hospitals is $\exp(\beta_0 + \beta_2)$=0.561.

We test whether the pandemic changed the local clustering coefficient of hospitals. We find a statistically significant impact for hospitals with low flow transitivity. Specifically, the estimate $\beta_1 = -0.019$ (p-value < 0.01) indicates that the local clustering coefficient of low flow transitivity hospitals after the pandemic is 1.9% lower than its pre-pandemic level.

Interestingly, we do not find the same result for hospitals with high flow transitivity. For those hospitals, the percentage impact of the pandemic is measured by $\beta_1 + \beta_3$. While both coefficients are statistically significant, they have opposite signs and similar magnitude. The pandemic effect for high type hospitals $(\beta_1 + \beta_3)$ is close to zero in magnitude and, based on a Wald test, we cannot reject the null H_0: $\beta_1 + \beta_3 = 0$ at the 5% significant level (p-value = 0.632).

Table 2: Parameter estimates

	Coefficient	**Robust Std. Err.**	**t**	**P-value**	**95% Conf. Int.**
β_0	-0.560	0.007	-80.21	0.000	[-0.573 , -0.546]
β_1	-0.019	0.007	-2.72	0.006	[-0.033 , -0.005]
β_2	-0.019	0.007	-2.86	0.004	[-0.032 , -0.006]
β_3	0.017	0.008	2.25	0.025	[0.002 , 0.032]

Notes: N=506,264. R-squared=0.69. Standard errors are clustered at the hospital level.

4. Discussion

The COVID-19 pandemic caused a public health crisis around the world. Brazil has taken much of the spotlight for being among the countries with highest infection rates and death tolls. Many scholars associate the scale of the pandemic in Brazil to poor federal government coordination that created a response vacuum to be filled by local health policies (Bigoni et al., 2022; Knaul et al., 2021; Touchton et al., 2021).

To curb the spread of the virus, Brazil (and other countries) resorted to a variety of public health policies. For example, as early as March 2020, Brazil had experienced schools and restaurants closures, lockdowns, quarantines, travel restrictions, and large event bans (Cheng et al., 2024, 2020; Porcher, 2020). Unfortunately, the sharp policy response resulted in serious unintended socioeconomic consequences (Wichmann and Moreira Wichmann, 2023; Wichmann and Wichmann, 2022).

The workforce and labor markets are areas that were significant impacted by the pandemic. Survey data reveals that the professional life of Brazilians was significantly impacted by pandemic-related restrictions (Faria de Moura Villela et al., 2021). According to a University of Oxford study that examines data from multiple countries, Brazil leads in using workplace closure as a non-pharmaceutical intervention to contain COVID-19 (Hale et al., 2021, 2020). For health care workers, mental health and burnout during the pandemic were significant issues(Cardwell et al., 2023). The collapse of health care systems and adverse working conditions contributed to exits from the health care workforce (Azzopardi-Muscat et al., 2023; Frogner and Dill, 2022; Poon et al., 2022). The pandemic also decreased the supply of health care professionals in rural areas of Brazil (Wichmann and Wichmann, 2022).

All these forces suggest that local clustering could be impacted by the pandemic. Interestingly, we only find an impact for hospitals with low flow transitivity. We do not find statistical support in the data for a pre- vs post-pandemic difference in the local clustering coefficient of hospitals with neighborhoods where transitive triads are formed by heavy physician flows. In other words, while the pandemic disrupted local clustering of low type hospitals, the local clustering in heavy flow neighborhoods was not affected by the pandemic.

Organizational support is potential mechanism for this differentiated effect. Hospitals in heavy physician flow neighborhoods may inspire organizational trust, which has demonstrated to decrease turnover intentions of health care professionals during the pandemic (Poon et al., 2022). Another possibility is differentiated working conditions. Hospitals in local systems with low physician flows may have less personnel substitution/complementarity opportunities and could rely more heavily on increased working hours in periods of high service demand such as a pandemic. This can contribute to higher turnover and consequently network ruptures. Future research with additional data should investigate these and other hypotheses to uncover the drivers of the impacts estimated here.

