Redistribution of Patients, Medical Resource Utilization, and Quality of Care after Hospital Closure

A Modern Diff-in-Diff Approach

Jingzou Ron Huang[1]

[1]Senior Undergraduate, Quantitative Sciences and Economics, Emory University

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Background and Motivations

- Increasing number of hospital closures (Kaufman et al., 2016), but lack of prompt government support before and after closures.
  - Debate on whether to bail out closing hospitals

- Inconsistent evidence on the impact of hospital closure
  - Hospital closures as an indication of market selection $\Rightarrow$ increasing social welfare after closures of inefficient hospitals (Capps et al., 2010; Lindrooth et al., 2003; Song and Saghafian, 2019)
  - No economically significant impact on quality of care and treatment efficiency using mortality and readmission rate (Gujral and Basu, 2019; Probst and et al.,1999)
  - Significant evidence on worsened patient accessibility to healthcare and negative economic impacts (Buchmueller et al., 2006; Hodgson et al., 2015)

Background and Motivations

- Inconclusive about the whether the cost outweighs the benefits from bailing out a closing hospital
- This is a niche topic in the literature; lack of comprehensive understanding of the impact of hospital closures (Mills et al., 2024)
- The variation and the noisy results can be attributed to 3 potential pitfalls:
  - Lack of robust causal inference methodology (imbalanced numbers of treated and untreated units + heterogeneous treatment timing)
  - Lack of rigorous treatment assignment (use of hospital service area or distance)
  - limited scope in distinguishing heterogeneous treatment (location, type of services, and level of analysis/aggregation of data)

The Focus of This Paper

- The magnitude, direction, and significance of the effect can vary across those dimensions
  - Mixing those heterogeneous effects together can confound the interpretation of the overall effects
- Rural-urban difference has been widely studied, but very few have been focused on inpatient-outpatient difference and hospital-regional level difference, and how they may interact with each other
- Contribution of this study:
  - Take all three dimensions of heterogeneity in to consideration
  - Data-driven approach for treatment assignment
  - Synthetic Diff-in-Diff + First-stage Ridge Forward Selection algorithm for donor pool selection

Preview of Main results

- 8 metrics to evaluate the redistribution of patients, quality of care, and medical resources utilization and cost
- Affected hospitals receive 20-40% more patients from the affected regions
- Quality of care overall remains unchanged
  - but inpatient department experience worse quality of care than outpatient department
- Patients have experienced significant accessibility difficulties
  - Revisit/readmission related outcomes reflect more about accessibility issues rather than the quality of care
- Increasing medical resources utilization and cost per patient per visit/admission

Preview of Main results

Heterogeneous Effect

- Inpatient tends to be less affected by the closure than the outpatient department, except for quality of care
- Effects are larger and more significant at the regional level than at the hospital level
- The more rural the affected hospital and region are, the more the closure exacerbates its impact on all the metrics
  - The correlation between rural scores and estimates is stronger at the regional level than at the hospital level
  - For quality of care, the correlation between rural score and estimate is stronger for inpatient than outpatient

Roadmap

1. Data and Methodology
   - Data Source, Closure Identification, and Treatment assignment
   - Econometric Model
   - Donor Pool Selection
2. Main Results
3. Discussion and Conclusion

Data and Methodology

Data Source and Closure Identification

- 3 main data sources
  - Healthcare Cost and Utilization Project (HCUP) inpatient (SID) and outpatient (SEDD) datasets of Georgia state in the United States from 2010 to 2020
  - USDA's Rural-Urban Continuum Codes for rural scores of patients and hospitals
  - AHA Annual Survey for hospital-level information
- Closure identification: testing if a certain hospital ID has no data after a certain month
  - confirm a closure if the corresponding hospital closure announcement could be found

Data and Methodology
Hospital Characteristics

- 8 hospital closures in Georgia from 2010-2020
  - All matched with official closure announcement
  - 5 of which matched with UNC's national-wide report of hospital closure
- Based on the USDA urban-rural continuum, none of the closed hospitals in our sample is located in metropolitan areas
  - Rural score ranges from 4 to 7
  - Sufficient rural variation (population 20000 or more adjacent to metro areas versus population 5000 or more not adjacent to any metro areas)
- 4 hospitals are significantly larger than the other 4 hospitals (in terms of number of employees and yearly visits/admissions)
  - But the scale of hospitals is not strongly correlated with rural scores

Data and Methodology

Treated Units Identification

- To identify affected hospital $\Rightarrow$ To identify alternative hospital based on patient's preference conditional on closure

- HSA and HRR: historic patient flow, revealing pre-closure preference, not post-closure preference
  - Rough demarcations approximating patient flow pattern

