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

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Abstract

Background: Over the past decade, an increasing number of hospitals across the nation, notably in rural areas, have been recognized as being at high risk of closure. Such increasing risk raises concerns about both direct and ripple effects on nearby healthcare systems. While bailing out failing hospitals is debated, empirical evidence on closures' broader impacts, such as medical resource utilization, treatment efficiency, and rural-urban disparities, remains limited due to methodological constraints and limited in the scope of previous analysis.

Methodology: We propose a data-driven approach to define treatment groups and employ a modern difference-in-differences framework with a novel donor selection method. Using HCUP inpatient and outpatient data, we analyze the impact of eight rural hospital closures in Georgia (2010–2020) across inpatient-outpatient, hospital-region, and rural-urban dimensions.

Results: Our findings indicate that (1) hospital closures lead to patient redistribution, (2) regional medical resource utilization increases per capita per visit/admission, with stronger effects in more rural areas, (3) impairment in patients access to healthcare, particularly in rural regions, (4) no significant negative effects are observed at the hospital level, but regional effects are larger in both magnitude and significance, and (5) care quality remains unchanged. We also question the validity of revisit and readmission rates as proxies for treatment efficiency and highlight potential survival bias in similar studies.

Keywords: Health Economics, Hospital Closure, Synthetic Diff-in-Diff, Donor Pool Selection

JEL codes: I11, I18, P46, C01, C23

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1 Introduction

Rural hospital closures have become more concerning in recent decades, given that the closure rate and the number of hospitals at high risk of closing have shown no sign of declining since 2010 (Kaufman et al. (2016)). Unlike hospital closures in urban regions, where the hospital care markets are usually competitive and geographically more condensed (Succi et al. (1997)), rural hospital closures could cause severe healthcare access and financial issues for patients. Since the main cities or communities in rural areas are usually at a distance from each other and there are often few hospitals or medical facilities serving each rural community, rural hospital closure could seriously limit healthcare accessibility by driving up travel costs. Several studies have shown the negative impact of rural hospital closure on the accessibility of healthcare services for local residents (McCarthy and et al. (2021), Buchmueller et al. (2006)). While patients in urban areas do not face significantly surging hospital prices and depleting healthcare resources after hospital closure due to sufficient close substitutes with relatively lower occupancy rates in the area (Lindrooth et al. (2003)), rural hospital closure could lead to more serious depletion and inflation of healthcare resources in those rural markets with weak ability to absorb patients from the closing hospitals. This further results in deterioration in health conditions and prolonged treatment periods, as presented in a couple of studies (Gujral and Basu (2019), Probst and et al. (1999)). This could potentially incur higher charges from hospitals due to the additional procedures undergone by patients whose health conditions have been affected by the closure.

Besides accessibility and quality of care, previous studies have also focused on the economic, operational efficiency, and financial impact on adjacent hospitals after hospital closure. Studies focusing on the efficiency of the hospital market, which estimate the impact on adjacent hospitals' operational efficiency by measuring the occupancy rate or number of patients per unit of capacity, have shown a positive relationship between closure and operational efficiency of the remaining hospital (Capps et al. (2010), Lindrooth et al. (2003), Song and Saghafian (2019)). As Capps et al. (2010) suggested, inefficient hospitals are more likely to shatter, but the total cost, including operational and treatment costs, decreases as a result of market forces, where hospitals that cannot generate more benefit than cost and break even are excluded. Both poor management and market forces accelerate the closure of inefficient hospitals in urban contexts. Net welfare increases when hospitals in urban areas shut down by abating local hospital competition and contributing to the efficiency and occupancy rate in adjacent hospitals (Song and Saghafian (2019)). While urban hospitals usually have excessive capacity and low occupancy rates, this enables them to absorb extra patients from the closing hospital and increase the number of patients treated per unit of capacity. Those pieces of evidence provide strong support for the argument that the government should not financially prop up closing hospitals as they are socially undesirable. Other studies focusing on economic and financial impact have found that hospital closures negatively impact surrounding hospitals' financial performance and lead to employment declines in local healthcare sectors (Hodgson et al. (2015)), while broader economic indicators like consumer financial health and housing markets may remain largely unaffected (Alexander and Richards (2023)).

However, as the debate on whether to bail out closing hospitals persists, although we have strong evidence on the impact of hospital's operational efficiency and patient's accessibility after hospital closure, we still have very limited and inconsistent evidence on some other major outcome of interest including the quality of care and medical resource utilization. While operational efficiency concerns with the hospital level management and cost, it does not reflect welfare of patient, especially when most researchers using bed utilization as a proxy, which can only provide managerial implication instead of any insight into medical resource utilization in response to impact of closure on patient's health. This is particularly evident in the study by Song and Saghafian (2019), where, at the same time patients redistribute to more efficient hospital, the hospital also react by speeding up the response and reducing the average length of duration. In general, as Mills et al. (2024) suggests, the comprehensive impact of rural hospital closures on communities has not been well studied.

A couple of major limitation in the previous studies may have imposed obstacles in providing a holistic review of the impact of hospital closure. (1) There is a limitation in the scope in terms of the heterogeneous treatment effect. Hospital closure could be highly heterogeneous depending on the location, type of services, and subject of analysis (regional or hospital level). Previous studies either focus on one of them or do not investigate heterogeneous treatment effect. (2) The reference to Hospital Service Area, Hospital referral region, and distance from the closed hospital are common method for treated hospital identification. Both HSA and HRR define service region based on historical pattern of patient flow (of Health Care (2025)). However, since identifying treated hospital is essentially equivalent to identifying alternative hospitals based on patient's preference conditional on hospital closure, historical patient flow may not accurately reflect patient choice after hospital closure. Distance is but is only of the many factors contributing to patient's decision making. (3) Due to the nature of hospital closure, Difference-in-Difference framework is a popular causal inference method in the literature of hospital closure. Most studies utilize traditional fixed effects specification, but it is confronted with the problem of justification of parallel trend, an assumption that can only be made on faith in tradition setting.

To potentially address these issues, in this paper, we propose a data-driven and evidence-based method of treated hospital identification, utilize a modern difference-in-difference approach, the Synthetic Diff-in-Diff (Arkhangelsky et al. (2021)) for causal inference, which is incorporated with a novel donor selection method, and provide a comprehensive analysis of the treatment effect of hospital closure across dimensions of inpatient-outpatient, hospital-region, and rural-urban levels.

Roadmap: Section 2 introduces the data source, treatment identification, variable description, and empirical model. Section 3.1 provides summary statistics of variables of interest across zip-code regions, hospitals, and treatment status. Section 3.2 introduces the major findings of the study, and Section 4 summarizes and discusses the main findings.

2 Methodology and Data

2.1 Data

We use the Healthcare Cost and Utilization Project (HCUP) inpatient (SID) and outpatient (SEDD) datasets of the Georgia state in the United States from 2010 to 2020 for our analysis. HCUP SID and SEDD core files record the comprehensive information for each visit and admission, including the demographics, medical procedures, and charges. We use USDA's Rural-Urban Continuum Codes for rural scores of patient and hospitals. We use AHA Annual Survey for hospital level information.

Table 1: Hospital Characteristics and Metrics

	Hospital Characteristics							
HOSPID	13112 (1)	13074 (2)	13106 (3)	13071 (4)	13002 (5)	13055 (6)	13056 (7)	13050 (8)
Panel A: Hospital Information								
Hospital Name	Stewart Webster Hospital	Charlton Memorial Hospital	Flint River Hospital	North Georgia Medical Center	Cook Medical Center	Chestatee Regional Hospital	Southwest Georgia Regional Medical Center	Northridge Medical Center
Closure Month	7	7	7	3	3	7	10	10
Closure Year	2012	2013	2013	2016	2017	2018	2020	2020
Rural-Urban Score	7.543	5.872	5.405	5.896	5.292	4.949	6.526	4.125
Panel B: Hospital Metrics								
Total Beds	25	22	49	150	155	49	105	257
Total Inpatient Days	2811	1225	3111	26139	34476	5187	25756	60311
Total outpatient Visits	3526	9719	16820	63234	15896	24222	27257	41186
Total Payroll	2086109	4655697	3046130	13432942	6170607	7530797	5902764	12200601
Total Facility Expense	4241290	4919820	8234127	34350514	13839324	19572229	13370260	18369155
Total Full-time Employees	36	98	74	403	218	137	213	268
Closure Announcement	✓	✓	✓	✓	✓	✓	✓	✓
Matched with UNC Report	✓	✓		✓			✓	✓

All values are reported as per HCUP and AHA Annual Survey data. Rural-Urban Score is based on the USDA classification. The rural score for each hospital is average score of where the patients come from. Based on USDA urban-rural continuum, 4 - population of 20000 or more adjacent to metro area, 5 - population of 20000 or more nonadjacent to metro area, 6 - population of 5000-20000 adjacent to metro area, 7 - population of 5000-20000 nonadjacent area.

2.2 Closure Identification

We identify hospital closures first by testing if a certain hospital ID has no data after a certain month. In order to distinguish real closure from temporary closure and hospital mergers, we decided to confirm a closure if the corresponding hospital closure announcement could be found. Currently, we identify 8 hospital closures in Georgia from 2010-2020, which largely overlaps with the Rural Hospital Closures Map reported by the Rural Health Research Program at the University of North Carolina at Chapel Hill. Table 1 summaries the closure and hospital level information. Among all eight hospitals, Hospital `13112`, `13074`, `13106` and `13055` have smaller scale of inpatient services in terms of total number of beds and inpatient days than the rest of hospitals. Hospital `13112` and `13074` have both smaller inpatient and outpatient services than the rest of hospital. Based on USDA urban-rural continuum, as the rural score ranges from 4 to 7, none of the closed hospital in our sample is located in metropolitan areas.

2.3 Treated Group Identification

Hospital Level Previous studies mostly employ distance from the closing hospitals or Hospital Service Area (HSA) and Hospital Referral Region (HRR) to identify treated hospitals, which share the same HSA or HRR as the closed hospital. However, histor-

Algorithm 1: Treated Hospital Identification

Given a closed hospital, let $\{z_i^t\}_{i=1}^{N^t}$ be a sequence of zip-code regions having the closed hospital as its top tth hospital in terms of number of visits or admissions, and $t = 1, 2, \ldots, T$. Let $\{h_j^{z_i^t}\}_{j=1}^{N_2}$ be the sequence of top N_2 alternative hospital for each zip-code z_i. Let $\tau(z_i^t, h_j^{z_i^t})$ be the average treatment effect estimator and $\hat{\tau}_{ij} = \tau(z_i^t, h_j^{z_i^t})$ be the estimated treatment effect of monthly influx of patient from zip-code z_i^t to $h_j^{z_i^t}$.

Input: Panel data $\mathcal{D}$,zip-codes z_i^t, hospitals $h_j^{z_i^t}$, average treatment effect estimator $\tau(\cdot)$

```
Output: set of treated hospital H
Initialize N ← the maximum number of rankings of the closed hospital, N_2 ← the
    maximum number of alternatives, α ← significance level
Initialize H ← ∅                                      ▷ Set to store selected hospitals
for t = 1, 2, ..., T do                 ▷ Iterate over zip-codes where closed hospital is top t
    for i = 1, 2, ..., N^t do
        for j = 1, 2, ..., N_2 do                        ▷ Iterate over top N_2 alternatives
            if t ≠ j then
                Compute τ̂_ij^t = τ(D, z_i^t, h_j^{z_i^t}) and its p-value p_ij^t
                if τ̂_ij^t > 0 and p_ij^t < α then
                    H ← H ∪ {h_j^{z_i^t}}                                ▷ Store hospital
                end if
            end if
        end for
    end for
end for
Return H                                   ▷ Set of hospitals with significant patient influx
```

ical patient flow may be necessarily indicative of post-closure patient's preference. For example, HSA may include only one hospital in most case of rural areas, but patients may choose to go to another hospital that turns out to be the nearest one after hospital closure. Indeed, as summarized in Table 2, since no hospital closures are identified in a major metro area, all HSA only include the closed hospital, so no treated hospital can be identified with HSA for the analysis of rural hospital closures. On the other hand, there are hospitals sharing the same HRR code as the closed hospital, but HRR is usually a very large referral region (only 11 HRR codes for Georgia), which leads to over-identification of treated hospitals. Another strategy is to determine by distance from the closed hospital. However, distance could only be one of the many factors, such as the type of specialized services, quality of care, and insurance network, that contribute to patient's preference for hospitals.

Therefore, instead of using historical data or distance as an indirect proxy of a patient's

Table 2: Treated Hospital Identification

HOSPID	13112	13074	13106	13071	13002	13055	13056	13050
N_{treated} by post-closure patient flow	3	2	1	3	5	2	1	2
$N_{treated}$ by HSA	0	0	0	0	0	0	0	0
$N_{treated}$ by HRR	6	7	19	57	11	57	6	57

Identification based on 2011 data before any identified closure occurred. As of 2011, there are 139 unique hospital IDs, 11 hospital referral regions, and 112 hospital service regions.

post-closure preference, we can directly estimate the magnitude and significance of patient influx in the nearby hospital from the affected zip-code regions. The generic algorithm for treated hospital identification is introduced in Algorithm 1. In summary, for each zip-code region that has the closed hospital as its top tth hospital receiving the most patient from the zip-code, we estimate the monthly influx into the zip-code's 1 to N_2th alternatives, and a hospital is treated if the influx estimate is positive and significant at 5% level. This enable us to identify hospitals that are truly affected by the closure empirically based on the estimate computed by the designated treatment effect estimator $\tau(\cdot)$. Section 2.6 introduces our choice of estimator.

Zip-code Level Zip-code levels are determined similarly to the historical pattern of patient flow, where the zip-code region that has the closed hospital as its top 3 hospital receiving the most patient from the zip-code region before the closure is treated.

2.4 Variable Definition

As we want to estimate the impact of closure on patient redistribution, medical resources utilization, and quality of care, we utilize 8 variables in total as proxies of the above outcomes. Each outcome variable is both constructed at the zip-code and hospital level, except the measurement for monthly influx which is only aggregated at the zip-code level. To summarize, the proportion of patient from the treated zip-codes in the alternative hospital measures the patient redistribution pattern, averaged total charges, and number of CPT/HCPCS codes per visit or admission to measure the medical resources utilization. The length of stay, revisit or readmission, and mortality measures the quality of care and treatment efficiency. Except for monthly influx, which is only at zip-code level, all outcomes are aggregated at both zip-code and hospital levels for respective analysis. All outcomes are directly adapted from the HCUP dataset before aggregation, except

Table 3: Outcome Variables Definition

Outcome Variable	**Description**
Monthly Influx	The number of patients from the treated zip-code divided by the number of patients in one of the alternative hospitals.
Total Charges	Averaged total line item charges per patient at either hospital or zip-code level; standardized for each hospital or zip-code region.
Total Medical Procedures	Averaged total number of CPT (Current Procedural Terminology)/HCPCS (Healthcare Common Procedure Coding System) per patient at either hospital or zip-code level; standardized for each hospital or zip-code region.
Length of Stay (inpatient)	Averaged number of stays at either hospital or zip-code level.
Length of Stay (outpatient)	Number of overnight stays divided by total number of outpatient visits from a zip-code region or in a hospital.
Revisit/Readmission Rate	Number of 30-day revisit/readmission events divided by total number of visits/admissions from a zip-code region or in a hospital.
Number of Revisit/Readmission	Total count of 30-day revisit/readmission events from a zip-code or in a hospital; standardized for each hospital or zip-code region.
Days between Revisit/Readmission	Average number of days between two visits/admissions within 30 days at the zip-code or hospital level.
Mortality Rate	Number of deaths occurring during a visit/admission divided by the total number of visits/admissions from a zip-code region or in a hospital.