Finally, low local clustering may decrease local information flows and have unfavorable system-wide implications. However, it is possible for a hospital with low clustering coefficient to have a competitive edge in its neighborhood. This occurs because a low clustering hospital is in a key local position as its neighbors are in a sparse region of the network. For example, if two hospitals j and p are linked to i but are not directly connected, then i is in a key position to control the flow of ideas between j and p. We also note that networks that facilitate information diffusion do not necessarily imply that behavioral changes (Centola and Macy, 2007). Future work is needed to test these hypotheses and examine the relationship between local clustering and the performance of hospitals.

5. Conclusion

By employing social network analysis to large datasets of Brazilian hospitals and their corresponding physicians, the paper sheds light on a relatively unexplored research area to offer new insights about how the COVID-19 pandemic disrupted local healthcare networks. Clustering in neighborhoods with heavy physician flow were not disrupted by the pandemic. In low flow neighborhoods, the pandemic decreased local clustering by 1.9%.

The pandemic exposed weaknesses of health care systems around the world. As we evolve past COVID-19, various parts of multifaceted health care systems need special attention and additional support to steer service levels back to pre-pandemic trajectories. The results in this paper suggest that the pandemic disruptions can be complex and propagate through networks. Health care delivery units have differentiated demands and policy should strive to accommodate this heterogeneity. On the positive side, just like disruptions may travel through networks, health policy can also leverage networks and use a targeted approach to optimize recovery efforts. For example, in trying to re-establish the connectivity lost during the pandemic, policy can use the methods developed in this paper to identify key hospitals, facilitate targeted partnerships, and incentivize stronger cooperation.

5.1 Limitations

This study has several limitations. First, the paper uses state-month physician-hospital affiliation data to construct networks. While utilizing state borders to delimit hospital networks is consistent with the state influence over the hospital system, the temporal resolution chosen to construct the network is arbitrary. While representing networks monthly allow us to use the highest level of detail available in the raw data, we note that network structure varies according to the chosen temporal resolution (Rocha et al., 2017). Further investigations of how sensitive topology properties of Brazilian healthcare networks are to the choice of temporal resolution is beyond the scope of this paper and should be the focus of future research.

Second, our hospital network is based on the projection of our affiliation data onto hospitals. An alternative network can be constructed by projecting the affiliation data onto physicians. While the hospital network approach creates networks with approximately 20 to 1,000 nodes (see Figure 1 A and Appendix), physician networks would be significantly larger (around from 1,000 to more than 150,000 nodes) and would require significant computational resources. These physician network are similar to contact networks where ‘contact’ represent proximity in space (e.g. hospital) and time (eg month). These contact networks have been used to study epidemic spread (Liljeros et al., 2007; Rocha et al., 2020). More work is needed to examine how the COVID-19 pandemic affected structural characteristics of physician networks.

Third, while our model controls for hospital fixed effects, we acknowledge that we cannot estimate the impact of the pandemic using a two-way fixed effect model as unobserved time effects are collinear with the pandemic indicator P_t. Instead, our empirical approach uses splines to control for unobserved state-specific nonlinear time trends. The possibility remains that time-varying or trending network characteristics may influence local clustering and therefore lead to omitted variable bias. As a robustness check, we estimate an augmented version of the empirical model that includes additional control variables to capture network characteristics. Specifically, we augmented model with four new variables with variability at the network level (i.e. state-month): number of hospitals, density, diameter, and average path length. Refer to the Appendix for descriptive statistics. Results indicate that the coefficients of interest and the model's r-squared are largely unaffected, which suggests that our splines are successfully controlling for unobserved state-specific time variation such as changes in the network.

Fourth, the paper examines the impact of the pandemic on local clustering. In doing so, the paper uncovers a mechanism that mediates this impact. Controlling for hospital fixed effects, we find that only nodes in neighborhoods with light (as opposed to heavy) physician flows had their clustering negatively affected by the pandemic. However, many different dynamics could be at play and need further examination. For instance, our approach does not allow for the estimation of the impacts of time-invariant hospital characteristics on local clustering. Future research using different estimators such as fixed effects filters (Pesaran and Zhou, 2018) is needed to examine how persistent (and other) hospital characteristics mediate shocks to local clustering.

