Essays in Industrial Organization and Health Economics

by

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Abstract

Healthcare expenditures in the United States have sharply increased during recent years. At the same time, the landscape of the healthcare industry has also changed significantly. This dissertation studies the interaction of the healthcare market structure and the prescription decisions of healthcare providers.

The first chapter studies whether merging hospitals eliminate duplicate services to save costs. Hospitals seeking mergers frequently claim substantial cost savings from consolidating their services to achieve economies of scale. Using the California Patient Discharge Data and Hospital Financial Report, we employ a difference-in-differences research design to empirically explore hospitals' post-merger service relocation. We find that targets and acquirers located within 10 miles of each other reduce on average 5.1 of their duplicate services. These adjacent merging hospitals also become more specialized in services, with the volume concentration measurement (Herfindahl-Hirschman Index) across services increasing by 10%. Compared to non-consolidated services, the consolidated services experience a roughly 20% reduction of per unit patient care costs. These effects are only evident when the merging hospitals are geographically close to one another.

The second chapter explores the effect of capitated payment models on physicians' treatment decisions. In response to the high cost of health care, capitated payment models have become more popular in recent years. Under capitation, physicians are paid a fixed amount per patient regardless of the services generated. This study quantifies the effects of capitated payment models on physicians' treatment decisions about patients with lower back pain in the United States. We use data from 2003 to 2006 from a large employer-sponsored health insurance claim database, and we leverage capitation variation within the plan and physician to mitigate selection concerns. We find that the treatment intensity—mainly from therapy, diagnostic testing, and drugs—of patients in a capitation system is 10% lower than otherwise similar patients under a noncapitated arrangement. We also find no evidence of increased readmission rates for patients under a capitated arrangement.

Chapter 1

Consolidations for Cost Savings? Hospital Mergers and Service Repositioning

with Chenyuan Liu

1.1 Introduction

Mergers and acquisitions have been strikingly frequent in the health care industry in recent years, with over 700 acquisition deals announced between 2011 and 2017 (Kaufman Hall, 2019). The standard antitrust concern is that such consolidations result in price increases due to reduced competition. The merging parties, however, argue that their proposed mergers would generate efficiency gains, and that the resulting cost reductions would be passed on to consumers. While many published studies have looked at the price effects of such mergers and found evidence of price increases (Dafny, 2009; Haas-Wilson and Garmon, 2009; Garmon, 2017; Lewis and Pflum, 2017; Cooper et al., 2018), there is limited systematic research about mergers' impact on cost savings.

A mechanism by which a merger of competing hospitals could generate cost savings is through the elimination of duplicate services. When confronted with antitrust challenges, hospitals seeking mergers frequently claim they can generate substantial efficiency gains through service consolidation.[1] Consolidation of duplicate services can benefit hospitals in several ways. First, eliminating duplicate services generates cost savings on hospitals' capital investment (like medical equipment expenses) and payroll expenditures. Second, consolidating duplicate services to a single facility helps hospitals achieve scale economies. Third, there is the potential for better coordination of care among physicians when hospitals remove services and become specialized. Despite these potential benefits, hospitals may have difficulty consolidating services due to organizational, regulatory, or financial constraints.[2] It is an open question whether merging hospitals actually remove duplicate services after mergers.

In this paper, we examine mergers in California between 2002-2014 and document how the merging hospitals reorganized their services. We investigate whether there exist post-merger consolidations of duplicate services and quantify the magnitude of service repositioning. We mainly use a difference-in-differences (DID) design to compare the service provision of merging hospitals before and after mergers. One may worry that the non-merging hospitals are not a proper control group for merging hospitals because of the endogenous selection of mergers. To avoid this concern, we exclude non-merging hospitals from our baseline analysis. We identify the effect of mergers by comparing the early merging hospitals and later merging hospitals. This strategy takes advantage of the variation in the timing of

[1]For instance, in the case where the Federal Trade Commission (FTC) challenged the horizontal merger between OSF Healthcare System and Rockford Health System, the hospitals stated that the proposed merger could generate "substantial efficiencies." The CEO of OSF asserted that they would achieve the saving by "consolidations of several services (such as trauma, women's and children's, and cardiovascular surgery)" and "combining patient volume [...] to meet or exceeds (the generally-accepted minimum patient volume) thresholds associated with improved outcomes" which both hospitals did not meet independently. Similarly, to defend the proposed merger between the Penn State Hershey Medical Center and PinnacleHealth System, the defendants argued that they "intend(ed) to move low acuity cases from Hershey to Pinnacle and high acuity cases from Pinnacle to Hershey" to achieve service consolidation.