CPT codes are used to report medical, surgical, and diagnostic services performed by healthcare professionals. HCPCS codes are used to report medical procedures and services to Medicare, Medicaid, and other health insurance programs.

for the revisit and readmission related outcomes (revisit/readmission rate, number of revisit/readmission, days between revisit/readmission), which requires extra steps for variable construction due privacy issue[1].

2.5 Hypothesis

In general, we expect that the hospital closure will redistribute patient to nearby hospital, increase medical resources utilization, and impair the quality of care and treatment efficiency because, as what the previous studies have found, hospital closures have been imposing difficulties on accessing healthcare services and have been associated with worse health outcome of patients.

Hypothesis 1. *Closing a hospital increases patient influx to nearby hospitals.*

Hypothesis 2. *The closure leads to an increase in total medical procedures and charges per patient per visit or admission.*

Hypothesis 3. *Patients will more frequently revisit or readmit to the hospital, and the days between two visit or admissions will be reduced after closure. The length of stay*

[1]The construction of revisit and readmission related outcomes requires computation using the `DaysToEvent` variable in the HCUP dataset. The documentation of the variable is available at https://hcup-us.ahrq.gov/db/vars/sedddistnote.jsp?var=daystoevent.

will be elongated on average after closure. The mortality rate will increase after hospital closure.

Although, similarly to earlier studies such as Song and Saghafian (2019), we attempt to estimate effect on revisit/readmission related outcomes as a proxy of the quality of care, we cast doubt on its ability to unbiasedly represent the quality of care after hospital closure. The probability of revisit/readmission could be a function of both the treatment efficiency and accessibility of healthcare, which can opposite effect on the probability of revisit/readmission. Let $P(R)$ denote the probability of a patient revisiting or being readmitted after an initial hospital visit. We assume that $P(R)$ is a function of both treatment efficiency E and healthcare accessibility A such that $P(R) = f(E, A)$, where E represents the quality and efficiency of treatment post-hospital closure and A represents the accessibility of healthcare, influenced by factors such as transportation costs and distance to alternative hospitals. We assume $f(E, A)$ is differentiable, allowing us to analyze the marginal effects. If treatment efficiency declines due to hospital closure (e.g., lower quality care at alternative hospitals), the probability of revisit/readmission increases such that $\frac{\partial P(R)}{\partial E} < 0$, which means that lower E leads to a higher $P(R)$, as poor quality of care necessitates additional visits. If accessibility decreases (e.g., due to higher transportation costs or longer travel times), revisit probability declines $\frac{\partial P(R)}{\partial A} > 0$, which means a lower A makes revisits more costly or difficult, thus reducing $P(R)$. Since E and A have opposite effects on $P(R)$, the total effect of hospital closure depends on the relative magnitudes of these effects:

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

where C represents hospital closure indicator. If treatment inefficiency dominates, then $P(R)$ increases after closure. If accessibility issues dominate, then $P(R)$ decreases after closure. The net effect is ambiguous and depends on which factor has the stronger influence.

Besides, we are also interested in the heterogeneous treatment effect between inpatient and outpatient services, between rural and urban hospital closure, and between regional (zip-code level) and hospital level analysis.

Hypothesis 4. *Rural hospital closures will have more negative impacts on all outcomes* *than urban hospital closures.*

Hypothesis 5. *Hospital closures will have a more significant impact on outpatient services than inpatient services in terms of monthly influx of patients from treated regions and quality of care.*

Hypothesis 6. *Hospital closures will have a more negative impact on regional level outcomes than hospital level outcomes.*

It is immediately obvious and reasonable to expect differential treatment between rural and urban hospital closures as they have different hospital characteristics and market structures. Urban area tends to have a more condensed hospital market, which results in competing for a better quality of care and excessive capacity. Therefore, the urban context benefits patients after hospital closure by providing more choices and rooms for accommodating influx than the rural context. Besides, the inpatient department in the hospital usually owns a smaller capacity to accommodate more patients, and to have one admission usually impose stricter requirements on patients than one visit to the outpatient department, so even though patients may attempt to redistribute for inpatient services, the eventual impact would be smaller than the outpatient services. Consideration of hospital and regional-level analysis is important due to their difference in terms of the subject of analysis. Hospital level analysis provides hospital-level managerial implications, but it not only has patients redistributed from the affected region but also those unaffected ones, which therefore is confounding in decomposing patient's level implication, while, on the other hand, regional-level analysis provides a direct measurement of outcomes of the affected patients.

2.6 Empirical Model

2.6.1 Synthetic Diff-in-Diff

The most commonly used inference strategy in the hospital closure literature is the Differences-in-Differences estimator, measuring the change in the difference of certain outcomes between the affected and unaffected units. As the model requires a strict assumption of the parallel trends before the event, the biggest challenge is to find untreated units or construct counterfactuals to treated units. Because we will also have a small

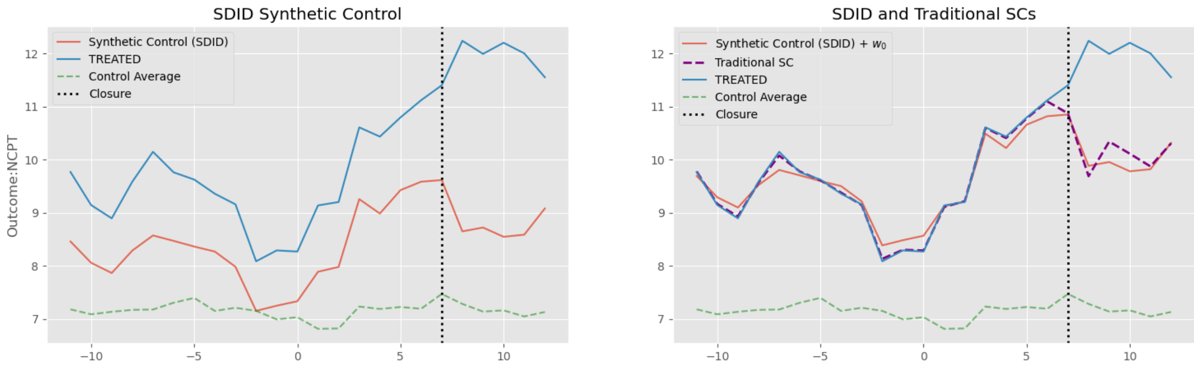


Figure 1: Example of Synthetic Diff-in-Diff Visualization

number of treated units with heterogeneous treatment effects and timing when analyzing zip-code or hospital-level aggregated data of closure at different points of time, this further induces more difficulties in the inference of the causal impact and casts doubts on the validity and robustness of past results. In this project, we follow a Synthetic Diff-in-Diff (SDID) framework proposed by Arkhangelsky et al. (2021), which introduces a seminal way for constructing counterfactual trends for the treated units by reweighting both periods and units. In contrast to the traditional synthetic control method, we have two weights for each unit of observation: an individual weight, $\hat{\lambda}^{sdid}$, and a time weight, $\hat{w}^{sdid}$. $\hat{\lambda}^{sdid}$ could be calculated as minimizing the 2-norm of the difference between the post-treatment outcome of the untreated units and the fitted post-treatment outcomes predicted by the weighted average pre-treatment outcomes of the untreated units subject to the constraint that the sum of weights equals to 1 with each of them being positive:

$$\hat{\lambda}^{\text{sdid}} = \underset{\lambda}{\operatorname{argmin}} \left\| \overline{\boldsymbol{y}}_{post,co} - (\boldsymbol{\lambda}_{\text{pre}} \, \boldsymbol{Y}_{\text{pre,co}} + \lambda_0) \right\|_2^2$$
$$\text{s.t} \sum \lambda_t = 1 \text{ and } \lambda_t > 0 \forall t$$

The individual weights are similar to that of synthetic control, where we minimize the 2-norm of the difference between the pre-treatment outcome of the treated and the weighted sum of the pre-treatment outcomes of untreated units with an additional intercept and penalization term:

$$\hat{w}^{\text{sdid}} = \underset{w}{\operatorname{argmin}} \left\| \overline{\boldsymbol{y}}_{\text{pre,tr}} - (\boldsymbol{Y}_{\text{pre,co}} \, \boldsymbol{w}_{\text{co}} + w_0) \right\|_2^2 + \zeta^2 T_{\text{pre}} \, \|\boldsymbol{w}_{co}\|_2^2$$
$$\text{s.t} \sum w_i = 1 \text{ and } w_i > 0 \forall i$$

Algorithm 2: First-Stage Ridge Regression with Forward Selection

Input: Panel data $\mathcal{D}$ with a set of donor $\mathcal{N}_{donor}$ and treated units $\mathcal{N}_{treated}$
Initialize $\mathcal{S} \leftarrow \emptyset$ (selected donor pool)
Split pre-treatment data:
  $\mathcal{D}_{\text{train}}, \mathcal{D}_{\text{test}} \leftarrow \text{split}(\mathcal{D}_{\text{pre}}, 0.7)$ ▷ First 70% periods for training, last 30% for testing
Initialize The outcome vector of treated unit y_{treated}, the outcome matrix of donor units Y_{donor} from $\mathcal{D}_{train}$, $J \leftarrow$ number of columns of Y_{donor}
Compute donor importance scores using Ridge regression on the training set:

$$\text{Importance}(\mathcal{N}_{donor}) = \text{Ridge}(\mathcal{D}_{\text{train}}, \mathcal{N}_{donor}, \lambda)$$

where λ is the regularization parameter to be chosen via cross-validation.
Rank donors based on their importance scores:

$$\mathcal{N}_{\text{ranked}} = \text{Sort}(\mathcal{N}_{donor}, \text{Importance}(\mathcal{N}_{donor}))$$

Initialize Best test error $\mathcal{E}_{\text{best}} \leftarrow \infty$, optimal donor pool size $k_{\text{opt}} \leftarrow 0$
for $k = 1, 2, \ldots, J$ **do** ▷ Iterate over number of donors
  $\mathcal{S} \leftarrow \mathcal{N}_{\text{ranked}}[1:k]$
  $\hat{w}_k = \arg\min_w \|y_{\text{treated}} - Y_{\mathcal{S}} w\|_2^2$, where $Y_{\mathcal{S}}$ is the matrix of outcomes for the selected donor pool $\mathcal{S}$.
  $\mathcal{E}_k = \|y_{\text{treated}} - Y_{\mathcal{S}} \hat{w}_k\|_2^2$
  if $\mathcal{E}_k < \mathcal{E}_{\text{best}}$ **then**
    $\mathcal{E}_{\text{best}} \leftarrow \mathcal{E}_k$ ▷ Update best error
    $k_{\text{opt}} \leftarrow k$ ▷ Update optimal number of donors
  end if
end for
Return: $\mathcal{S}_{\text{opt}} \leftarrow \mathcal{D}_{\text{ranked}}[1:k_{\text{opt}}]$ ▷ Optimal donor pool

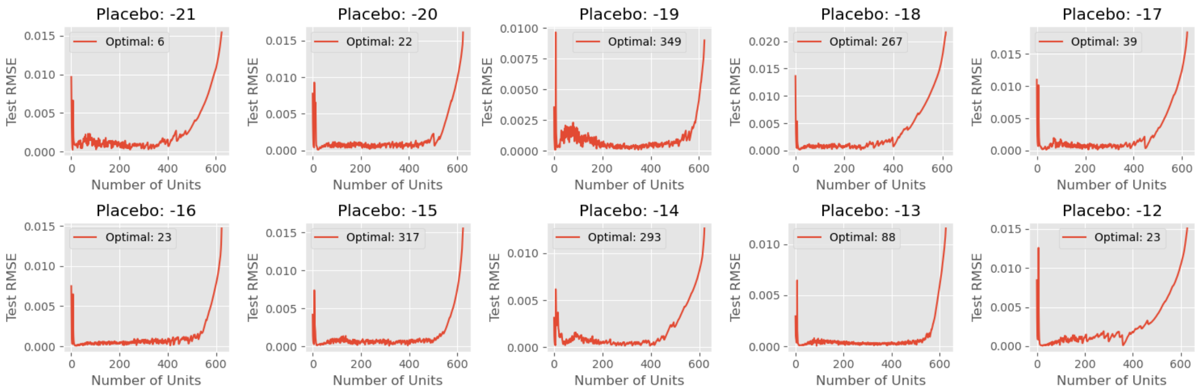
At last, we join the two weights together and calculate the synthetic Diff-in-Diff estimates by solving the following problem.

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

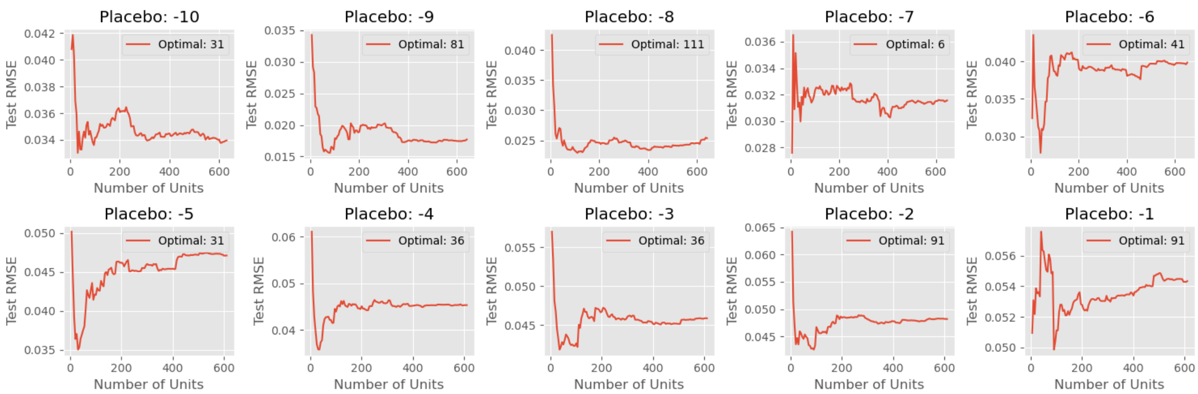
This setup allows us to construct counterfactuals to the treated units as a weighted sum of the untreated units, using both time and individual weights. In contrast to synthetic control, synthetic Diff-in-Diff results in parallel trends that allow selection bias to exist and are artificially manipulated to be constant across periods. Figure 1 is an example of the visualization of this method using the HCUP data. We can see that the counterfactual of synthetic Diff-in-Diff evolves in a very similar pattern to that of the treated units. Eliminating the intercept from this counterfactual, we can compare it with the canonical synthetic control and see that they both fit the pre-trend of the

Figure 2: Optimal Number of Donor Units

(a) Foward Selection



(b) First-stage Ridge



treated units well. The synthetic Diff-in-Diff, as simulated by Arkhangelsky et al. (2021), provides desirable asymptotic properties such that the estimate is less biased and more normally distributed compared to canonical Diff-in-Diff and synthetic control when we have a large panel with a minimal number of treated units.