Finally, the paper focus on local clustering, which is a node level network variable that has been shown to mediate network diffusion. As we are interested in identifying impacts of COVID-19 on a node level characteristic, it is important to use panel data methods, such as node level (hospital) fixed effects, to control for confounding variation based on persistent but unobserved hospital characteristics. Nevertheless, it is plausible that the pandemic also affected (global) network structure. Future research should examine global measures of hospital networks and access possible changes caused by the COVID-19 pandemic.

Data Availability Statement

Replication data and codes are available upon reasonable requests.

Funding Declaration

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Appendix

Summary Statistics of Selected Networks

State/Initial		July 2016 Hospitals (nodes)	July 2016 Links	July 2016 Density	July 2016 Diameter	July 2016 Average Path Length	July 2017 Hospitals (nodes)	July 2017 Links	July 2017 Density	July 2017 Diameter	July 2017 Average Path Length
Acre	AC	21	56	0.267	4	1.883	21	58	0.276	4	1.858
Alagoas	AL	71	537	0.216	4	1.932	71	534	0.215	4	1.943
Amazonas	AM	108	416	0.072	8	2.646	99	387	0.08	8	2.86
Amapá	AP	10	18	0.4	3	1.583	11	16	0.291	2	1.429
Bahia	BA	529	3998	0.029	7	2.968	537	4337	0.03	7	2.891
Ceará	CE	255	1857	0.057	6	2.585	274	1990	0.053	5	2.56
Distrito Federal	DF	42	408	0.474	3	1.543	46	446	0.431	3	1.488
Espírito Santo	ES	107	955	0.168	7	2.284	105	1003	0.184	6	2.166
Goiás	GO	417	2111	0.024	10	3.233	432	2395	0.026	8	3.168
Maranhão	MA	239	746	0.026	7	3.086	250	845	0.027	9	3.236
Minas Gerais	MG	604	5722	0.031	7	2.882	602	6098	0.034	7	2.824
Mato Grosso do Sul	MS	111	425	0.07	6	2.739	113	448	0.071	6	2.637
Mato Grosso	MT	162	556	0.043	8	3.07	161	546	0.042	9	3.051
Pará	PA	230	1082	0.041	7	2.967	229	1101	0.042	7	2.877
Paraíba	PB	137	880	0.094	5	2.325	138	836	0.088	6	2.436
Pernambuco	PE	250	2070	0.067	7	2.649	253	2216	0.07	6	2.505
Piauí	PI	112	326	0.052	6	2.824	115	360	0.055	7	2.839
Paraná	PR	461	3154	0.03	8	2.976	449	3347	0.033	8	2.907
Rio de Janeiro	RJ	455	6066	0.059	6	2.416	465	6333	0.059	6	2.407
Rio Grande do Norte	RN	95	504	0.113	6	2.31	97	529	0.114	6	2.415
Rondônia	RO	81	266	0.082	4	2.368	83	281	0.083	5	2.421
Roraima	RR	12	22	0.333	3	1.556	11	16	0.291	2	1.429
Rio Grande do Sul	RS	328	3273	0.061	6	2.536	331	3592	0.066	5	2.462
Santa Catarina	SC	224	1794	0.072	5	2.593	221	2009	0.083	6	2.492
Sergipe	SE	43	266	0.295	3	1.703	42	258	0.3	4	1.735
São Paulo	SP	889	20945	0.053	6	2.441	891	22285	0.056	6	2.399
Tocantins	TO	61	99	0.054	9	2.998	63	114	0.058	8	2.956

