TO REGULATE COSTS OR ACCESS? TWO APPROACHES TO HEALTH CARE REGIONALIZATION

Lindsey J. Patterson

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Supervisor of Dissertation

Guy David, Gilbert and Shelley Harrison Professor of Health Care Management

Graduate Group Chairperson

Nancy Zhang, Professor of Statistics

Dissertation Committee

Abby E. Alpert, Assistant Professor of Health Care Management
Daniel E. Polsky, Distinguished Professor of Health Economics, Johns Hopkins University

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Dedicated to my parents.

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ABSTRACT

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Guy David

The first chapter examines the effect of Marylands Global Budget Revenue (GBR) payment system on hospital volume. Under this payment system, the rate regulating authority prospectively determines each hospital's revenue budget based on historic utilization to slow total hospital spending growth in the state. Theory suggests that hospitals will meet this target by reducing volume only when they have exhausted their ability to adjust reimbursement rates. Due to Marylands unique history of hospital payment, estimation of causal effects has been limited by availability of suitable comparison groups. This paper develops three measures of in state hospital-level exposure—hospitals with above median growth in predicted disease burden, hospitals with above median predicted growth in hospital inpatient service lines, and hospitals without revenue exclusions. For the two exposure measures based on growth, I apply a trend-break difference-in-difference under the a priori assumption that hospital volume would continue along pre-intervention trends in the absence of the payment system change. I find no evidence that the GBR is associated with any divergence of hospital inpatient volume from pre-intervention trends. The second chapter studies the effect of regional systems of care on health care delivery and outcomes for time critical illnesses of acute stroke and ST-elevation myocardial infarction (STEMI) in Philadelphia, Pennsylvania. Regionalization in Philadelphia trades off small increases in patient transportation time for improved access to appropriate treatment at the receiving hospital. This paper leverages the differential impact of regionalization on neighborhoods where the nearest hospital is not designated as a regional center of care. In these treated areas, emergency medical services (EMS) personnel bypass the nearest hospital to transport acute stroke and

STEMI patients to the nearest regional center of care. Using a difference-in-differences empirical approach, this paper estimates the effect of regionalization on the probability of admission to a non-designated facility and a number of short-term utilization and outcome measures. Regionalization is effective in channeling volume to designated facilities, but the effects of regionalization are both condition and market specific.

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PREFACE

This dissertation examines two approaches to changing health care delivery in local health care markets. While the policy examined in my first paper focuses on access and quality, the policies examined in the second paper focus on costs and access. Together these papers touch on all three corners of the Iron Triangle of health care—cost, quality, and access. In my first paper, I look at Maryland's 2014 implementation of an annual total hospital revenue cap, the Global Budget Revenue (GBR) system—an explicit constraint on hospital spending in the state of Maryland. Under the GBR system, Maryland's hospital rate-regulating authority prospectively determines each hospital's revenue budget based on historic utilization to slow total hospital spending growth in the state. My conceptual framework suggests that hospitals will meet this target by reducing volume only when they have exhausted their ability to adjust reimbursement rates (as allowed by the rate regulator). I develop three potential measures of within-Maryland exposure to the payment system change, but find that volume in hospitals predicted to be more exposed trended differently than volume in hospitals predicted to be less exposed prior to the payment system change. While current and former policy makers are confident that the GBR has changed the trajectory of hospital care in Maryland, findings to date have been mixed as defining a suitable comparison group is difficult (Sharfstein et al., 2018a; Roberts et al., 2018c; Sharfstein et al., 2018b).

My second paper, joint research with Guy David, looks at health care regionalization in Philadelphia, and specifically two destination policies for time critical emergencies. The destination policies require emergency medical services (EMS) providers to transport acute stroke patients to hospitals certified as primary stroke centers and ST elevation myocardial infarction (STEMI) patients to hospitals capable of percutaneous coronary intervention (PCI). The policy differentially affects patients living in areas of the city where the nearest hospital is not a primary stroke center or PCI-capable as EMS crews transporting stroke and STEMI incidents in these areas presumably bypass the nearest hospital to comply with the destination policies, trading off a small increase in transportation time for improved access to appropriate treatment at the destination. We find the destination policy for STEMI patients results in the near elimination of patients admitted to non-PCI capable hospitals; but that stroke regionalization has an economically small, but statistically significant effect on transportation patterns for acute stroke patients. These differences likely stem from the reliability of diagnosing stroke and STEMI in the pre-hospital setting.

CHAPTER 1 : Volume Responses to Hospital Revenue Targets: Evidence from Maryland's Global Budget Revenue System

Health care spending in the United States is higher than in other industrialized countries without commensurate returns to health; in addition, spending is growing at a faster rate than income, consequently putting a strain on the U.S. economy and individual household finances. Shifting financial risk to health care providers is one lever to change the level and trajectory of health care spending. Along with the federal government, states are pioneering health care reform, but vary in their approaches to shifting risk to health care providers. An interesting case is Maryland's all-payer system, which transitioned from per admission rate regulation to a Global Budget Revenue (GBR) model for hospital care as a steppingstone to full capitation based on total per capita cost of care.

This paper focuses on hospital responses to the Maryland GBR—a hospital payment system that limits per hospital spending per year by constraining total hospital revenue to a prospectively determined amount. Under the GBR system, hospitals are permitted to meet their revenue targets by adjusting the reimbursement rates or by changing hospital volume, or a combination thereof. Several studies have examined the impact of Maryland's GBR system on hospital utilization in the Medicare population using matched out of state Medicare beneficiaries as comparisons, but find differences in pre intervention trends, limiting their ability to ascribe causality to the results (Roberts et al., 2018b; Beil et al., 2019).

This paper explores three within-Maryland hospital level measures of exposure to the payment system change. Five Maryland hospitals negotiated revenue exemptions from the global budget—exempt categories include revenue from non-Maryland residents and/or revenue for specific hospital service lines. I argue that the remaining 30 general acute care hospitals without revenue streams exempt from the global budget more acutely feel the pressure to reduce volume and/or adjust reimbursement rates than the five hospitals with separate revenue streams. In a second measure of within-Maryland hospital exposure, I classify the 30 hospitals without revenue exclusions into two categories—hospitals with above median growth in the predicted disease burden of their catchment area and hospitals with below median growth. I calculate predicted disease burden following Costinot et al. (2019), leveraging variation in the age-sex profile of hospitals' catchment areas and variation in the burden of disease by age and sex. Hospitals with above median growth in predicted disease burden are more exposed to the payment system change to the extent that this growth is not reflected in their total revenue targets. In a third measure, I separate the 30 hospitals without revenue exclusions into two groups based on predicted growth in inpatient service lines. I construct an exposure-weighted measure of hospital inpatient growth, commonly known as a shift-share measure (Goldsmith-Pinkham et al., 2018; Borusyak et al., 2018), using pre period growth in total charges by service line across all Maryland GBR hospitals and each hospital's share of admissions in a given service line. Hospitals with above median predicted growth are more exposed to the GBR payment system change to the extent that this growth is not reflected in their revenue targets.

Across all three measures, I find evidence of differences in pre intervention trends in hospital inpatient volume between my more exposed and less exposed hospital groups. Inpatient visits decreased faster at hospitals without revenue exclusions than at hospitals with revenue exclusions prior to the payment system change. Inpatient visits to hospitals with above median growth in predicted disease burden or above median predicted growth in inpatient service lines decreased slower prior to the payment system change than did visits at hospitals with below median values of these respective measures. I find no evidence that the Maryland GBR payment system was associated with any deviation from pre intervention trends for inpatient volume. I present descriptives for volume in these hospital settings due to limited pre intervention data for observation and outpatient hospital volume.

The paper proceeds as follows. In Section 1.1, I review the recent history of hospital payment in Maryland and describe the GBR payment system. In Section 1.2, I discuss the relevant literature. Section 1.3 presents a framework for thinking about hospital behavior under the GBR system. Section 1.4 describes my sample, defines my three measures of within-Maryland exposure to the payment system change, and discusses the outcomes of interest. Section 1.5 outlines my empirical approach, while Section 1.6 presents results. Section 1.7 summarizes limitations and concludes.

1.1. Policy Background

The state of Maryland is unique in its approach to paying hospitals. In this section I describe Maryland's history with all-payer rate regulation and the state's transition to hospital global budgets first for rural hospitals and then for all acute hospitals in the state.

1.1.1. Rate regulation

Since the late 1970s, Maryland has operated an all-payer rate setting system for hospital inpatient and on-campus outpatient care. The impetus for rate regulation was a combination of rising hospital costs and increasing levels of uncompensated care (Murray, 2009). Initiated by hospital trustees and supported by the Maryland Hospital Association (MHA), legislation creating an authority to regulate hospital payment rates was passed by the Maryland legislature in 1971. The Health Care Services Cost Review Commission (HSCRC) remains the rate regulating body today.

The original goal of rate regulation in Maryland was to control per admission spending. This was accomplished by prospectively determining rates and constraining per admission revenue for all payers. One vital part of the longevity in Maryland's hospital payment experiment has been cooperation of public payers—Medicare and Medicaid. In 1977, the HSCRC negotiated a waiver with the Health Care Financing Administration (HCFA) under which Medicare and Medicaid agreed to pay hospitals following the regulated rates.[1] Still true today, the rate setting authority determines the rates by which all payers must abide, including Medicare and Medicaid which receive a six percent discount on the regulated rates. Compared to national averages, Medicare and Medicaid reimburse above average and com-

[1]HCFA was the predecessor to the Centers for Medicare and Medicaid Services (CMS).

mercial insurers reimburse below average in Maryland. A second vital part of the continued operation of Maryland's all-payer rate regulation has been the skill and transparency of regulators at the HSCRC, and commitment from policy makers, hospitals, payers, and the public (Pauly and Town, 2012).

Although rate regulation in Maryland succeeded in controlling spending per admission, it has not succeeded in controlling growth in total hospital spending. Between 1976 and 2000, the HSCRC adjusted rates based on overages and underages in hospital volume. Rates for new volume were set lower than rates for existing volume in an effort to reimburse for only variable costs, as the original rate and volume determinations reflected fixed costs (Advisory Board Health Policy, 2016). This volume adjustment was dropped in 2000 under negotiations with the hospital industry, and over the next seven years hospital admissions increased annually by 2.7 percent on average compared to the 1 percent national average over the same time period (Murray, 2009). Between 2000 and 2008, the rate regulation system encouraged hospital volume by reimbursing new volume at the same rates as historic volume (Kalman et al., 2014; Pauly and Town, 2012). The volume adjustment was re-implemented in 2008.

Maryland has also been an early adopter of pay-for-performance, including Quality-Based Reimbursement (QBR) in 2009, Maryland Hospital Acquired Conditions (MHAC) in 2010, the Admission-Readmission Revenue (ARR) program in 2011, and Readmission Shared Savings Policy (RSSP) in 2013. Despite success in controlling per admission spending and attempts to change incentives through pay for performance, Maryland risked losing it's original waiver after experiencing a period of spending growth that exceeded the national average.

1.1.2. Global budgets

The impetus behind the payment system shift from per admission revenue regulation to total revenue regulation was twofold. As discussed above, Maryland experienced a period of spending growth that exceeded the national average. Both the state and CMS were concerned that Maryland risked violating the terms of its original waiver. Second, regulating costs per-admission was poorly aligned with pay-for-performance initiatives in the state and the desire to focus on comprehensive coordinated care delivery (Haber et al., 2016).

In 2014, Maryland started a five year All-Payer Model Demonstration with CMS. To achieve the terms of its updated waiver, and specifically the requirement to limit all-payer per capita total hospital cost growth to 3.58%, Maryland transitioned all general acute care hospitals to one of two global budget programs. Ten rural hospitals participate in the TPR payment system.[2] All remaining general hospitals participate in the GBR payment system. Both systems set a limit on the total revenue a hospital can earn in a given year. The revenue target applies to both inpatient and outpatient hospital services and all patients receiving care in Maryland hospitals regardless of residence.[3]

Hospitals in the GBR system are given a prospectively determined global budgets based on historic (2013) volume, costs, and utilization. Rates remain regulated by the rate setting authority, but hospitals are allowed to adjust rates across all service lines within a 5% corridor without prior approval and up to 10% with approval to meet their target. In addition to assuming increased financial risk through the global payment, hospitals are penalized or rewarded for rates of potentially avoidable utilization and performance in the state's quality based reimbursement program. A generalization of the target formula is given below (Haber et al., 2016):

$$Rev_{ht} = Rev_{h,2013} \cdot [(1 + Infl_t + Adj_t) \cdot (1 + \Delta Vol_{ht})]$$

where hospital h revenue in year t is limited to 2013 revenue adjusted for inflation $Infl_t$, a year specific adjustment Adj_t, and allowed growth in hospital volume ΔVol_{ht} (changes to market share, service area demographics, and rates of potentially avoidable utilization).

[2]Eight of the ten TPR rural hospitals have accepted global budget payments since 2010.

[3]Four hospitals negotiated revenue limits that excluded revenue for non-Maryland residents. More information on these hospitals and exclusions is provided in Section 1.1.3.

Hospitals are penalized for both overruns and underruns in total revenue.

1.1.3. Hospitals with global budget-excluded revenue

The global budgets for four Maryland hospitals excluded revenue from non-Maryland residents in the first two years of the GBR system. The University of Maryland Medical Center, the Johns Hopkins Hospital, Suburban Hospital (also within the Johns Hopkins Health System), and Johns Hopkins Bayview Medical Center each had non-resident revenue excluded from the hospital's global budget. Payment rates for non-resident visits to these hospitals are regulated by the HSCRC, but non-resident volume for these four hospitals remained unconstrained by the global budget. The University of Maryland Medical Center operated under this revenue exclusion for non-residents through June 2015; while the three Johns Hopkins Health System hospitals kept this revenue exclusion through June 2017.

In addition to the exclusion of non-resident revenue from the global budget, three of the four hospitals negotiated carve outs of specific service lines from their global budgets. Revenues from burn cases at the Johns Hopkins Hospital and Johns Hopkins Bayview Medical center are excluded from the global budget (Health Services Cost Review Commission, 2014a). Global budgets for the University of Maryland Medical Center and the Johns Hopkins Hospital do not include revenue from inpatient solid organ transplants, inpatient and outpatient blood marrow transplants, inpatient oncology research, inpatient oncology transfers in, inpatient hematologic malignancies, and inpatient transfers in from acute care hospitals as these facilities are considered "statewide resource[s] for tertiary and quaternary care" (Health Services Cost Review Commission, 2014a,b).

The University of Maryland Charles Regional Medical Center is the fifth Maryland hospital participating in the GBR that negotiated revenue exclusions from the hospital global budget, specifically revenues for services covered under Medicare Part B (Health Services Cost Review Commission, 2014b). Part B covers diagnostic and treatment services in the hospital outpatient and observation settings (Medicare.gov, 2019). Rates for these services remain regulated by the HSCRC, but volume is not limited by the global budget.

1.2. Literature

This paper draws from and contributes to research on hospital budgets in Maryland, which I discuss in this section.

Several studies have examined Maryland's Total Patient Revenue (TPR) program, with mixed results. Mortensen et al. (2014) study the effect of TPR on hospital readmissions through the first 18 months of the policy (starting July 1, 2010) for eight of those rural hospitals. The authors use inpatient discharge data to compare hospital readmissions for the eight treated hospitals to three rural non-treated hospitals and 30 total non-treated Maryland hospitals for the 18 month periods pre and post intervention using a difference-in-difference linear probability model. Results of this study find no effect of the TPR on hospital readmissions.

Focusing on Medicare fee-for-service beneficiaries, Roberts et al. (2018a) similarly use an in-state comparison group. The authors identify beneficiaries residing in zip codes that are at least 15 minutes farther to a TPR hospital than all other hospitals for the comparison sample. They estimate the differential change in hospital stays, emergency department visits, and price-standardized measures of inpatient and outpatient hospital spending three years after the program implementation. Despite pursuing multiple sensitivity analyses, the authors do not find evidence the TPR program changed inpatient admissions, observation stays, emergency department visits, or hospital spending.

Pines et al. (2019) compare changes in inpatient admissions, emergency department visits, and hospital outpatient visits at the eight TPR hospitals to changes at seven non-TPR Maryland hospitals before and after the TPR system implementation. This paper differs from the study by Roberts et al. (2018a) in that utilization for all payers, not just Medicare, is examined. Pines et al. (2019) find that the TPR decreased inpatient admissions, admissions from the emergency department, and hospital outpatient visits in the first three years of the system.

Malmmose et al. (2018) study the same eight rural hospitals operating under TPR to determine the impact of the program implementation on hospitals' reported revenues, expenses, and margins. In their common size analysis the authors examine gross and net patient revenue, other operating revenue, and expenses for regulated and unregulated services as well as non-operating revenue and expenses 2007 through 2013. They find a decrease in growth of gross revenue for both treatment and control hospitals, consisting of an increase in growth of unregulated gross revenue in treatment hospitals but a decrease in control hospitals. Malmmose et al. (2018) also find evidence that the TPR program shifted costs from regulated to non-regulated settings, and explain that some treatment hospitals subsidized non-employed physicians to align incentives—an expense that is recorded as an unregulated cost.

Roberts et al. (2018b) examine the first two years of the GBR system, and specifically the program's impact on hospital and primary care utilization in the Medicare fee-for-service population. The authors focus on beneficiaries residing in eight Maryland counties served by 32 of the 36 GBR hospitals participating in the inaugural year of the policy change. The authors use coarsened exact matching to identify control counties outside of Maryland. Many aspects of this paper are of interest. First, the authors find evidence of violation of the parallel trends assumption underlying the difference-in-differences estimator. As the authors acknowledge, differences in pre intervention trends will bias the difference-in-differences estimates. They report finding a statistically significant decrease in return hospital stays and increase in primary care visits. The authors specify an additional set of analyses that allow for differences in pre-intervention trends, and find the policy change to be associated with a statistically significant decrease in hospital stays but no change in primary care visits. They conclude that there is no consistent evidence of change to hospital and primary care utilization in the Medicare fee-for-service population resulting from the GBR.

Beil et al. (2019) combine findings from the first three years of the CMS evaluation of the GBR payment system change. Similar to Roberts et al. (2018b), the authors find evidence of differences in pre intervention trends in outcomes for Maryland Medicare beneficiaries and matched comparison Medicare beneficiaries residing outside of Maryland. The authors modify their empirical approach to allow the intervention and comparison groups to follow different trends over the study period and find decreases in hospital spending and inpatient admissions for Maryland beneficiaries after the GBR. As the authors do not present standard difference-in-difference results without allowing for differences in pre intervention trends, it is not possible to determine whether the addition of pre intervention trends changed their findings.

Galarraga et al. (2019) examine the impact of the GBR on admissions from the emergency department (ED) by comparing four MedStar Maryland hospitals to two MedStar D.C. hospitals before and after the payment system change in a difference-in-difference design. The authors find evidence that admissions from the ED were declining prior to the GBR in Maryland while admissions from the ED in D.C. hospitals were stable, and possibly increasing. They apply a standard difference-in-difference framework including hospital and year fixed effects despite evidence of differences in pre 2014 trends, and find that admissions from the ED declined in Maryland following the GBR relative to changes in D.C.

Existing studies of the Maryland GBR, at the hospital or area level, have used out of state comparison groups with limited success. This paper contributes to the study of hospital budgets in Maryland by exploring three within Maryland measures of hospital exposure. Further, I estimate the effect of the GBR on hospital volume across all payers, assuming the existence of pre intervention trends for at least two of the within Maryland measures—above median growth in predicted disease burden, and above median predicted growth in inpatient service lines.

This paper contributes to the study of Maryland global budgets, first by examining changes at the hospital level across all payers. Prior work on the GBR has compared utilization at the beneficiary or area level and focused on the Medicare population. Second, I develop three measures exposure within Maryland.

1.3. Conceptual Framework

In this section I provide intuition for thinking about hospital behavior under the GBR payment system.

Suppose there are three types of hospital volume: volume that the hospital cannot influence and must provide e (e.g., motor vehicle accidents, stabilization), volume that the hospital can influence by providing primary care in the community setting (b) but must treat when presented to the hospital g (e.g., acute complications from diabetes), and volume that the hospital cannot influence through primary care and has discretion in providing d (e.g., pregnancy). Prior to the payment system change, per admission revenue was set through rate regulation by the HSCRC with admissions from all payers reimbursed the same rate. Assume that these three types of volume each earn the same reimbursement, p_v, and that hospitals are reimbursed p_b for primary care provided in the community, with $p_b < p_v$ Hospital profit under rate regulation is given by:

$$\pi = p_v\left(e + g(b) + d\right) + p_b b - C(e, g(b), d, b) \tag{1.1}$$

where $g(b)$ is a function of hospital-provided community primary care b and $C(.)$ is the cost function. Assuming that hospital utility is solely a function of profit, the objective of the hospital under rate regulation is to maximize π through it's choice of d and b. Taking first order conditions of 1.1:

$$\begin{aligned}
&\text{w.r.t. } d: p_v - \frac{\partial C}{\partial d} = 0 \\
&\text{w.r.t. } b: p_v \frac{\partial g(b)}{\partial b} + p_b - \frac{\partial C}{\partial b} - \frac{\partial C}{\partial g(b)}\frac{\partial g(b)}{\partial b} = 0
\end{aligned}$$

Hospitals will provide discretionary volume d to the point where the marginal cost of the visit is equal to the marginal reimbursement. Rearranging the second condition:

$$p_b = \frac{\partial C}{\partial b} + \frac{\partial C}{\partial g(b)}\frac{\partial g(b)}{\partial b} - p_v\frac{\partial g(b)}{\partial b}$$

Assuming that $C'(.) > 0$ and $\frac{\partial g(b)}{\partial b} < 0$, if lost hospital revenue from providing community primary care $p_v\frac{\partial g(b)}{\partial b}$ is greater than the hospital cost offset from moving care out of the hospital $\frac{\partial C}{\partial g(b)}\frac{\partial g(b)}{\partial b}$, the hospital acts as if it has a higher effective marginal cost, providing a lower level of b than it would otherwise.

Suppose $\frac{\partial g(b)}{\partial b} = -1$, a one unit increase in b decreases $g(b)$ by one unit. The hospital provides primary care in the community b to the point where the difference in reimbursement is equal to the difference in marginal costs:

$$p_b = \frac{\partial C}{\partial b} - \frac{\partial C}{\partial g(b)} + p_v$$

If I further assume that $p_v > \frac{\partial C}{\partial g(b)}$, the hospital acts as if it has a higher marginal cost to providing b and thereby provides less than it otherwise would.

If e were to increase under rate regulation, the hospital would make no change to the amount of d or b provided, as e does not enter their first order conditions. If $g(b)$ we to increase under rate regulation, the marginal cost of $g(b)$, $\frac{\partial C}{\partial g(b)}$, would be higher, meaning the hospital's effective marginal cost of providing b would be lower, and the hospital increases the amount of community primary care b provided.