Placebo Variance Estimation Because of the imbalance between the number of treated and untreated units, the traditional setup of robust standard errors would be biased, and we will follow the placebo variance estimation to construct the estimator's variance. The main idea is to resample $\mathcal{N}_{treated}$ out of $\mathcal{N}_{donor}$ without replacement within the maximum iterations B and rerun the synthetic diff-in-diff algorithm to estimate $\hat{\tau}^{(b)}$ for each placebo sample. Compute $\hat{V}_{\tau}^{\text{placebo}} = \frac{1}{B}\sum_{b=1}^{B}\left(\hat{\tau}^{(b)} - \frac{1}{B}\sum_{b=1}^{B}\hat{\tau}^{(b)}\right)^2$, such that $\tau \in \hat{\tau}^{sdid} \pm z_{\alpha/2}\sqrt{\hat{V}_{\tau}^{placebo}}$. For a more detailed discussion of the method, please refer to section 5 of Arkhangelsky et al. (2021).

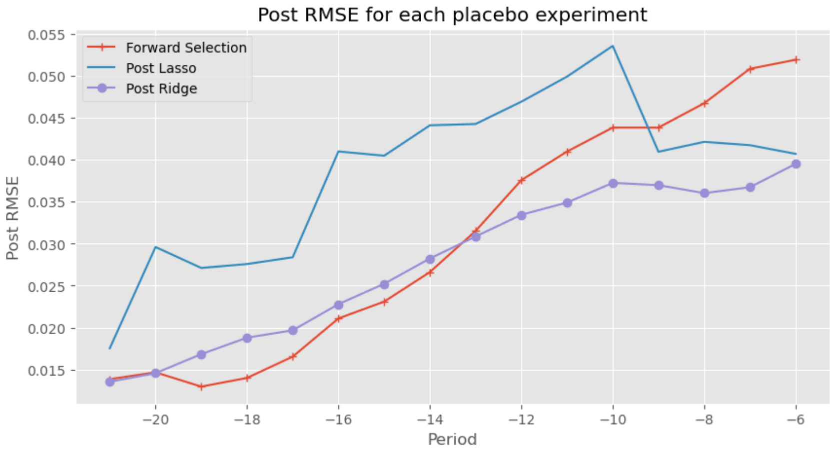


Figure 3: Test RMSE

Stacked Estimates Due to the heterogeneous treatment timing, we will adapt the staggered version of the synthetic diff-in-diff algorithm as introduced by Porreca (2022). A similar idea is also introduced in the appendix of Arkhangelsky et al. (2021): we compute $\hat{\tau}_l$ for each treatment cohort l and compute $\hat{\tau} = \sum_l^L(\mu_l \cdot \hat{\tau}_l)$, where the weight is defined as the proportion of treated units belong to each treatment cohort, $\mu_l = \frac{N_l}{\sum_l^L N_l}$. The variance of $\hat{\tau}$ can be computed by $\hat{V}_\tau = \mu^\top \hat{V} \mu$, where μ is the $l \times 1$ vector of weights and $\hat{V}$ is the variance-covariance matrix by stacking all $\hat{V}_l$ together so that the diagonal entries are the variance for each $\hat{\tau}_l$ estimated by placebo variance estimation introduced previously.

2.6.2 Donor Pool Selection

While the synthetic control methods provide relatively more robust causal inference than the traditional Diff-in-Diff framework by taking advantage of the artificial parallel trend, their robustness relies heavily on the predictive power of the artificial counterfactual trend, which the choice of the initial set of donors can significantly influence. As Greathouse et al. (2023) and Cerulli (2024) suggested, the synthetic control method can be theoretically biased when the number of donors is way larger than the number of pre-treatment periods, which can raise serious overfitting issues when constructing the counterfactual pre-trend. This is the exact context we have in this study of hospital closure, where the donor pool for closed hospitals includes over 100 hospitals, and the donor pool for affected zip-code regions includes over 600 to 700 zip codes. Therefore, to address this particular overfitting issue, the initial number of donors, J, can be seen as a trainable hyperparameter to

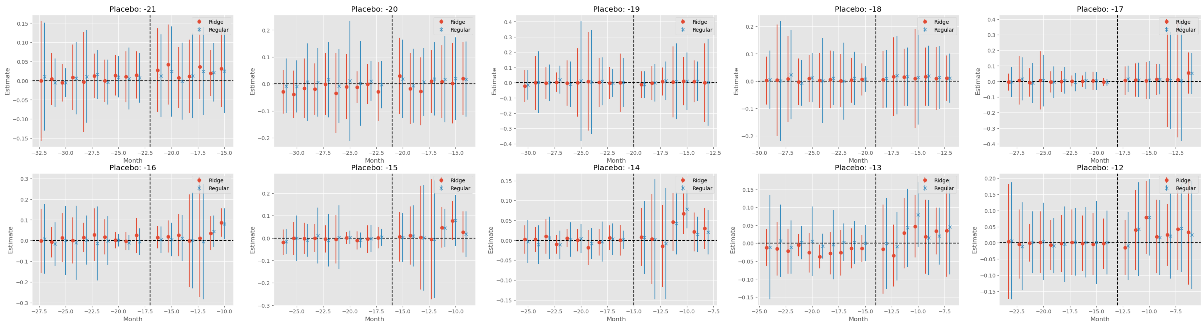


Figure 4: Event Studies for Placebo Experiments

improve the predictive power of the counterfactual trend. A popular choice is the forward stepwise selection, which is a parsimonious algorithm that starts with 0 donors and adds one donor, which brings the best fitness among all donors, at each step, until all donors are selected. The optimal number of donors is the one where the mean squared error between the treated units and synthetic control is the smallest. The suggestion of hyperparameter tuning of J is not limited to synthetic control methods and is proposed in the more general panel data setting to choose the optimal cross-sectional control units (Shi and Huang (2023)).

However, the major drawback is the computational cost of the forward selection algorithm. Assuming we begin with N donors, at each step, from $j = 1$ to N, we need to compute the estimate $\hat{\tau}$ for $N - (j - 1)$ times. Since the total iteration is N, we have to compute $\hat{\tau}$ for $\frac{(N+1)N}{2}$, so if we have 700 zip codes in the donor, the total number of computation will be 245350, which practically can be very computationally burdensome for large datasets. Besides, the forward selection method has another major limitation. The parsimony of the algorithm can again overfit the data, and the algorithm is contingent on the previous selection of donors and will not go back to eliminate previously selected donors, which means that, even if a donor is important in predicting the treated units, its selection heavily depends on its interaction with the previously selected donors.

To combat these issues, we propose the first-stage Ridge forward selection algorithm as described in 2. The main idea is to generate a relative importance rank of donors and forwardly select the most important to least important donors. The first advantage is its computational cost, which, in contrast to the regular forward selection method, only takes N computations of $\hat{\tau}$. Second, in practice, it has comparable predictive performance with the regular forward selection method. As shown in 2, both methods identify the optimal number of donors way less than the total number of donors, and the first-stage ridge and forward selection methods do not dominate each other in terms of the test root mean squared error in 3 (while in comparison, LASSO can eliminate too many donors when they are correlated, which is plausible in the case of trend prediction). Eventually, it turns out that the parallel trend is more robust as the confidence interval of the event studies in 4 is narrower for first-stage Ridge than the regular forward selection algorithm, while the estimates do not vary too much between methods. This suggests that the first-stage forward selection method could be a good substitute for the regular forward selection method when the computational cost imposes great obstacles in practice, as first-stage Ridge does not differ from the regular forward selection and even outperforms in our case in terms of the robustness of parallel trend.

3 Results and Analysis

In this section, we will discuss the summary statistics of outcomes by level of analysis, source of data, and treatment status in Table 4, and present the treatment effect estimates for all outcomes of interest computed by synthetic diff-in-diff combined with the first-stage Ridge forward selection method (Result Table 5 for the monthly influx, A4 for total charges, A3 for total medical codes, A6 for the length of stay, A5 for mortality rate, A1 for revisit rate, A7 for the number of days between visits/admissions, A2 for number of revisits/readmissions; Event study Plot 5 for the monthly influx, A7 for total charges, A6 for total medical codes, A5 for the length of stay, A4 for mortality rate, A1 for revisit rate, A3 for the number of days between visits/admissions, A2 for number of revisits/readmissions).

3.1 Summary Statistics

Table 4 presents the summary statistics of outcomes and characteristics for all treated and donor zip codes and hospitals in both outpatient and inpatient data. These statistics are based on 2011 data, prior to any hospital closures. A few key observations emerge from this table. First, treated hospitals and zip-code regions tend to be smaller in scale compared to donor units, as reflected in the lower number of visits, admissions, revisits, and readmissions. Additionally, treated units are more likely to be located in rural areas.

Table 4: Summary Statistics for Hospital and Zip-code Levels

	Hospital		Zip-code	
Panel A: Outpatient Data	Treated	Donor	Treated	Donor
Count	8	132	82	869
Number of visits	13900	56271	5363	8169
Average total charges per visit	1336	1918	1938	2269
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	2915	11065	1089	1638
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 stays	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 occurred.

Second, there are notable differences in medical resource utilization. In inpatient services, both the total medical codes and charges per admission are significantly lower in treated hospitals than in donor hospitals. However, at the zip-code level, the difference in average medical codes per admission for inpatients is much less pronounced. In contrast, for outpatient services, the number of medical codes and charges per visit are relatively similar across treated and donor units at both the hospital and zip-code levels. These differences may stem from the distinct medical constraints faced by inpatient departments in rural hospitals. Inpatient departments typically handle more severe health conditions that require advanced medical technologies and specialized services—resources that may be lacking in rural hospitals. As a result, when local inpatient departments are unable to provide adequate care, patients may be redirected to better-equipped hospitals. This is reflected in the higher inpatient mortality rates compared to outpatient services and the relatively similar medical charges and codes per admission at the zip-code level. The latter suggests that once patients seek inpatient care, their conditions are often more severe, necessitating higher levels of medical intervention at more urban hospitals.

These stark differences in demand and medical resource utilization patterns between rural and urban inpatient departments might impose obstacles in matching counterfactuals as they might have very distinct evolving trends of outcomes across the times and may react differently in response to external shocks like hospital closures. Beyond this key difference, there are no significant disparities in other observed outcomes and characteristics.

3.2 Main Results

Redistribution According to what we have found and presented in Table 5, there is a significant impact on the monthly influx of patients from the treated zip-code regions to the nearby hospital. To recap, the outcome here is defined as the proportion of patients in a zip-code region's secondary hospital who come from the corresponding zip-code region. The primary hospital of a zip-code region is defined as the hospital receiving the most patients from the corresponding region before any hospital closure. The secondary hospital is similarly defined as the hospital receiving the second most patients before any hospital closure. Here the treated zip-code region is defined slightly differently than the treatment assignment in other outcome analyses: the treated zip-code region is the one that has the closed hospital as the primary hospital. In contrast, the treated group is defined as the regions that have the closed hospital as one of its top 3 hospitals. The previous treatment assignment is more granular so that it can accurately identify the affected hospital. Algorithm 1 describes the comprehensive analysis of the monthly influx into more alternative hospitals from zip-code regions with different degrees of preference for the closed hospital. For ease of presentation, we only present the redistribution of patients from the zip code that has the closed hospital as the primary to their secondary hospital.

The impact of the closure on outpatient redistribution is more positive and significant than the inpatient services, where 30% of patients are redistributed for outpatient services, but only about 2% of patients are redistributed for inpatient services. This corresponds to our hypothesis 5 and could be potentially attributed to the limited capacity and distinct demand pattern for inpatient services as mentioned in the previous section, where the inpatient department is usually limited by the number of beds and related facilities to accommodate more patients after closure. Figure 5 presents the event studies for each

Table 5: Effects of Hospital Closure on Monthly Influx

	Hospital Closures							
HOSPID	13112 (1)	13074 (2)	13106 (3)	13071 (4)	13002 (5)	13055 (6)	13056 (7)	13050 (8)
Panel A: Outpatient Data								
Monthly Influx	0.233 (0.0636) [0.0106]	0.493 (0.050) [6.29e-05]	0.289 (0.0575) [0.00241]	0.366 (0.0503) [0.00034]	0.293 (0.0299) [6.47e-05]	0.232 (0.0319) [0.000341]	0.372 (0.0452) [0.000172]	0.104 (0.0481) [0.0743]
Stacked Estimate	0.298 (0.0171) [2.28e-06]							
Rural-Estimate Correlation	0.0469							
N_{obs}	616	579	579	626	646	624	619	619
$N_{treated}$	1	1	1	1	1	1	1	1
Panel B: Inpatient Data								
Monthly Influx	0.151 (0.0388) [0.00816]	-0.00314 (0.0388) [0.938]	0.0218 (0.0364) [0.572]	-0.0123 (0.0336) [0.726]	-0.0146 (0.0312) [0.655]	0.00478 (0.0343) [0.894]	-0.00314 (0.0481) [0.950]	0.00449 (0.0441) [0.922]
Stacked Estimate	0.0186 (0.0136) [0.222]							
Rural-Estimate Correlation	0.035							
N_{obs}	469	444	442	483	473	486	485	484
$N_{treated}$	1	1	1	1	1	1	1	1
Urban-Rural Score	7.54	5.87	5.41	5.90	5.29	4.95	6.53	4.12
T	19	19	19	20	20	19	16	16
$T_{treated}$	6	6	6	7	7	6	3	3
Year	2012	2013	2013	2016	2017	2018	2020	2020

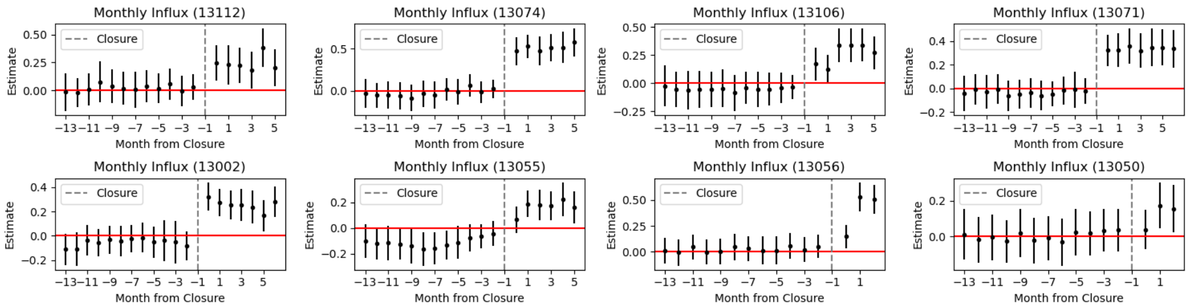
P-values are presented in square brackets, standard errors in parentheses, and all values are estimates from the model.

hospital closure, which test the parallel trend before and significance of impact after the closures.