- Treatment assignment by distance from the closed hospital is usually subjective and arbitrary
  - The standard can be hard to adjusted when we consider rural-urban comparison; ground-truth treated units could be within 20 miles for more urban closed hospital but no treated unit until 50 miles away from the more rural closed hospital
  - Only one of many factors that contribute to patients' post-closure preference

Data and Methodology

Treated Units Identification

zip code 1

zip code 2

zip code 3

⋮

zip code K

$$\longrightarrow$$

$$\{z_i^1\}_{i=1}^{N_1} \longrightarrow \begin{cases} \left\{\hat{\tau}_j^{z_1^1}\right\} = \tau\left(D,\ z_1^1,\ h_j^{z_1^1}\right) \\ \left\{\hat{\tau}_j^{z_1^1}\right\} = \tau\left(D,\ z_2^1,\ h_j^{z_2^1}\right) \\ \vdots \\ \left\{\hat{\tau}_j^{z_{N1}^1}\right\} = \tau\left(D,\ z_{N^1}^1,\ h_j^{z_{N1}^1}\right) \end{cases} \longrightarrow \mathcal{H} \leftarrow h_j^{z_i^t} \text{ if } p_j^{z_i^t} < \alpha$$

$$\{z_i^2\}_{i=1}^{N_2} \longrightarrow$$

$$\{z_i^3\}_{i=1}^{N_3} \longrightarrow$$

$$\vdots$$

$$\{z_i^t\}_{i=1}^{N_t} \longrightarrow \quad \ldots$$

- An data-driven solution: empirically test which hospitals have encountered significant influx from the affected regions
- Treated if significant influx from z_i^t (regions where closed hospital is the tth hospital) to $h_j^{z_i^t}$ (jth alternative hospital for z_i^t)
  - a more granular analysis of whether patients from the "affected regions" redistribute to "potential alternative" hospitals

$$\hat{\lambda}^{\text{sdid}} = \underset{\lambda}{\operatorname{argmin}} \left\| \overline{\boldsymbol{y}}_{post,co} - (\boldsymbol{\lambda}_{\text{pre}} \ \boldsymbol{Y}_{\text{pre,co}} + \lambda_0) \right\|_2^2$$

$$\text{s.t} \sum \lambda_t = 1 \text{ and } \lambda_t > 0 \forall t$$

$$\hat{w}^{\text{sdid}} = \underset{w}{\operatorname{argmin}} \left\| \overline{\boldsymbol{y}}_{\text{pre,tr}} - (\boldsymbol{Y}_{\text{pre,co}} \ \boldsymbol{w}_{\text{co}} + w_0) \right\|_2^2 + \zeta^2 T_{\text{pre}} \ \|\boldsymbol{w}_{co}\|_2^2$$

$$\text{s.t} \sum w_i = 1 \text{ and } w_i > 0 \forall i$$

$$\hat{\tau}^{\text{sdid}} = \underset{\mu,\alpha,\beta,\tau}{\operatorname{argmin}} \left\{ \sum_{i=1}^{N} \sum_{t=1}^{T} \left(Y_{it} - (\mu + \alpha_i + \beta_t + \tau D_{it} \right)^2 \hat{w}_i^{\text{sdid}} \ \hat{\lambda}_t^{\text{sdid}} \right\}$$

- Placebo variance estimation: resample $\mathcal{N}_{treated}$ out of $\mathcal{N}_{donor}$ without replacement within the maximum iterations B and estimate $\hat{\tau}^{(b)}$

$$\hat{V}_{\tau}^{\text{placebo}} = \frac{1}{B}\sum_{b=1}^{B}\left(\hat{\tau}^{(b)} - \frac{1}{B}\sum_{b=1}^{B}\hat{\tau}^{(b)}\right)^2$$

$$\tau \in \hat{\tau}^{sdid} \pm z_{\alpha/2}\sqrt{\hat{V}_{\tau}^{placebo}}$$

- Stacked Estimates (Porreca, 2022):

$$\hat{\tau} = \sum_{l}^{L}(\mu_l \cdot \hat{\tau}_l)$$

$$\mu_l = \frac{N_l}{\sum_l^L N_l}$$

Donor Pool Selection

Forward Stepwise Selection Algorithm

- $T \ll N_{donor} \Rightarrow$ Overfitting the pre-treatment trend
- Problem: Less predictive power of the counterfactual trend $\Rightarrow$ less credible parallel trend
- Solution: trim donor pool by forward selection (Greathouse et al., 2023; Cerulli, 2024; Shi and Huang, 2023)
  - Start with 0 donors, add one donor that brings the best fit at each step, and select the optimal number of donors that minimize the test errors.
- Downsides of the forward selection algorithm
  - Computationally burdensome
  - Parsimonious algorithm
  - Contingent on previous selection at each step