[2]FTC pointed out, there "may exist possible physician resistance and regulatory approval difficulty, [...] numerous cultural, financial, regulatory and other practical issues", which may thwart a hospital's pursuit of service consolidation.

mergers and it relies on the assumption of parallel pre-trends across early merging hospitals and later merging hospitals. Our validity tests confirm the parallel pre-trend assumption holds.

We construct two types of measures for service repositioning: the number of services of hospitals and the concentration of patient volume across services. For both measures, we define services based on procedure codes from the California Patient Discharge Data. Specifically, we map the procedures performed to services based on the Clinical Classification Software's (CCS) Level 2 categorization of procedure codes.

For the first type of measure, we construct dummy variables indicating whether each service is offered in a hospital. Then we analyze the post-merger change in three outcome variables. The first outcome variable is the number of services offered by individual hospitals. We take the number of duplicate services offered at merging hospital pairs as the second outcome. Analysis with this variable helps to examine whether the services removed by hospitals are duplicates or not. The third outcome variable is the change in the total number of services of hospital pairs. We study this outcome to explore if the observed service reposition is driven by duplicate deletion at a single hospital, or is because of services removal at both members of a merging pair. Further, we compare the heterogeneous effects of geographically close and distant mergers. This analysis aims to study whether service consolidation is effective only for hospitals that are close to one another. The results show that a hospital removes approximately 4.6 services if merging facilities are within 10 miles of one another. But this effect is not evident when merging hospitals are more distant. For merging pairs within 10 miles, they on average remove 5.1 duplicate services. And the total number of services offered by these pairs does not have a significant change.

Second, we measure service offerings based on the concentration of patient volume across services. While it may be difficult or undesirable to shut down a service entirely, hospitals may steer the majority of patients to one location to achieve scale economies.[3] Analysis of service volume allows us to identify this

[3]Traditional work using aggregated hospital financial and output data finds mixed evidence

form of service repositioning, which is not captured in the investigation with the previous outcomes. We find that the volume Herfindahl-Hirschman Index (HHI) across the services at individual hospital level increases by 10-12% for merging hospitals within 10 miles of one another. We then aggregate the service volume of the merging pairs and build the HHI measure across services for each merging pair. We find that the pair HHI across services remains stable after mergers. These results suggests that the service composition remains stable for merging pairs. That is to say, the effect is due to individual hospitals' switching services within merging pairs. Besides, we find that service consolidation mostly occurs in cardiac procedures, obstetrics, and other female-related services.

Finally, we find evidence that the service consolidations of merging hospitals lead to cost reductions and no significant change in service quality change and patients' travel distance. We use the service-specific direct expense from the California Hospital Financial Report as our measure of cost and build per-unit cost measurement for services.[4] We compare the per-unit service cost of consolidated and non-consolidated services of merging hospital pairs. We also analyze the heterogeneous changes of service costs across merging pairs of different geographic distances. The results show that service consolidation brings a cost reduction of 20%, which is roughly $277 for cardiac catheterization, and $13 for echocardiology services. When it comes to the impacts on patients, we find the readmission rate of consolidated services remains stable. And the travel distance of patients increases by a minor and insignificant amount.

This paper contributes to the ongoing literature evaluating the cost savings of hospitals from mergers. Prior literature has found mixed evidence on whether

about the existence of scale economies in hospital production. For instance, Carey (1997), Preyra and Pink (2006), Kristensen et al. (2012), Gonçalves and Barros (2013) find evidence of scale economics in hospitals, while Dranove (1998) find limited evidence of scale economies. The literature on scope economies in hospital production is also inconclusive. More recent work by Gaynor et al. (2015) uses micro data to control output variation and finds substantial scale economies and scope diseconomies in some services.

[4]The direct expense of service mainly includes the payroll expenditure for the physicians, supplies, and capital costs like leases, rentals, and equipment depreciation. The non-service costs, like fiscal and administrative spending, are not included.

mergers lead to cost reduction. Some researchers find significant cost reductions post-merger (Harrison, 2011; Schmitt, 2017), while some others do not (Dranove and Lindrooth, 2003; Spang et al., 2009). This literature typically searches for evidence of cost reductions directly in the hospital financial data. By contrast, in this paper, we concentrate on a specific mechanism, service consolidation, whereby hospital mergers are purported to generate cost savings from scale economies. We find that service consolidation brings significant cost savings for the geographically close mergers. This paper also adds new insights to the emerging literature exploring the efficiency improvement mechanism of the merging hospitals. Craig et al. (2018) identified a specific mechanism that hospitals can decrease costs via leveraging their bargaining power to purchase medical supplies at lower prices. We identify another mechanism of service consolidation that is neglected in the present literature. Our results suggest that a critical question for policymakers is how to pass the cost reduction after mergers to consumers.