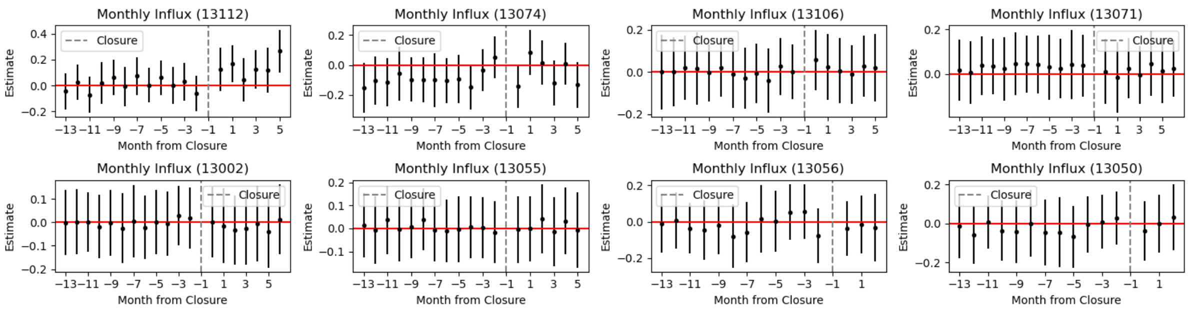
Medical Resources Utilization At the zip-code level, the total charges per visit increase on average for outpatient and inpatient services. The stacked estimates for outpatient service, as shown in A4, is 0.637 (shift upward by 0.637 standard deviations on average for treated hospitals), and the individual estimates for each case of hospital closures are all positive except the one for 2013 closure; similarly, the stacked estimates for inpatient service is 0.499, and individual estimates are positive expect two for 2020 closures. As the total charge per visit/admission provides a good indication of the cost of medical resources, these shreds of evidence suggest increasing medical resource utilization and cost after hospital closures. Meanwhile, the stacked estimate for the total number of medical codes on average is positive for outpatient services at the zip-code level but is negative for inpatient services and less significant. In particular, there is wide variation in the individual estimates for medical resources for both inpatient and outpatient services, which range from -1.59 to 1.41. The simultaneous increase between medical codes and total charges is sensible since the line-item charge is determined by what medical services and procedures patients receive. The mismatch between them and the variation in estimates

Figure 5: Effect of Hospital Closure on Monthly Influx

(a) Outpatient Data



(b) Inpatient Data



for total medical costs might be accounted for by the increase in average line-item charge (patients might receive more expensive services and procedures after closure) while no significant increase in total services and procedures.

Nonetheless, in both cases, outpatient and inpatient at zip-code level, the estimates are positively correlated with the rural score, meaning that patients coming from the more rural areas tend to consume more medical resources after hospital closure. In contrast, the effect of closure on hospital-level medical resource utilization is less positive and significant, as shown in the rural-estimate correlation in Table A4 and A3 as well as the slopes presented in Figure 7.

Revisit and Readmission In general, there is no evidence of increasing 30-day revisit or readmission in terms of both number and rate, except for the impact of the closure on the number of revisits at the hospital level, which is positive and significant. While the impact on revisit and readmission rate is no different from 0 at both hospital and zip-code levels for inpatient and outpatient services, the impact on the number of revisit and readmission is negative and significant for inpatient and outpatient services at the zip-code level. This indicates that, though hospitals do not experience higher numbers of revisits (the positive

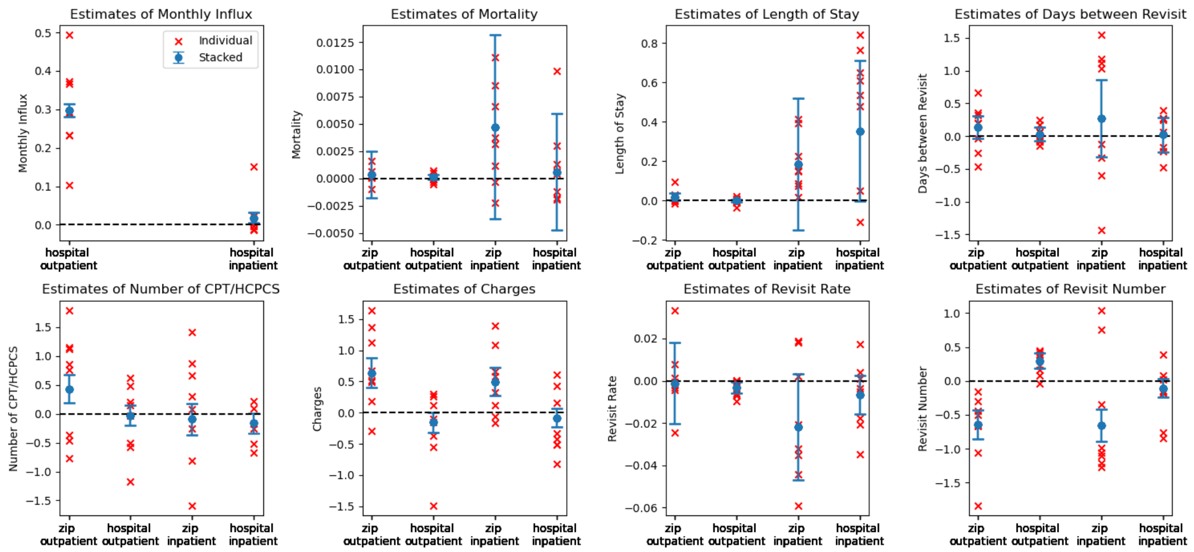


Figure 6: Stakced and Individual Estimates

increase in the number of revisits for outpatient services at the hospital level may not be due to revisits of affected patients after closure as the number of affected patients' revisits instead decreases), patients are less frequently revisiting hospitals within 30 days. This is not directly reflected by the nonsignificant impact on the rate of revisit, which can be explained by the simultaneous drop in numbers of both the total number of visits and the number of revisits. This suggests that the revisit rate may not be a good proxy for quality of care or treatment efficiency, as changes in both the numerator and denominator when computing the rate can confound the interpretation of the effect. On the other hand, while we expect the number, which is not confounded by the overall change in visits/admissions, of revisits/readmissions would increase in response to the closure, the decreasing number of revisits/readmissions suggests that the negative effect of accessibility obstacles dominating the positive effect of impaired treatment efficiency on the probability of revisit/readmission as we discussed in Section 2.5, and we cannot separate these two effects to solely focus on the effect of treatment efficiency and quality of care.

However, it still provides useful information on accessibility difficulties after hospital closure. While there is no impact at the hospital level, the number of revisits/readmissions at the zip-code level, and the individual cohort estimates are negatively correlated with the rural score, which indicates that patients from the more rural area have less access to healthcare resources when they need to revisit or readmit to hospital.

Quality of Care and Treatment Efficiency There is no evidence of the impact of closures on the quality of care and treatment efficiency measured by the length of stay for inpatients, proportion over more 1-day stay for outpatients, and mortality rate, but notably the estimates of mortality rate and length of stay consistently tend to be more positive for inpatient services at both hospital and zip-code level, suggesting that inpatients department suffers from worsened quality of care and treatment efficiency as it has experienced higher mortality rate and longer stay per patient. The quality of care is also negatively correlated with the rural score for inpatient outpatient services at the zip-code level, where patients from more rural areas tend to have higher mortality rates and longer lengths of stay. Nonetheless, the overall insignificance of impact on quality of care and treatment efficiency arguably may not fully capture the comprehensive impact of closure, as, due to the nature of discharge data, we can only capture those who can access healthcare resources, and those who are less able to afford higher transportation cost to overcome the accessibility issues and afford higher medical cost due to deteriorating health condition as a result of delayed treatment are excluded from our analysis. In other words, there exists survival bias where we only observe those who make it to the hospital, which is likely to be correlated with better health and financial condition to afford the cost, so eventually we may underestimate the impact of closure on metrics like mortality rate.

3.2.1 Heterogeneous Effect

To summarize the heterogeneous treatment effects, we find that, between rural and urban hospital closures, patients redistribute more to their secondary hospital in rural areas than in urban areas, they tend to consume more medical resources than in urban areas after hospital closure, they encounter more serious accessibility issues than in more urban areas, and they have experienced more worsened quality of care than those in more urban areas. Between inpatient and outpatient services, the outpatient department appears to accommodate more patients redistributed after hospital closure, and the inpatient department tends to suffer from slightly worse quality of care and treatment efficiency, as the inpatient department tends to admit patients with more serious health conditions that require surgical intervention. Between hospital and zip-code level analyses, the impact of the closure is overall larger on affected patients than on affected hospitals, in

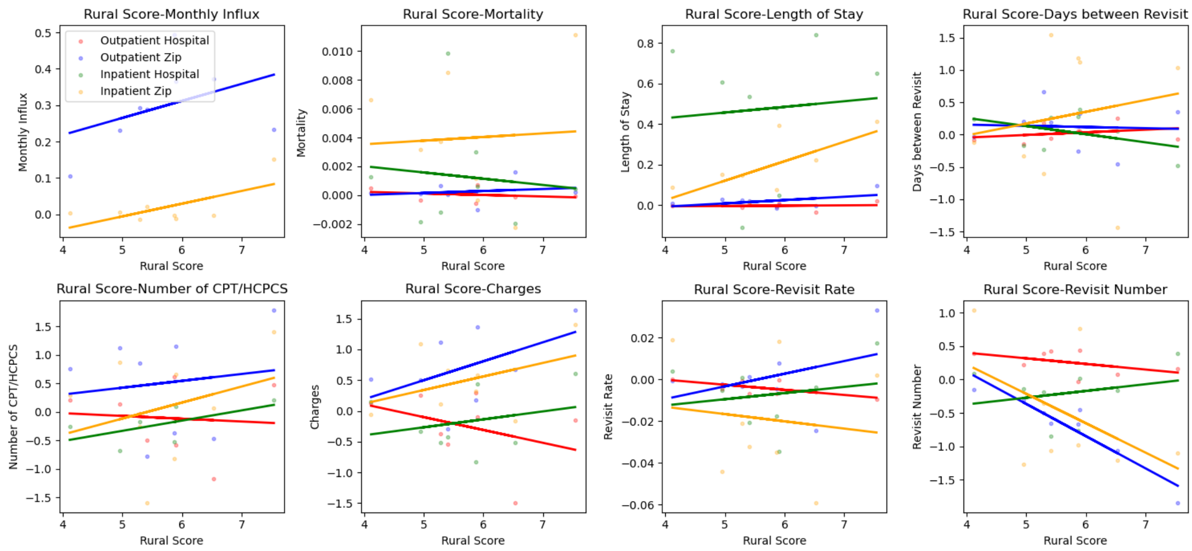


Figure 7: Correlation between Rural score and Estimates

terms of both magnitude and significance level. These results coincide with the proposed mechanism and our expected consequence of the heterogeneous characteristics across those dimensions of analyses as discussed in Section 2.5.

4 Discussion

The findings of this study contribute to the growing body of literature on the impacts of hospital closures, particularly in rural areas. Our results align with previous research that highlights the challenges rural communities face when hospitals close, including reduced access to healthcare services and increased medical resource utilization. However, our study extends the literature by providing a more nuanced understanding of the heterogeneous effects of hospital closures across different dimensions, such as inpatient versus outpatient services, rural versus urban areas, and hospital versus regional levels.

Comparison with Existing Literature Our results are consistent with studies that have documented the negative impacts of rural hospital closures on healthcare access and patient outcomes. For instance, McCarthy and et al. (2021) and Buchmueller et al. (2006) found that rural hospital closures lead to increased travel distances for patients, which can delay care and worsen health outcomes. Similarly, our findings show that patients from more rural areas experience greater difficulties in accessing healthcare after a closure, as evidenced by the decrease in the number of revisits and readmissions at the zip-code level.

However, our study diverges from some previous research in its findings on medical resource utilization. While Song and Saghafian (2019) and Capps et al. (2010) found that hospital closures in urban areas lead to increased operational efficiency and reduced costs, our results suggest that rural hospital closures lead to increased medical resource utilization per patient, particularly in more rural areas. This discrepancy may be due to the differences in market structures between rural and urban areas. In rural settings, the lack of alternative healthcare providers and the limited capacity of remaining hospitals may lead to higher per-patient costs and resource use, whereas urban hospitals can more easily absorb additional patients without significantly increasing costs.

Implications for Policy The findings of this study have important implications for policymakers. The significant increase in medical resource utilization and the challenges faced by rural patients in accessing care after a hospital closure suggest that rural hospital closures may have broader societal costs that are not captured by traditional measures of hospital efficiency. Policymakers should consider these broader impacts when deciding whether to provide financial support to struggling rural hospitals. While bailing out inefficient hospitals may not always be the optimal solution, the potential negative consequences of closures on rural communities—particularly in terms of healthcare access and resource utilization—should not be overlooked. Therefore, if reopening a local hospital could be financially burdensome for the local government, outreach health services in the local community would be necessary to alleviate the impact of the closure by providing, for example, transportation services to help patients overcome accessibility difficulties.

Additionally, our findings raise questions about the validity of certain metrics, such as revisit and readmission rates, as proxies for treatment efficiency. The decrease in the number of revisits and readmissions at the zip-code level suggests that these metrics may be confounded by changes in healthcare accessibility. Policymakers and researchers should be cautious when using these metrics to evaluate the impact of hospital closures or other healthcare interventions.

Limitations and Future Research This study has several limitations. First, due to the nature of discharge data, we can only observe patients who are able to access healthcare services. This introduces potential survival bias, as patients who are unable to afford the increased costs or travel distances associated with hospital closures may be excluded from our analysis. This is a major drawback not only in our study but also in the literature on hospital closure, where hospital-level data is the dominating source. Future research could address this limitation by incorporating data on patient health outcomes outside of hospital settings.

Second, while our study focuses on rural hospital closures in Georgia, the findings may not be generalizable to other states or regions with different healthcare market structures. Future research could expand the scope of analysis to include urban hospital closures or compare the impacts of closures across different states.

5 Conclusion

This study provides a comprehensive analysis of the impacts of rural hospital closures on patient redistribution, medical resource utilization, and quality of care. Using a data-driven approach and a modern difference-in-differences framework, we find that hospital closures lead to significant patient redistribution, particularly for outpatient services, and increase medical resource utilization at the regional level. These effects are more pronounced in rural areas, where patients face greater challenges in accessing healthcare services. Our findings also highlight the limitations of using revisit and readmission rates as proxies for treatment efficiency, as these metrics may be confounded by changes in healthcare accessibility. Furthermore, we identify potential survival bias in studies of hospital closures, as patients who are unable to access healthcare services after closure are excluded from the analysis.