State/Initial		July 2018 Hospitals (nodes)	Links	Density	Diameter	Average Path Length	July 2019 Hospitals (nodes)	Links	Density	Diameter	Average Path Length
Acre	AC	20	62	0.326	3	1.766	21	53	0.252	5	2.012
Alagoas	AL	70	546	0.226	4	1.916	67	530	0.24	5	1.958
Amazonas	AM	100	478	0.097	9	2.818	96	411	0.09	9	3.025
Amapá	AP	10	12	0.267	2	1.571	10	17	0.378	3	1.583
Bahia	BA	537	4456	0.031	7	2.862	531	4646	0.033	6	2.849
Ceará	CE	282	2019	0.051	6	2.627	266	1847	0.052	6	2.627
Distrito Federal	DF	55	563	0.379	3	1.615	57	605	0.379	5	1.715
Espírito Santo	ES	102	931	0.181	5	2.148	103	983	0.187	5	2.12
Goiás	GO	428	2504	0.027	11	3.168	407	2424	0.029	9	3.053
Maranhão	MA	247	951	0.031	8	3.257	250	832	0.027	8	3.283
Minas Gerais	MG	605	6940	0.038	6	2.734	597	7615	0.043	7	2.621
Mato Grosso do Sul	MS	108	465	0.08	6	2.49	106	452	0.081	5	2.587
Mato Grosso	MT	166	569	0.042	8	3.044	167	676	0.049	7	2.742
Pará	PA	238	1112	0.039	8	3.074	232	1248	0.047	9	2.91
Paraíba	PB	136	820	0.089	5	2.417	128	716	0.088	7	2.443
Pernambuco	PE	253	2208	0.069	6	2.533	256	2311	0.071	6	2.52
Piauí	PI	113	339	0.054	6	2.705	110	324	0.054	6	2.684
Paraná	PR	443	3659	0.037	7	2.825	431	3822	0.041	7	2.754
Rio de Janeiro	RJ	459	6153	0.059	6	2.414	441	6176	0.064	5	2.373
Rio Grande do Norte	RN	100	502	0.101	5	2.458	97	483	0.104	7	2.489
Rondônia	RO	83	278	0.082	5	2.414	80	274	0.087	5	2.472
Roraima	RR	13	33	0.423	2	1.5	12	25	0.379	3	1.564
Rio Grande do Sul	RS	314	3932	0.08	5	2.366	304	4149	0.09	5	2.309
Santa Catarina	SC	222	2472	0.101	5	2.322	219	2647	0.111	5	2.264
Sergipe	SE	43	278	0.308	4	1.735	40	264	0.338	3	1.691
São Paulo	SP	893	25219	0.063	6	2.344	883	26562	0.068	5	2.314
Tocantins	TO	66	131	0.061	5	2.646	68	132	0.058	4	2.491

State/Initial		July 2020 Hospitals (nodes)	Links	Density	Diameter	Average Path Length	July 2021 Hospitals (nodes)	Links	Density	Diameter	Average Path Length
Acre	AC	20	53	0.279	4	1.794	25	75	0.25	3	1.866
Alagoas	AL	82	664	0.2	5	2.045	81	709	0.219	4	1.972
Amazonas	AM	99	626	0.129	8	2.403	101	828	0.164	5	2.242
Amapá	AP	14	24	0.264	3	1.618	12	26	0.394	2	1.422
Bahia	BA	547	5173	0.035	7	2.828	565	5526	0.035	7	2.836
Ceará	CE	279	2375	0.061	6	2.496	292	2549	0.06	6	2.555
Distrito Federal	DF	60	778	0.44	3	1.578	68	970	0.426	3	1.575
Espírito Santo	ES	104	997	0.186	5	2.122	105	1028	0.188	6	2.15
Goiás	GO	411	2645	0.031	8	3.071	421	3123	0.035	8	2.803
Maranhão	MA	268	929	0.026	8	3.165	270	1003	0.028	7	3.122
Minas Gerais	MG	616	8538	0.045	6	2.582	626	9574	0.049	6	2.567
Mato Grosso do Sul	MS	108	484	0.084	7	2.633	108	530	0.092	5	2.518
Mato Grosso	MT	164	693	0.052	8	2.886	164	708	0.053	7	2.643
Pará	PA	248	1453	0.047	8	2.95	249	1436	0.047	8	2.917
Paraíba	PB	132	836	0.097	5	2.35	137	873	0.094	6	2.28
Pernambuco	PE	297	2961	0.067	6	2.507	297	2872	0.065	8	2.588
Piauí	PI	109	371	0.063	6	2.647	114	415	0.064	6	2.634
Paraná	PR	437	4106	0.043	7	2.707	429	4407	0.048	6	2.627
Rio de Janeiro	RJ	440	6788	0.07	5	2.33	446	7929	0.08	6	2.275
Rio Grande do Norte	RN	104	695	0.13	6	2.31	109	761	0.129	6	2.35
Rondônia	RO	83	318	0.093	5	2.441	88	348	0.091	5	2.436
Roraima	RR	14	28	0.308	2	1.491	13	28	0.359	4	1.773
Rio Grande do Sul	RS	315	4490	0.091	5	2.28	309	4773	0.1	5	2.225
Santa Catarina	SC	220	2744	0.114	5	2.225	225	3112	0.123	5	2.212
Sergipe	SE	42	283	0.329	4	1.704	41	283	0.345	3	1.605
São Paulo	SP	953	30365	0.067	5	2.304	969	34764	0.074	5	2.266
Tocantins	TO	70	146	0.06	6	2.655	71	191	0.077	4	2.377