The GBR system introduced a total hospital revenue constraint, Y, and additionally permitted the hospital to adjust payment rates above a regulated floor rate $\underline{p}_v$ and below a regulated ceiling rate $\overline{p}_v$. While adjusting p_v may increase fixed costs (e.g., cost to train billing department to monitor and adjust rates), it does not affect variable costs. Hospitals choose d, b, and p_v to maximize profits subject to the revenue constraint $Y = p_v\,(e + g(b) + d)$ and the constraints on reimbursement p_v.

$$\mathcal{L}(d,b,p_v) = p_v\,(e+g(b)+d) + p_b b - C(e,g(b),d,b) \\ + \lambda\,(Y - p_v\,(e+g(b)+d)) + \mu_1(p_v - \underline{p}_v) + \mu_2(\overline{p}_v - p_v) \quad (1.2)$$

Taking first order KKT optimality conditions:

$$\begin{aligned}
&\text{w.r.t. } d: \; p_v - \frac{\partial C}{\partial d} - \lambda p_v = 0 \\
&\text{w.r.t. } b: \; p_v\frac{\partial g(b)}{\partial b} + p_b - \frac{\partial C}{\partial b} - \frac{\partial C}{\partial g(b)}\frac{\partial g(b)}{\partial b} - \lambda\left(p_v\frac{\partial g(b)}{\partial b}\right) = 0 \\
&\text{w.r.t. } p_v: \; e+g(b)+d - \lambda(e+g(b)+d) + \mu_1 - \mu_2 \\
&Y = p_v\,(e+g(b)+d) \\
&\mu_1(p_v - \underline{p}_v) = 0 \\
&\mu_1 \geq 0 \\
&p_v - \underline{p}_v \geq 0 \\
&\mu_2(\overline{p}_v - p_v) = 0 \\
&\mu_2 \geq 0 \\
&\overline{p}_v - p_v \geq 0
\end{aligned}$$

One could imagine a number of scenarios in which e or $g(b)$ increases at a faster rate than growth in Y—perhaps the disease burden of the community served by the hospital grows faster than growth reflected in Y. To meet Y a hospital would need to decrease p_v or d, or increase b to decrease $g(b)$. Because increasing b is costly, $\frac{\partial C}{\partial b} > 0$, the hospital will reduce either discretionary volume d or p_v. If we imagine that decreasing d is also costly—in terms of reputation (not modeled here) or penalties served by the HSCRC—hospitals will decrease p_v to meet Y.

I empirically test for whether hospitals more exposed to the revenue target respond by decreasing total volume, $e + g(b) + d$. Future work could assess changes separately by e, $g(b)$, and d.

1.4. Data and Descriptive Statistics

In this section I describe the sources of data used in my analyses, outline my sample construction, define three ways to measure within-Maryland hospital exposure to the payment system change, and define my outcomes of interest. Additionally, I provide descriptive statistics on inpatient, outpatient, and observation visits in the year prior to the payment system change; and present baseline measurements of my outcomes of interest.

1.4.1. Sample Definitions

The main data used in this analysis are from the Health Services Cost Review Commission (HSCRC), which is also Maryland's rate regulating authority. I use hospital inpatient discharge data July 1, 2009 through June 30, 2017 (4.5 pre policy years and 3.5 post policy years); hospital observation data July 1, 2012 through June 30, 2017 (1.5 pre policy years and 3.5 post policy years); and hospital outpatient discharge data July 1, 2012 through June 30, 2017 (1.5 pre policy years and 3.5 post policy years). The data describe hospital utilization for all hospitals providing acute care located in Maryland. I make several sample restrictions, as described in Table 1. Importantly, I keep only the 35 general hospitals participating in the GBR with complete pre period data.[4] In total, I exclude 14 percent of inpatient visits July 2009 - June 2017; 12 percent of observation stays July 2012 - June 2017; and 16 percent of outpatient visits July 2012 - June 2017.

[4] I exclude the University of Maryland Rehabilitation and Orthopeadic Institute and the Levindale Hebrew Geriatric Center and Hospital, both of which are regulated by the GBR but provide limited inpatient services; three free standing emergency departments which are regulated by the GBR—Germantown Emergency Center, Queen Anne's Emergency Center, Bowie Emergency Center; and Holy Cross Germantown Hospital, which opened after the implementation of the GBR payment system.

Table 1: Maryland hospital inpatient, observation, and outpatient visits, sample exclusions

	Inpatient	Observation	Outpatient
All visits	5,420,891	357,358	28,007,389
Non-short term acute visit	26,781	501	79,516
Invalid admission or discharge status	58,598	2,918	520,540
Other invalid field	402	1,736	48,300
Invalid or missing zip code	22,414	666	109,897
Closed hospital or non-GBR	601,389	35,619	2,965,146
Facility regulated by GBR but excluded from analysis	41,399	1,301	643,098
Excluded visits	750,983	42,741	4,366,497
Included visits	4,669,908	314,617	23,640,892

Source: Maryland Health Services Cost Review Commission (HSCRC inpatient discharge data, July 2009 - June 2017, observation discharge data July 2012 - June 2017, outpatient discharge data July 2012 - June 2017.

1.4.2. Within-Maryland measures of hospital exposure

As discussed in Section 2.2, studies of the GBR are limited by selection of an appropriate comparison group. Though a possible comparison group of hospitals could consist of facilities operating in the surrounding regions of the District of Columbia (D.C.), Delaware, Pennsylvania, Virginia, or West Virginia, I outline several differences in the timing and extent of Medicaid expansions that are likely correlated with both exposure to the GBR and with hospital utilization. First, Maryland has provided insurance coverage for low income adults since July 2007 under a Section 1115 waiver, with these low income adults expanded to full Medicaid benefits under the Affordable Care Act (ACA) Medicaid expansion in 2014 (Medicaid.gov, 2019b; Blumberg et al., 2012). D.C. adopted a full Medicaid expansion early, in 2010, through a Section 1115 waiver and early ACA federal matching funds (The Kaiser Commission on Medicaid and the Uninsured, 2012; The Centers for Medicare & Medicaid Services, 2014). Delaware and West Virginia expanded Medicaid in 2014, Pennsylvania expanded Medicaid in 2015, and Virginia expanded in 2019. In addition to differences in timings of Medicaid expansions by regions surrounding Maryland, there are differences in the extent of the expansions. D.C. offers more generous expansion, covering higher levels of low income adults than Maryland, Delaware, Pennsylvania, and Virginia. Both Maryland and D.C. offer more inclusive coverage levels for traditionally covered Medicaid populations of pregnant women and children than dp Pennsylvania and Virginia (Medicaid.gov, 2019c). From the Oregon Health Insurance experiment, we know that Medicaid expansion increases emergency department utilization and hospitalizations (Taubman et al., 2014; Finkelstein et al., 2012). Using hospitals from any of the surrounding regions could confound the effects of Medicaid expansion and the GBR payment system change.[5]

In this section, I discuss three within-Maryland measures of hospital exposure to the payment system change: absence or presence of revenue exclusions from the target, above/below median growth in predicted disease burden of the hospital catchment area, and above/below median predicted growth in inpatient service lines.

Hospitals with revenue exclusions from the GBR

As discussed in Section 1.1.3, five hospitals negotiated revenue exclusions from their global budgets. As a result of revenue exclusions from the global budget, these hospitals may be less incentivized to reduce hospital volume than Maryland hospitals without revenue exclusions from the global budget. My first measure of within-Maryland exposure to the global budget compares the 30 hospitals without revenue exclusions to these five hospitals with exclusions. I examine overall volume by inpatient, observation, and outpatient setting though the revenue exclusions apply more specifically. Future work could examine the association between revenue exclusions and changes in the specific service lines or groups of patients to which they apply.

Table 2 compares baseline, 2013, admission characteristics for the 30 hospitals without revenue exclusions and the 5 hospitals with revenue exclusions. Patients admitted to hospitals without revenue exclusions are more likely to be female on average than patients admitted to hospitals with revenue exclusions; older on average than patients admitted to hospitals with revenue exclusions; more likely to be a race other than white or black; and are more likely to

[5]The regions also differ in the extent of managed care penetration. Maryland and Delaware operate mandatory managed care enrollment for most Medicaid enrollees, while other states do not (Medicaid.gov, 2019b,a).

be Maryland residents than patients admitted to hospitals with revenue exclusions. There are no statistically significant differences in characteristics of observation stay patients between the two groups of hospitals in the year prior to the payment system change. Patients visiting the outpatient setting of hospitals without revenue exclusions are more likely to be female, older, and more likely to have Medicare insurance or be uninsured, ceteris paribus. Similar to the inpatient setting, I find that patients in the outpatient setting of hospitals without revenue exclusions are more likely to be Maryland residents than are patients in the outpatient setting of hospitals with revenue exclusions.

Table 2: Baseline visit characteristics for hospitals with and without revenue exclusions, 2013

	Inpatient			Observation		Outpatient		
	No revenue excluded	Any revenue excluded		No revenue excluded	Any revenue excluded	No revenue excluded	Any revenue excluded	
Female	59.36	50.81	***	59.42	57.77	60.62	55.57	***
Age								
0-14	13.74	12.45		3.05	4.18	9.68	12.95	
15-34	17.90	18.34		11.30	11.91	23.73	22.04	
35-49	14.15	16.62	**	19.56	21.15	18.72	19.13	
50-64	20.50	25.25	***	29.67	29.38	23.42	26.83	***
65+	33.70	27.35		36.42	33.39	24.46	19.06	
Race								
White	49.39	55.24		49.98	50.42	50.38	51.27	
Black	33.44	35.43		43.31	42.32	40.63	38.36	
Other race	17.17	9.33	**	6.70	7.26	8.99	10.37	
Hispanic/Latino origin/descent	5.22	3.14		3.04	2.81	4.17	3.00	
Payer								
Commercial	34.41	34.07		30.78	29.84	39.46	42.22	
Medicare	38.05	32.51		40.55	38.00	27.37	21.89	***
Medicaid	20.30	25.69		17.96	22.65	20.52	26.22	
Uninsured	5.51	5.41		8.78	7.51	10.09	5.47	***
Other government	1.34	1.78		1.37	1.62	1.74	2.44	
Other/unknown payer	0.39	0.54		0.57	0.39	0.82	1.76	***
Maryland resident	95.59	89.34	*	95.48	96.30	95.38	89.24	*
N	30	5		30	5	30	5	

*** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.
Pooled means are weighted by number of admissions. Standard errors used to estimate p-values clustered by hospital.
Source: Maryland Health Services Cost Review Commission discharge data 2013.

Hospitals serving areas with higher growth in disease burden

My second measure of within-Maryland hospital exposure to the payment system change uses pre period growth in the predicted disease burden of the hospital's catchment area to separate the 30 hospitals without revenue exclusions into two groups—those with above median growth in predicted disease burden and those with below median growth in predicted disease burden. The measure of predicted disease burden comes directly from Costinot et al. (2019) who use cross-sectional variation in disease burden by country as a demand shifter to test the home-market effect for pharmaceuticals.[6] Their approach is based on Acemoglu and Linn (2004) who use variation in demographic composition over time in the U.S. to develop a plausibly exogenous measure of market size for pharmaceuticals.

I combine annual measures of Maryland's all-cause disease burden from the Institute of Health Metrics and Evaluation (IHME) with annual zip code tabulation area (ZCTA) population by age and sex from American Community Survey (ACS) 5-year estimates to measure the predicted disease burden of a zip code in a given year (Global Burden of Disease Collaborative Network, 2018). I define hospital catchment areas using the primary and secondary service areas defined by the hospital GBR agreements negotiated with the HSCRC. Primary and secondary services combined represent 75 percent of the hospital's 2013 admissions. All hospitals define their primary and secondary service areas at the zip code level, except for Peninsula Regional Medical Center which uses counties. I map the zip codes and counties to ZCTAs used by the ACS. Several hospitals include non-Maryland zip codes in their service areas, so I calculate predicted disease burden for these out of state areas following the same procedure.

Disease burden is used to measure mortality and morbidity at a population level and was first used in the World Bank's 1993 World Development Report (World Bank, 1993). It is defined as the sum of disability-adjusted life years (DALYs) over a population, where a single DALY corresponds to one lost year of "healthy" life (World Health Organization, 2019). Predicted disease burden for ZCTA z in a given year is calculated as per capita disease burden for an age-sex cohort, as, weighted by the ZCTA's population in that age-

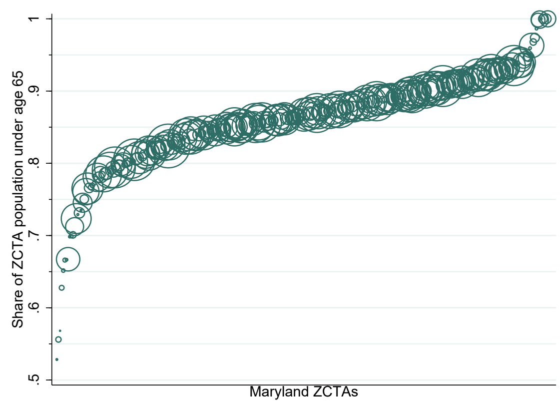
[6] The home-market effect in the pharmaceutical industry predicts that countries with larger local demand for drugs have larger sales of drugs abroad (Costinot et al., 2019).

sex cohort and summed over all age-sex cohorts (Costinot et al., 2019):

$$PDB_z = \sum_{as} \left[\text{population}_{zas} \times \frac{\text{disease burden}_{as}}{\sum_z \text{population}_{zas}} \right] \tag{1.3}$$

Due to limitations in the granularity of measures of disease burden in the United States, I measure disease burden for the state of Maryland overall. Unlike Costinot et al. (2019), I am unable to exclude a ZCTA's own measure of disease burden from $\frac{\text{disease burden}_{as}}{\sum_z \text{population}_{zas}}$. In other words, this ratio does not vary by ZCTA—it is the total Maryland all cause disease burden for a given age-sex cohort divided by the total Maryland population in that age-sex cohort in a given year.

Figure 1: Age profiles across Maryland ZCTAs, 2013

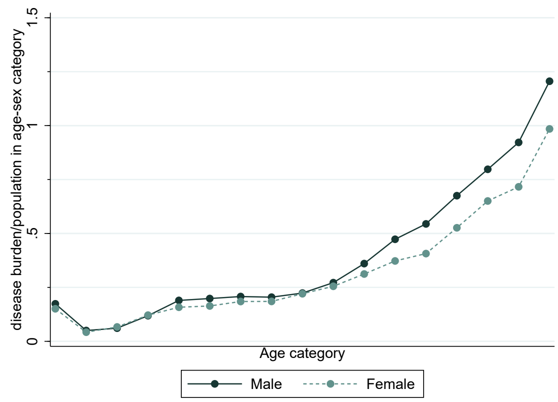


(a) Age

ZCTAs = zip code tabulation areas.
Source: 2013 American Community Survey (ACS) 5-year estimates for Maryland ZCTAs.

Figure 1 visually shows the variation in age by Maryland ZCTAs that are part of at least one GBR hospital's catchment area. I plot the share of each area's population under 65 years of age in 2013. The majority of areas range between just above 70 percent and just below 95 percent of the population below age 65. The size of the the circles corresponds to the ZCTA's total 2013 population. Areas at the tail ends of the graph are those with small overall populations.

Figure 2: Maryland disease burden by age-sex cohort



Source: Global Burden of Disease Collaborative Network. Global Burden of Disease Study 2017 (GBD 2017) Results. Seattle, United States: Institute for Health Metrics and Evaluation (IHME), 2018

Figure 2 visually shows the variation in disease burden by age-sex cohort for the 2013 Maryland population. Excluding the initial four years of life for both sexes, disease burden per capita increases with age, with female disease burden below male disease burden starting with age 50 years.

After calculating the predicted disease burden in each ZCTA in each year prior to the payment system change following Equation 1.3, I aggregate the measures to the hospital year level using the hospital's defined catchment area. I calculate the year over year growth in each hospital's predicted disease burden, and take the simple average of these growth rates across the pre period years. I separate hospitals by the median average growth rate in predicted disease burden.

Table 3 compares baseline, 2013, admission characteristics for the 15 hospitals with above median growth in predicted disease burden to baseline admission characteristics for the 15 hospitals with below median growth. Patients admitted to hospitals with above median growth are younger on average, more likely to have commercial insurance, and less likely to be uninsured than patients admitted to hospitals with below median growth in predicted disease burden. Patients staying as observation status in hospitals with above median growth are older, more likely to have commercial insurance coverage, and less likely to have Medicaid insurance coverage than their counterpart patients at hospitals with below median growth. There are an additional number of economically, but not statistically, significant differences in the characteristics of patients treated at hospitals with above median growth, most notably differences in racial composition.

Table 3: Baseline visit characteristics for hospitals above and below median growth in predicted disease burden, 2013

	Inpatient			Observation			Outpatient		
	Above median	Below median		Above median	Below median		Above median	Below median	
Female	60.42	57.93		59.68	59.20		59.51	61.76	
Age									
0-14	15.90	10.82	*	3.59	2.57		11.41	7.91	**
15-34	18.17	17.54		10.29	12.20		22.44	25.05	
35-49	13.35	15.24		17.76	21.15	**	17.96	19.49	*
50-64	18.50	23.21	*	27.75	31.37	**	22.08	24.78	
65+	34.07	33.20		40.62	32.71	**	26.12	22.77	
Race									
White	54.30	42.74		54.59	45.92		55.49	45.16	
Black	32.07	35.28		36.94	48.94		34.29	47.11	
Other race	13.62	21.98		8.47	5.14		10.22	7.73	
Hispanic/Latino origin/descent	6.13	3.98		3.49	2.65		5.43	2.89	
Payer									
Commercial	38.00	29.56	*	34.12	27.83	*	41.42	37.46	
Medicare	37.17	39.26		42.42	38.89		27.71	27.01	
Medicaid	18.46	22.78		12.96	22.36	***	18.41	22.67	
Uninsured	4.54	6.82	*	8.18	9.30		9.98	10.20	
Other government	1.34	1.34		1.31	1.41		1.67	1.81	
Other/unknown payer	0.49	0.25		1.00	0.20		0.81	0.84	
Maryland resident	94.98	96.42		94.59	96.26		94.22	96.56	
N	15	15		15	15		15	15	

Pooled means are weighted by number of admissions. Standard errors used to estimate p-values clustered by hospital.
Source: Maryland Health Services Cost Review Commission discharge data 2013.

Hospitals treating faster growing service lines

A third way to classify hospitals is by predicted growth in spending. Spending on certain service lines is growing faster than spending on others due to advancements in technology or drugs, and hospitals vary in the breadth and depth of service lines they offer. Instead of using observed hospital growth in inpatient charges, I combine state-wide growth in inpatient charges by service line with each hospital's service line share to calculate an exposure-weighted average of growth in charges, what is commonly referred to as a shift-share measure (Goldsmith-Pinkham et al., 2018; Borusyak et al., 2018). Hospitals with above median exposure-weighted growth in charges may more acutely feel the constraint on total revenue to the extent that this growth is not completely reflected in the revenue target.

The Maryland hospital utilization data report charges, not actual spending, but to the extent that growth in total charges reflects growth in both utilization and in price, total charges can be used to identify growth in service lines. Another concern with using total charges in Maryland is that per admission revenue growth was regulated by the HSCRC prior to the payment system change. If growth in per admission revenue was uniformly regulated across hospital and service line, any variation I find in growth of total charges reflects growth in utilization only.

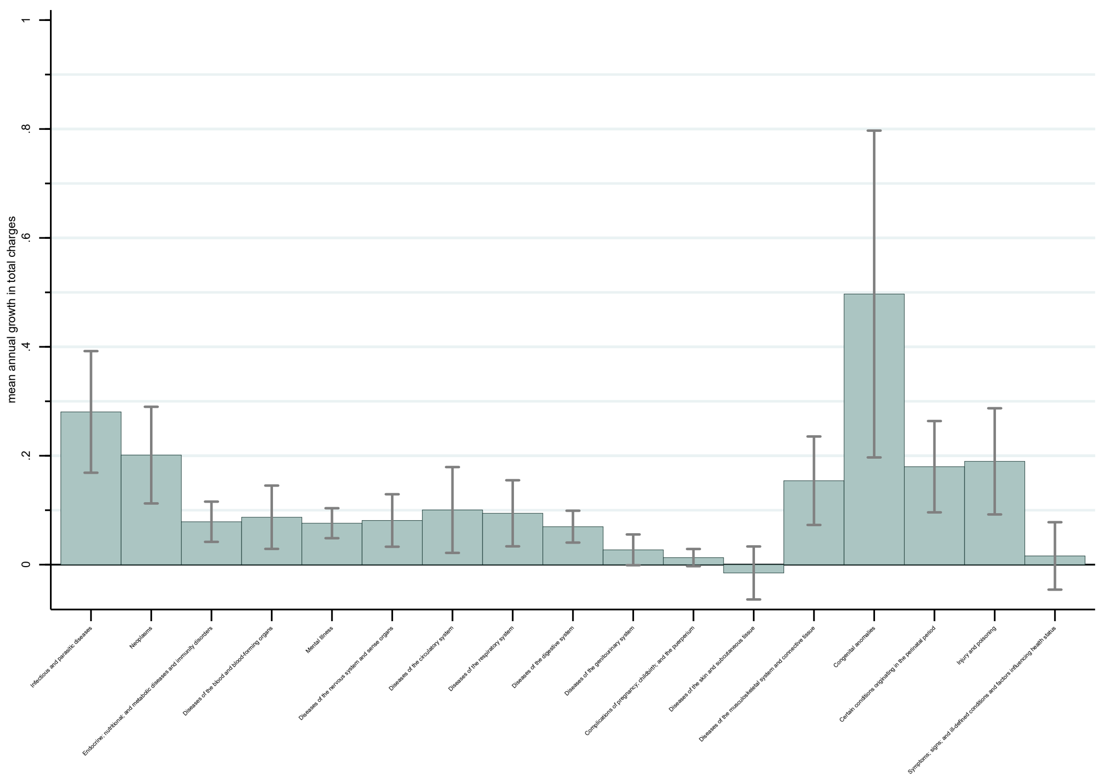
I start by grouping inpatient admissions for all 35 GBR general acute care hospitals and additionally acute inpatient visits from the University of Maryland Rehabilitation and Orthopeadic Institute and the Levindale Hebrew Geriatric Center and Hospital (both of which are regulated by the GBR but provide limited inpatient services) by primary diagnosis on the visit using the Healthcare Cost and Utilization Project (HCUP) Clinical Classifications Software (CCS). Specifically, I collapse the primary diagnois on the visit to one of 135 HCUP CCS "second-level categories." These second-level categories aggregate to 17 first-level categories. For example, within the first-level category of neoplasms there are 16 second-level categories including breast cancer, ovarian cancer, and colorectal cancer. In this text, I refer to these first-level categories as hospital service lines.

I next calculate year over year growth in total charges for each second-level category across all inpatient facilities.[7] At the first-level category, I take the average of all second-level category growth rates across all pre period years. Figure 3 shows the average pre period growth in charges across these 17 first-level categories, or service lines. Among the condi-

[7] I annualize charges for 2009 by doubling the total amount observed in the last six months of 2009. This assumes that the first half of the year experienced the same patterns of utilization and price as the second half of the year.

tions with the highest pre period growth rates in total charges are infectious and parasitic diseases, neoplasms, disease of the musculoskeletal system and connective tissue, congenital anomolies, perinatal conditions, and injuries and poisonings.

Figure 3: Average growth in total inpatient charges by HCUP diagnosis category, 2009-2013



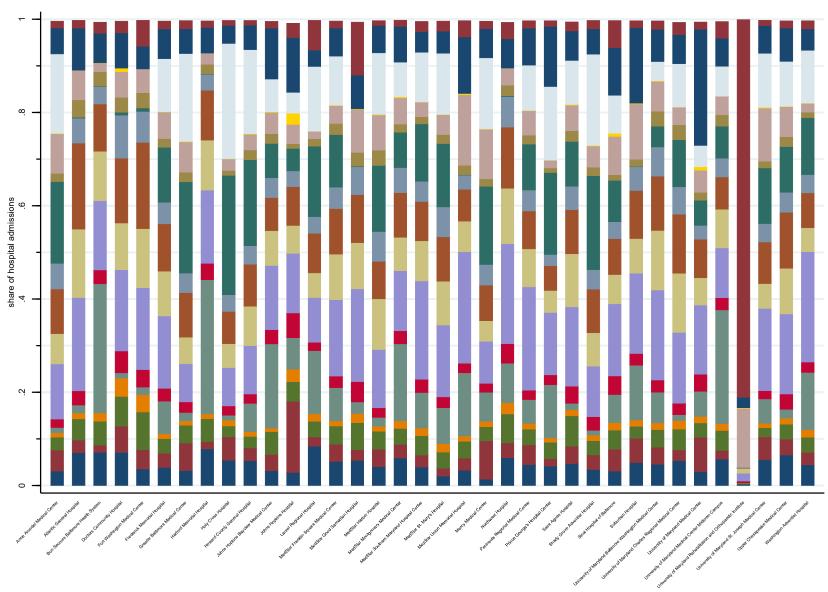
Source: Health Service Cost Review Commission (HSCRC) hospital inpatient discharge data, July 2009 to December 2013; Health Care Cost and Utilization Project (HCUP) clinical classification software (CCS) for ICD-9-CM.