Donor Pool Selection

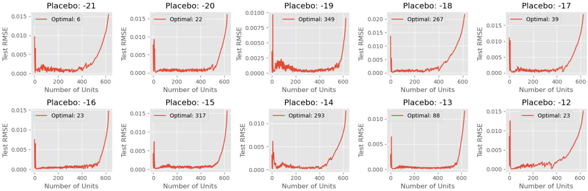
First-stage Ridge Forward selection

- First-stage Ridge Froward Selection:
  - Ranks the relative importance of donors based on L2 regularized coefficients, start from 0 donors, add one donor sequentially from the most important to the least important donor, and choose the optimal donor
- Less computationally burdensome (compute N_{donor} versus $\frac{(N+1)N}{2}$ times of $\hat{\tau}$) without loss of predictive power
- Similar strategy: First-stage LASSO and random forest

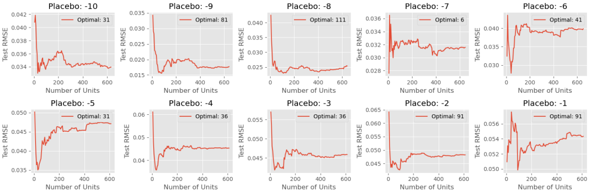
Donor Pool Selection

Placebo Experiments

Figure 1: Optimal Number of Donor Units



(a) Foward Selection



(b) First-stage Ridge

Donor Pool Selection

Placebo Experiments

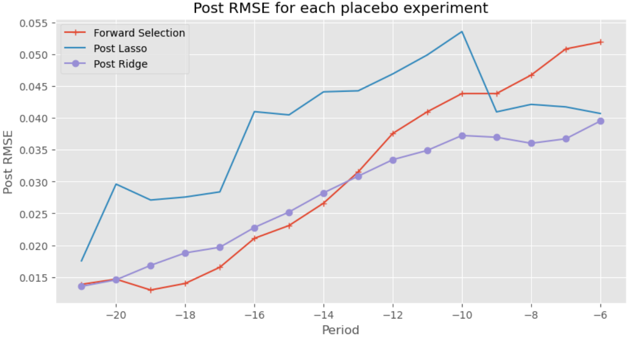


Figure 2: Avg. Post-treatment RMSE

Data and Methodology

Variable Definition

- Redistribution: monthly proportion of patients from the affected regions in the treated hospital

- Quality of care:
    - Mortality rate
    - Length of stay: proportion of overnight stay (LOS$>$0) for outpatient, length of stay for inpatient
    - *30-day Revisit/readmission rate*
    - *Number of 30-day revisit/readmission*
    - *Days between revisit/readmission within 30 days*

- Medical resource utilization and cost:
    - total medical procedures and diagnostic services per patient per visit/admission
    - total charges per patient per visit/admission

Data and Methodology

Decomposition of Effect on Revisit/Readmission

- Revisit/readmission-related outcomes were conventionally seen as a measure of the quality of care (Song and Saghafian, 2019; Mills et al., 2024)

- Decomposing the effect of hospital closure on Revisit/readmission-related outcomes

- $P(R)$ probability of revisit/readmission, $P(R) = f(E, A)$
  - E quality and efficiency of treatment, $\frac{\partial P(R)}{\partial E} < 0$
  - A represents the accessibility of healthcare, $\frac{\partial P(R)}{\partial A} > 0$
  - Post closure $\Rightarrow \frac{dE}{dC} < 0$ and $\frac{dA}{dC} < 0$

$$\frac{dP(R)}{dC} = \frac{\partial P(R)}{\partial E}\frac{dE}{dC} + \frac{\partial P(R)}{\partial A}\frac{dA}{dC}$$

- Patient will distribute to their alternative hospitals
- Quality and efficiency of care will reduce (especially for inpatient care)
- More consumption of healthcare resources per patient per visit
- Heterogeneous impact
  - The magnitude of the effect will be larger for more rural areas
  - Smaller impact on inpatients than outpatient care due to different capacity of the facility
  - Smaller impact at the hospital level than at the regional level due to the different subjects of analysis