State/Initial		July 2022 Hospitals (nodes)	Links	Density	Diameter	Average Path Length	July 2023 Hospitals (nodes)	Links	Density	Diameter	Average Path Length
Acre	AC	24	79	0.286	3	1.79	24	90	0.326	3	1.753
Alagoas	AL	77	810	0.277	5	1.851	79	807	0.262	5	1.896
Amazonas	AM	103	868	0.165	6	2.212	101	797	0.158	6	2.245
Amapá	AP	19	34	0.199	6	2.283	20	41	0.216	3	1.75
Bahia	BA	565	6166	0.039	6	2.686	573	6857	0.042	6	2.637
Ceará	CE	291	2789	0.066	6	2.449	290	2978	0.071	5	2.352
Distrito Federal	DF	66	871	0.406	3	1.625	67	890	0.403	3	1.598
Espírito Santo	ES	109	1093	0.186	6	2.09	106	1075	0.193	6	2.052
Goiás	GO	426	3592	0.04	8	2.731	420	3723	0.042	9	2.723
Maranhão	MA	275	1220	0.032	8	3.045	281	1364	0.035	7	2.931
Minas Gerais	MG	615	9735	0.052	6	2.532	610	10105	0.054	6	2.511
Mato Grosso do Sul	MS	112	645	0.104	5	2.438	111	765	0.125	6	2.317
Mato Grosso	MT	170	891	0.062	8	2.628	169	965	0.068	6	2.558
Pará	PA	255	1633	0.05	9	2.892	249	1658	0.054	7	2.787
Paraíba	PB	141	979	0.099	6	2.284	143	1058	0.104	5	2.222
Pernambuco	PE	284	3029	0.075	6	2.475	303	3145	0.069	6	2.492
Piauí	PI	111	450	0.074	5	2.529	113	577	0.091	5	2.469
Paraná	PR	415	4611	0.054	6	2.58	412	4774	0.056	6	2.574
Rio de Janeiro	RJ	451	8125	0.08	6	2.266	453	8403	0.082	5	2.257
Rio Grande do Norte	RN	117	831	0.122	6	2.378	122	897	0.122	7	2.406
Rondônia	RO	95	406	0.091	6	2.414	92	385	0.092	6	2.552
Roraima	RR	13	31	0.397	3	1.455	14	33	0.363	3	1.654
Rio Grande do Sul	RS	313	5020	0.103	5	2.204	308	4909	0.104	5	2.19
Santa Catarina	SC	225	3453	0.137	5	2.153	218	3581	0.151	5	2.11
Sergipe	SE	38	288	0.41	3	1.573	43	379	0.42	3	1.594
São Paulo	SP	928	35438	0.082	5	2.235	922	36969	0.087	5	2.198
Tocantins	TO	73	184	0.07	6	2.469	73	238	0.091	5	2.411