I take the share of hospital pre period admissions in each service line, s_{hl}. Figure 4 shows the share of each hospital's inpatient admissions in each of the 17 service lines. In the most extreme example of this variation, over 80% of the University of Maryland Rehabilitation and Orthopeadic Institute's inpatient admissions were for diseases of the musculoskeletal system and connective tissue, as would be expected. Following the shift-share literature, I take the product of s_{hl} and the industry-level growth rate, $\bar{g}_l$ and sum the products over service lines to construct a hospital level measure of predicted growth:

$$z_h = \sum_l (s_{hl}\bar{g}_l) \tag{1.4}$$

I split my sample of 30 hospitals without revenue exclusions into those with above median z_h and those with below median z_h.

Figure 4: Service line share of hospital admissions, 2009-2013



Source: Health Service Cost Review Commission (HSCRC) hospital inpatient discharge data, July 2009 to December 2013; Health Care Cost and Utilization Project (HCUP) clinical classification software (CCS) for ICD-9-CM.

Table 4 compares visit characteristics for hospitals with above median z_h to visit characteristics for hospitals with below median z_h. There are few statistically significant differences between hospitals with above/below median predicted growth in the characteristics of inpatient and observation stays, but there are a number of economically significant differences. First, inpatient visits to hospitals with above median predicted growth are younger; while observation visits to hospitals with above median predicted growth are older. Inpatient visits to hospitals with above median predicted growth in service lines are more likely to be covered by commercial insurance—corresponding to the lower average age—than inpatient visits to hospitals with below median predicted growth. These inpatient age and insurance coverage differences are not surprising, as Figure 3 showed charges for both perinatal conditions and congenital anomalies were increasing in the pre intervention period. There are a number of statistically significant differences between the two hospitals groups in terms of sex and insurance payer for outpatient visits, with patients in the outpatient setting of hospitals with above median predicted growth being older and more likely to have commercial or Medicare insurance coverage and less likely to have Medicaid insurance coverage. There are also economically significant, but not statistically significant, differences in race between the groups across in the inpatient and outpatient setting.

Table 4: Baseline visit characteristics for hospitals above and below median growth in service lines, 2013

	Inpatient			Observation			Outpatient		
	Above median	Below median		Above median	Below median		Above median	Below median	
Female	60.42	57.80		58.87	59.91		61.43	59.34	
Age									
0-14	15.65	10.95		3.18	2.93		9.03	10.72	
15-34	18.30	17.33		12.01	10.67		21.58	27.14	***
35-49	13.49	15.12	*	18.25	20.73		17.96	19.93	**
50-64	19.33	22.21		28.00	31.17	*	24.21	22.15	
65+	33.23	34.38		38.56	34.50		27.22	20.06	**
Race									
White	51.96	45.63		50.46	49.56		52.73	46.65	
Black	34.74	31.53		42.68	43.88		38.85	43.47	
Other race	13.30	22.84		6.86	6.56		8.42	9.89	
Hispanic/Latino origin/descent	5.47	4.84		3.63	2.52		4.26	4.03	
Payer									
Commercial	37.94	29.26	*	33.40	28.44		42.09	35.28	**
Medicare	36.53	40.28		41.29	39.88		29.38	24.16	*
Medicaid	19.39	21.63		15.16	20.45		17.55	25.25	**
Uninsured	4.93	6.36		8.60	8.94		9.20	11.51	
Other government	0.92	1.95		0.91	1.77		1.13	2.71	*
Other/unknown payer	0.29	0.52		0.63	0.52		0.66	1.09	
Maryland resident	94.83	96.70		94.09	96.72		94.46	96.85	
N	15	15		15	15		15	15	

Pooled means are weighted by number of admissions. Standard errors used to estimate p-values clustered by hospital.
Source: Maryland Health Services Cost Review Commission discharge data 2013.

Table 5 presents the three measures of within-Maryland hospital exposure for each facility regulated by the GBR. Hospitals with revenue exclusions are listed first, and are not included in the other measures of exposure. The final rows list the six facilities regulated by the GBR but not included in my analysis.

Table 5: Hospital exposure measures

				Predicted Disease Burden			Shift Share Charges		
Hospital name			Revenue Exclusions	below 25%tile	above median	above 75%tile	below 25%tile	above median	above 75%tile
University of Maryland Medical Center	210002	GBR	Y						
Johns Hopkins Hospital	210009	GBR	Y						
Johns Hopkins Bayview Medical Center	210029	GBR	Y						
University of Maryland Charles Regional Medical Center	210035	GBR	Y						
Suburban Hospital	210022	GBR	Y						
Fort Washington Medical Center	210060	GBR		Y			Y		
Prince George's Hospital Center	210003	GBR		Y				Y	Y
MedStar Good Samaritan Hospital	210056	GBR		Y			Y		
Doctors Community Hospital	210051	GBR		Y				Y	Y
Bon Secours Baltimore Health System	210013	GBR		Y			Y		
University of Maryland Medical Center Midtown Campus	210038	GBR		Y			Y		
MedStar Union Memorial Hospital	210024	GBR		Y				Y	Y
MedStar Franklin Square Medical Center	210015	GBR		Y					
Howard County General Hospital	210048	GBR			Y	Y		Y	
Shady Grove Adventist Hospital	210057	GBR			Y	Y			
MedStar Southern Maryland Hospital Center	210062	GBR			Y	Y	Y		
Northwest Hospital	210040	GBR			Y	Y	Y		
Atlantic General Hospital	210061	GBR			Y	Y		Y	
Upper Chesapeake Medical Center	210049	GBR			Y	Y		Y	Y
Laurel Regional Hospital	210055	GBR			Y	Y			
Holy Cross Hospital	210004	GBR			Y			Y	
Harford Memorial Hospital	210006	GBR			Y				
MedStar Montgomery Medical Center	210018	GBR			Y			Y	
Frederick Memorial Hospital	210005	GBR			Y				
Sinai Hospital of Baltimore	210012	GBR			Y			Y	Y
Anne Arundel Medical Center	210023	GBR			Y			Y	
Saint Agnes Hospital	210011	GBR			Y			Y	
Peninsula Regional Medical Center	210019	GBR			Y			Y	Y
Mercy Medical Center	210008	GBR						Y	
MedStar St. Mary's Hospital	210028	GBR					Y		
Greater Baltimore Medical Center	210044	GBR						Y	
University of Maryland St. Joseph Medical Center	210063	GBR						Y	Y
MedStar Harbor Hospital	210034	GBR							
University of Maryland Baltimore Washington Medical Center	210043	GBR							
Washington Adventist Hospital	210016	GBR					Y		
University of Maryland Rehabilitation and Orthopaedic Institute	210058	GBR							
Queen Anne's Emergency Center	210088	FSE GBR							
Levindale Hebrew Geriatric Center and Hospital	210064	GBR							
Bowie Emergency Center	210333	FSE GBR							
Germantown Emergency Center	210087	FSE GBR							
Holy Cross Germantown Hospital	210065	GBR							
N			5	8	15	7	8	15	7

1.4.3. Outcomes

I focus on measures of total hospital volume, as outside of changing reimbursement rates, changing volume is the only way for hospitals to meet revenue targets. Specifically, I look at inpatient visits per hospital, observation stays per hospital, ED visits per hospital, non-ED outpatient visits per hospital; and the number of procedures in each of the aforementioned settings. I also examine inpatient days. Visits, days, and services are three types of hospital volume. In a fee-for-service setting, hospital total revenue would be determined by the mix of visits, days, and services. Increasing visits, days, or services would increase revenue. In the GBR, setting increasing visits, days, or services generally does not change hospital revenue.

Inpatient procedures per visit are defined as the unique count of International Classification of Diseases 9th Clinical Modification (ICD-9-CM) procedure codes or ICD-10-Procedure Coding System (PCS) codes, while observation and outpatient procedures per visit are defined as the unique count of Healthcare Common Procedure Coding System (HCPCS) codes.

I do not expect to find any changes to the number of emergency department visits. Rewards from investing in community health or preventative care are unlikely to accrue in the form of reduced ED use in the short term and incentives for patients have not changed. In the inpatient setting, I expect to find a decrease in visits if hospitals reduce "discretionary" services, improve the health of the population served, or move patients on the margin to the outpatient or observation setting. If this is the case, the average number of services provided in the inpatient setting could increase or decrease—as patients remaining in the inpatient setting may be more complex. In the outpatient setting, I would expect to see a decrease in outpatient non-ED visits if hospitals are trying to move care to non-hospital based settings, but I could find an increase if hospitals are moving patients on the margin from the inpatient to the outpatient setting.

Tables 6 through 8 present 2013 baseline levels of these outcomes by the three measures of within-Maryland exposure.

Table 6: Unadjusted outcomes per quarter for hospitals with and without revenue exclusions, pre and post GBR

	No revenue excluded		Any revenue excluded	
	Pre	*Post*	*Pre*	*Post*
Inpatient visits	4,096.74	3,489.59	6,440.79	5,891.03
	(2,035.80)	(2,009.06)	(3,700.67)	(3,590.89)
Days per inpatient visit	3.99	4.22	4.86	5.31
	(0.46)	(0.57)	(0.88)	(1.33)
Services per inpatient visit	1.47	1.43	1.75	1.98
	(0.48)	(0.41)	(0.44)	(0.72)
Inpatient hospital-quarters	540	420	90	70
Observation visits	405.11	492.05	309.70	367.80
	(275.09)	(296.76)	(168.20)	(150.60)
Services per observation visit	21.04	20.76	19.21	20.34
	(2.12)	(1.74)	(3.23)	(1.74)
Observation hospital-quarters	180	420	30	70
ED visits	12,623.10	12,164.38	12,963.90	13,125.30
	(4,313.37)	(4,172.07)	(3,672.15)	(3,834.95)
Services per ED visit	6.07	6.19	6.01	6.57
	(0.84)	(0.76)	(0.66)	(0.76)
Non-ED outpatient visits	14,487.28	14,069.73	62,643.23	65,081.59
	(11,028.05)	(11,214.19)	(61,291.37)	(65,299.25)
Services per non-ED outpatient visit	3.47	3.73	3.37	3.72
	(0.81)	(0.98)	(0.75)	(1.07)
Outpatient hospital-quarters	180	420	30	70

ED = emergency department. Services defined using unique procedure codes per admission. Source: Maryland Health Services Cost Review Commission inpatient discharge data July 2008 - June 2017, observation and outpatient discharge data July 2012 - June 2017.

Table 7: Unadjusted outcomes per quarter for hospitals above and below median growth in predicted disease burden, pre and post GBR

	Above median		Below median	
	Pre	*Post*	*Pre*	*Post*
Inpatient visits	4,577.49	4,003.71	3,615.99	2,975.46
	(2,330.58)	(2,298.21)	(1,552.04)	(1,509.63)
Days per inpatient visit	3.92	4.14	4.07	4.30
	(0.37)	(0.51)	(0.53)	(0.61)
Services per inpatient visit	1.45	1.41	1.48	1.46
	(0.45)	(0.45)	(0.51)	(0.37)
Inpatient hospital-quarters	270	210	270	210
Observation visits	371.51	499.70	438.71	484.39
	(238.71)	(280.62)	(304.84)	(312.55)
Services per observation visit	20.83	20.64	21.25	20.88
	(2.41)	(1.90)	(1.77)	(1.57)
Observation hospital-quarters	90	210	90	210
ED visits	13,301.93	13,020.50	11,944.27	11,308.27
	(4,183.63)	(4,519.97)	(4,357.12)	(3,604.53)
Services per ED visit	6.19	6.43	5.95	5.95
	(0.73)	(0.55)	(0.94)	(0.86)
Non-ED outpatient visits	14,099.11	13,494.96	14,875.46	14,644.50
	(8,595.84)	(9,390.83)	(13,054.08)	(12,777.56)
Services per non-ED outpatient visit	3.64	3.90	3.30	3.56
	(0.91)	(1.00)	(0.66)	(0.92)
Outpatient hospital-quarters	90	210	90	210

ED = emergency department. Services defined using unique procedure codes per admission.
Source: Maryland Health Services Cost Review Commission inpatient discharge data July 2008 - June 2017, observation and outpatient discharge data July 2012 - June 2017.

Table 8: Unadjusted outcomes per quarter for hospitals hospitals above and below median predicted service line growth, pre and post GBR

	Above median		Below median	
	Pre	*Post*	*Pre*	*Post*
Inpatient visits	4,781.94	4,271.93	3,411.54	2,707.24
	(2,042.81)	(2,020.77)	(1,785.73)	(1,666.87)
Days per inpatient visit	3.95	4.12	4.03	4.31
	(0.43)	(0.57)	(0.50)	(0.55)
Services per inpatient visit	1.68	1.58	1.26	1.29
	(0.38)	(0.33)	(0.48)	(0.43)
Inpatient hospital-quarters	270	210	270	210
Observation visits	383.12	483.82	427.10	500.27
	(236.58)	(250.15)	(308.62)	(337.41)
Services per observation visit	21.16	20.73	20.92	20.79
	(2.16)	(1.59)	(2.08)	(1.89)
Observation hospital-quarters	90	210	90	210
ED visits	13,310.62	13,386.25	11,935.58	10,942.51
	(3,771.77)	(3,876.19)	(4,715.62)	(4,107.38)
Services per ED visit	6.31	6.39	5.83	6.00
	(0.88)	(0.72)	(0.73)	(0.75)
Non-ED outpatient visits	19,838.33	19,204.48	9,136.23	8,934.98
	(12,571.86)	(12,698.13)	(5,351.59)	(6,155.60)
Services per non-ED outpatient visit	3.36	3.62	3.58	3.83
	(0.59)	(0.67)	(0.97)	(1.20)
Outpatient hospital-quarters	90	210	90	210

ED = emergency department. Services defined using unique procedure codes per admission.
Source: Maryland Health Services Cost Review Commission inpatient discharge data July 2008 - June 2017, observation and outpatient discharge data July 2012 - June 2017.

1.5. Empirical Strategy

I estimate the association between my measures of within-Maryland hospital exposure and hospital visits, days, and services in the inpatient, observation, and outpatient settings. I first estimate the following event study specification, allowing the effect of hospital h exposure, d_h to vary over time across my three measures of hospital exposure—revenue exclusions, above median growth in predicted disease burden, and above median predicted growth in inpatient service lines.

$$ln(y_{hyq}) = \alpha_h + \delta_y + \sum_{y=2009}^{y=2017} \beta_y \left(d_h \times \mathbb{1}\left(year_y\right)\right) + \varepsilon_{hyq} \tag{1.5}$$

$ln(y_{hyq})$ is the natural log of the outcome of interest for hospital h in quarter q of calendar year y. d_h is an indicator for whether the hospital is more exposed to the revenue target and is interacted with a full set of calendar year fixed effects. Due to a limited sample size, I am unable to estimate the event study using quarter fixed effects, and instead include calendar year fixed effects δ_y. I include hospital fixed effects α_h to account for time-invariant heterogeneity by hospital. Standard errors are robust to heteroscedasticity and clustered at the hospital level.

The β_y coefficients are estimated relative to the year prior to the payment system change, 2013. For years prior to the payment system change, these coefficients can serve as tests of the parallel trends assumption, which I expect not to hold a priori for two of my three exposure measures. The two growth measures separate hospitals based on difference in pre-intervention trends. The β_y coefficients for years after the introduction of the GBR measure the differential change from 2013 to year y in outcomes for more exposed hospitals relative to the change from 2013 to year y for less exposed hospitals.

As will be shown in Section 1.6, the event study specifications confirm the existence of pre intervention trends in outcomes. I run the following linear regression, allowing for differences in the baseline trends by group of hospital exposure, for inpatient outcomes only. With six quarters of pre policy data in the outpatient and observation settings, the estimate of a linear time trend across the study sample would be determined mostly by the post period trend (Angrist and Pischke, 2009). For each of the three measures of within-Maryland hospital exposure, d_h—hospitals without revenue exclusions, hospitals with above median growth in predicted disease burden, and hospitals with above median predicted growth in inpatient service lines, I estimate:

$$ln(y_{hyq}) = \alpha_h + \delta_y + \gamma_1 trend_y + \gamma_2 trend_y \times d_h + \beta post_y \times d_h + \varepsilon_{hyq} \qquad (1.6)$$

Again, α_h are hospital fixed effects, δ_t are year fixed effects, and standard errors are robust to heteroscedasticity and clustered at the hospital level. $trend_y$ is a linear time trend ranging from 1 to 9 in the inpatient regressions (1 for calendar year 2009 and 9 for calendar year 2017). The coefficient γ_1 measures the trend in outcomes for less exposed hospitals over the entire study period, with the coefficient γ_2 measuring the difference in trends for more exposed hospitals. If the introduction of the total revenue constraint under the GBR differentially affects hospitals without revenue exclusions, hospitals with above median growth in predicted disease burden, or hospitals with above median predicted growth in service lines, I would expect β to be negative. Again, noting the significant differences in baseline trends, it is not possible to infer a casual relationship from these associations.

1.6. Results

In this section I provide estimation results of equation 1.5 for inpatient visits, inpatient days, inpatient services, observation visits, observation services, outpatient emergency department (ED) visits, ED services, outpatient non-ED visits, and outpatient non-ED services using three measures of within-Maryland hospital exposure to the GBR's total revenue constraint. I additionally present estimation results for equation 1.6 for inpatient measures of volume.

1.6.1. *Inpatient volume*

Figure 5 graphs the β_y coefficients from the event-study specification presented in equation 1.5 for inpatient visits, inpatient days, and inpatient services per visit. I include year and hospital fixed effects and cluster standard errors at the hospital level. All panels report 95% confidence intervals around the β_y coefficients. Graphs to the left present estimated event-study coefficients splitting the sample of hospitals into those without and those with revenue exclusions. There is clear evidence of differences in pre period trends in inpatient visits using this measure of hospital exposure. Hospitals without revenue exclusions experienced faster decline in inpatient visits than hospitals with revenue exclusions prior to the payment system change. There are no significant differences in changes to inpatient days or inpatient services between the two hospital groups before or after the payment system change. Though not significant, inpatient services appear to have experienced faster decline in hospitals without revenue exclusions than in hospitals with revenue exclusions prior to the GBR implementation.

The center column of Figure 5 plots the estimated event study coefficients comparing inpatient volume for hospitals with above median growth in predicted disease burden to hospitals with below median growth. Again, as expected, there is evidence of differences in pre intervention trends in inpatient admissions and what appears to be a continuation of these trends following the GBR. Hospitals with above median growth in predicted disease burden experienced slower decline in inpatient visits than did hospitals with below median growth in predicted disease burden. There are no significant differences in inpatient days between the two groups before or after the payment system change. Coefficient estimates for the event study looking at inpatient services per visit are noisy, but close to zero across all years.

Finally, graphs to the right present the β_y coefficients from the event study specification in equation 1.5 for inpatient volume splitting the sample of hospitals into those with above/below median predicted growth in service lines. I find evidence that hospitals with above median predicted growth in service lines experienced slower decline in inpatient visits prior to the GBR implementation. This differential trend appears to continue after the 2014 implementation. Again, there are no significant differences in changes to inpatient days or inpatient services between the two hospital groups before or after the payment system change.

Table 9 presents the results from equation 1.6, looking at hospital deviation from trends in inpatient visits, days, and services after the payment system change. I find no evidence of deviation from trends across all three measures of within-Maryland exposure for all inpatient volume outcomes. Even when allowing for differences in pre intervention trends, there is no association between the GBR and my measures of within-Maryland hospital exposure to the revenue constraint.

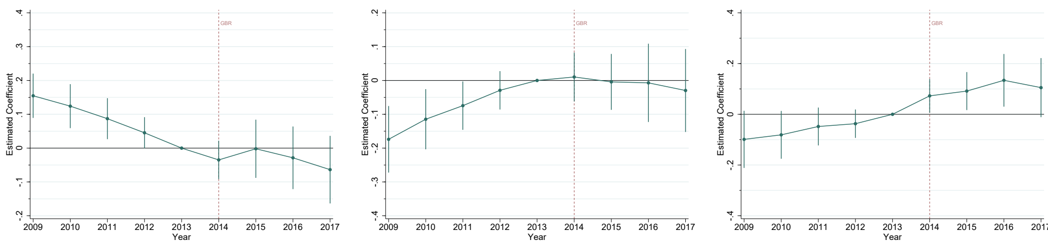
Table 9: Relationship between Inpatient Volume and within-Maryland Hospital Exposure

	ln(inpatient visits)			ln(inpatient days)			ln(inpatient services)		
	Rev. excl.	PDB growth	Serv. growth	Rev. excl.	PDB growth	Serv. growth	Rev. excl.	PDB growth	Serv. growth
trend	-0.016**	-0.053***	-0.058***	0.016**	0.014***	0.016***	0.018	-0.006	0.004
	(0.007)	(0.008)	(0.009)	(0.007)	(0.003)	(0.003)	(0.012)	(0.010)	(0.011)
$trend \times d_h$	-0.029***	0.025**	0.022**	-0.003	-0.004	-0.006	-0.019	0.019	-0.009
	(0.008)	(0.010)	(0.011)	(0.005)	(0.005)	(0.005)	(0.016)	(0.020)	(0.020)
$post \times d_h$	0.017	-0.037	0.057	-0.012	0.016	-0.005	-0.030	-0.120	-0.054
	(0.032)	(0.041)	(0.040)	(0.024)	(0.013)	(0.013)	(0.060)	(0.096)	(0.098)
Observations	1120	960	960	1120	960	960	1120	960	960

*** p<0.01, ** p<0.05, and * p<0.10.
Rev. excl. compares hospitals without revenue exclusions to hospitals with revenue exclusions.
PDB growth compares hospitals with above median growth in pre period predicted disease burden to hospitals with below median growth, excluding hospitals with revenue exclusions.
Serv. growth compares hospitals with above median growth in pre period service lines to hospitals with below median growth, excluding hospitals with revenue exclusions.
Robust standard errors clustered at the hospital level are reported in parentheses.
Source: Maryland Health Services Cost Review Commission (HSCRC) inpatient discharge data, July 2009 - June 2017.