Overall, this study underscores the need for policymakers to consider the broader societal impacts of rural hospital closures, particularly in terms of healthcare access and medical resource utilization. While bailing out inefficient hospitals may not always be the optimal solution, the potential negative consequences of closures on rural communities should not be ignored. Future research should continue to explore the heterogeneous effects of hospital closures across different regions and healthcare markets at a more granular level, as well as the more long-term impacts on patient health outcomes. If possible, future research should extend the analysis outside the hospital setting to address the problem of survival bias.

References

Alexander, D. E. and Richards, M. R.: 2023, Economic consequences of hospital closures, *Journal of Public Economics* **221**, 104821.
URL: *https://www.sciencedirect.com/science/article/pii/S0047272723000038*

Arkhangelsky, D., Athey, S., Hirshberg, D. A., Imbens, G. W. and Wager, S.: 2021, Synthetic difference-in-differences, *American Economic Review* **111**(12), 4088–4118.

Buchmueller, T. C., Jacobson, M. and Wold, C.: 2006, How far to the hospital?: The effect of hospital closures on access to care, *Journal of Health Economics* **25**(4), 740–761.

Capps, C., Dranove, D. and Lindrooth, R. C.: 2010, Hospital closure and economic efficiency, *Journal of Health Economics* **29**(1), 87–109.

Cerulli, G.: 2024, Optimal initial donor selection for the synthetic control method, *Economics Letters* **244**, 111976.
URL: *https://www.sciencedirect.com/science/article/pii/S0165176524004609*

Greathouse, J. A., Bayani, M. and Coupet, J.: 2023, Splash! robustifying donor pools for policy studies, *arXiv preprint arXiv:2308.13688* .
URL: *https://arxiv.org/abs/2308.13688*

Gujral, K. and Basu, A.: 2019, Impact of rural and urban hospital closures on inpatient mortality, *Working Paper w26182*, National Bureau of Economic Research.
URL: *https://www.nber.org/papers/w26182*

Hodgson, A., Roback, P., Hartman, A., Kelly, E. and Li, Y.: 2015, The financial impact of hospital closures on surrounding hospitals, *Journal of Hospital Administration* **4**(3), 25–34.
URL: *https://www.sciedupress.com/journal/index.php/jha/article/view/6358*

Kaufman, B. G., Thomas, S. R., Randolph, R. K., Perry, J. R., Thompson, K. W., Holmes, G. M. and Pink, G. H.: 2016, The rising rate of rural hospital closures, *The Journal of Rural Health* **32**(1), 35–43.

Lindrooth, R. C., Lo Sasso, A. T. and Bazzoli, G. J.: 2003, The effect of urban hospital closure on markets, *Journal of Health Economics* **22**(5), 691–712.

McCarthy, S. and et al.: 2021, Impact of rural hospital closures on health-care access, *Journal of Surgical Research* **258**, 170–178.

Mills, C. A., Yeager, V. A., Unroe, K. T., Holmes, A. and Blackburn, J.: 2024, The impact of rural general hospital closures on communities—a systematic review of the literature, *The Journal of Rural Health* **40**(2), 238–248.
URL: *https://onlinelibrary.wiley.com/doi/abs/10.1111/jrh.12810*

of Health Care, D. A.: 2025, Research methods: Defining hospital service areas and hospital referral regions. Accessed: 2025-03-18.
URL: *https://www.dartmouthatlas.org/research-methods/*

Porreca, Z.: 2022, Synthetic difference-in-differences estimation with staggered treatment adoption, *Economics Letters* **215**, 110516.
URL: *https://www.sciencedirect.com/science/article/pii/S0165176522003482*

Probst, J. C. and et al.: 1999, Economic impact of hospital closure on small rural counties, 1984 to 1988: demonstration of a comparative analysis approach, *The Journal of Rural Health* **15**(4), 375–390.

Shi, Z. and Huang, J.: 2023, Forward-selected panel data approach for program evaluation, *Journal of Econometrics* **234**(2), 512–535.
URL: *https://www.sciencedirect.com/science/article/pii/S0304407621001536*

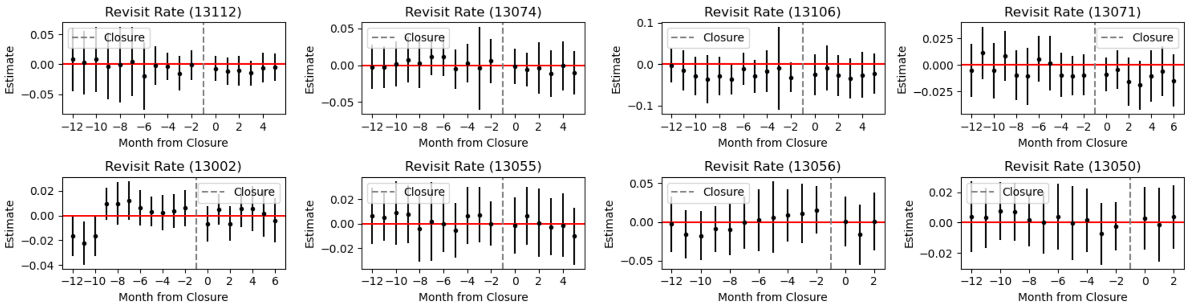
Song, L. and Saghafian, S.: 2019, The spillover effects of hospital closures on the efficiency and quality of other hospitals, *John F Kennedy School of Government Faculty Research Working Paper Series* .
URL: *https://www.hks.harvard.edu/publications/spillover-effects-hospital-closures-efficiency-and-quality-other-hospitals*

Succi, M. J., Lee, S. Y. and Alexander, J. A.: 1997, Effects of market position and competition on rural hospital closures, *Health Services Research* **31**(6), 679–99.

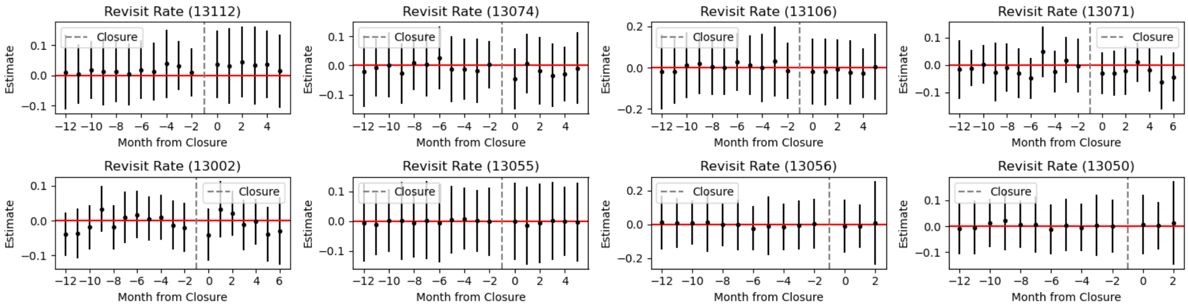
A Appendix: Figures

Figure A1: Effect of Hospital Closure on 30-day Revisit/Readmission Rate

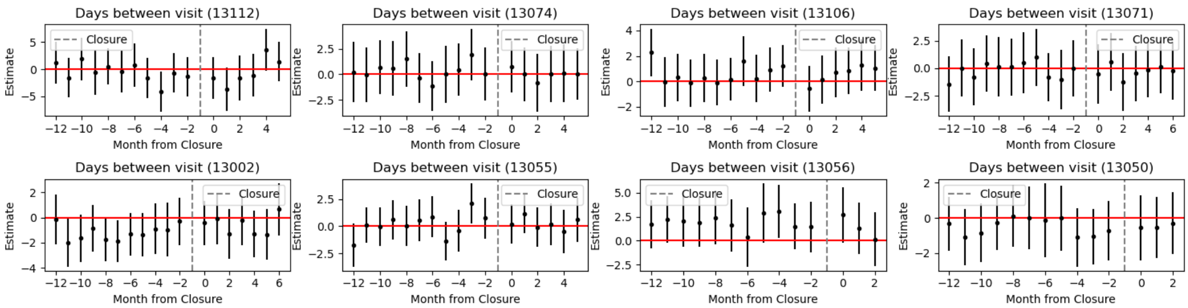
(a) Outpatient Data



(b) Inpatient Data



(c) Inpatient Data



(d) Inpatient Data

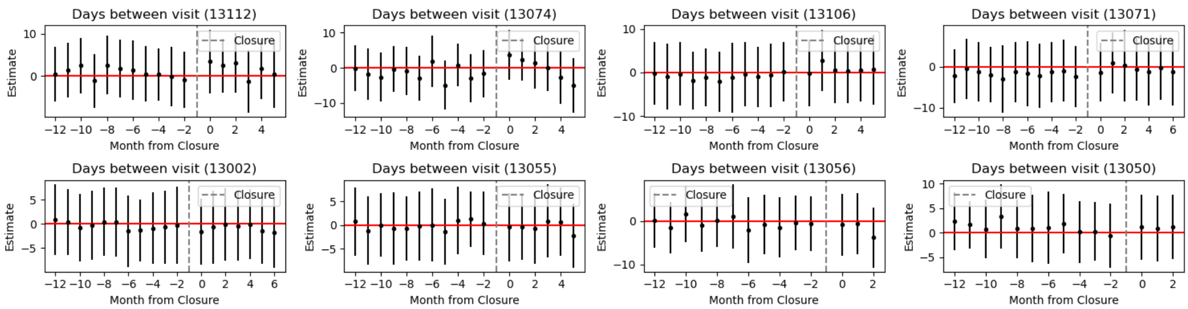
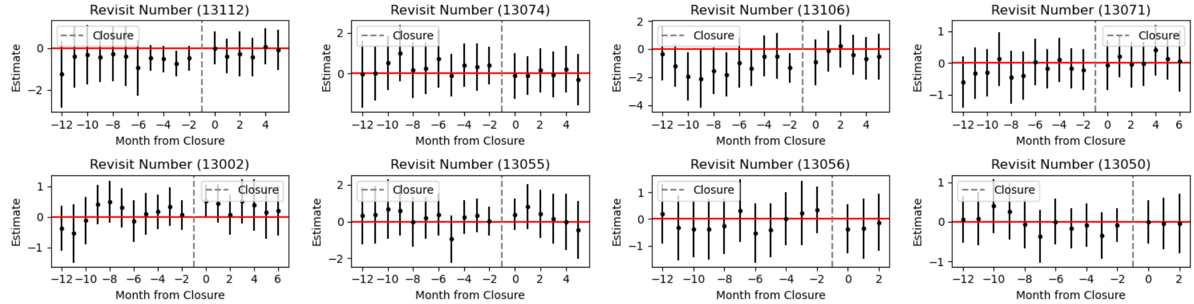
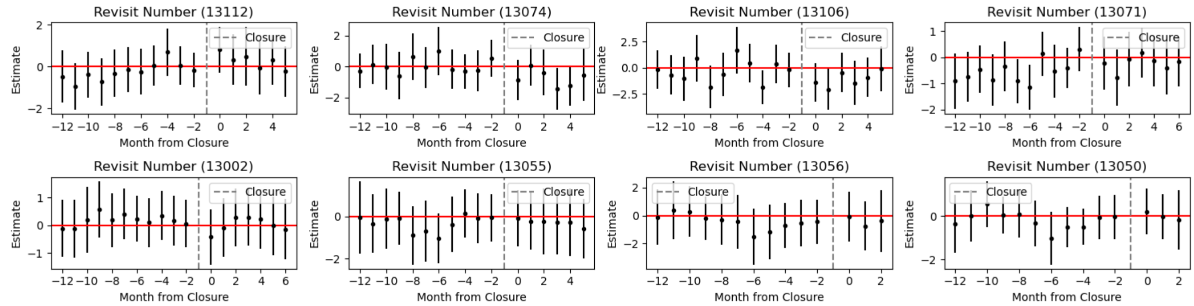


Figure A2: Effect of Hospital Closure on 30-day Revisit/Readmission Number

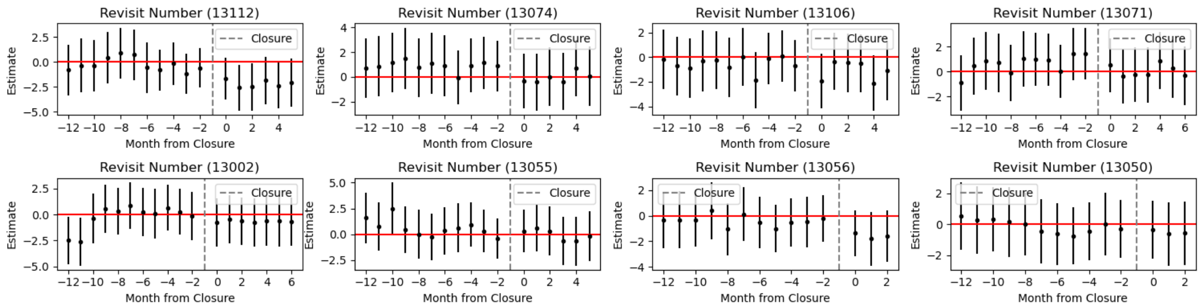
(a) Outpatient Data



(b) Inpatient Data



(c) Inpatient Data



(d) Inpatient Data

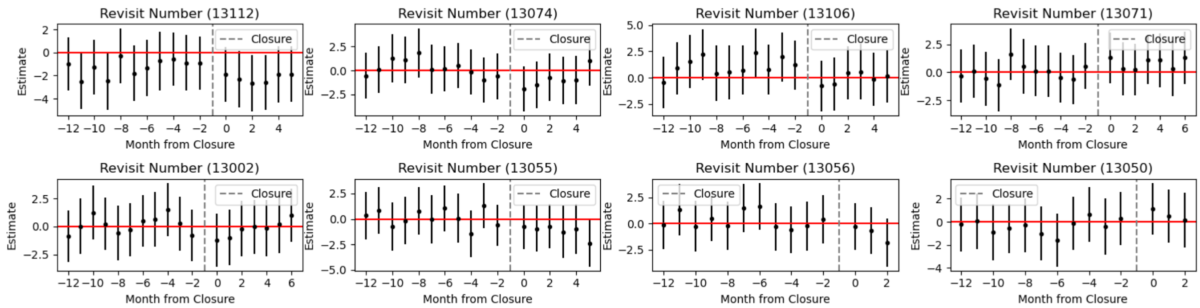
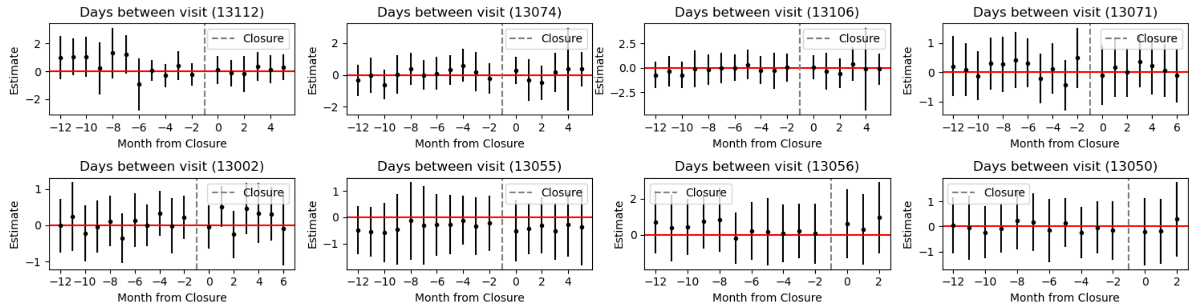
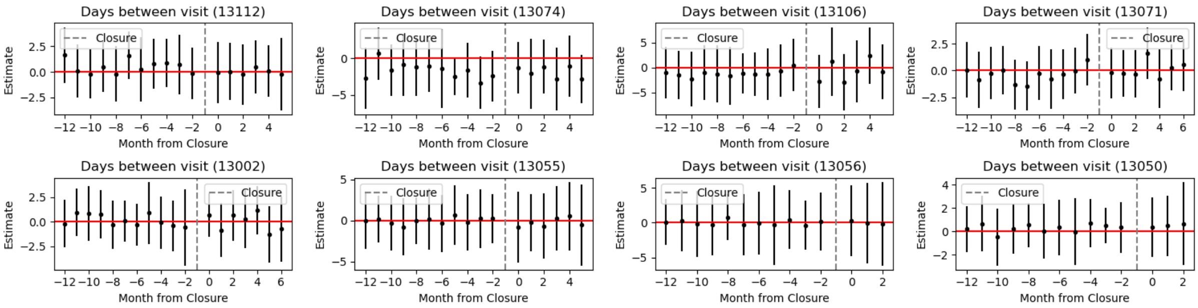