Roadmap

Main Results

Summary Statistics

	Hospital		Zip-code	
Panel A: Outpatient Data	Treated	Donor	Treated	Donor
Count	8	132	82	869
Number of visits	13,900	56,271	5,363	8,169
Average total charges per visit	1,336	1,918	1,938	2,269
Average total medical codes per visit	5.11	5.03	5.11	5.23
Average proportion of overnight stay	0.089	0.139	0.137	0.160
Average 30-day revisit rate	0.202	0.197	0.199	0.193
Average number of 30-day revisits	2,915	11,065	1,089	1,638
Average days between visits within 30 days	11.4	11.3	11.2	11.1
Mortality rate (%)	0.209	0.182	0.207	0.184
Rural Score	5.99	3.81	5.61	3.34
Panel B: Inpatient Data				
Count	8	156	82	867
Number of visits	1,437	12,810	1,234	2,208
Average total charges per admission	11,013	30,160	26,897	30,149
Average total medical codes per admission	5.31	14.13	15.31	17.09
Average length of stay	3.67	6.27	4.51	4.75
Average 30-day revisit rate	0.28	0.24	0.25	0.23
Average number of 30-day revisits	376	2,775	284	492
Average days between visits within 30 days	10.26	11.43	10.60	10.86
Mortality rate (%)	2.35	2.66	2.31	1.84
Rural Score	6.10	3.72	5.60	3.35

The base year of all summarized outcomes is 2011, which is before any identified closures

Main Results

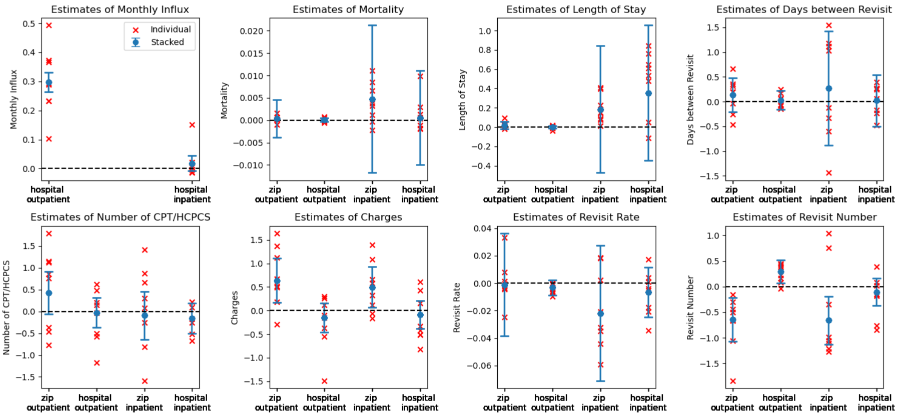


Figure 3: Stakced and Individual Estimates

- Mostly coincides with our expectations, except for quality of care
- Both numerator and denominator of revisit/readmission rate may decrease

Main Results

Heterogeneous Effect

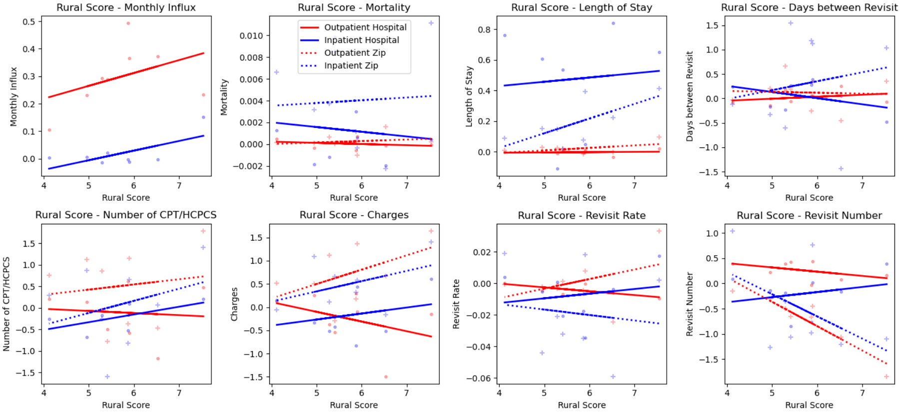


Figure 4: Correlation between Rural score and Estimates

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Discussion and Conclusion

Policy Implication

- Consistent with negative impacts of rural hospital closures on healthcare access (Buchmueller et al., 2006; Hodgson et al., 2015)
- Improve in operational efficiency of hospital markets (Capps et al., 2010; Lindrooth et al., 2003; Song and Saghafian, 2019), but increasing consumption and cost of medical resources and impaired accessibility to healthcare at the patient level
  - Hospital efficiency does not capture broader societal cost
- While bailing out inefficient hospitals may not be the optimal solution, especially at the level of the hospital market, the potential negative consequences of closures on rural communities should not be overlooked
  - Outreach health services

Discussion and Conclusion

Limitations

- Survival Bias of hospital-based data
  - Only captures those who are able to reach the hospital $\Rightarrow$ underestimate the negative effect on quality and efficiency of care
  - A major drawback not only in our study but also in the literature on hospital closure
- Only Georgia data: lack of generalizability
  - Future study: expand the scope

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