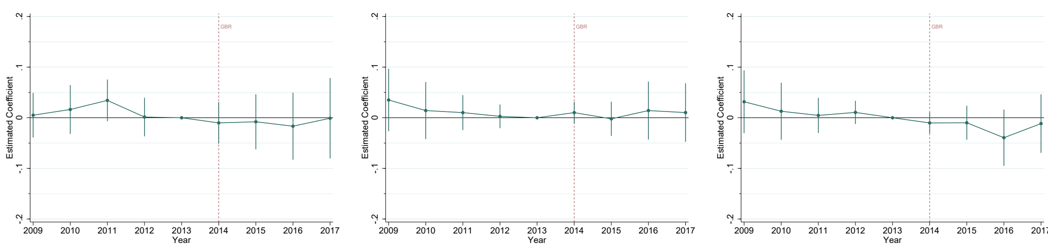
Figure 5: Relationship between Inpatient Volume and within-Maryland Hospital Exposure, Event-Studies

(a) ln(inpatient visits)



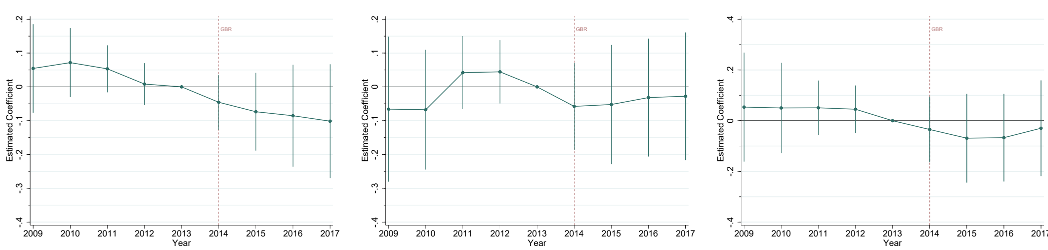
without/with revenue exclusions | above/below median predicted disease burden | above/below median inpatient service line

(b) ln(inpatient days)



without/with revenue exclusions | above/below median predicted disease burden | above/below median inpatient service line

(c) ln(inpatient services)



without/with revenue exclusions | above/below median predicted disease burden | above/below median inpatient service line

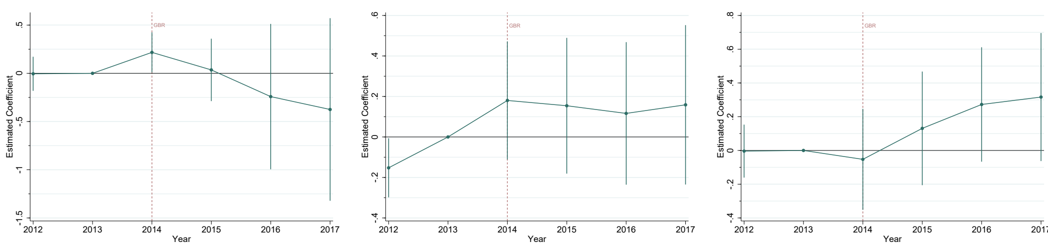
Estimated using hospital and year fixed effects, with standard errors clustered at the hospital level. Source: Maryland Health Services Cost Review Commission (HSCRC) inpatient discharge data, July 2009 - June 2017.

1.6.2. Observation volume

Figure 6 presents event study coefficients across the three measures for hospital observation volume. Without longer pre period data, it is not possible to evaluate pre intervention trends, though I expect hospitals with above median growth-based exposure measures to trend differently than below median hospitals. Changes to observation visits are imprecisely estimated, as shown by the wide confidence intervals in the first row of the figure. There are no statistically significant changes to volume of services provided in the observation setting across all three measures.

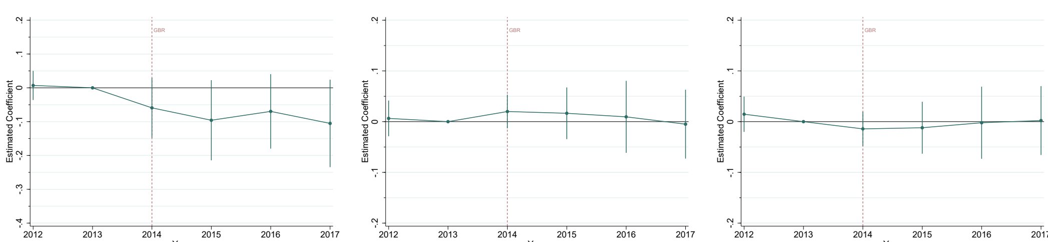
Figure 6: Relationship between Observation Volume and within-Maryland Hospital Exposure, Event-Studies

(a) ln(observation visits)



without/with revenue exclusions | above/below median predicted disease burden | above/below median inpatient service line

(b) ln(observation services)



without/with revenue exclusions | above/below median predicted disease burden | above/below median inpatient service line

Estimated using hospital and year fixed effects, with standard errors clustered at the hospital level.
Source: Maryland Health Services Cost Review Commission (HSCRC) observation discharge data, July 2012 - June 2017.

1.6.3. Outpatient volume

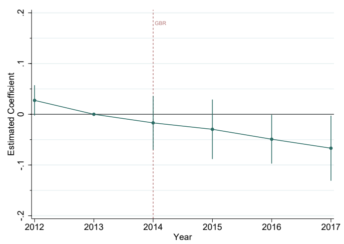
Figure 7 presents event study coefficients across the three measures for hospital outpatient ED volume. Without longer pre period data, it is not possible to rule out the existence of differences in pre intervention trends. Here I discuss changes in volume relative to the 2013 baseline year. I find that ED visits grew slower at hospitals without revenue exclusions relative to 2013 compared to hospitals with revenue exclusions, as shown by the downward sloping coefficients in the top left panel of Figure 1.5. These changes are marginally significant in 2016 and 2017. I find that ED services per visit significantly decreased more in hospitals without revenue exclusions than in hospitals with revenue exclusions in the years after the payment system change relative to 2013. Without a longer pre intervention period, I cannot rule out that these changes are merely continuations of diverging pre period trends.

Looking at the center column of Figure 7, I find no statistically significant differences in changes to ED visits or ED services between hospitals with above median growth in predicted disease burden relative to hospitals with below median growth in predicted disease burden. The event-study coefficient graphs presented in the right column of Figure 7 suggest that ED visits in hospitals with above median predicted growth in service lines grew faster than did visits in hospitals with below median growth in services lines after 2013. Again without a longer pre period, I cannot rule out that these changes are merely continuations of diverging pre period trends.

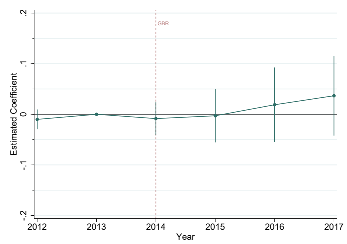
Finally, I look at non-ED outpatient volume in Figure 8. I find no significant differences in changes to non-ED outpatient services between hospital groups across all three measures, as shown in the bottom row of the figure. I find no significant differences in changes to non-ED outpatient visits between hospital groups when using measures of growth in predicted disease burden and predicted growth in service lines. I find that hospitals without revenue exclusions experienced slower growth in outpatient visits relative to hospitals with revenue exclusions. I am not able to determine whether these differences are continuations in pre GBR trends.

Figure 7: Relationship between Emergency Department Volume and within-Maryland Hospital Exposure, Event-Studies

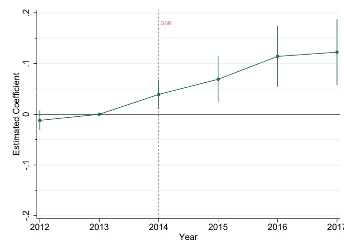
(a) ln(ED visits)



without/with revenue exclusions

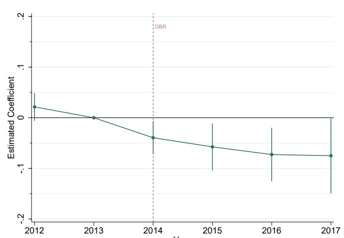


above/below median predicted disease burden

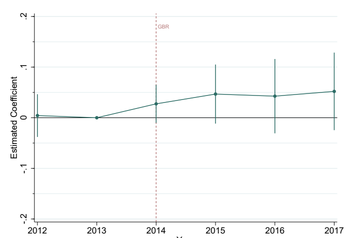


above/below median inpatient service line

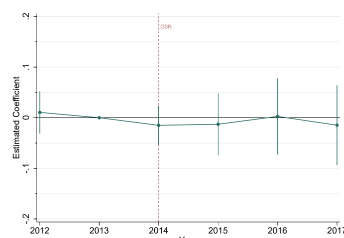
(b) ln(ED services)



without/with revenue exclusions



above/below median predicted disease burden

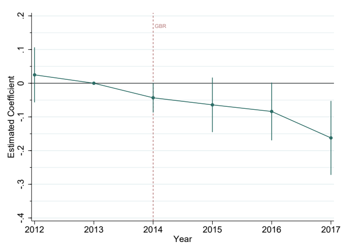


above/below median inpatient service line

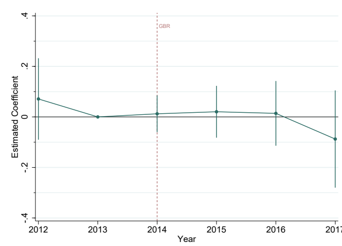
ED = emergency department.
Estimated using hospital and year fixed effects, with standard errors clustered at the hospital level.
Source: Maryland Health Services Cost Review Commission (HSCRC) observation discharge data, July 2012 - June 2017.

Figure 8: Relationship between Non-Emergency Department Outpatient Volume and within-Maryland Hospital Exposure, Event-Studies

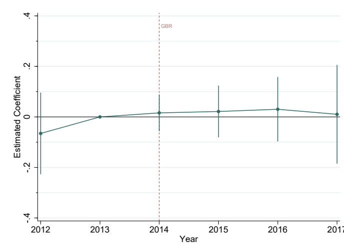
(a) ln(outpatient visits)



without/with revenue exclusions

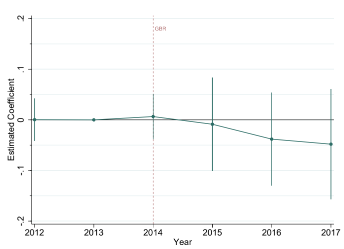


above/below median predicted disease burden

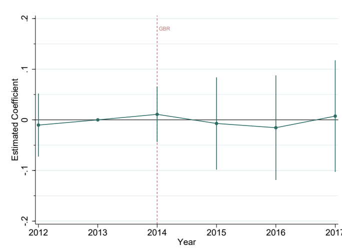


above/below median inpatient service line

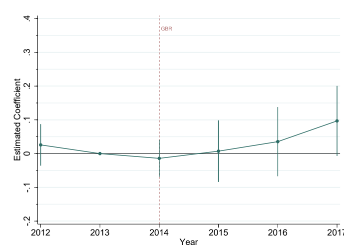
(b) ln(outpatient services)



without/with revenue exclusions



above/below median predicted disease burden



above/below median inpatient service line

Estimated using hospital and year fixed effects, with standard errors clustered at the hospital level. Source: Maryland Health Services Cost Review Commission (HSCRC) observation discharge data, July 2012 - June 2017.

1.7. Conclusion

This study is limited in a number of ways. First, given the short pre period in outpatient and observation discharge data, I am unable to determine whether changes to ED volume and outpatient non-ED volume diverge from pre intervention trends. Further, my study is under powered, as evident in the wide confidence intervals in a number of the event study figures. Though I explore three measures of within-Maryland exposure to the payment system change and assume the existence of pre intervention trends, I find no evidence that the GBR is associated with decreases in inpatient hospital volume.

This study could be extended in few ways. First, though my framework suggests that hospitals will respond to the GBR by reducing "discretionary" volume, here I look at overall hospital volume. Disentangling the volume response by type of hospital volume (e, d, $g(b)$) could uncovered different effects. Second, revenue exclusions from the GBR apply specifically to non-Maryland residents and certain inpatient and outpatient service lines. Examining the association between revenue exclusions and changes in the specific service lines or groups of patients to which they apply could uncover different effects.

I add to the growing literature that fails to identify a suitable comparison group for studying the Maryland payment system change—once again highlighting the uniqueness of the hospital payment environment. Maryland's distinctive system makes both developing an internally consistent estimate of policy effect and generalizing the state's experience to other markets difficult.

CHAPTER 2 : The Economics of Care Regionalization: Evidence from Philadelphia's Time Critical Illness Destination Policies, with Guy David

Approximately 795,000 people in the United States suffer a stroke each year, with over 80% suffering a stroke for the first time. Not only is stroke the fifth leading cause of death in the United States, causing 140,000 deaths annually, it is also a leading cause of long term disability (Benjamin et al., 2017; Heron, 2018). Myocardial infarction (MI)—a form of coronary heart disease—afflicts approximately 580,000 people for the first time and reoccurs in 210,000 people each year in the United States (Benjamin et al., 2017). Mortality from MI reached nearly 115,000 in 2014. Similar to those surviving stroke, survivors of MI have a higher chance of illness and death when compared to the general population (Benjamin et al., 2017). Regionalization—a coordinated system of care that spans a defined geographic area—is one way to potentially improve outcomes for these time critical illnesses (Fowler, 2015).

In the context of time critical emergencies such as acute stroke and ST-elevation myocardial infarction (STEMI), regional systems of care have the potential to improve outcomes in at least two ways. First, regional systems often incorporate destination policies requiring emergency medical services (EMS) providers to transport patients to specified locations based on the EMS providers' impression of the illness. Bypassing the closest hospital for the appropriate facility may increase transportation time but reduce time from first medical contact to diagnosis and treatment, thereby improving outcomes and reducing mortality (Fowler, 2015). Second, regional systems capitalize on the volume-outcome relationship—higher hospital volume is associated with improved outcomes through static economies of scale or learning-by-doing (Gaynor et al., 2005).

Extensive evaluations of acute stroke services centralization in the United Kingdom find that regionalization reduces all-cause risk-adjusted mortality and hospital length of stay in the region, but that patients who continue to receive care in non-designated facilities have worse outcomes following regionalization (Morris et al., 2014; Friebel et al., 2018; Morris et al., 2019). Evaluations of STEMI regionalization focus on changes to time to percutaneous coronary intervention (PCI) and are limited by availability of pre-period data and adequate comparison groups.

This paper focuses on regional systems of care for acute stroke and STEMI in Philadelphia, Pennsylvania and identifies the causal effect of regionalization by leveraging the differential impact of such policies on areas of the city where the nearest hospital is not a designated facility. Though we do not disentangle the effect of reduced time to appropriate treatment from the volume-outcome effect, in a difference in differences framework we estimate the effect of regionalization on the probability of admission to a non-designated facility, the probability of any hospital inpatient transfer, hospital length of stay, discharge disposition, total charges, the probability of receipt of stroke-specific interventions, and the probability of receipt of STEMI-specific interventions. We find that acute stroke regionalization decreased the probability of admission to a non-primary stroke center (PSC) by 5.0 percentage points (11% of baseline) in the two years following regionalization; and that STEMI regionalization decreased the probability of admission to a hospital incapable of percutaneous coronary interventions (non PCI-capable) by 6.4 percentage points (87% of baseline) in the first year of regionalization. We find that stroke regionalization increased the probability of inpatient brain MRI by 7.1 percentage points (43%), but no evidence that stroke regionalization was associated with changes in hospital inpatient transfers, hospital length of stay, hospital discharge status, total charges, or probability of receiving other stroke-specific imaging or interventions. These effects are concentrated in the ischemic stroke subtype. In addition to moving admissions from non-designated facilities, STEMI regionalization weakly increased the probability of undergoing percutaneous transluminal coronary angioplasty (PTCA) and increased hospital charges.

The remainder of the paper proceeds as follows. Section 2.1 provides background on stroke and STEMI regionalization in Philadelphia. Section 2.2 summarizes the current state of the literature. Section 2.3 describes our data set, defines our measures of exposure to regionalization, outlines our outcomes of interest, and provides descriptive statistics. Section 2.4 presents our empirical strategy. Section 2.5 discusses our results. Section 2.6 concludes and proposes directions for future work.

2.1. Policy Background

Philadelphia implemented a destination policy for acute stroke in October 2011; and organized a regional system for STEMI starting in July 2012 as part of the American Heart Association *Mission: Lifelife* STEMI Accelerator demonstration project. In this section, we provide background on Philadelphia's regional systems of care for acute stroke and STEMI.

2.1.1. Acute Stroke Regionalization

Philadelphia's stroke destination policy was implemented in October 2011, following policy recommendations from expert panels. To address fragmentation in the emergency care system, the Institute of Medicine recommended regionalized systems for stroke care in 2006 (Institute of Medicine, 2006). In 2007 an expert panel on EMS systems convened by the American Heart Association and the American Stroke Association along with the Stroke Council made similar recommendations. Building on their 2004 recommendations, the expert panel called for pre-hospital providers, emergency physicians, and stroke experts to develop system protocols for transportation of stroke patients to the nearest stroke center (either primary stroke center or comprehensive stroke center) (Acker et al., 2007). The Brain Attack Coalition recommended EMS providers transport stroke patients to the nearest stroke center (Alberts et al., 2011). The American College of Emergency Physicians (ACEP) endorsed regionalization for time-critical illnesses, including stroke, in 2013 (ACEP, 2013). Philadelphia was not the only region to take these policy recommendations to practice. From 2010 to 2014, the number of states with stroke destination policies increased from 16 states (and 3 counties) to 24 states (Song and Saver, 2012; Report Card Task Force

Members and ACEP Staff, 2014).

The Pennsylvania Department of Health, Bureau of Emergency Medical Services' 2011 statewide protocols specified that acute stroke patients be transported to certified primary stroke centers, potentially bypassing the nearest non-certified hospital (Bureau of Emergency Medical Services, 2011a,b). This protocol update was announced March 1, 2011 to be implemented by July 1, 2011 or at the time of provider education if earlier (Bureau of Emergency Medical Services, 2011c).

Certified primary stroke centers (PSCs) differ from non-certified hospitals in a number of ways. We select a few examples to highlight here. In terms of labor, PSCs are required to have acute stroke teams available 24/7; must have a neurologist accessible 24/7 in person or via telemedicine; and must have an emergency department (ED) physician perform the initial assessment for patients presenting in the ED. In terms of capital, PSCs are required to operate stroke units or designate beds for acute stroke patients; keep CT and labs (and MRI if used) available 24/7 for diagnostic testing; and be capable of delivering IV thrombolytics. Finally, PSCs must adhere to the 2011 Brain Attack Coalition guidelines and track performance on at least 8 core stroke measures (The Joint Commission, 2018b,c).

PSC hospital admission is associated with lower 30-day all-cause mortality and higher rates of thrombolytic therapy administration in the ischemic stroke population (Xian et al., 2011). Thrombolytic therapy, and specifically tissue plasminogen activator (tPA), is used in the treatment of ischemic stroke to dissolve clots blocking blood flow to the brain. PSC admission is associated with lower 7-day and lower 30-day mortality for Medicare patients suffering from ischemic or hemorrhagic stroke (Bekelis et al., 2016).[1]

We identify PSCs in Philadelphia using The Joint Commission's PSC certification in partnership with the American Heart Association (AHA) and American Stroke Association

[1]Both Xian et al. (2011) and Bekelis et al. (2016) estimate the causal effects of stroke center admission on mortality using differential distance (or travel time) to the nearest PSC as an instrument for PSC admission—as observed hospital choice is not random but correlated with both mortality and unobserved patient characteristics (e.g., severity of stroke).

(ASA).[2] We use the Joint Commission's Quality Check tool to classify Philadelphia area hospitals as PSCs or non-PSCs at the start of the destination policy (The Joint Commission, 2018a). We crosscheck this classification with a list of Philadelphia hospitals that receive stroke patients in 2010 and 2011 according to the PFD (Philadelphia Regional EMS, 2010, 2011).[3] The PFD has provided emergency medical services for the City of Philadelphia since 1974, meaning that all emergency 911 transits to hospitals follow these protocols (Butkovitz, 2011). Table 10 shows PSC certification dates for Philadelphia area hospitals and flags whether the facility received stroke patients from the PFD in 2010 and 2011. With implementation of the destination policy, the number of Philadelphia area hospitals receiving acute stroke patients decreased from 20 to 12; and the number of hospitals within Philadelphia limits decreased from 17 to 9.

2.1.2. ST-Elevation Myocardial Infarction Regionalization

Philadelphia joined fifteen other regions across the country in the American Heart Association Regional Systems of Care Demonstration Project: *Mission: Lifelife* STEMI Accelerator in July 2012. The goals of *Mission: Lifeline* were to accelerate regional STEMI system development, facilitate care coordination, and improve clinical outcomes for STEMI patients (Bagai et al., 2014). The demonstration built on the experience of regional STEMI systems in North Carolina where coordination between regional PCI hospitals, non-PCI hospitals, and EMS contributed to decreases in time to reperfusion.[4]

Updates to STEMI treatment guidelines in 2009 by the American College of Cardiology Foundation (ACCF) and the AHA recommended that each community develop a STEMI

[2] As of 2019, the Joint Commission offers four levels of stroke certification: Acute Stroke Ready Hospital (ASRH), Primary Stroke Center (PSC), Thrombectomy-Capable Stroke Center (TSC), and Comprehensive Stroke Center (CSC).

[3] The Philadelphia Patient Hospital Receiving List for 2013 is available on the City of Philadelphia's Regional EMS resource page: `http://www.phila.gov/regionalems/Resources/Pages/default.aspx`

[4] Reperfusion therapies restore blood flow and limit infarct (dead tissue) size. Reperfusion therapies include primary PCI and fibrinolytic therapy (Gibson et al., 2018). Primary PCI is defined by Keeley and Hillis (2007) as "urgent balloon angioplasty (with or without stenting) without the previous administration of fibrinolytic therapy [...] to open the infarct-related artery during an acute myocardial infarction with ST-segment elevation."

Table 10: Philadelphia Area Hospitals, Primary Stroke Center Certification and Percutaneous Coronary Intervention (PCI) Capability

	Stroke			**STEMI**
Hospital	Joint Commission PSC Certification	PFD 2010	PFD 2011	PFD 2013
Albert Einstein Medical Center	July 22, 2009	Y	Y	Y
Aria Health - Frankford	January 11, 2013	Y	N	N
Aria Health - Torresdale	January 11, 2013	Y	N	Y
Chestnut Hill	September 20, 2011	Y	Y	N
Episcopal	N/A	Y	N	N
Hahnemann	April 14, 2010	Y	Y	Y
Holy Redeemer	June 22, 2011	Y	Y	Y
Hosp of the Univ of PA	June 10, 2010	Y	Y	Y
Jeanes	January 14, 2010	Y	Y	Y
Lankenau	September 23, 2009	Y	Y	Y
Mercy Fitzgerald	April 24, 2009	Y	Y	Y
Mercy Hosp of Phila	April 24, 2009	Y	Y	N
Methodist	N/A	Y	N	N
Nazareth	September 14, 2010	Y	Y	Y
Pennsylvania	July 14, 2012	Y	N	Y
Presbyterian	July 27, 2012	Y	N	Y
Roxborough	July 9, 2014	Y	N	N
St. Joseph's	N/A	Y	N	N
Temple	September 4, 2011	Y	Y	Y
Thomas Jefferson	July 31, 2009	Y	Y	Y

PSC = Primary Stroke Center; PCI = Percutaneous Coronary Intervention; STEMI = ST Elevation Myocardial Infarction.
Source: Joint Commission's Quality Check tool (The Joint Commission, 2018a). Philadelphia Regional Emergency Medical Services (EMS) hospital receiving lists 2010, 2011, and 2013 (Philadelphia Regional EMS, 2010, 2011, 2013).

system of care including 1) ongoing meetings between EMS, PCI-capable hospitals, and non-capable hospitals, 2) prehospital identification of STEMI and activation of the STEMI system, 3) destination protocols for PCI-capable hospitals, and 4) transfer protocols for patients who arrive at non-capable hospitals (Kushner et al., 2009). Based on a 2008-2010 survey by Jollis et al. (2012), we know that of the 381 surveyed STEMI systems of care across the United States, 61% had destination policies in place, voluntarily or through legislation, allowing for bypass of the nearest hospital in favor of the closest PCI-capable hospital for patients diagnosed with STEMI in a pre-hospital setting. For the purposes of the survey, a STEMI system was defined as a group of at least one PCI-capable hospital and at least one EMS agency within a geographic region focused on reperfusion therapy. In addition to detailing STEMI system processes, analysis of the survey found hospital competition and EMS transport to be the most commonly reported challenges in implementing regional systems of care.