Figure A3: Effect of Hospital Closure on Days between Revisit/Readmission within 30 Days

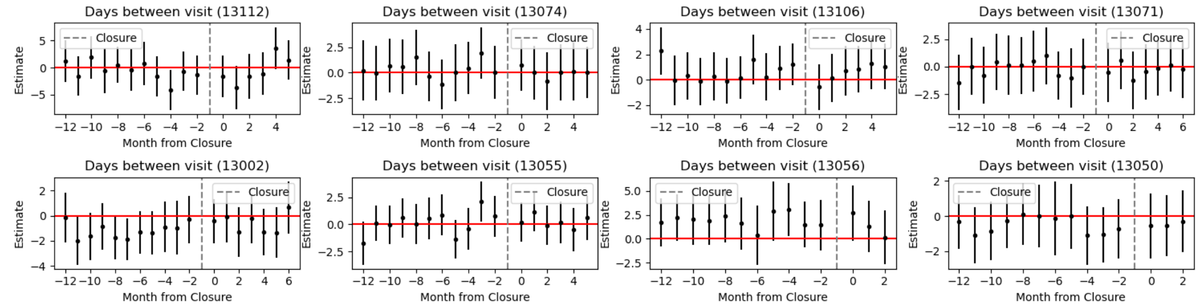
(a) Outpatient Data



(b) Inpatient Data



(c) Inpatient Data



(d) Inpatient Data

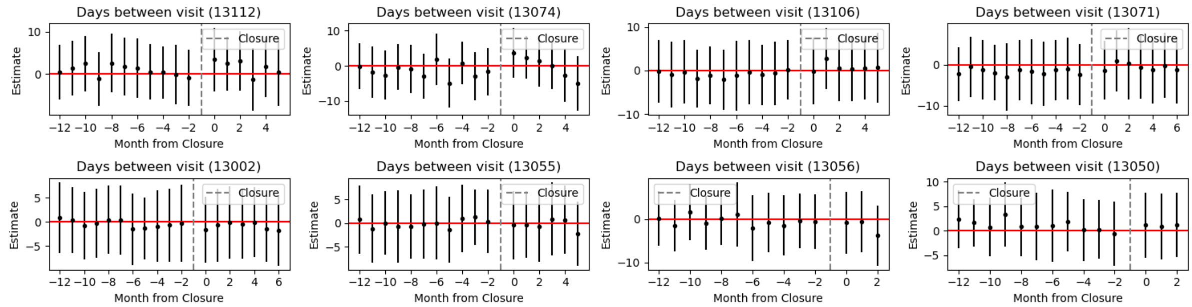
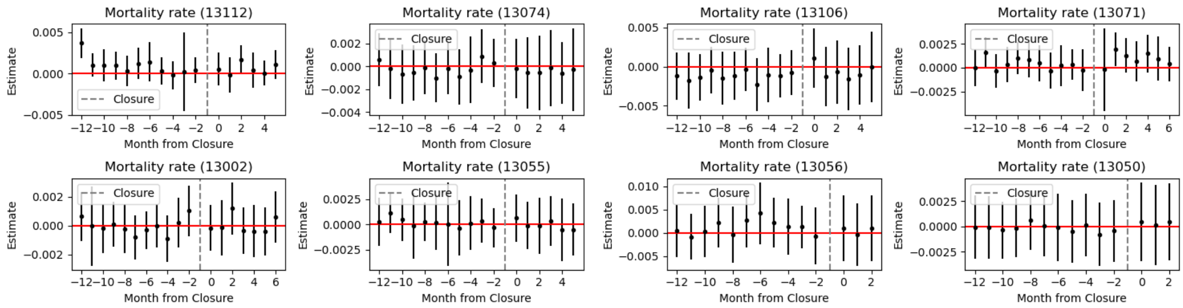
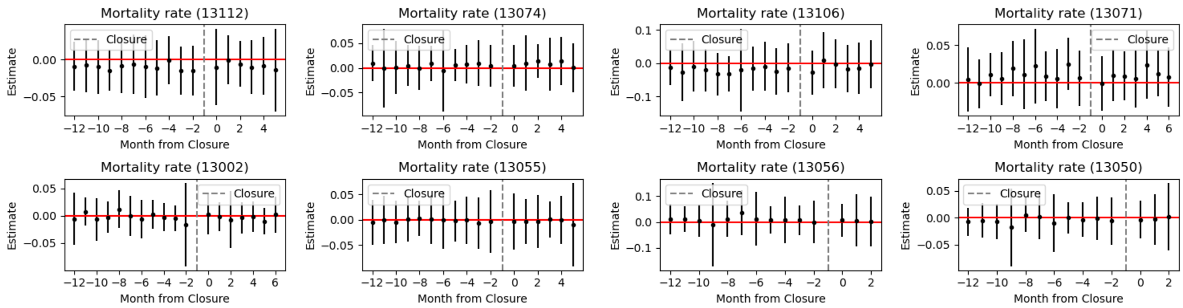


Figure A4: Effect of Hospital Closure on Mortality Rate

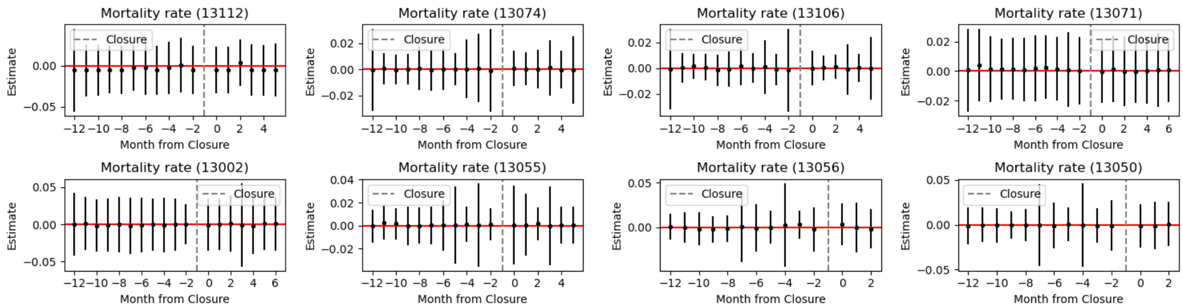
(a) Outpatient Data



(b) Inpatient Data



(c) Inpatient Data



(d) Inpatient Data

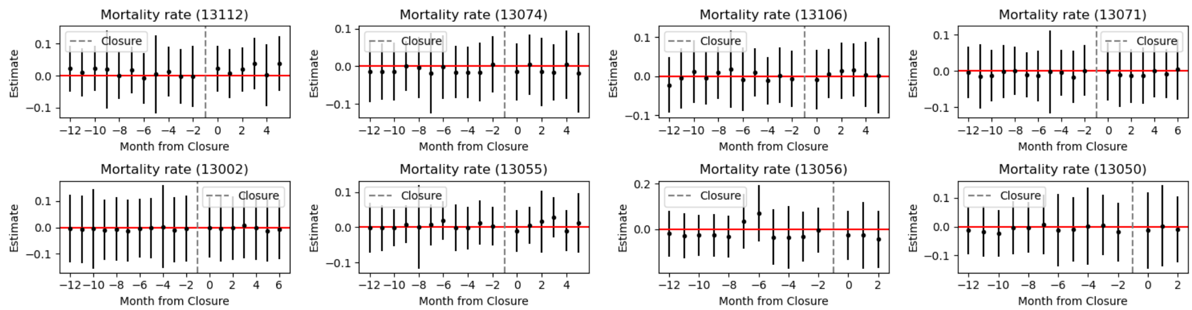
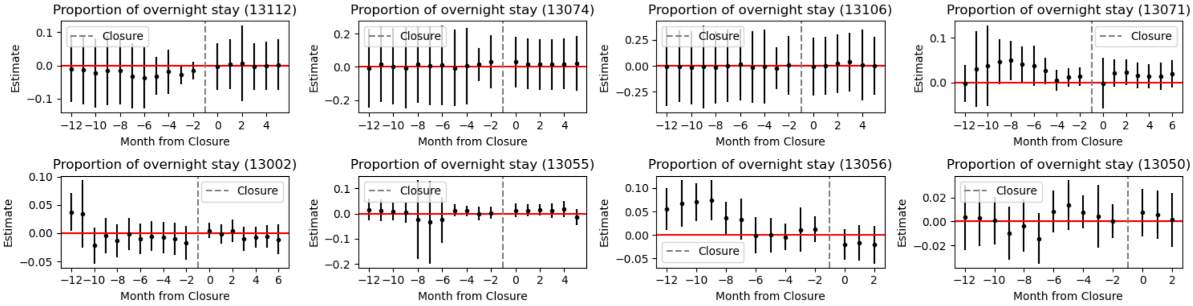
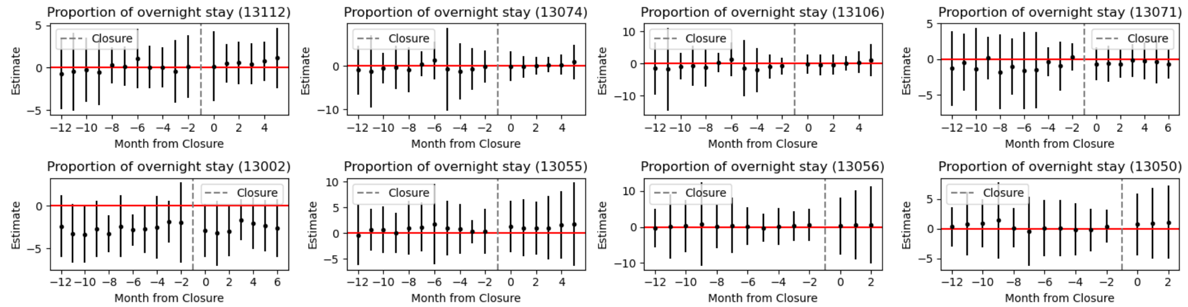


Figure A5: Effect of Hospital Closure on Length of Stay/Proportion of Overnight Stay

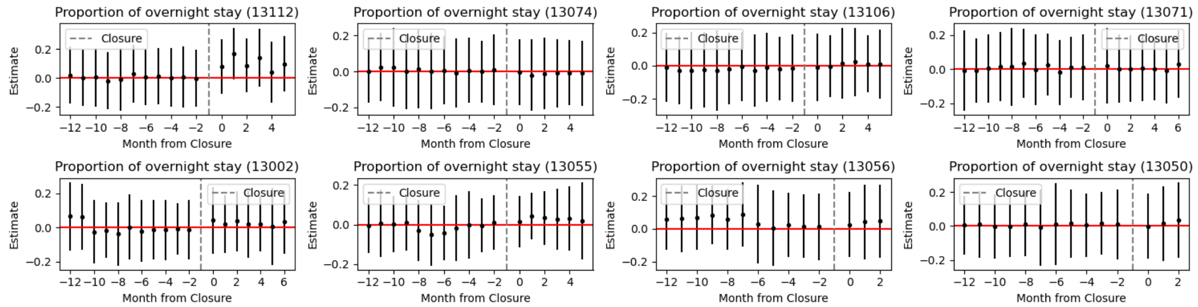
(a) Outpatient Data



(b) Inpatient Data



(c) Inpatient Data



(d) Inpatient Data

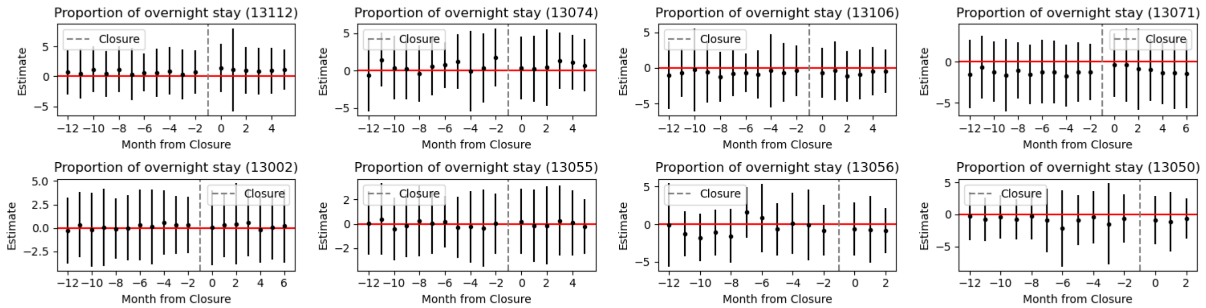
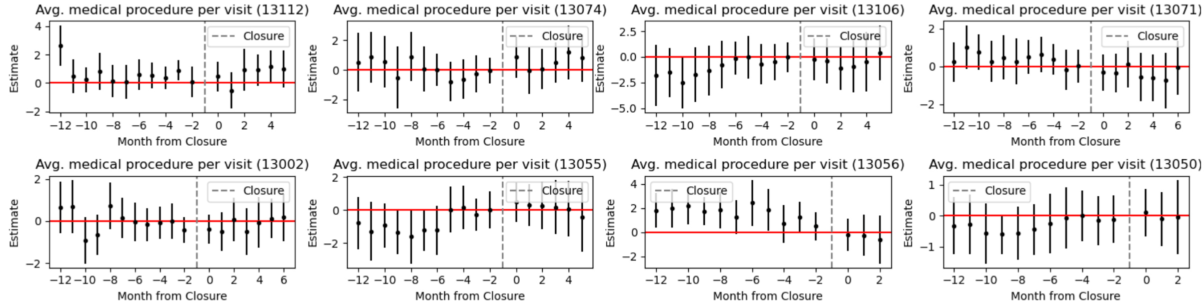
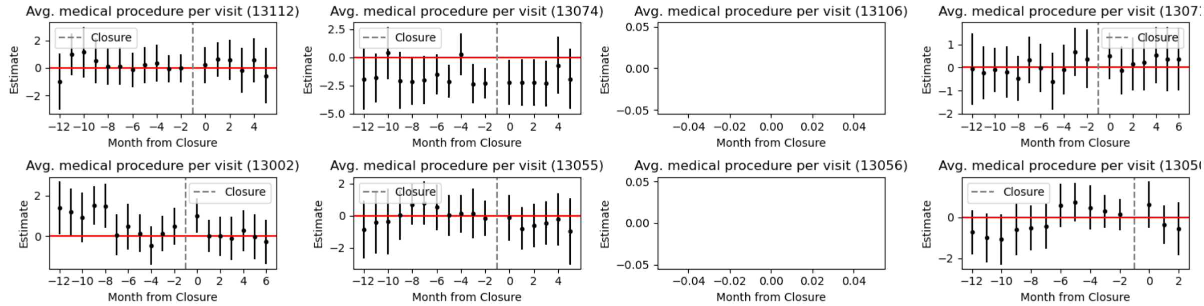