Our work also contributes to the literature on post-merger endogenous product choice of multi-product firms. Theoretical work by Gandhi et al. (2008) and Mazzeo et al. (2013) shows that a merging firm may choose to reposition its products to differentiate from its merging partners. This repositioning may mitigate the post-merger increase in product prices. Product choice by merging firms is also empirically investigated in music radio (Sweeting, 2010, 2013; Berry et al., 2016), smartphones (Fan and Yang, 2016), the airline industry (Ciliberto et al., 2016), and the shampoo market (Mao, 2019). We contribute to this string of literature by documenting endogenous product choice in the healthcare industry.

The rest of the paper is organized as follows. Section 1.2 describes the data we use and provides information about the sample. In Section 1.3, we outline the empirical methodology and present the results with the service repositioning patterns of merging hospitals. Section 1.4 presents the implications for providers and patients, including the post-repositioning provider cost changes, service quality analysis, and impact on the patients' travel distance. In Section 1.5, we discuss and conclude.

1.2 Data & Background

We mainly use four data sources to study the service repositioning of post-merger hospitals: (1) Hospital Merger Activity Dataset (Cooper et al., 2018), (2) California Patient Discharge Dataset, (3) California Hospital Financial Report, and (4) American Hospital Association Annual Survey.

Hospital Merger Activity Dataset The Merger Activity Dataset built by Cooper et al. (2018) provides information about the horizontal hospital mergers. The dataset contains a panel of hospitals from the year 2000-2014. It includes the following variables: the system identifier of hospitals, the indicator for whether the hospital is a target/acquirer in every year, and the longitude and latitude of the hospitals. The geographic information and the system identifier together help us to recognize the geographically closest merging counterparts for every target/acquirer. We categorize the mergers based on the target/acquirer's distance to its closest merging counterparts.

California Patient Discharge Data All non-federal California-licensed hospitals are required to report every patient discharge record from their facilities, and we use these discharge data from 2002-2014 to determine which services each hospital offered. Each reported discharge includes detailed patient demographic information, the diagnoses and procedures related to the discharge in the form of ICD-9 code, and charge based on the listed price. We mainly exploit the diagnosis and procedures to build metrics of hospital services and service volumes, which is discussed in full detail in section 1.2.1.

California Hospital Financial Disclosure Reports All California-licensed general acute hospitals are required to file detailed annual financial disclosure reports. The report is audited and provides information about various aspects of hospital operations, including capacity, medical staff, utilization, ownership type, balance sheets, income statements, revenue, and expenses. For the medical staff, beds, utilization, and expenses, the reports provide detailed information by service categories. We mainly use the comprehensive cost information from the financial dataset to evaluate the cost change related to service consolidation by comparing the per-unit cost of consolidated and non-consolidated services. The per-unit service cost is defined as the adjusted direct expenses of each service category over the total units performed by the hospitals for that service.

American Hospital Association Annual Survey (AHA) To test whether the repositioning differs across the targets and acquirers, we expand the study to a national sample of hospitals. The sample size in the AHA data is significantly larger than California, thus enables us to study the targets and acquirers separately. We use the American Hospital Association (AHA) Annual Survey to study the services provided by the hospitals. The AHA dataset covers over 80% of all hospitals in the U.S. and contains general information like ownership type, the total number of beds, total discharges. Moreover, it contains the service provision indicators for a list of 120 services. We adopt these service indicators to determine the service offered by the hospitals and test if merging hospitals remove duplicates. However, unlike the discharge data, the AHA dataset does not cover service volume information. It thus does not allow us to investigate whether service repositioning occurs in any form subtler than complete service removal.