Over the course of the *Mission: Lifeline* demonstration, the percent of patients meeting guideline recommendations for reperfusion (within 90 minutes of first medical contact for patients presenting at PCI-capable hospitals and within 120 minutes for patients presenting at non-capable hospitals) increased for participating regions relative to baseline rates (Jollis et al., 2016). Hospitals in participating regions were more likely to allow pre-hospital catheterization laboratory activation for patients transported by EMS, single call transfers for patients presenting at non-capable hospitals, emergency department bypass for patients transported by EMS, and emergency department bypass for patients transferred from non-capable hospitals after enrolling in the demonstration (Fordyce et al., 2017). Patients treated at hospitals implementing these procedures had shorter times from first medical contact to reperfusion, but did not differ in the rate of in-hospital morality (Fordyce et al., 2017). Studies performed by the the *Mission: Lifeline* research and implementation team, such as Jollis et al. (2016) and Fordyce et al. (2017) are limited by the extent of pre-demonstration data (single quarter) and adequate comparison groups.

We identify PCI-capable hospitals in Philadelphia using the PFD's list of hospitals that receive STEMI patients in 2013 as shown in Table 10 (Philadelphia Regional EMS, 2013). STEMI regionalization decreased the number of acute care hospitals within Philadelphia receiving STEMI patients from 17 to 10. In our analyses, we use the first quarter of 2013 as the first quarter of destination policy treatment, although efforts to transport patients to PCI-capable hospitals likely began with enrollment in the *Mission: Lifeline* demonstration. Studies such as Green et al. (2018) similarly use the start of 2013 to study STEMI destination policies in Pennsylvania. Pennsylvania statewide Advanced Life Support (ALS) and Basic Life Support (BLS) EMS protocols were updated in 2015 directing EMS providers to transport patients with ECG confirmed STEMI to a STEMI-receiving center—either a *Mission: Lifeline* center or a Chest Pain Center with PCI accredited by the Society of

Cardiovascular Patient Care, or a facility designated by regional EMS to be PCI-capable Bureau of Emergency Medical Services (2015a,b).

As described in Section 2.3, we leverage the differential impact of these destination policies on Philadelphia residents in areas where the nearest hospital was not certified as a PSC or was not PCI-capable to study the effect of regional systems of care on short term outcomes.

2.2. Existing Literature

Stroke regionalization in the United Kingdom has been studied extensively. London in July 2010 and Greater Manchester in April 2010 reconfigured acute stroke care such that suspected stroke patients were transported to designated stroke facilities instead of the nearest emergency department (Fulop et al., 2013; Morris et al., 2014). This reduced the number of hospitals receiving stroke patients from 30 to 8 in London and from 10 to 3 in Greater Manchester (Fulop et al., 2013; Morris et al., 2014).

Morris et al. (2014) use a difference-in-differences framework to study the effect of stroke regionalization on risk-adjusted mortality and risk-adjusted length of stay. Using hospital episode and mortality data from January 2008 to March 2012, the authors compare changes in their outcomes of interest before and after the reorganization in London and Greater Manchester to changes in the unaffected regions of England. They find significant decreases in 3-day, 30-day, and 90-day mortality and hospital length of stay in London (by 1.4 days); and significant decreases in hospital length of stay in Greater Manchester (by 2.0 days).

Ramsay et al. (2015) attempt to explain the decrease in mortality found in London but not Greater Manchester by focusing on changes in receipt of clinical interventions. The authors do not identify the causal impact of regionalization, but suggest that London patients were more likely to receive all clinical interventions while Greater Manchester patients were more likely to receive brain scans but less likely to be admitted to a stroke unit, receive physiotherapy, and receive swallowing assessments.

Morris et al. (2019) extend Morris et al. (2014) and Ramsay et al. (2015) by incorporating mortality and length of stay data through March 2016, studying a modification to the Greater Manchester centralization that occurred by April 2015, and studying trends in clinical interventions through March 2016. They find that reductions in mortality and length of stay in London have been sustained since the 2010 centralization; risk-adjusted 90-day mortality significantly decreased at stroke centers in Greater Manchester (compared to the rest of England) but not for Greater Manchester overall; risk-adjusted hospital length of stay decreased in Greater Manchester compared to changes in the rest of England.

Friebel et al. (2018) separately identify the effects of stroke centralization in London on patients who are treated at designated hospitals and those who remain treated at non-designated hospitals. They find that regionalization increased rates of thrombolysis treatment and decreased the percent of patients with aspiration pneumonia for patients treated at designated facilities. They find that regionalization worsened outcomes for patients who were treated at non-designated facilities following regionalization. Specifically, they find regionalization to have caused lower rates of brain scans, higher death at seven days, higher death at 30 days, lower rates of thrombolysis treatment, and higher readmissions (Friebel et al., 2018).

Counties in California and New York, among others, enacted destination policies for acute stroke patients in the first few years of the 2000s. Gropen et al. (2006) study an EMS destination policy implemented in May 2003 for acute stroke patients in Brooklyn and Queens, New York, while Sanossian et al. (2015) focus on a destination policy in Los Angeles County implemented in November 2009. Both studies rely on time series difference methodologies. Gropen et al. (2006) pull inpatient records with an admitting diagnosis of stroke during a baseline period (March 1, 2002 through May 31, 2002) and a re-measurement period (August 1, 2003 through October 31, 2003) to compare utilization at 14 hospitals designated as stroke centers by the New York State Department of Health prior to implementation of the destination policy and 18 hospitals not designated. By comparing designated and non-designated hospitals in the baseline period and again in the re-measurement period, the authors find that the hospitals differ in measurable ways, but they do not identify whether those differences changed following the destination policy.[5] Sanossian et al. (2015) study whether access to approved stroke centers (ASCs)—certified PSCs that signed agreements with Los Angeles EMS to follow policies and share data—and receipt of tPA therapy increased after the implementation of a destination policy. Using a simple difference methodology with one year pre-policy and one year post-policy, the authors find that the percent of patients transported to ASCs increased but found no difference in receipt of tPA therapy or transportation time from scene to emergency department (Sanossian et al., 2015).

Prabhakaran et al. (2013) study rates of rt-PA use in Chicago at 10 PSCs before and after a regional policy to route stroke patients to PSCs started on March 1, 2011. The authors found increase in rate of intravenous tPA administration in the 6 months following the policy implementation vs. the 6 months prior to the policy start date. The authors do not consider treatment for patients routed to non-PSCs and cannot identify patients who bypass nearest hospital for a PSC.

Hastrup et al. (2018) study the effects of stroke centralization on length of stay, hospital bed days over the next year, quality of acute stroke care, hospital readmissions, and mortality in the Central Denmark Region (CDR). Centralization in the CDR required all stroke patients to be admitted to one of two acute stroke units, where previously only candidates for revascularization therapy would be admitted to these units. They compare changes in outcomes in the CDR to changes in the rest of Denmark in a difference-in-differences approach using 12 months prior to implementation as the before period (May 2011 - April 2012) and 12 months after implementation as the after period (May 2013-April 2014), adjusting for admission characteristics including stroke severity and stroke subtype (improvement on prior lit without stroke severity). They find centralization to be associated with a decrease in the

[5] Designated hospitals had lower median door to CT performed time in the baseline period but not the re-measurement period; and higher percentage of patients received tPA therapy and higher percentage of ED diagnosed cases admitted to stroke unit in the baseline and re-measurement periods (Gropen et al., 2006).

median length of stay, an increase in the percent of stroke events treated as outpatients, but no change to total all-cause bed days or length of stay including rehabilitation. No significant changes in the quality of acute stroke care, hospital readmissions, or mortality were found relative to changes in the rest of Denmark.

As mentioned in Section 2.1.2, evidence on the causal impact of STEMI regionalization on hospital utilization and outcomes is limited. The *Mission: Lifeline* evaluations focus on time to reperfusion, mortality, and hospital processes Jollis et al. (2016); Fordyce et al. (2017), and are limited to time-series differences. Green et al. (2018) compare six states, including Pennsylvania, that reported statewide STEMI destination policies to Kupas et al. (2015) to six comparison states without destination policies. Comparing rates of reperfusion at 90 and 120 minutes from first medical contact and overall receipt of reperfusion therapy in treated states to rates in untreated states, Green et al. (2018) find that STEMI patients living in states with destination policies were more likely to receive reperfusion therapy within guideline recommended timing than patients living in states without destination policies.

In this paper, we discuss regional systems of care as they relate to time critical illnesses; however, regionalization can apply to any condition or any set of services. Ho et al. (2007) consider the volume-outcome relationship and the potential effects of regionalization on consumer surplus using the market for the Whipple procedure for pancreatic cancer. Although regionalization for complex surgical procedures may increase consumer surplus by improving outcomes, reduced hospital competition may increase prices thereby reducing consumer surplus (Ho et al., 2007). The overall effect of regionalization on consumer surplus depends on relative sizes of these effects. Ho et al. (2012) look at the relationship between hospital volume and mortality and costs for pancreatic cancer surgery and colon cancer surgery, while also considering the effect that reduced hospital competition has on mortality, costs, and prices to study the welfare implications of regionalization. The authors conclude that regionalization for pancreatic cancer improves welfare, but finds less evidence to support the same welfare-improving claim for colon cancer surgery (Ho et al., 2012). Bendzsak et al. (2017) describe regionalization for lung cancer surgery in Ontario, Canada while Nelen et al. (2017) describe regionalization for gastric cancer surgery in the Netherlands.

2.3. Data and Descriptive Statistics

We use hospital inpatient discharge data for Philadelphia obtained from the Pennsylvania Health Care Cost Containment Council (PHC4) for calendar years 2008 through 2013 to estimate the impact of regional systems of care on inpatient utilization and short term outcomes. The data contain patient demographics, facility characteristics, diagnosis and procedure codes, and charges for facilities located in Philadelphia (PHC4 region 9). In this section we describe our sample inclusion criteria, define our measures of exposure, and define our outcomes of interest.

2.3.1. Sample definitions

Of the two million inpatient admissions over our study period, we make several sample exclusions as depicted in Figure 9. We exclude admissions to specialty hospitals as these facilities should not receive patients suffering time critical illnesses before or after the regionalization policies.[6] As our measure of exposure to regionalization depends on patient residence, we exclude admissions with invalid or missing zip codes and admissions for patients who reside outside of Philadelphia. We exclude admissions for patients under the age of 18 years as well as pregnancy and childbirth admissions. Incidences of stroke and STEMI in the under age 18 population are low (Fullerton et al., 2003; Mahle et al., 2007). Further, pregnancy and childbirth related admissions differ from stroke and STEMI admissions in measurable ways—age, sex, comorbidities, and priority of admission—and likely differ in unmeasurable ways that influence hospital choice and outcomes. We exclude admissions with invalid or missing outcomes of interest; and finally, we keep only admissions recorded

[6]We also exclude admissions to Temple East/Northeastern Hospital that transitioned to ambulatory non-emergency services only in 2009.

as being of emergency or urgent priority to remove scheduled admissions.[7]

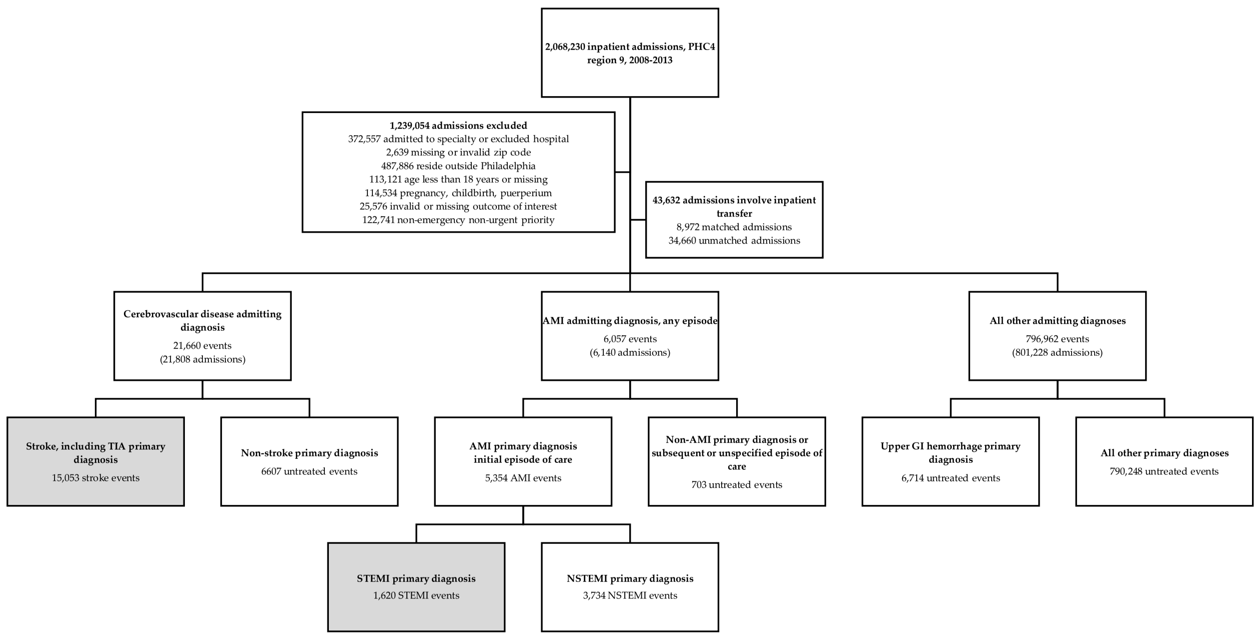
Of the remaining 829,176 admissions, 5.3% involve at least one inpatient transfer. We are able to match 8,972 (20.6%) of these admissions using information available in the PHC4 data, such as masked patient identifiers, discharge quarter, admission and discharge day of week, and admission and discharge hour of day. We are unable to match the remaining admissions due to a combination of data limitations, including missing patient identifiers, restricted admission and discharge date identifiers, transfers to or from hospitals outside Philadelphia, and transfers that occurred before 2008 or after 2013. In our analyses we treat hospitalizations with matched transfers as single events, but do not exclude unmatched transfers.

As the regional systems of care apply only to patients suspected of having the conditions of interest, we divide the remaining 824,679 events by admitting diagnosis categories—cerebrovascular disease [International Classification of Diseases, Ninth Revision, Clinical Modification (ICD-9-CM) with first three digits 430-438], acute myocardial infarction (AMI) (ICD-9-CM 410.xx), and all other admitting diagnoses. As admitting diagnosis better fits with the spirit of destination policies, which rely on EMS providers' impression of the patient's condition at time of transport, we require admissions in the stroke group have an admitting diagnosis of any cerebrovascular disease and admissions in the STEMI group have an admitting diagnosis of AMI (STEMI or non-STEMI) of any episode of care (initial, subsequent, or unspecified). For events that contain more than one hospital admission, we use admitting diagnosis on the first observed admission in our data.

The stroke group consists of 15,053 events with admitting diagnosis of any cerebrovascular disease and primary diagnosis of stroke including transient ischemic attack (TIA) as defined by the AHA and ASA in Sacco et al. (2013). Primary stroke diagnosis consists of central nervous system (CNS) infarction (primary diagnosis of ICD-9-CM 433.x1, 434.x1, 366.1,

[7] Facilities do not uniformly report emergency versus urgent priority in the PHC4 data. We include both emergency and urgent admissions. We are unable to identify patients admitted through the emergency department.

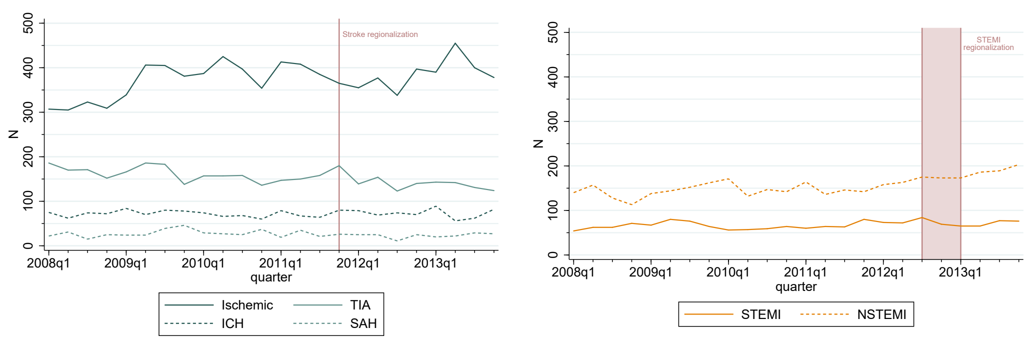
Figure 9: Philadelphia Inpatient Hospital Admissions, Stroke and STEMI Sample Creation



PHC4 = Pennsylvania Health Care Cost Containment Council; AMI = Acute Myocardial Infarction; TIA = Transient Ischemic Attack; STEMI = ST elevation myocardial infarction; NSTEMI = non-STEMI; GI = Gastrointestinal.

362.31, or 362.32), CNS hemorrhage (primary diagnosis of ICD-9-CM 430 or 431), or TIA (primary diagnosis of ICD-9-CM 435.x or 362.34) (Sacco et al., 2013).[8] The left panel of Figure 10 plots the volume of treated stroke events over our study period by stroke type. A vertical line marks the start of Philadelphia's stroke destination policy in the fourth quarter of 2011. Again, we refer to Sacco et al. (2013) for definitions of stroke type. The majority of strokes are ischemic in nature throughout our study period. Volume by type of stroke appears steady mid-2009 through the start of 2012, after which there appears to be a rise in the number of hospital events for ischemic stroke and a decline in the number of hospital events for transient ischemic attacks (TIA). Both ischemic strokes and TIAs are caused by a blockage of blood flow to the brain, often a blood clot (American Heart Association/American Stroke Association, 2018). In the case of TIAs, these blockages are temporary, though often warnings of future ischemic strokes. Because pre-hospital providers cannot distinguish between types of stroke without imaging (discussed in Section 2.3.3), the acute stroke destination policy applies uniformly across stroke subtypes.

Figure 10: Volume of Inpatient Hospital Events, by Condition



(a) Stroke

(b) AMI

TIA = transient ischemic attack; ICH = intracerebral hemorrhage; SAH = subarachnoid hemorrhage; AMI = acute myocardial infarction; STEMI = ST-elevation myocardial infarction; NSTEMI = non-STEMI
Source: Pennsylvania Health Care Cost Containment Council (PHC4) inpatient discharge data for Philadelphia (region 9), 2008 to 2013

[8] We follow the expert definition of stroke including TIA outlined in Sacco et al. (2013), but the definition of stroke hospitalization varies widely in the literature. For example, Gropen et al. (2006) use admitting diagnoses of 430, 431, 432.9, 433.x1, 434.x1, or 436; Xian et al. (2011) use primary diagnoses 433.x1, 434.x1, or 436; and Bekelis et al. (2016) use primary diagnoses 430.xx, 431.xx, 434.xx, or 434.xx.

We identify 5,354 events with admitting diagnosis of AMI and primary diagnosis of AMI initial episode (ICD-9-CM 410.x1).[9] Thirty percent of these events have a primary diagnosis of STEMI, while the remaining 70% have primary diagnosis of non-ST elevation myocardial infarction (NSTEMI). STEMI is distinguished from NSTEMI using electrocardiogram (ECG), which can be performed by ALS EMS providers (Simmons and Alpert, 2018). The right panel of Figure 10 shows the volume of STEMI events and untreated NSTEMI events over our study period. A shaded vertical panel between July 2012 and January 2013 marks Philadelphia's enrollment in the *Mission: Lifeline* demonstration project. While STEMI volume appears flat in the quarters before and after regionalization, NSTEMI volume trends upward starting with the first quarter of 2012. In addition to examining the impact of STEMI regionalization on short term outcomes for STEMI patients, we test for spillovers in the NSTEMI population.

In later work, we will incorporate our untreated sample of hospital events in a triple difference. The untreated sample consists of 796,962 hospital events unrelated to stroke or AMI, 6,607 events admitted with cerebrovascular disease but without a primary diagnosis of stroke, and 703 events with an admitting diagnosis of AMI but without a primary diagnosis of STEMI or NSTEMI initial episode of care. We further classify a subset of the untreated events as upper gastrointestinal hemorrhage (UGIH) events. Similar to stroke and AMI, acute gastrointestinal hemorrhage can be life threatening; however, no regional system of care for gastrointestinal hemorrhage exists in Philadelphia (Barkun et al., 2010). In their study of primary stroke center outcomes, Xian et al. (2011) similarly use admissions for gastrointestinal hemorrhage as part of falsification tests.

2.3.2. Exposure by Geography

The development of regional systems of care differentially affects areas where the nearest acute care facility is not designated as the regional center of care. We leverage this dif-

[9] Patients with subsequent episodes of AMI may return to the hospital that treated their first episode, not the nearest hospital or PCI-capable hospital. We will include these episodes in our untreated group in later work.

ferential exposure by geography to classify Philadelphia zip codes as treated or untreated by the stroke and STEMI regionalization. Treated zip codes are those most impacted by the destination policy—areas where the nearest hospital is not a PSC/PCI-capable facility. EMS crews transporting stroke and STEMI incidents in these areas presumably bypass the nearest hospital to comply with destination policies, trading off a small increase in transportation time for improved access to appropriate treatment at the destination.

We classify zip codes as treated by the stroke destination policy if differential distance from the zip code to a PSC is greater than zero. Similarly, we classify zip codes as treated by the STEMI destination policy if differential distance from the zip code to a PCI-capable facility is greater than zero. Differential distance is a widely used predictor of hospital choice as it explains variation in observed hospital choice, but is unlikely to be correlated with unobserved confounders (e.g., stroke severity).[10]

Table 11 compares pre-regionalization characteristics for stroke patients in treated zip codes to those for stroke patients in untreated zip codes. Stroke patients admitted from treated zip codes are older than stroke patients admitted from untreated zip codes, by 2.43 years, in the years prior to regionalization. The racial composition of admissions differs significantly in treated and untreated zip codes prior to treatment—with stroke patients from treated zip codes more likely to be white or Asian, and less likely to be black or another race. The proportions of uninsured and Medicaid patients are lower in treated zip codes, while the proportion of Medicare patients is higher—corresponding with the higher average age of stroke patients from treated zip codes. We use Charlson comorbidities to compare health status. These comorbidity indicators are defined following Quan et al. (2005) using primary diagnoses and the first eight secondary diagnoses.[11] Stroke admissions from treated zip codes

[10] Differential distance was formally defined in(McClellan et al., 1994) and Newhouse and McClellan (1998) as the additional distance beyond the distance to the nearest hospital to reach a hospital with the characteristic of interest.

[11] The number of reported secondary diagnoses expanded from 8 to 17 in January 2011. Using the expanded set of diagnoses in the post period, when not available for the majority of the pre period would artificially make the post period group appear sicker than the treatment period group. This would pose an issue for identification if diagnosis field expansion differentially affected treatment and untreated diagnosis groups or zip codes.

have lower rates congestive heart failure (CHF), uncomplicated diabetes, and renal disease; while they are more likely to have myocardial infarction, diabetes with complications, and metastatic solid tumors. Although we compare rates of pre-regionalization Charlson comorbidities, we do not include these measures as admission-level controls in our empirical analysis. Because these measures are defined using diagnoses from the same hospital event as our event of interest, they may represent complications of treatment. Including these comorbidities (or complications) in our estimation would prevent us from obtaining a consistent estimate.[12] These differences only pose an issue for identification of the causal effect if the differences are trending differently over time.

Table 12 compares pre-regionalization characteristics for STEMI patients in treated zip codes to those for STEMI patients in untreated zip codes. STEMI patients from treated zip codes and STEMI patients from untreated zip codes are generally similar across a number of characteristics in the years prior to regionalization, with a few exceptions. STEMI patients from treated zip codes are less likely to be white and more likely to be black; and less likely to be of Hispanic or Latino origin/descent. STEMI patients from treated zip codes are less likely to have commercial insurance than STEMI patients from untreated zip codes. In Table 31, we report pre-period characteristics for untreated NSTEMI patients coming from treated and untreated zip codes.

[12]Present on admission indicators are available in the PHC4 data starting with the first quarter of 2011.