Figure A6: Effect of Hospital Closure on Number of CPS/HCPCS Medical Codes

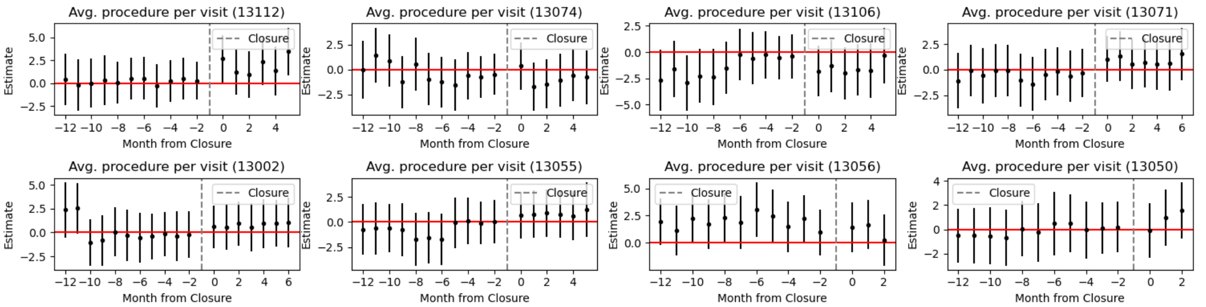
(a) Outpatient Data



(b) Inpatient Data



(c) Inpatient Data



(d) Inpatient Data

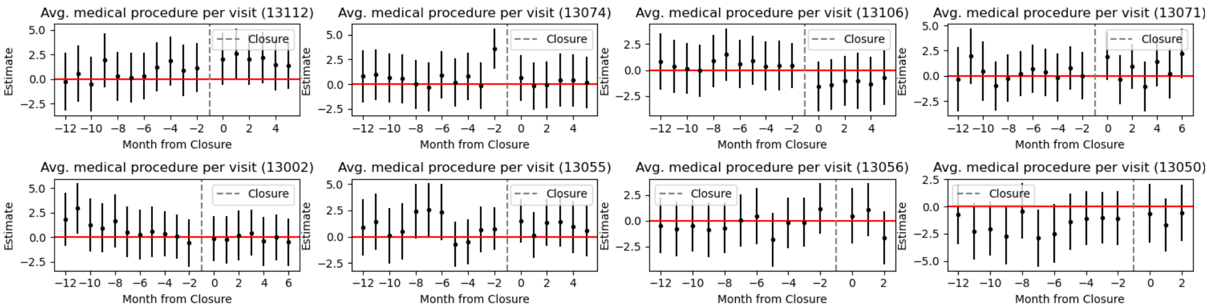
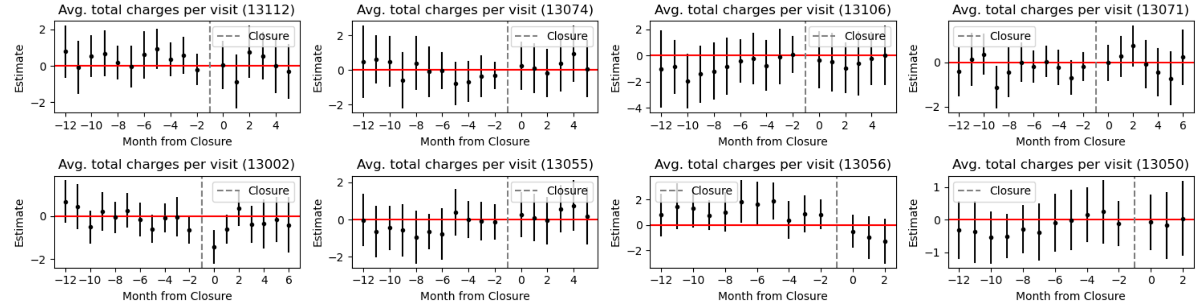
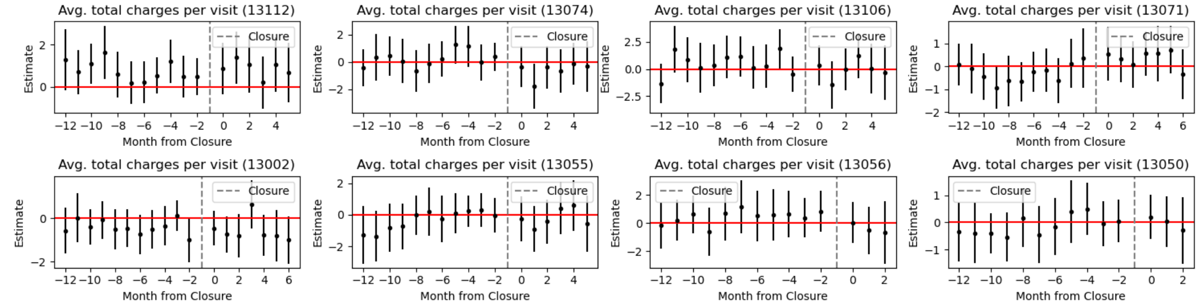


Figure A7: Effect of Hospital Closure on Total Charges

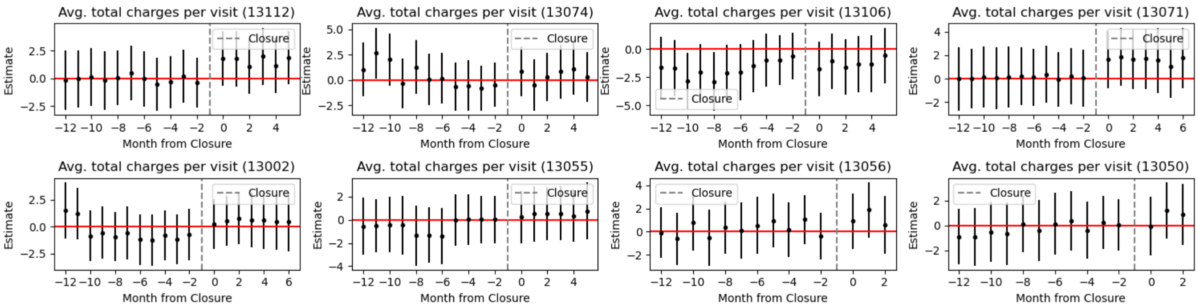
(a) Outpatient Data



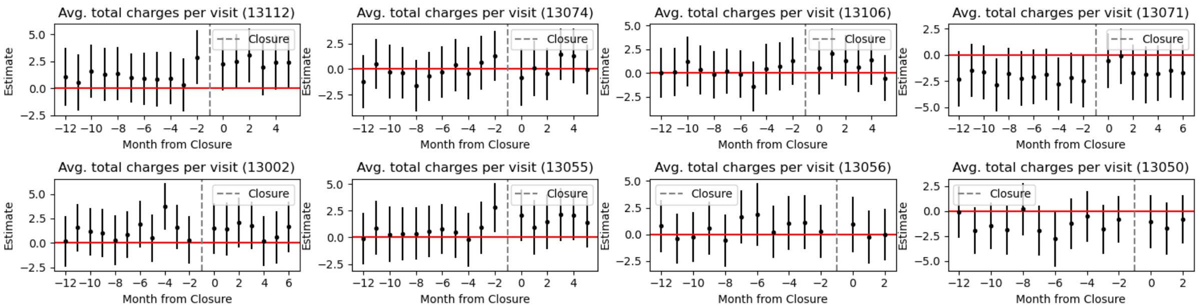
(b) Inpatient Data



(c) Inpatient Data



(d) Inpatient Data



B Tables

Table A1: Effects of Hospital Closure on 30-day Revisit and Readmission Rate

	Hospital Closures							
HOSPID	13112 (1)	13074 (2)	13106 (3)	13071 (4)	13002 (5)	13055 (6)	13056 (7)	13050 (8)
Panel A: Outpatient Data								
				A1 Hospital Level				
Revisit Rate	-0.00955 (0.00721) [0.234]	-0.00688 (0.0102) [0.527]	-0.00664 (0.0140) [0.652]	0.000254 (0.00694) [0.972]	-0.000810 (0.00455) [0.865]	-0.00434 (0.00684) [0.549]	-0.00587 (0.0134) [0.676]	0.000067 (0.00781) [0.993]
Stacked Estimate				-0.00326 (0.00273) [0.277]				
Rural-Estimate Correlation				-0.00245				
N_{obs} $N_{treated}$	128 3	121 2	121 1	126 4	126 5	124 2	123 1	123 3
				A2 Zip-code Level				
Revisit Rate	0.0333 (0.0468) [0.503]	-0.00434 (0.0454) [0.927]	0.00130 (0.0448) [0.978]	0.00794 (0.0542) [0.888]	-0.00333 (0.0524) [0.951]	-0.00221 (0.0294) [0.942]	-0.0247 (0.0585) [0.687]	-0.000617 (0.0599) [0.992]
Stacked Estimate				-0.00114 (0.0191) [0.954]				
Rural-Estimate Correlation				0.00610				
N_{obs} $N_{treated}$	857 7	845 7	840 13	845 5	837 15	706 10	805 11	802 14
Panel B: Inpatient Data								
				B1 Hospital Level				
Readmission Rate	0.0174 (0.0253) [0.518]	-0.0178 (0.0278) [0.546]	-0.0206 (0.0384) [0.612]	-0.0346 (0.0167) [0.0831]	0.000928 (0.0155) [0.954]	-0.00523 (0.0368) [0.892]	-0.00373 (0.0580) [0.951]	0.00410 (0.0293) [0.893]
Stacked Estimate				-0.00666 (0.00919) [0.496]				
Rural-Estimate Correlation				0.00299				
N_{obs} $N_{treated}$	153 3	144 2	144 1	148 4	147 5	146 2	142 1	142 3
				B2 Zip-code Level				
Readmission Rate	0.00207 (0.0633) [0.975]	-0.0350 (0.0622) [0.594]	-0.0323 (0.0583) [0.599]	0.0181 (0.0620) [0.780]	-0.0209 (0.0563) [0.724]	-0.0443 (0.0551) [0.452]	-0.0591 (0.0778) [0.477]	0.0188 (0.0729) [0.805]
Stacked Estimate				-0.0219 (0.0251) [0.417]				
Rural-Estimate Correlation				-0.00345				
N_{obs} $N_{treated}$	748 7	742 2	736 10	727 4	722 12	654 3	698 6	701 2
Urban-Rural Score	7.54	5.87	5.41	5.90	5.29	4.95	6.53	4.13
T	18	18	18	19	19	18	15	15
$T_{treated}$	6	6	6	7	7	6	3	3
Year	2012	2013	2013	2016	2017	2018	2020	2020

P-values are presented in square brackets, standard errors in parentheses, and all values are estimates from the model.

Table A2: Effects of Hospital Closure on Numbers of 30-day Revisit and Readmission

	Hospital Closures							
HOSPID	13112 (1)	13074 (2)	13106 (3)	13071 (4)	13002 (5)	13055 (6)	13056 (7)	13050 (8)
Panel A: Outpatient Data								
	A1 Hospital Level							
Revisit Number	0.158 (0.297) [0.614]	-0.0351 (0.390) [0.931]	0.429 (0.551) [0.466]	0.443 (0.245) [0.121]	0.385 (0.277) [0.213]	0.218 (0.410) [0.614]	0.0787 (0.359) [0.834]	0.390 (0.207) [0.109]
Stacked Estimate	0.296 (0.114) [0.0414]							
Rural-Estimate Correlation	-0.0841							
N_{obs}	128	121	121	126	126	124	123	123
$N_{treated}$	3	2	1	4	5	2	1	3
	A2 Zip-code Level							
Revisit Number	-1.84 (0.604) [0.0224]	-0.662 (0.596) [0.309]	-0.655 (0.603) [0.319]	-0.445 (0.553) [0.452]	-0.497 (0.581) [0.426]	-0.303 (0.565) [0.611]	-1.06 (0.565) [0.109]	-0.156 (0.565) [0.792]
Stacked Estimate	-0.642 (0.216) [0.0249]							
Rural-Estimate Correlation	-0.484							
N_{obs}	857	845	840	845	837	706	805	802
$N_{treated}$	7	7	13	5	15	10	11	14
Panel B: Inpatient Data								
	B1 Hospital Level							
Revisit Number	0.389 (0.323) [0.273]	-0.763 (0.389) [0.0978]	-0.846 (0.569) [0.188]	0.0166 (0.320) [0.960]	-0.185 (0.302) [0.562]	-0.142 (0.422) [0.748]	-0.160 (0.667) [0.818]	0.0843 (0.378) [0.831]
Stacked Estimate	-0.107 (0.137) [0.462]							
Rural-Estimate Correlation	0.102							
N_{obs}	153	144	144	148	147	146	142	142
$N_{treated}$	3	2	1	4	5	2	1	3
	B2 Zip-code Level							
Revisit Number	-1.10 (0.547) [0.0919]	-0.982 (0.575) [0.139]	-1.06 (0.583) [0.120]	0.760 (0.542) [0.210]	-0.351 (0.555) [0.551]	-1.27 (0.552) [0.0605]	-1.21 (0.660) [0.115]	1.04 (0.635) [0.154]
Stacked Estimate	-0.661 (0.237) [0.0317]							
Rural-Estimate Correlation	-0.438							
N_{obs}	748	742	736	727	722	654	698	701
$N_{treated}$	7	2	10	4	12	3	6	2
Urban-Rural Score	7.54	5.87	5.41	5.90	5.29	4.95	6.53	4.12
T	18	18	18	19	19	18	15	15
$T_{treated}$	6	6	6	7	7	6	3	3
Year	2012	2013	2013	2016	2017	2018	2020	2020

P-values are presented in square brackets, standard errors in parentheses, and all values are estimates from the model.