Table 11: Admission Characteristics by Geography (differential distance PSC >0), Pre Stroke Regionalization Policy, January 2008 - September 2011

	Treated Zip	Untreated Zip	
Admission Characteristics			
Age, in years	69.58 (14.62)	67.15 (15.17)	***
Sex (%)			
Female	57.67	56.76	
Male	42.33	43.24	
Race (%)			
White	59.35	33.72	***
Black	31.26	54.38	***
Asian	2.72	1.60	***
Other race	6.68	10.30	***
Hispanic/Latino origin/descent (%)	2.97	6.15	***
Payer (%)			
Uninsured	0.54	1.86	***
Medicare	64.00	59.00	***
Medicaid	17.41	20.96	***
Blue Cross	11.97	11.46	
Commercial	5.39	5.48	
Government	0.45	0.47	
Comorbidities (%)			
Myocardial infarction	7.52	6.12	**
Congestive heart failure	10.93	13.39	***
Peripheral vascular disease	6.13	5.28	
Cerebrovascular disease	99.95	99.96	
Dementia	2.87	2.95	
Chronic pulmonary disease	12.51	12.95	
Rheumatic disease	1.38	1.67	
Peptic ulcer disease	0.20	0.43	
Mild liver disease	1.19	1.68	
Diabetes without complications	23.99	28.77	***
Diabetes with complications	3.96	3.10	*
Hemiplegia or paraplegia	23.74	24.59	
Renal disease	7.86	9.72	**
Malignancy, except skin	3.21	3.07	
Moderate or severe liver disease	0.10	0.20	
Metastatic solid tumor	1.48	0.96	**
AIDS/HIV	0.20	0.39	
Exposure			
Zip exposure group PFD 1 (%)	73.84	25.67	
Zip exposure group PFD 2 (%)	66.67	22.25	
Zip exposure group d.distance PSC (%)	100.00	0.00	
Differential distance PSC, in miles	1.55 (0.96)	0.00 (0.00)	
N	2,022	7,429	

*** $p < 0.01$ ** $p < 0.05$ * $p < 0.10$.
PFD = Philadelphia Fire Department; PSC = primary stroke center.
All characteristics, except for comborbidities, are defined using the first observed stay for a hospitalization, unless the characeristic is missing. Comorbidities are defined using the primary diagnoses from each observed stay of the hospitalization and secondary diagnoses in order of observed stay, up to nine diagnoses. The percent of stroke hospitalizations with cerebrovascular disease comorbidity may be less than 100%, as patients with acute infarction of the spinal cord or retinal vascular occlusions are included in the stroke sample.
Source: Pennsylvania Health Care Cost Containment Council (PHC4) inpatient discharge data for Philadelphia (region 9), 2008 through September 2011.

Table 12: Admission Characteristics by Geography (differential distance PCI >0), Pre STEMI Regionalization Policy, January 2008 - December 2012

	Treated Zip	Untreated Zip	
Admission Characteristics			
Age, in years	63.27 (14.07)	62.67 (14.87)	
Sex (%)			
Female	41.18	37.01	
Male	58.82	62.99	
Race (%)			
White	36.76	52.96	***
Black	50.29	30.49	***
Asian	1.47	2.81	
Other race	11.47	13.74	
Hispanic/Latino origin/descent (%)	2.35	6.12	***
Payer (%)			
Uninsured	1.47	1.81	
Medicare	46.47	45.24	
Medicaid	20.59	23.17	
Blue Cross	22.35	18.96	
Commercial	6.18	9.23	*
Government	2.65	1.50	
Comorbidities (%)			
Myocardial infarction	100.00	100.00	
Congestive heart failure	23.82	26.58	
Peripheral vascular disease	5.00	4.61	
Cerebrovascular disease	3.82	2.81	
Dementia	0.29	1.30	
Chronic pulmonary disease	12.35	15.85	
Rheumatic disease	2.06	1.00	
Peptic ulcer disease	1.18	0.40	
Mild liver disease	2.94	4.01	
Diabetes without complications	25.59	26.28	
Diabetes with complications	1.76	1.71	
Hemiplegia or paraplegia	0.88	0.30	
Renal disease	10.59	9.03	
Malignancy, except skin	1.76	2.11	
Moderate or severe liver disease	0.00	0.10	
Metastatic solid tumor	0.59	0.50	
AIDS/HIV	0.00	0.60	
Exposure (%)			
Zip exposure group d.distance PCI	100.00	0.00	
Differential distance PCI, in miles	1.73 (1.33)	0.00 (0.00)	
N	340	997	

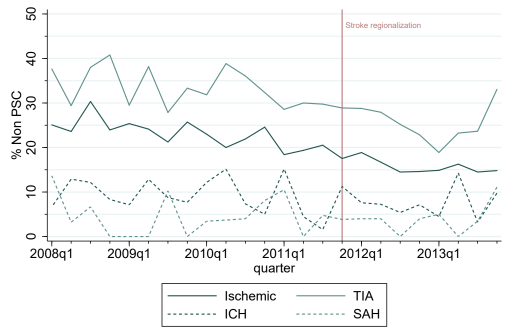
*** $p < 0.01$ ** $p < 0.05$ * $p < 0.10$.
PCI = percutaneous coronary intervention; STEMI = ST-elevation myocardial infarction.
All characteristics, except for comborbidities, are defined using the first observed stay for a hospitalization, unless the characeristic is missing. Comorbidities are defined using the primary diagnoses from each observed stay of the hospitalization and secondary diagnoses in order of observed stay, up to nine diagnoses.
Source: Pennsylvania Health Care Cost Containment Council (PHC4) inpatient discharge data for Philadelphia (region 9), 2008 through December 2012.

2.3.3. Outcomes

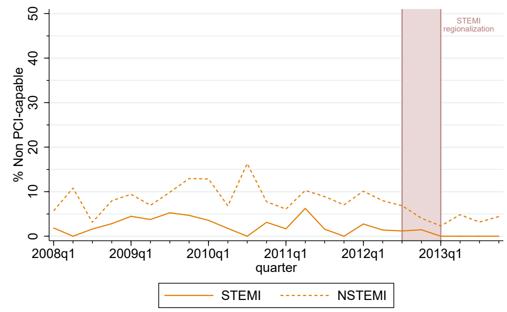
First, we test whether the destination policies achieve their stated goal of routing eligible patients to regional centers of care. Our outcomes of interest are probability of admission to a non-PSC in our stroke analysis, and probability of admission to a non PCI-capable hospital in our STEMI analysis. We expect to see a decline in the percent of stroke patients admitted to non-PSCs and a decline in the percent of STEMI patients admitted to non PCI-capable hospitals. Forty-four percent of stroke hospital events from treated zip codes are admitted to non-PSCs in the pre-period compared to 18% admitted to non-PSCs from untreated zip codes (Table 13). Only 7% of STEMI hospital events from treated zip codes are admitted to non PCI-capable hospitals in the pre-period, compared to 1% of STEMI hospital events from untreated zip codes (Table 14). Figure 11 shows unadjusted trends in admissions to non-designated facilities over time by stroke type, STEMI and NSTEMI groups combined for treated and untreated zip codes. While stroke patients of all types remain treated at non-PSCs after regionalization, the percent of STEMI patients treated at non PCI-capable hospitals drops to zero in the four quarters observed after STEMI regionalization. We also examine the effects of regionalization on the probability of any hospital inpatient transfer, under the hypothesis that transfers should decrease if more patients are directly transported to regional centers, but could increase if non-regional centers cease all treatment for these conditions.

We study a number of outcomes specific to stroke care. We examine the receipt of inpatient thrombolytic therapy (ICD-9-CM procedure code 99.10). Tissue plasminogen activator (tPA) is a type of thrombolytic therapy used in treatment of ischemic stroke to dissolve the blood clot blocking blood flow to the brain. Non-invasive brain magnetic resonance imaging (MRI) and head computed tomography (CT) are used to distinguish ischemic stroke from hemorrhage and should be performed prior to initiating thrombolytic therapy for ischemic stroke (Latchaw et al., 2009; Morgenstern et al., 2010; Connolly et al., 2012; Jauch et al., 2013). We define brain MRI using ICD-9-CM procedure code 88.91 and head

Figure 11: Percent of Admissions to Non-Designated Facilities over Study Period



(a) Stroke



(b) AMI

TIA = transient ischemic attack; ICH = intracerebral hemorrhage; SAH = subarachnoid hemorrhage; AMI = acute myocardial infarction; STEMI = ST-elevation myocardial infarction; NSTEMI = non-STEMI
Source: Pennsylvania Health Care Cost Containment Council (PHC4) inpatient discharge data for Philadelphia (region 9), 2008 to 2013

CT using ICD-9-CM procedure code 87.03. Minimally invasive imaging, such as cerebral arteriography (digital subtraction angiography or DSA) which requires catheterization, may be performed if the results of noninvasive imaging are inconclusive or contradictory (Jauch et al., 2013; Danzinger, 2018). We measure rates of cerebral arteriography using ICD-9-CM procedure code 88.41. Since we do not observe detailed timing of procedures in the PHC4 data, we examine changes in the probabilities of inpatient administration of tPA, head CT, brain MRI, and cerebral angiography.

We test whether intensity of treatment changes as a result of regionalization by examining surgical interventions for acute stroke, including intracranial vascular procedures and craniotomy. We identify hospitalizations with any intracranial vascular intervention using Medicare Severity Diagnosis Related Groups (MS-DRGs) 020, 021, and 022; and the intracranial vascular operating room procedures that comprise these MS-DRGs. Hospitalizations with craniotomy are identified using MS-DRGs 023 through 027 and the craniotomy operating room procedures that comprise these MS-DRGs. Intracranial hemorrhages may be treated with surgical removal of the hemorrhage; subarachnoid hemorrhages may be treated with surgical clipping, endovascular coiling, or complete obliteration of the aneurysm; and ischemic stroke may be treated with mechanical thrombectomy (included in craniotomy) (Morgenstern et al., 2010; Connolly et al., 2012; Jauch et al., 2013).

Specific to care for STEMI, we examine rates of percutaneous transluminal coronary angioplasty (PTCA) and coronary bypass (CABG). We identify PTCA using ICD-9-CM procedure codes 00.66, 36.09, and 17.55. We identify CABG using ICD-9-CM procedure codes 36.1x. Primary percutaneous coronary intervention (PCI) including PTCA is the Class I level A guideline recommended treatment for STEMI patients; and CABG is recommended for patients who are not amenable to PCI (Class I level B) (O'Gara et al., 2013).[13]

Next, we focus on short term outcomes, including hospital length of stay, in hospital mortality, discharge status, and total charges. Hospital length of stay is defined as the sum of reported days across all observed stays per hospital event. We expect hospital length of stay to decrease if patients receive reperfusion therapy sooner in the case of ischemic stroke and STEMI, or if patients receive monitoring and medical management to control pressure in the case of hemorrhagic stroke.

Total charges represent the sum of charges for room and board, ancillary services, drugs, medical equipment and supplies, specialty care units, and miscellaneous charges excluding professional fees. These charges represent the amount billed by the hospital, not necessarily the amount paid. If direct transportation to regional centers reduces between hospital transfers for patients who are eligible for surgical intervention and/or reduces length of stay, we would expect destination policies to lower charges. Charges could increase as a result of regionalization if intensity of treatment increases. We test for this directly by examining receipt of surgical interventions.

Finally, if regional systems of care optimize patient outcomes as intended, we would expect the probability of discharge to home to increase with regionalization. Our measure of discharge to home includes routine discharges without care, discharges to home with home

[13] Here, "primary" refers to intervention without prior administration of fibrinolytic or antiplatlet therapy (Keeley and Hillis, 2007).

health care, discharges to home hospice, and discharges to court/law enforcement. Patients who expire in the hospital are excluded from the regressions estimating the effect of regionalization on discharge to home. For completeness, we also report rates of in hospital mortality, though do not expect regionalization to have a noticeable effect.

Table 13: Unadjusted Outcomes of Interest by Geography (differential distance PSC >0), Pre and Post Stroke Regionalization Policy

	Treated Zip		Untreated Zip	
Outcomes of Interest	*Pre*	*Post*	*Pre*	*Post*
Non primary stroke center (%)	44.11	33.39	17.58	12.45
Any inpatient hospital transfer (%)	5.59	14.95	4.79	10.32
Imaging (%)				
Head CT	6.87	7.69	9.68	3.70
Brain MRI	16.37	19.41	22.30	17.77
Cerebral angiography	20.13	10.66	22.36	9.96
Interventions (%)				
Received tPA	2.97	4.02	3.14	3.84
Intracranial vascular procedures	2.23	2.53	2.52	2.40
Craniotomy	5.19	7.43	5.73	6.53
Discharged to home (%)	54.75	54.28	50.64	51.46
Length of stay	6.27 (7.63)	5.59 (12.13)	6.25 (8.26)	5.49 (7.53)
Total charges ($)	89,578 (173,772)	91,929 (181,779)	97,311 (158,426)	102,497 (144,049)
N	2,022	1,144	7,429	4,458

PSC = primary stroke center; tPA = tissue plasminogen activator; MRI = magnetic resonance imaging; CT = computed tomography; STAC = short term acute care.
All outcomes, except for arrival at non primary stroke center and discharge status, are defined used the sum of outcomes across all observed stays in the hospitalization. Arrival at non primary stroke center is defined using the first observed stay for a hospitalization. Discharge status is defined using the last observed stay for a hospitalization.
Source: Pennsylvania Health Care Cost Containment Council (PHC4) inpatient discharge data for Philadelphia (region 9), January 2008 through December 2013.

Table 14: Unadjusted Outcomes of Interest by Geography (differential distance PCI >0), Pre and Post STEMI Regionalization Policy

	Treated Zip		Untreated Zip	
Outcomes of Interest	*Pre*	*Post*	*Pre*	*Post*
Non PCI capable hospital (%)	7.35	0.00	0.80	0.00
Any inpatient hospital transfer (%)	16.47	11.67	6.22	8.52
Interventions (%)				
PTCA	79.12	86.67	80.14	80.72
Coronary bypass	2.65	6.67	5.52	7.17
Discharged to home	80.88	85.00	77.53	80.27
Length of stay	5.64 (5.97)	5.48 (4.82)	6.28 (8.16)	5.56 (9.08)
Total charges ($)	148,846 (127,573)	209,502 (186,806)	162,959 (217,231)	173,416 (289,555)
N	340	60	997	223

PCI = percutaneous coronary intervention; STEMI = ST-elevation myocardial infarction; PTCA = percutaneous transluminal coronary angioplasty; STAC = short term acute care.
All outcomes, except for arrival at non PCI capable hospital and discharge status, are defined used the sum of outcomes across all observed stays in the hospitalization. Arrival at non PCI capable hospital is defined using the first observed stay for a hospitalization. Discharge status is defined using the last observed stay for a hospitalization.
Source: Pennsylvania Health Care Cost Containment Council (PHC4) inpatient discharge data for Philadelphia (region 9), January 2008 through December 2013.

2.4. Empirical Strategy

We estimate the causal impact of regionalization by leveraging variation in Philadelphia zip code exposure. Zip codes with non-zero differential distance to PSCs are more exposed to stroke regionalization than zip codes where the differential distance to the nearest PSC is zero. Zip codes with non-zero differential distance to PCI-capable hospitals are more exposed to STEMI regionalization than zip codes where the differential distance is zero. We study whether the probability of admission to non-designated facilities, probability of inpatient hospital transfer, and average length of stay declined more in treated zip codes relative to changes in untreated zip codes. We examine whether the probability of discharge to home and the probability of receiving stroke-specific or STEMI-specific interventions increased more in treated zip codes relative to changes in untreated zip codes. Finally, we test the impact of regionalization on total charges, as charges could decrease with reductions in length of stay or inpatient hospital transfers but increase with stroke-specific and STEMI-specific interventions. We assume that absent regionalization, the change in outcomes for treated zip codes would not have differed from the change in outcomes for untreated zip codes.

First, we estimate the following event study specification, allowing the effect of zip code z condition c treatment, d_z^c to vary over time, separately by condition.

$$y_{izt}^c = \alpha_z^c + \delta_t + \sum_{t=2008}^{t=2013} \beta_t \left(d_z^c \times \mathbb{1}\left(year_t\right)\right) + \Gamma X_{izt} + \varepsilon_{izt} \tag{2.1}$$

y_{izt} is the outcome of interest for hospital event i from zip code z in 12-month period t. Twelve month periods run from October through September in our stroke analyses and correspond to calendar years in our STEMI analyses. d_z^c indicates whether the zip code is treated for condition c (stroke or STEMI) and is interacted with a full set of 12-month period fixed effects. X_{izt} is a vector of admission-varying characteristics, including age, sex, race, and insurance coverage included to improve precision. Comorbidities are not included as they are defined using diagnoses reported on the inpatient admission, which may represent complications correlated with treatment. We include zip code fixed effects α_z to control for time-invariant heterogeneity by zip code and 12-month period fixed effects δ_t to account for unobserved heterogeneity over time. Standard errors are robust to heteroscedasticity and clustered at the zip code level. The coefficients of interest are the β_t estimates, which are presented relative to the 12-month period prior to treatment (October 2010 through September 2011 for stroke and January 2012 through December 2012 for STEMI). We examine pre-period coefficients for evidence of violation of our parallel trends assumption.

We also estimate the following difference-in-differences, separating our study period into a pre and post period:

$$y_{izt}^c = \alpha_z^c + \delta_t + \beta \left(d_z^c \times post_t^c\right) + \Gamma X_{izt} + \varepsilon_{izt} \tag{2.2}$$

$post_t^c$ indicates the hospitalization occurs after condition c regionalization takes effect. β represents our difference in differences estimate. In our main analysis, we estimate equations 2.1 and 2.2 using linear regression. We present estimates from a multinomial logit model for nominal hospital discharge status in addition to the linear probability model for discharge to home.

As shown in Figure 11, stroke patients remain treated at non-PSCs following regionalization. In future work, we separate the effect of regionalization for patients who are admitted to non-PSCs from those who are admitted to PSCs following Friebel et al. (2018):

$$\begin{aligned} y_{izt}^{stroke} &= \alpha_z^{stroke} + \delta_t + \beta_1 \left(d_z^{stroke} \times nonPSC_i \right) + \beta_2 \left(post_t^{stroke} \times nonPSC_i \right) \\ &+ \beta_3 \left(d_z^{stroke} \times post_t^{stroke} \right) + \beta_4 \left(d_z^{stroke} \times post_t^{stroke} \times nonPSC_i \right) + \Gamma X_{izt} + \varepsilon_{izt} \end{aligned} \quad (2.3)$$

β_3 captures the average differential change in outcomes for patients admitted to PSCs from treated zip codes relative to the change for patients admitted to PSCs from untreated zip codes, while β_4 captures how different the differential change in outcomes is for patients treated at non-PSCs. The total effect of regionalization on patients treated at non-PSCs is the sum of β_3 and β_4. Our vector of admission level characteristics includes an indicator for non-PSC admission.

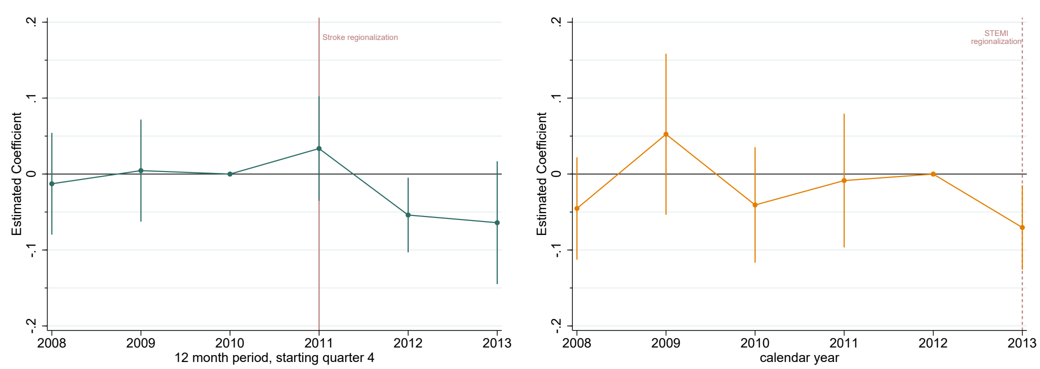
2.5. Results

First, we provide evidence that regionalization is associated with a decrease in admissions to non-designated hospitals as intended. We proceed to estimate the causal effect of regionalization on the probability of receiving care specific to stroke and the probability of receiving care specific to STEMI. Finally, we estimate the causal effect of regionalization on our short term outcomes—probability of discharge to home, hospital length of stay, and total charges.

2.5.1. Admission to Designated Hospitals

Figure 12 graphs the β_t coefficients from our event-study specification presented in equation 2.1 for the probability of admission to a non-PSC in the stroke sample and for the probability of admission to a non PCI-capable hospital for the STEMI sample. We include year and zip code fixed effects, control for age, sex, race, and payer for each admission, and cluster standard errors at the zip code level. Both panels report 95% confidence intervals around the β_t coefficients. For both stroke and STEMI, we find no evidence of differences in pre-intervention trends for treated and untreated zip codes. In the first year of stroke regionalization, 2011, we find a non statistically significant increase in the probability of admission to a non-PSC in zip codes exposed to stroke regionalization. Recall that this year is partially treated, as regionalization did not begin until the third quarter of 2011. In the first full year of stroke regionalization, 2012, we estimate a statistically significant decrease in the probability of admission to a non-PSC in treated zip codes by 5.4 percentage points. Our coefficient estimate for the 2013 suggests the decline in the probability of admission to a non-PSC from treated zip codes persists, though this coefficient is not statistically significant at the 5% level. In the first year of STEMI regionalization, we estimate a significant decrease in the probability of admission to a non PCI-capable hospital for STEMI patients living in treated zip codes by seven percentage points.

Figure 12: Relationship between Regionalization and Admission to Designated Hospitals, Event-Study



(a) Stroke

(b) STEMI

STEMI = ST elevation myocardial infarction.
Source: Pennsylvania Health Care Cost Containment Council (PHC4) inpatient discharge data for Philadelphia (region 9), 2008 to 2013

In the first three columns of Table 15 we present the estimates from equation 2.2 for probability of admission to a non-PSC. The specification of the difference in differences shown in column (1) includes an indicator for $post_t$ and an indicator for d_z, instead of year and zip code fixed effects. The estimate implies that regionalization is associated with a 5.6 percentage point decrease in the probability of admission to a non-PSC and is statistically significant at the 5% level. In column (2) we add zip code fixed effects to control for time-invariant heterogeneity in zip codes and calendar year fixed effects to control for unobserved heterogeneity over time. In column (3) we add admission-level covariates for age, sex, race, and payer. Though the magnitude of the effect remains around 5 percentage points, our estimate is no longer significant at the 5% level (it is significant at 10%). In columns (4) through (7) we present the results of our preferred specification including zip code and year fixed effects and admission-level covariates by stroke type. Stroke regionalization is associated with a decrease in the probability of admission to a non-PSC by 6.6 percentage points in the ischemic stroke subgroup. Regionalization has no significant effect on the probability of admission to a non-PSC for patients with intracerebral hemorrhage, subarachnoid hemorrhage, or TIA.

Table 15: Relationship between Stroke Regionalization and Admission to Non-PSC

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$d_z^{stroke} \times post_t^{stroke}$	-0.056**	-0.052**	-0.050*	-0.066***	-0.046	-0.059	-0.007
	(0.022)	(0.026)	(0.025)	(0.024)	(0.039)	(0.052)	(0.041)
Observations	15053	15053	15053	8999	1734	629	3691
Zip code FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Admission-level covariates	No	No	Yes	Yes	Yes	Yes	Yes
Condition	Stroke	Stroke	Stroke	Ischemic	ICH	SAH	TIA

*** p<0.01, ** p<0.05, and * p<0.10.
ICH = intracerebral hemorrhage; SAH = subarachnoid hemorrhage; TIA = transient ischemic attack.
Robust standard errors clustered at the patient zip code level are reported in parentheses.
Source: Pennsylvania Health Care Cost Containment Council (PHC4) inpatient discharge data for Philadelphia (region 9), 2008 to 2013.