Table A3: Effects of Hospital Closure on Total Number of CPT/HCPCS Codes per Visit/Admission

	Hospital Closures							
HOSPID	13112 (1)	13074 (2)	13106 (3)	13071 (4)	13002 (5)	13055 (6)	13056 (7)	13050 (8)
Panel A: Outpatient Data								
				A1 Hospital Level				
NCPT	0.483 (0.548) [0.413]	0.619 (0.579) [0.326]	-0.499 (0.748) [0.529]	-0.576 (0.373) [0.174]	-0.034 (0.350) [0.926]	0.143 (0.570) [0.810]	-1.17 (0.667) [0.130]	0.205 (0.370) [0.600]
Stacked Estimate				-0.0264 (0.171) [0.882]				
Rural-Estimate Correlation				-0.0472				
N_{obs}	122	116	116	126	126	124	123	123
$N_{treated}$	3	2	1	4	5	2	1	3
				A2 Zip-code Level				
NCPT	1.79 (0.703) [0.0432]	-0.369 (0.673) [0.603]	-0.772 (0.659) [0.286]	1.15 (0.680) [0.142]	0.861 (0.626) [0.218]	1.12 (0.637) [0.130]	-0.460 (0.697) [0.534]	0.764 (0.691) [0.311]
Stacked Estimate				0.432 (0.248) [0.132]				
Rural-Estimate Correlation				0.123				
N_{obs}	857	845	840	845	837	706	805	802
$N_{treated}$	7	7	13	5	15	10	11	14
Panel B: Inpatient Data								
				B1 Hospital Level				
NCPT	0.211 (0.642) [0.760]	-0.526 (0.731) [0.511]		0.0992 (0.361) [0.797]	-0.175 (0.286) [0.575]	-0.678 (0.466) [0.22]		-0.259 (0.429) [0.579]
Stacked Estimate				-0.160 (0.175) [0.413]				
Rural-Estimate Correlation				0.179				
N_{obs}	153	144	144	148	147	146	142	142
$N_{treated}$	3	2	1	4	5	2	1	3
				B2 Zip-code Level				
NCPT	1.41 (0.531) [0.0376]	-0.815 (0.764) [0.328]	-1.59 (0.784) [0.0890]	0.662 (0.624) [0.329]	-0.252 (0.610) [0.694]	0.867 (0.634) [0.221]	-0.0737 (0.725) [0.922]	0.295 (0.695) [0.686]
Stacked Estimate				-0.0951 (0.277) [0.743]				
Rural-Estimate Correlation				0.283				
N_{obs}	748	742	736	727	722	654	698	701
$N_{treated}$	7	2	10	4	12	3	6	2
Urban-Rural Score	7.54	5.87	5.41	5.90	5.29	4.95	6.53	4.12
T	18	18	18	19	19	18	15	15
$T_{treated}$	6	6	6	7	7	6	3	3
Year	2012	2013	2013	2016	2017	2018	2020	2020

P-values are presented in square brackets, standard errors in parentheses, and all values are estimates from the model.

Table A4: Effects of Hospital Closure on Total Charges per Visit/Admission

	Hospital Closures							
HOSPID	13112 (1)	13074 (2)	13106 (3)	13071 (4)	13002 (5)	13055 (6)	13056 (7)	13050 (8)
Panel A: Outpatient Data								
				A1 Hospital Level				
Charges	-0.15 (0.534) [0.788]	0.298 (0.522) [0.589]	-0.545 (0.658) [0.440]	-0.101 (0.374) [0.795]	-0.372 (0.295) [0.253]	0.26 (0.546) [0.651]	-1.49 (0.663) [0.0654]	0.123 (0.322) [0.715]
Stacked Estimate				-0.156 (0.158) [0.364]				
Rural-Estimate Correlation				-0.209				
N_{obs}	128	120	120	125	126	124	123	123
$N_{treated}$	3	2	1	4	5	2	1	3
				A2 Zip-code Level				
Charges	1.64 (0.669) [0.0497]	0.179 (0.656) [0.794]	-0.292 (0.663) [0.675]	1.37 (0.653) [0.0798]	1.12 (0.581) [0.103]	0.497 (0.599) [0.438]	0.675 (0.681) [0.360]	0.522 (0.675) [0.468]
Stacked Estimate				0.637 (0.239) [0.0374]				
Rural-Estimate Correlation				0.310				
N_{obs}	856	845	840	845	837	706	805	802
$N_{treated}$	7	7	13	5	15	10	11	14
Panel B: Inpatient Data								
				B1 Hospital Level				
Charges	0.605 (0.386) [0.169]	-0.824 (0.457) [0.121]	-0.424 (0.698) [0.566]	0.432 (0.361) [0.277]	-0.512 (0.304) [0.142]	-0.326 (0.490) [0.530]	-0.516 (0.637) [0.449]	0.155 (0.397) [0.710]
Stacked Estimate				-0.0855 (0.149) [0.588]				
Rural-Estimate Correlation				0.130				
N_{obs}	153	144	144	148	147	146	142	142
$N_{treated}$	3	2	1	4	5	2	1	3
				B2 Zip-code Level				
Charges	1.40 (0.490) [0.0286]	0.32 (0.512) [0.554]	0.658 (0.508) [0.243]	0.579 (0.516) [0.305]	0.114 (0.546) [0.842]	1.09 (0.538) [0.0883]	-0.158 (0.589) [0.798]	-0.056 (0.598) [0.928]
Stacked Estimate				0.499 (0.220) [0.0638]				
Rural-Estimate Correlation				0.222				
N_{obs}	747	742	736	727	722	654	698	701
$N_{treated}$	7	2	10	4	12	3	6	2
Urban-Rural Score	7.54	5.87	5.41	5.90	5.29	4.95	6.53	4.12
T	18	18	18	19	19	18	15	15
$T_{treated}$	6	6	6	7	7	6	3	3
Year	2012	2013	2013	2016	2017	2018	2020	2020

P-values are presented in square brackets, standard errors in parentheses, and all values are estimates from the model.

Table A5: Effects of Hospital Closure on Mortality Rate

	Hospital Closures							
HOSPID	13112 (1)	13074 (2)	13106 (3)	13071 (4)	13002 (5)	13055 (6)	13056 (7)	13050 (8)
Panel A: Outpatient Data								
	A1 Hospital Level							
Mortality	-7.77e-05	-0.000541	0.000147	0.000725	0.000138	-0.000348	-0.000102	0.000498
	(0.000432)	(0.000712)	(0.000854)	(0.000540)	(0.000310)	(0.000580)	(0.00138)	(0.000732)
	[0.863]	[0.476]	[0.869]	[0.228]	[0.672]	[0.571]	[0.943]	[0.522]
Stacked Estimate	0.000148 (0.000211) [0.507]							
Rural-Estimate Correlation	-0.000108							
N_{obs}	128	121	121	126	126	124	123	123
$N_{treated}$	3	2	1	4	5	2	1	3
	A2 Zip-code Level							
Mortality	0.000239	0.000246	4.46e-05	-0.00100	0.000649	9.79e-05	0.00161	0.000152
	(0.00379)	(0.00330)	(0.00403)	(0.00319)	(0.00442)	(0.00513)	(0.00715)	(0.00826)
	[0.952]	[0.943]	[0.992]	[0.763]	[0.888]	[0.985]	[0.829]	[0.986]
Stacked Estimate	0.000360 (0.00214) [0.872]							
Rural-Estimate Correlation	0.000138							
N_{obs}	857	845	840	845	837	706	805	802
$N_{treated}$	7	7	13	5	15	10	11	14
Panel B: Inpatient Data								
	B1 Hospital Level							
Mortality	0.000439	0.00299	0.00983	0.000625	-0.00117	-0.00182	-0.00196	0.00128
	(0.0106)	(0.0107)	(0.0163)	(0.00653)	(0.00636)	(0.00906)	(0.0642)	(0.0229)
	[0.968]	[0.789]	[0.570]	[0.927]	[0.860]	[0.848]	[0.977]	[0.957]
Stacked Estimate	0.000573 (0.00534) [0.918]							
Rural-Estimate Correlation	-0.000437							
N_{obs}	153	144	144	148	147	146	142	142
$N_{treated}$	3	2	1	4	5	2	1	3
	B2 Zip-code Level							
Mortality	0.0111	0.00118	0.00850	-0.000335	0.00370	0.00318	-0.00224	0.00659
	(0.0191)	(0.0165)	(0.0198)	(0.0162)	(0.0205)	(0.0140)	(0.0249)	(0.0260)
	[0.584]	[0.945]	[0.682]	[0.984]	[0.863]	[0.827]	[0.931]	[0.808]
Stacked Estimate	0.00472 (0.00841) [0.595]							
Rural-Estimate Correlation	0.000248							
N_{obs}	748	742	736	727	722	654	698	701
$N_{treated}$	7	2	10	4	12	3	6	2
Urban-Rural Score	7.54	5.87	5.41	5.90	5.29	4.95	6.53	4.12
T	18	18	18	19	19	18	15	15
$T_{treated}$	6	6	6	7	7	6	3	3
Year	2012	2013	2013	2016	2017	2018	2020	2020

P-values are presented in square brackets, standard errors in parentheses, and all values are estimates from the model.

Table A6: Effects of Hospital Closure on Length of Stay per Visit/Admission

	Hospital Closures							
HOSPID	13112 (1)	13074 (2)	13106 (3)	13071 (4)	13002 (5)	13055 (6)	13056 (7)	13050 (8)
Panel A: Outpatient Data								
	A1 Hospital Level							
Proportion of Overnight Stay	0.0202 (0.027) [0.483]	-0.00673 (0.0297) [0.828]	0.00578 (0.0473) [0.907]	0.0083 (0.011) [0.478]	-0.0111 (0.00869) [0.250]	0.00117 (0.0124) [0.928]	-0.0348 (0.0168) [0.0845]	-0.00124 (0.0109) [0.913]
Stacked Estimate	-0.000258 (0.00641) [0.969]							
Rural-Estimate Correlation	0.00173							
N_{obs}	128	121	121	126	126	124	123	123
$N_{treated}$	3	2	1	4	5	2	1	3
	A2 Zip-code Level							
Proportion of Overnight Stay	0.0958 (0.0449) [0.0766]	-0.0154 (0.0471) [0.754]	0.0205 (0.0446) [0.662]	0.00345 (0.0431) [0.939]	0.0263 (0.0398) [0.534]	0.0288 (0.0301) [0.375]	-0.000803 (0.0596) [0.990]	0.00869 (0.060) [0.890]
Stacked Estimate	0.02 (0.018) [0.308]							
Rural-Estimate Correlation	0.0163							
N_{obs}	857	845	840	845	837	706	805	802
$N_{treated}$	7	7	13	5	15	10	11	14
Panel B: Inpatient Data								
	B1 Hospital Level							
Length of Stay	0.651 (0.83) [0.463]	0.479 (1.17) [0.697]	0.535 (1.92) [0.789]	0.0489 (0.688) [0.946]	-0.11 (0.687) [0.878]	0.609 (0.985) [0.559]	0.84 (1.77) [0.653]	0.764 (1.26) [0.568]
Stacked Estimate	0.354 (0.357) [0.359]							
Rural-Estimate Correlation	0.0279							
N_{obs}	153	144	144	148	147	146	142	142
$N_{treated}$	3	2	1	4	5	2	1	3
	B2 Zip-code Level							
Length of Stay	0.412 (0.822) [0.634]	0.0751 (0.893) [0.936]	0.016 (0.856) [0.986]	0.394 (0.908) [0.680]	0.148 (0.718) [0.844]	0.152 (0.577) [0.801]	0.224 (0.989) [0.828]	0.0882 (1.01) [0.933]
Stacked Estimate	0.185 (0.336) [0.602]							
Rural-Estimate Correlation	0.0961							
N_{obs}	857	845	840	845	837	706	805	802
$N_{treated}$	7	7	13	5	15	10	11	14
Urban-Rural Score	7.54	5.87	5.41	5.90	5.29	4.95	6.53	4.12
T	18	18	18	19	19	18	15	15
$T_{treated}$	6	6	6	7	7	6	3	3
Year	2012	2013	2013	2016	2017	2018	2020	2020

P-values are presented in square brackets, standard errors in parentheses, and all values are estimates from the model.

Table A7: Effects of Hospital Closure on Days between Revisit and Readmission within 30 days

	Hospital Closures							
HOSPID	13112 (1)	13074 (2)	13106 (3)	13071 (4)	13002 (5)	13055 (6)	13056 (7)	13050 (8)
Panel A: Outpatient Data								
	A1 Hospital Level							
Revisit Days	-0.0649 (0.325) [0.849]	0.0575 (0.347) [0.874]	-0.0575 (0.542) [0.919]	0.0563 (0.189) [0.776]	0.172 (0.157) [0.315]	-0.149 (0.247) [0.569]	0.249 (0.569) [0.677]	-0.087 (0.315) [0.791]
Stacked Estimate	0.0305 (0.0996) [0.770]							
Rural-Estimate Correlation	0.0406							
N_{obs}	126	119	119	125	125	124	123	123
$N_{treated}$	3	2	1	4	5	2	1	3
	A2 Zip-code Level							
Revisit Days	0.352 (0.698) [0.632]	-0.261 (0.558) [0.656]	0.192 (0.377) [0.628]	0.325 (0.498) [0.538]	0.664 (0.332) [0.0924]	0.199 (0.381) [0.620]	-0.460 (0.700) [0.536]	-0.0356 (0.430) [0.937]
Stacked Estimate	0.136 (0.174) [0.465]							
Rural-Estimate Correlation	-0.018							
N_{obs}	704	690	690	692	695	640	658	658
$N_{treated}$	7	7	13	5	15	10	11	14
Panel B: Inpatient Data								
	B1 Hospital Level							
Readmission Days	-0.477 (0.651) [0.492]	0.271 (0.725) [0.722]	0.267 (1.04) [0.806]	0.39 (0.467) [0.436]	-0.232 (0.495) [0.656]	-0.176 (0.869) [0.846]	0.0578 (1.97) [0.977]	0.243 (0.882) [0.793]
Stacked Estimate	0.0221 (0.266) [0.936]							
Rural-Estimate Correlation	-0.127							
N_{obs}	146	131	131	139	137	140	130	130
$N_{treated}$	3	2	1	4	4	2	1	3
	B2 Zip-code Level							
Readmission Days	1.03 (1.38) [0.482]	1.18 (1.47) [0.451]	1.54 (1.43) [0.321]	1.12 (1.34) [0.436]	-0.603 (1.29) [0.656]	-0.327 (1.34) [0.815]	-1.44 (1.91) [0.479]	-0.124 (1.93) [0.951]
Stacked Estimate	0.269 (0.589) [0.665]							
Rural-Estimate Correlation	0.183							
N_{obs}	549	556	552	540	543	546	542	542
$N_{treated}$	7	2	10	4	12	3	6	2
Urban-Rural Score	7.54	5.87	5.41	5.90	5.29	4.95	6.53	4.12
T	18	18	18	19	19	18	15	15
$T_{treated}$	6	6	6	7	7	6	3	3
Year	2012	2013	2013	2016	2017	2018	2020	2020

P-values are presented in square brackets, standard errors in parentheses, and all values are estimates from the model.