Table 16 presents our difference in differences estimates for the probability of admission to a non PCI-capable hospital in the STEMI group. Again, column (1) presents difference in difference estimates without fixed effects or controls, but with $post_t^c$ and d_z^c indicators. We find STEMI regionalization to be associated with a decrease in the probability of admission to a non PCI-capable hospital by 6.6 percentage points—an estimate that is significant at the 1% level. Adding zip code and calendar year fixed effects reduces the magnitude of the estimate, only slightly, to 6.4 percentage points. Adding admission-level covariates has no effect on the estimate. Interestingly, we find regionalization to be associated with a marginally significant decline in the probability of admission to a non PCI-capable hospital for NSTEMI patients from treated zip codes by 5.6 percentage points [column (6)] (22% of baseline). This is surprising because ALS EMS providers can distinguish STEMI from NSTEMI in a pre-hospital setting using ECG.

These results, taken together, suggest that both stroke and STEMI regionalization in Philadelphia has been successful in reducing the probability of admission to non-designated facilities. In the case of STEMI, the reduction represents a complete elimination of STEMI admissions to non PCI-capable facilities. In the case of stroke, in the last quarter of our sample nearly 18% of stroke patients are admitted to non-PSCs. It remains to be answered whether regionalization worsens care for stroke at non-PSCs. This is a potential direction for future work.

Table 16: Relationship between STEMI Regionalization and Admission to Non PCI-Capable Hospital

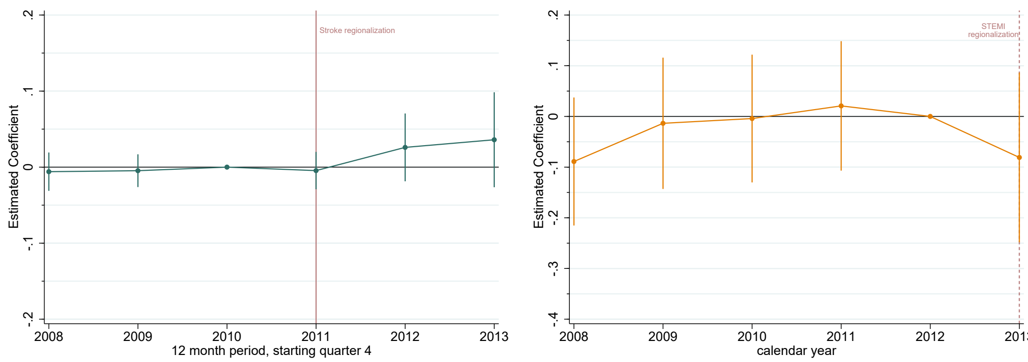
	(1)	(2)	(3)	(4)	(5)	(6)
$d_z^{STEMI} \times post_t^{STEMI}$	-0.066***	-0.064***	-0.064***	-0.061*	-0.057*	-0.056*
	(0.016)	(0.016)	(0.014)	(0.032)	(0.030)	(0.028)
Observations	1620	1620	1620	3734	3734	3734
Zip code FE	No	Yes	Yes	No	Yes	Yes
Year FE	No	Yes	Yes	No	Yes	Yes
Admission-level covariates	No	No	Yes	No	No	Yes
Condition	STEMI	STEMI	STEMI	NSTEMI	NSTEMI	NSTEMI

*** p<0.01, ** p<0.05, and * p<0.10.
STEMI = ST elevation myocardial infarction. NSTEMI = non-STEMI.
Robust standard errors clustered at the patient zip code level are reported in parentheses.
Source: Pennsylvania Health Care Cost Containment Council (PHC4) inpatient discharge data for Philadelphia (region 9), 2008 to 2013.

2.5.2. Hospital Inpatient Transfer

Figure 13 presents the estimates of our event-study specification for probability of any hospital inpatient transfer. Combined with the difference in difference estimates in Table 17, we find no convincing evidence that regionalization reduced the probability of any inpatient hospital transfer for stroke or STEMI. The stroke event study coefficients for 2012 and 2013, the first two full years of regionalization, are positive in direction, but not statistically significant. The STEMI event study coefficient for 2013 (right panel of Figure 13) and the difference in difference regression results in Table 17 are not statistically significant, but are negative in direction.

Figure 13: Relationship between Regionalization and Hospital Inpatient Transfer, Event-Study



(a) Stroke (b) STEMI

STEMI = ST elevation myocardial infarction.
Source: Pennsylvania Health Care Cost Containment Council (PHC4) inpatient discharge data for Philadelphia (region 9), 2008 to 2013

Table 17: Relationship between Regionalization and Hospital Inpatient Transfers

	(1)	(2)	(3)	(4)	(5)	(6)
$d_z^{stroke} \times post_t^{stroke}$	0.038*	0.036	0.034			
	(0.021)	(0.022)	(0.021)			
$d_z^{STEMI} \times post_t^{STEMI}$				-0.071	-0.063	-0.064
				(0.060)	(0.059)	(0.062)
Observations	15053	15053	15053	1620	1620	1620
Zip code FE	No	Yes	Yes	No	Yes	Yes
Year FE	No	Yes	Yes	No	Yes	Yes
Admission-level covariates	No	No	Yes	No	No	Yes
Condition	Stroke	Stroke	Stroke	STEMI	STEMI	STEMI

*** p<0.01, ** p<0.05, and * p<0.10.
STEMI = ST elevation myocardial infarction. Robust standard errors clustered at the patient zip code level are reported in parentheses.
Source: Pennsylvania Health Care Cost Containment Council (PHC4) inpatient discharge data for Philadelphia (region 9), 2008 to 2013

2.5.3. Stroke-Specific Imaging and Interventions

Here we report our event-study and regression results specific to stroke imaging and interventions.

Figure 14 shows estimated coefficients from our event-study for the probability of head CT (left panel) and for the probability of brain MRI (right panel). Though the coefficient estimates in the pre-period for probability of head CT are not statistically significant from zero at the 5% level, taken together they suggest the existence of differences in pre-intervention trends leading up to regionalization—a violation of the parallel trends assumption required for identification of the causal estimate. As such, the difference in difference results presented in Table 18 should not be taken as the causal estimates of regionalization on the probabilities of receiving head CT for stroke diagnosis. Instead, the event study figure on the left shows that the rate of head CT was increasing at a faster rate in treated zip codes. Future work should account for these differences in pre-intervention trends.

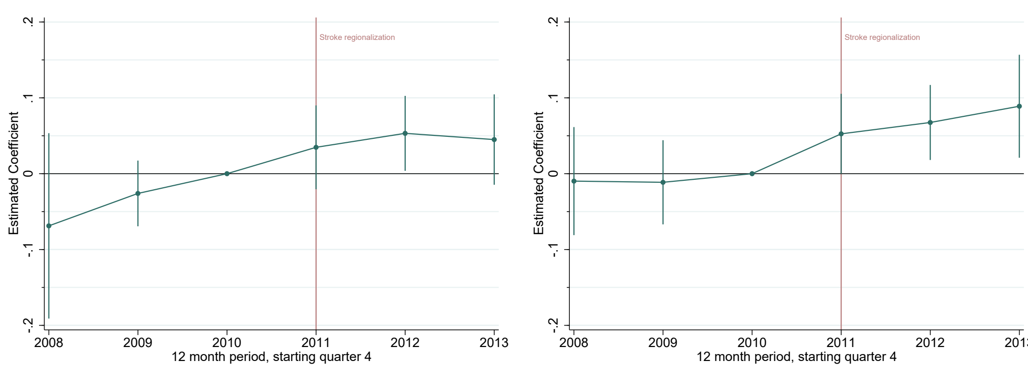
The right panel of Figure 14 shows a statistically significant increase in the probability of inpatient brain MRI starting with the first full year of regionalization, 2013, and continuing into the second full year of regionalization. Table 19 quantifies this effect in the post period as an increase in the probability of inpatient brain MRI by 7.1 percentage points [column (3)]. As shown in column (4), the effect comes from the statistically significant increase in the ischemic stroke subtype.

Figure 15 presents the estimated coefficients from our event-study for the probability of receiving in hospital tPA (left panel) and the probability of cerebral arteriography (right panel). We find no evidence that regionalization is associated with increased probability of receipt of tPA in the inpatient setting or with increased probability of cerebral arteriography. Table 20 similarly reports no significant results from the difference in differences estimate for probability of inpatient receipt of tPA for all types of acute stroke combined and by stroke subtype. Table 21 reports the difference in differences results for probability of cerebral arteriography.

Figure 16 presents the coefficient estimates of the event-studies for probability of any intracranial vascular procedure and probability of craniotomy. Both panels suggest that stroke regionalization has no effect on probability of undergoing surgical intervention for stroke. Tables 22 and 23 present the difference in differences estimates for probability of any intracranial vascular procedure and probability of craniotomy, respectively. Just as the event-study reports no effect, the difference in differences estimation finds no effect of regionalization on receipt of stroke-specific surgical interventions for stroke overall or for stroke subsample.

These stroke-specific results suggest that stroke regionalization is associated with limited changes in diagnostic imaging, inpatient receipt of thrombolytic therapy, or surgical interventions for stroke.

Figure 14: Relationship between Stroke Regionalization and Imaging, Event-Study



(a) Head CT (b) Brain MRI

MRI = magnetic resonance imaging; CT = computed tomography.
Pennsylvania Health Care Cost Containment Council (PHC4) inpatient discharge data for Philadelphia (region 9), 2008 to 2013

Table 18: Relationship between Stroke Regionalization and Head CT

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$d_z^{stroke} \times post_t^{stroke}$	0.068***	0.070***	0.070**	0.086***	0.073**	-0.066	0.058*
	(0.025)	(0.026)	(0.026)	(0.028)	(0.032)	(0.070)	(0.032)
Observations	15053	15053	15053	8999	1734	629	3691
Zip code FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Admission-level covariates	No	No	Yes	Yes	Yes	Yes	Yes
Condition	Stroke	Stroke	Stroke	Ischemic	ICH	SAH	TIA

*** p<0.01, ** p<0.05, and * p<0.10.
CT = computed tomography; ICH = intracerebral hemorrhage; SAH = subarachnoid hemorrhage; TIA = transient ischemic attack.
Robust standard errors clustered at the patient zip code level are reported in parentheses.
Source: Pennsylvania Health Care Cost Containment Council (PHC4) inpatient discharge data for Philadelphia (region 9), 2008 to 2013.

Table 19: Relationship between Stroke Regionalization and Brain MRI

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$d_z^{stroke} \times post_t^{stroke}$	0.076***	0.074***	0.071***	0.092***	0.026	-0.019	0.045
	(0.021)	(0.022)	(0.022)	(0.032)	(0.044)	(0.048)	(0.030)
Observations	15053	15053	15053	8999	1734	629	3691
Zip code FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Admission-level covariates	No	No	Yes	Yes	Yes	Yes	Yes
Condition	Stroke	Stroke	Stroke	Ischemic	ICH	SAH	TIA

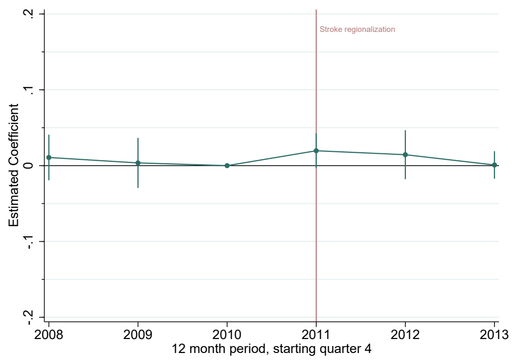
*** p<0.01, ** p<0.05, and * p<0.10.
MRI = magnetic resonance imaging; ICH = intracerebral hemorrhage; SAH = subarachnoid hemorrhage; TIA = transient ischemic attack.
Robust standard errors clustered at the patient zip code level are reported in parentheses.
Source: Pennsylvania Health Care Cost Containment Council (PHC4) inpatient discharge data for Philadelphia (region 9), 2008 to 2013.

Table 20: Relationship between Stroke Regionalization and tPA

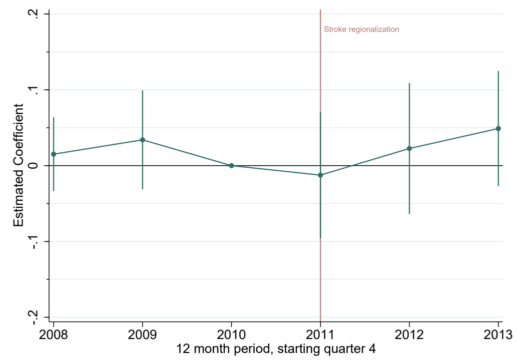
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$d_z^{stroke} \times post_t^{stroke}$	0.004	0.003	0.003	0.002	0.005	-0.010	-0.002
	(0.008)	(0.008)	(0.008)	(0.013)	(0.005)	(0.011)	(0.001)
Observations	15053	15053	15053	8999	1734	629	3691
Zip code FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Admission-level covariates	No	No	Yes	Yes	Yes	Yes	Yes
Condition	Stroke	Stroke	Stroke	Ischemic	ICH	SAH	TIA

*** p<0.01, ** p<0.05, and * p<0.10.
tPA = tissue plasminogen activator; ICH = intracerebral hemorrhage; SAH = subarachnoid hemorrhage; TIA = transient ischemic attack.
Robust standard errors clustered at the patient zip code level are reported in parentheses.
Source: Pennsylvania Health Care Cost Containment Council (PHC4) inpatient discharge data for Philadelphia (region 9), 2008 to 2013.

Figure 15: Relationship between Stroke Regionalization and tPA Administration, Cerebral Arteriography, Event-Study



(a) tPA



(b) Cerebral arteriography

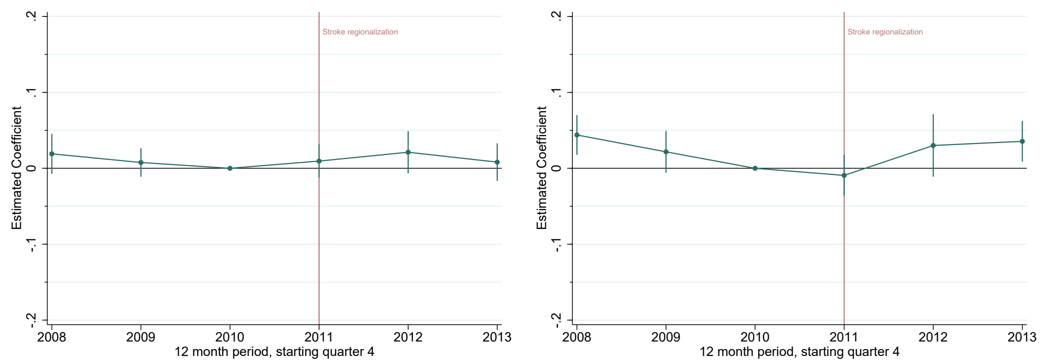
tPA = tissue plasminogen activator.
Pennsylvania Health Care Cost Containment Council (PHC4) inpatient discharge data for Philadelphia (region 9), 2008 to 2013

Table 21: Relationship between Stroke Regionalization and Cerebral Arteriography

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$d_z^{stroke} \times post_t^{stroke}$	0.029 (0.029)	0.026 (0.028)	0.022 (0.026)	0.034 (0.032)	-0.024 (0.034)	-0.074 (0.132)	0.027 (0.022)
Observations	15053	15053	15053	8999	1734	629	3691
Zip code FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Admission-level covariates	No	No	Yes	Yes	Yes	Yes	Yes
Condition	Stroke	Stroke	Stroke	Ischemic	ICH	SAH	TIA

*** p<0.01, ** p<0.05, and * p<0.10.
tPA = tissue plasminogen activator; ICH = intracerebral hemorrhage; SAH = subarachnoid hemorrhage; TIA = transient ischemic attack.
Robust standard errors clustered at the patient zip code level are reported in parentheses.
Source: Pennsylvania Health Care Cost Containment Council (PHC4) inpatient discharge data for Philadelphia (region 9), 2008 to 2013.

Figure 16: Relationship between Stroke Regionalization and Surgical Interventions, Event-Study



(a) Intracranial vascular procedure

(b) Craniotomy

Pennsylvania Health Care Cost Containment Council (PHC4) inpatient discharge data for Philadelphia (region 9), 2008 to 2013

Table 22: Relationship between Stroke Regionalization and Intracranial Vascular Procedure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$d_z^{stroke} \times post_t^{stroke}$	0.004	0.004	0.004	-0.001	0.004	0.113	-0.002
	(0.006)	(0.006)	(0.006)	(0.002)	(0.010)	(0.083)	(0.002)
Observations	15053	15053	15053	8999	1734	629	3691
Zip code FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Admission-level covariates	No	No	Yes	Yes	Yes	Yes	Yes
Condition	Stroke	Stroke	Stroke	Ischemic	ICH	SAH	TIA

*** p<0.01, ** p<0.05, and * p<0.10.
ICH = intracerebral hemorrhage; SAH = subarachnoid hemorrhage; TIA = transient ischemic attack.
Robust standard errors clustered at the patient zip code level are reported in parentheses.
Source: Pennsylvania Health Care Cost Containment Council (PHC4) inpatient discharge data for Philadelphia (region 9), 2008 to 2013.

Table 23: Relationship between Stroke Regionalization and Craniotomy

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$d_z^{stroke} \times post_t^{stroke}$	0.014	0.014	0.013	0.015	0.022	0.054	-0.002
	(0.011)	(0.011)	(0.011)	(0.011)	(0.069)	(0.080)	(0.002)
Observations	15053	15053	15053	8999	1734	629	3691
Zip code FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Admission-level covariates	No	No	Yes	Yes	Yes	Yes	Yes
Condition	Stroke	Stroke	Stroke	Ischemic	ICH	SAH	TIA

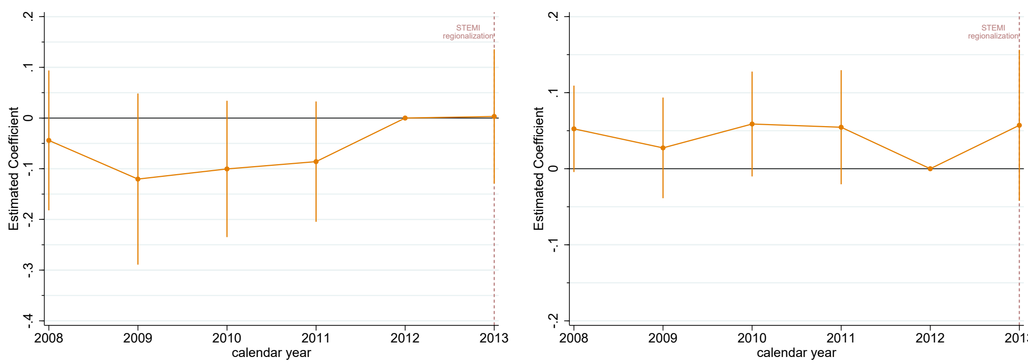
*** p<0.01, ** p<0.05, and * p<0.10.
ICH = intracerebral hemorrhage; SAH = subarachnoid hemorrhage; TIA = transient ischemic attack.
Robust standard errors clustered at the patient zip code level are reported in parentheses.
Source: Pennsylvania Health Care Cost Containment Council (PHC4) inpatient discharge data for Philadelphia (region 9), 2008 to 2013.

2.5.4. STEMI-Specific Interventions

In this section, we explore the causal effects of STEMI regionalization on the probability of undergoing PTCA and the probability of undergoing coronary bypass. The left panel of Figure 17 reports the coefficients from estimating our event-study specification for the probability of PTCA. The 2008 through 2011 estimated coefficients are below zero (2012 estimate is normalized to zero), but not significantly different from zero at the 5% level, suggesting that treated zip codes experienced larger increase in probability of PTCA in the year Philadelphia enrolled in the *Mission: Lifeline* demonstration (2012) and in 2013 than did untreated zip codes, at the 10% level. This is confirmed in our difference in differences regression estimates presented in Table 24. Column (3) shows our preferred specification that includes zip code and year fixed effects and admission-level covariates for age, sex, race, and payer. We find that STEMI regionalization is associated with an increase in the probability of PTCA by 6.9 percentage points. We find no effect on the probability of PTCA for NSTEMI patients [columns (4) through (6) of Table 17] who are not covered by regionalization.

The right panel of Figure 17 shows the coefficients from the event study estimated for probaility of coronary bypass. The differential change in probability of coronary bypass for STEMI patients from treated zip codes is not statistically different from the change for STEMI patients from untreated zip codes in any year of our study, before or after regionalization. Table 25 reports the corresponding difference in difference estimates for the probability of coronary bypass, again showing that regionalization did not affect rates of bypass for STEMI patients (or NSTEMI patients).

Figure 17: Relationship between STEMI Regionalization and Coronary Intervention, Event-Study



(a) PTCA (b) Coronary bypass

PTCA = percutaneous transluminal coronary angioplasty.
Pennsylvania Health Care Cost Containment Council (PHC4) inpatient discharge data for Philadelphia (region 9), 2008 to 2013

Table 24: Relationship between STEMI Regionalization and PTCA

	(1)	(2)	(3)	(4)	(5)	(6)
$d_z^{STEMI} \times post_t^{STEMI}$	0.070	0.069	0.069*	-0.016	-0.016	-0.019
	(0.051)	(0.047)	(0.041)	(0.053)	(0.054)	(0.045)
Observations	1620	1620	1620	3734	3734	3734
Zip code FE	No	Yes	Yes	No	Yes	Yes
Year FE	No	Yes	Yes	No	Yes	Yes
Admission-level covariates	No	No	Yes	No	No	Yes
Condition	STEMI	STEMI	STEMI	NSTEMI	NSTEMI	NSTEMI

*** p<0.01, ** p<0.05, and * p<0.10.
PTCA = percutaneous transluminal coronary angioplasty; STEMI = ST elevation myocardial infarction; NSTEMI = non-STEMI.
Robust standard errors clustered at the patient zip code level are reported in parentheses.
Source: Pennsylvania Health Care Cost Containment Council (PHC4) inpatient discharge data for Philadelphia (region 9), 2008 to 2013.

Table 25: Relationship between STEMI Regionalization and Coronary Bypass

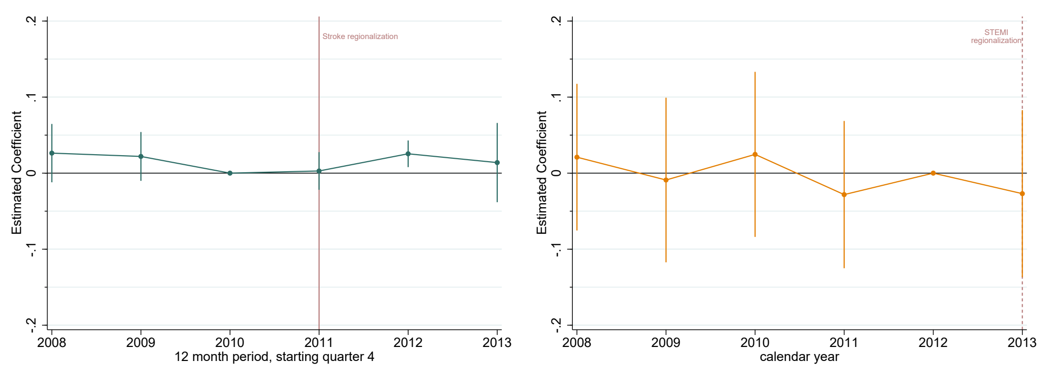
	(1)	(2)	(3)	(4)	(5)	(6)
$d_z^{STEMI} \times post_t^{STEMI}$	0.024	0.024	0.021	-0.029	-0.032	-0.031
	(0.042)	(0.041)	(0.040)	(0.019)	(0.021)	(0.020)
Observations	1620	1620	1620	3734	3734	3734
Zip code FE	No	Yes	Yes	No	Yes	Yes
Year FE	No	Yes	Yes	No	Yes	Yes
Admission-level covariates	No	No	Yes	No	No	Yes
Condition	STEMI	STEMI	STEMI	NSTEMI	NSTEMI	NSTEMI

*** p<0.01, ** p<0.05, and * p<0.10.
STEMI = ST elevation myocardial infarction; NSTEMI = non-STEMI.
Robust standard errors clustered at the patient zip code level are reported in parentheses.
Source: Pennsylvania Health Care Cost Containment Council (PHC4) inpatient discharge data for Philadelphia (region 9), 2008 to 2013.

2.5.5. Discharge Status

The next few sections examine the effect of regionalization on short term outcomes, common to stroke and STEMI. Specifically we look at the probability of in-hospital mortality, probability of discharge to home, average length of stay, and total charges.

Figure 18: Relationship between Regionalization and in-Hospital Mortality, Event-Study



(a) Stroke (b) STEMI

STEMI = ST elevation myocardial infarction.
Pennsylvania Health Care Cost Containment Council (PHC4) inpatient discharge data for Philadelphia (region 9), 2008 to 2013

Figure 18 plots the coefficients from the event-study estimation for the probability of in-hospital mortality for stroke (left) and STEMI (right), while Table 26 presents the results of the difference in differences estimates. We find no evidence that implementation

Table 26: Relationship between Regionalization and in-Hospital Mortality

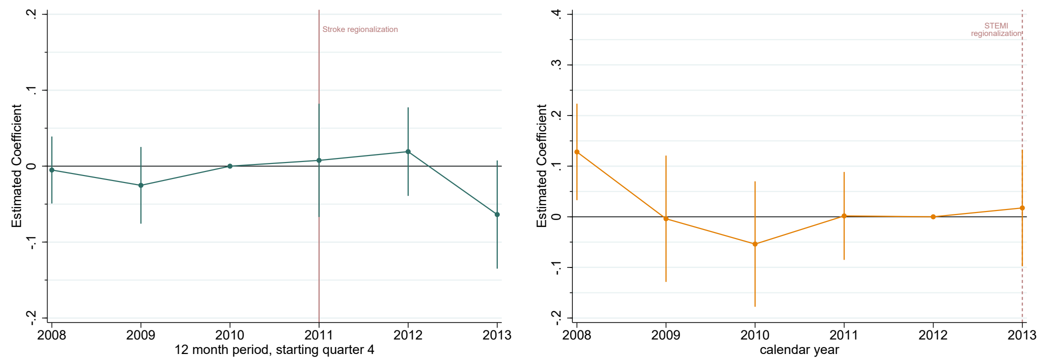
	(1)	(2)	(3)	(4)	(5)	(6)
$d_z^{stroke} \times post_t^{stroke}$	0.002	0.001	0.002			
	(0.012)	(0.012)	(0.012)			
$d_z^{STEMI} \times post_t^{STEMI}$				-0.020	-0.030	-0.028
				(0.045)	(0.040)	(0.037)
Observations	15053	15053	15053	1620	1620	1620
Zip code FE	No	Yes	Yes	No	Yes	Yes
Year FE	No	Yes	Yes	No	Yes	Yes
Admission-level covariates	No	No	Yes	No	No	Yes
Condition	Stroke	Stroke	Stroke	STEMI	STEMI	STEMI

*** p<0.01, ** p<0.05, and * p<0.10.
STEMI = ST elevation myocardial infarction. Robust standard errors clustered at the patient zip code level are reported in parentheses.
Source: Pennsylvania Health Care Cost Containment Council (PHC4) inpatient discharge data for Philadelphia (region 9), 2008 to 2013

of either regional systems of care impacted in-hospital mortality.

Figure 19 plots the coefficients of our event-study estimation for the probability of discharge to home for patient surviving the hospitalization. For both stroke (left panel) and STEMI (right panel), regionalization had no effect on the probability of discharge to home. Table 27 reports the difference in differences estimates which similarly find no effect of regionalization on the probability of discharge to home for stroke and STEMI. Table 28 shows the results of an alternative set of specifications used to estimate the effect of regionalization on discharge status for stroke. Here we estimate a multinomial logit model using discharge to home as the baseline category. Again, we find no evidence that stroke regionalization affected discharge status.

Figure 19: Relationship between Regionalization and Discharge to Home, Event-Study



(a) Stroke (b) STEMI

STEMI = ST elevation myocardial infarction.
Pennsylvania Health Care Cost Containment Council (PHC4) inpatient discharge data for Philadelphia (region 9), 2008 to 2013

Table 27: Relationship between Regionalization and Discharge to Home

	(1)	(2)	(3)	(4)	(5)	(6)
$d_z^{stroke} \times post_t^{stroke}$	-0.012	-0.012	-0.021			
	(0.019)	(0.018)	(0.017)			
$d_z^{STEMI} \times post_t^{STEMI}$				-0.005	0.002	0.001
				(0.052)	(0.057)	(0.052)
Observations	14228	14228	14228	1483	1483	1483
Zip code FE	No	Yes	Yes	No	Yes	Yes
Year FE	No	Yes	Yes	No	Yes	Yes
Admission-level covariates	No	No	Yes	No	No	Yes
Condition	Stroke	Stroke	Stroke	STEMI	STEMI	STEMI

*** p<0.01, ** p<0.05, and * p<0.10.
STEMI = ST elevation myocardial infarction. Robust standard errors clustered at the patient zip code level are reported in parentheses.
Source: Pennsylvania Health Care Cost Containment Council (PHC4) inpatient discharge data for Philadelphia (region 9), 2008 to 2013

Table 28: Relationship between Regionalization and Discharge Status

	(1)	(2)	(3)	(4)
Skillednursing				
$dz^{stroke} \times postt^{stroke}$	0.099	0.088	0.143	
	(0.105)	(0.098)	(0.121)	
$dz^{STEMI} \times postt^{STEMI}$				0.134
				(0.410)
Inpatientrehab				
$dz^{stroke} \times postt^{stroke}$	0.016	0.015	0.031	
	(0.112)	(0.115)	(0.110)	
$dz^{STEMI} \times postt^{STEMI}$				-0.628
				(0.748)
Expired				
$dz^{stroke} \times postt^{stroke}$	0.052	0.031	0.079	
	(0.200)	(0.201)	(0.207)	
$dz^{STEMI} \times postt^{STEMI}$				-0.453
				(0.853)
Observations	15053	15053	15053	1620
Zip code FE	No	Yes	Yes	No
Year FE	No	Yes	Yes	No
Admission-level covariates	No	No	Yes	No
Condition	Stroke	Stroke	Stroke	STEMI

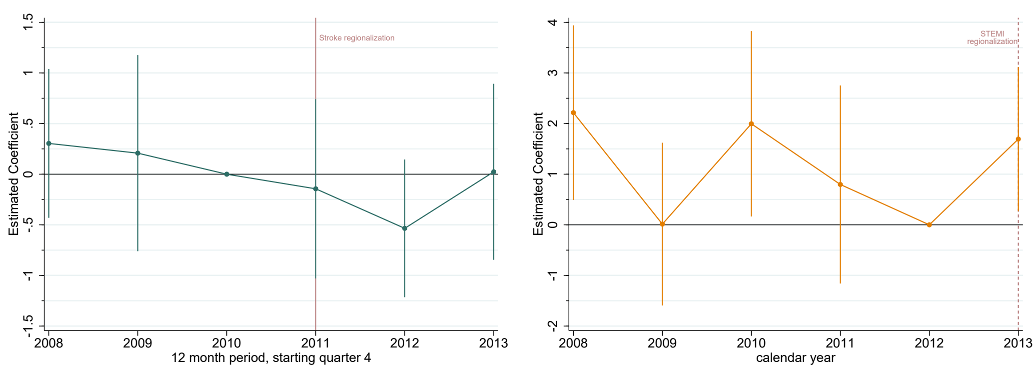
*** p<0.01, ** p<0.05, and * p<0.10.
STEMI = ST elevation myocardial infarction.
Robust standard errors clustered at the patient zip code level are reported in parentheses.
Source: Pennsylvania Health Care Cost Containment Council (PHC4) inpatient discharge data for Philadelphia (region 9), 2008 to 2013.

2.5.6. *Length of Stay*

Figure 20 presents the estimates of our event-study specification for length of stay. Though the stroke coefficient estimates in the pre-period are not statistically significant from zero at the 5% level, taken together they suggest the existence of differences in pre-intervention trends leading up to regionalization—length of stay for stroke patients from treated zip codes was decreasing at a faster rate than length of stay for stroke patients from untreated zip codes. The difference in difference results presented in Table 29 that suggest stroke regionalization is associated with a decrease in length of stay should not be taken as causal estimates of the policy, as they likely reflect an continuation of the pre-intervention trends. Future work should adjust equation 2.2 to allow for treatment group specific pre-intervention trends.

The right panel of Figure 20 plots the estimated event-study coefficients for length of stay for STEMI hospitalizations, suggests that regionalization has no effect on length of stay of STEMI. This null effect is also shown in our difference in differences estimates reported in Table 29.

Figure 20: Relationship between Regionalization and Length of Stay, Event-Study



(a) Stroke (b) STEMI

STEMI = ST elevation myocardial infarction.
Pennsylvania Health Care Cost Containment Council (PHC4) inpatient discharge data for Philadelphia (region 9), 2008 to 2013

Table 29: Relationship between Regionalization and Length of Stay

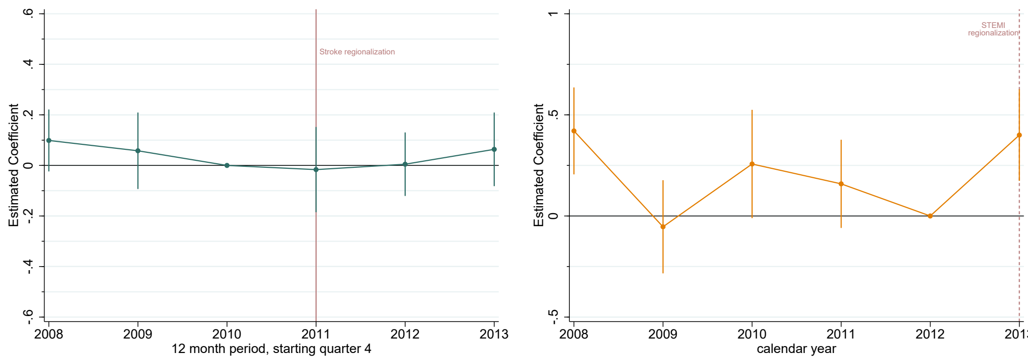
	(1)	(2)	(3)	(4)	(5)	(6)
$d_z^{stroke} \times post_t^{stroke}$	-0.262	-0.350*	-0.355*			
	(0.187)	(0.195)	(0.196)			
$d_z^{STEMI} \times post_t^{STEMI}$				0.865	0.840	0.790
				(0.624)	(0.684)	(0.647)
Observations	15053	15053	15053	1620	1620	1620
Zip code FE	No	Yes	Yes	No	Yes	Yes
Year FE	No	Yes	Yes	No	Yes	Yes
Admission-level covariates	No	No	Yes	No	No	Yes
Condition	Stroke	Stroke	Stroke	STEMI	STEMI	STEMI

*** p<0.01, ** p<0.05, and * p<0.10.
STEMI = ST elevation myocardial infarction. Robust standard errors clustered at the patient zip code level are reported in parentheses.
Source: Pennsylvania Health Care Cost Containment Council (PHC4) inpatient discharge data for Philadelphia (region 9), 2008 to 2013

2.5.7. Charges

Our examination of the effect of regionalization on total charges finds no evidence that the system change affected charges for stroke hospital events, as shown by the coefficients plotted in the left panel of Figure 21 and the first three columns of Table 30. The right panel of Figure 21 reports a significant positive effect of STEMI regionalization on total charges. STEMI regionalization increased total charges in 2013 relative to 2012. Columns (4) through (6) of Table 30 report the difference in difference estimates for logged-total charges in STEMI. Our preferred specification includes zip code and year fixed effects and admission-level coviariates age, sex, race, and payer, the results of which are presented in column (6). STEMI regionalization increased total charges by 29.6% ($100 \times exp(0.259) - 1$)) in the first year (2013). This result makes sense if regionalization moves patients from low charge to higher charge hospitals, even if utilization of acute care services remains the same.

Figure 21: Relationship between Regionalization and ln(Total Charges), Event-Study



(a) Stroke (b) STEMI

STEMI = ST elevation myocardial infarction.
Pennsylvania Health Care Cost Containment Council (PHC4) inpatient discharge data for Philadelphia (region 9), 2008 to 2013

Table 30: Relationship between Regionalization and ln(Total Charges)

	(1)	(2)	(3)	(4)	(5)	(6)
$d_z^{stroke} \times post_t^{stroke}$	0.007	0.003	-0.005			
	(0.038)	(0.038)	(0.039)			
$d_z^{STEMI} \times post_t^{STEMI}$				0.260***	0.253***	0.259***
				(0.085)	(0.089)	(0.090)
Observations	15053	15053	15053	1620	1620	1620
Zip code FE	No	Yes	Yes	No	Yes	Yes
Year FE	No	Yes	Yes	No	Yes	Yes
Admission-level covariates	No	No	Yes	No	No	Yes
Condition	Stroke	Stroke	Stroke	STEMI	STEMI	STEMI

*** p<0.01, ** p<0.05, and * p<0.10.
STEMI = ST elevation myocardial infarction. Robust standard errors clustered at the patient zip code level are reported in parentheses.
Source: Pennsylvania Health Care Cost Containment Council (PHC4) inpatient discharge data for Philadelphia (region 9), 2008 to 2013

2.6. Conclusion and Future Work

Our results to date suggest that Philadelphia's acute stroke and STEMI regional systems of care are associated with improved matching of patients to facilities best equipped to treat stroke/STEMI. Specifically, we find that regionalization decreases the probability of admission to a non-PCI capable hospital by 6.4 percentage points, representing anear complete elimination of STEMI admissions to non PCI-capable facilities. In the case of stroke, while we find that regionalization decreases the probability of admission to a non-PSC by 5.0 percentage points, in the last quarter of our sample nearly 18% of stroke patients are admitted to non-PSCs. Future work will look specifically at the effect of regionalization for stroke patients who remain treated at non-PSCs.

We find evidence that the probability of receiving inpatient head CT was increasing faster in treated zip codes than in untreated zip codes prior to regionalization; and that length of stay in was decreasing faster for stroke hospital events from treated zip codes than for events from untreated zip codes prior to regionalization. Future work should address this by adjusting equation 2.2 to allow for differences in pre-intervention trends. We find a statistically significant increase in the probability of inpatient brain MRI. Our stroke-specific results suggest that stroke regionalization is not associated with any change in inpatient receipt of thrombolytic therapy, or surgical interventions for stroke. We find no evidence that stroke regionalization affected hospital discharge status. Though we find no effect of STEMI regionalization on hospital length of stay or discharge status, we estimate that STEMI regionalization is associated with a marginally significant increase in the probability of PTCA and an economically and statistically significant increase in total charges by 29.6%. Taken together, these results suggest that while regionalization may reduce time to receipt of services (something we cannot measure with our data), it has little effect of the eventual receipt of services.

What do our results imply for the future of regional systems of care? First, regionalization is effective in channeling volume to designated facilities. Second, the effects of regionalization may be condition and market specific. Even when considering two similar time-critical illnesses in a single market, we found only one system to have short term effects beyond the initial impact on admissions volume. While this paper does not investigate reasons why the STEMI regional system was more effective than the stroke regional system, we have a number of ideas. First, hospitals face significantly higher barriers to entering the STEMI regional system of care. In order to receive STEMI patients, hospitals must not only have a catheterization lab, they must be capable of performing bypass surgery or have an exception from the state of Pennsylvania. In contrast, the barriers to entering the stroke regional system of care are relatively low as shown by the four hospitals that enter the stroke care system after regionalization (Table 10). Second, stroke is difficult to diagnose in the pre-hospital setting, as definitive diagnosis requires imaging. In contrast, STEMI can be diagnosed in the pre hospital setting with ECG, common to both physician offices and ALS EMS providers.

APPENDIX

A.1. Hospital revenue target deviation from mean historic revenue

I compare mean historic hospital revenue to target hospital revenue for hospitals participating in the GBR. Hospital gross patient revenue is sourced from the Health Service Cost Review Commission (HSCRC) annual hospital disclosure reports, fiscal years 2008 to 2013.[1] Hospital base period approved revenue under the GBR is outlined in each hospital's GBR agreement with the HSCRC. All agreements were signed after December 2013. Academic Medical Centers Johns Hopkins Hospital, Johns Hopkins Bayview Medical Center, Suburban Hospital (Johns Hopkins), and University of Maryland Medical Center initially agreed to a payment system change that excluded revenue from out-of-state patients. The University of Maryland Medical Center included out-of-state patient revenue starting fiscal year 2015; Johns Hopkins facilities included out-of-state patient revenue starting fiscal year 2017. I add the HSCRC's estimate of out-of-state revenue to approved GBR revenue to calculate $target_h$ for these facilities, as historic revenues do not separately identify revenue from nonresidents.[2]

While $target_h$ is taken directly from GBR agreements, mean historic gross patient revenue is calculated as follows using gross patient revenue from annual hospital disclosure reports:

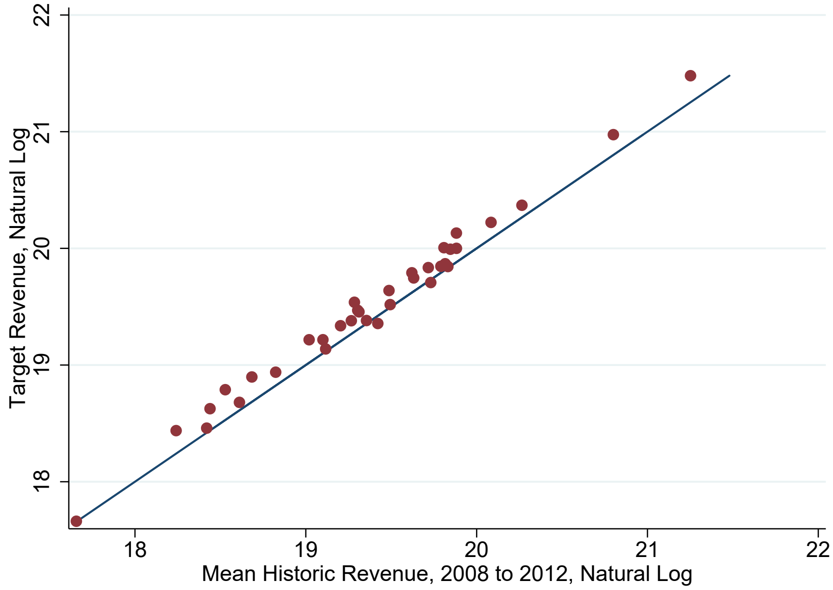
$$\overline{rev}_h = \frac{\sum_{t=2008}^{2012} rev_{ht}}{n_h}$$

I plot the natural log of target revenue against the natural log of mean historic revenue in Figure 22. There is little to no variation in deviation of target revenue from mean historic revenue, as shown by distance from the 45-degree line in Figure 22, to exploit.

[1] The majority of hospitals have fiscal years ending June 30th. Bon Secours Hospital uses a fiscal year ending August 31. Fort Washington Medical Center, Shady Grove Adventist Hospital, UM Harford Memorial Hospital, UM Upper Chesapeake, and Washington Adventists Hospital have fiscal years ending December 31.

[2] These AMCs, and specifically Johns Hopkins, argued that its tertiary care was designed to attract nonresidents; therefore, limiting revenues for these patients would make offering these services less attractive (Haber et al., 2016).

Figure 22: Maryland Hospital Target Revenue vs. Mean Historic Revenue



Source: Health Service Cost Review Commission (HSCRC) annual hospital disclosure reports, fiscal years 2008 to 2013, and HSCRC Global Budget Revenue agreements.

A.2. NSTEMI characteristics

Table 31: Admission Characteristics by Geography (differential distance PCI >0), Pre STEMI Regionalization Policy, January 2008 - December 2012

	Treated Zip	Untreated Zip
Admission Characteristics		
Age, in years	66.75 (14.02)	67.80 (14.42)
Sex (%)		
Female	46.80	47.31
Male	53.20	52.69
Race (%)		
White	31.03	47.95
Black	58.50	34.55
Asian	1.35	1.57
Other race	9.11	15.94
Hispanic/Latino origin/descent (%)	1.85	8.71
Payer (%)		
Uninsured	2.46	1.29
Medicare	56.40	60.85
Medicaid	18.23	18.33
Blue Cross	13.18	11.79
Commercial	5.91	6.22
Government	2.96	1.43
Comorbidities (%)		
Myocardial infarction	100.00	100.00
Congestive heart failure	38.05	40.30
Peripheral vascular disease	5.30	7.37
Cerebrovascular disease	5.30	5.76
Dementia	2.09	1.34
Chronic pulmonary disease	21.18	21.05
Rheumatic disease	1.23	1.20
Peptic ulcer disease	0.49	0.60
Mild liver disease	2.09	2.03
Diabetes without complications	31.53	30.77
Diabetes with complications	3.45	4.01
Hemiplegia or paraplegia	0.25	0.64
Renal disease	18.23	20.77
Malignancy, except skin	3.20	3.27
Moderate or severe liver disease	0.37	0.37
Metastatic solid tumor	0.74	0.92
AIDS/HIV	0.25	0.46
Exposure (%)		
Zip exposure group d.distance PCI	100.00	0.00
Differential distance PCI, in miles	1.53 (1.21)	0.00 (0.00)
N	812	2,171

PCI = percutaneous coronary intervention; STEMI = ST-elevation myocardial infarction.
All characteristics, except for comborbidities, are defined using the first observed stay for a hospitalization, unless the characeristic is missing. Comorbidities are defined using the primary diagnoses from each observed stay of the hospitalization and secondary diagnoses in order of observed stay, up to nine diagnoses.
Source: Pennsylvania Health Care Cost Containment Council (PHC4) inpatient discharge data for Philadelphia (region 9), 2008 through December 2012.

Table 32: Unadjusted Outcomes of Interest by Geography (differential distance PCI >0), Pre and Post STEMI Regionalization Policy

	Treated Zip		Untreated Zip	
Outcomes of Interest	*Pre*	*Post*	*Pre*	*Post*
Non PCI capable hospital (%)	25.25	17.39	2.44	0.65
Any inpatient hospital transfer (%)	17.98	26.09	9.44	7.01
Interventions (%)				
PTCA	38.55	37.68	37.77	38.50
Coronary bypass	7.88	7.25	8.15	10.44
Discharged to home	70.32	73.91	72.18	75.86
Length of stay	6.64 (18.81)	6.38 (8.48)	6.62 (7.26)	5.82 (7.34)
Total charges ($)	135,397 (169,274)	162,391 (311,393)	132,342 (178,329)	153,015 (222,631)
N	812	138	2,171	613

PCI = percutaneous coronary intervention; STEMI = ST-elevation myocardial infarction; PTCA = percutaneous transluminal coronary angioplasty; STAC = short term acute care.
All outcomes, except for arrival at non PCI capable hospital and discharge status, are defined used the sum of outcomes across all observed stays in the hospitalization. Arrival at non PCI capable hospital is defined using the first observed stay for a hospitalization. Discharge status is defined using the last observed stay for a hospitalization.
Source: Pennsylvania Health Care Cost Containment Council (PHC4) inpatient discharge data for Philadelphia (region 9), January 2008 through December 2013.

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