1.2.1 Service Definition using Patient Discharge Data

The primary dataset we use to build the service spectrum of hospitals is the California Patient Discharge Data. For the baseline analysis, we define the services based on the procedures hospitals performed. In the California Discharge Data, each discharge records includes the detailed ICD-9 procedure codes. There are 3,948 distinct ICD-9 procedure codes, and we use the Clinical Classifications Software (CCS) for ICD-9-CM to categorize procedure codes and map them into more broadly defined services. The CCS is a diagnosis and procedure categorization scheme that is developed as part of the Healthcare Cost and Utilization Project

(HCUP). CCS collapses the ICD codes into a smaller number of clinically meaningful categories, and we define the services at Level 2 of the multiple level procedure categories. The Level 2 of procedure categories classifies procedure codes into 207 distinct categories. We map all the procedures hospitals performed to these 207 services and analyze changes in hospitals' provision of these services. Additionally, CCS also classifies the diagnosis codes, which serve as an alternative definition of service. We also use CCS to map diagnosis codes from discharges to services and run robustness checks in Section 1.3.4.1.

1.2.2 Merger Activity & Sample

Merger Activity The Hospital Merger Activity Dataset provides us the information about merger activities, and we categorize these mergers based on distances between merging entities. For two systems of hospitals involving in a merger, System S_1 and System S_2, let L and K stand for the number of hospitals belonging of each system, where $L \geq 1$ and $K \geq 1$. We denote these two systems as $S_1 = \{H_1^1, H_2^1, .., H_L^1\}$ and $S_2 = \{H_1^2, H_2^2, .., H_K^2\}$, where H_i^s stands for a hospital i belonging to System $s \in \{1, 2\}$, with $i \leq L$ for S_1 and $i \leq K$ for S_2. For a hospital H_l^1 belonging to S_1, we call $H_1^2, H_2^2, .., H_K^2$ its merging counterparts because they are from the other system involving in the merger transaction. This merging hospital H_l^1 is said to have a merging counterparts within 10 miles if there exists a hospital H_k^2 from S_2 whose geographic distance with H_1^1 is no larger than 10 miles. This hospital pair (H_l^1, H_k^1) is called a within-10-mile merging pair. We define a merger transaction to be within 10 miles as long as there exists a hospital pair (H_l^1, H_k^2) whose distance is no larger than 10 miles.

Figure 1.1 summarizes hospital horizontal merger transactions in the U.S. from the year 2001 to 2014. The grey dashed line stands for all transactions, the orange solid line is the number of mergers whose closest merging entities are no further than 100 miles geographically, and the blue dotted line is for the transactions with merging hospitals no further than 10 miles. The figure shows that horizontal mergers of hospitals frequently involve merging hospitals that are geographically close to one another. A similar situation also exists in California. Figure 1.2 exhibits the scatter of merging hospitals in California in the sample we built (described in the next paragraph. The yellow points indicate merging hospitals with counterparts within 10 miles, blue is for hospitals with merging counterparts between 10-100 miles, and purple stands for the merging hospitals further away. There exists a nontrivial proportion of geographically close mergers.

Sample Construction For our primary analysis, we use a similar sample as Gaynor et al. (2015) with the California data. We concentrate on the general hospitals and exclude children's hospitals, hospitals specializing in psychiatric, chemical dependency, or long-term care. After all data trimming, our sample includes 355 California hospitals. Based on the previous service definition, the summary statistics of the California hospitals in the beginning year of the sample period (year 2002) is presented in Table 1.1.[5] The first to the third columns show the summary statistics of merging hospitals based on their distance to the closest merging counterparts, and the fourth column presents the statistics of the non-merging hospitals. In the first three columns, the merging hospital characteristics are similar across distance groups. However, the non-merging hospitals are different from the merging entities in some characteristics. The merging hospitals offer more services than the non-merging hospitals and are not as concentrated in service offerings as the non-merging hospitals. Meanwhile, the merging hospitals are operated at lower total patient care costs compared to the non-merging hospitals. Moreover, the merging hospitals treat more complicated patients because they are of a higher case-mix index.[6]

Figure 1.3 depicts the change in the number of services over time for merging

[5]Hospital HHI across services in Table 1.1 is defined in Section 1.3.3.1.

[6]The Case-Mix Index (CMI) is the average relative DRG weight of a hospital's inpatient discharges, calculated by summing the Medicare Severity-Diagnosis Related Group (MS-DRG) weight for each discharge and dividing the total by the number of discharges. The CMI reflects the diversity, clinical complexity, and resource needs of all the patients in the hospital. A higher CMI indicates a more complex and resource-intensive case load. Although the MS-DRG weights, provided by the Centers for Medicare & Medicaid Services (CMS), were designed for the Medicare population, they are applied here to all discharges regardless of payer.

hospitals from different distance group and non-merging hospitals. We find that non-merging hospitals offer similar number of services over time, but the merging hospitals offer a decreasing number of services across time. The graph also shows that the merged hospitals within 10 miles experience larger reduction in the number of services compared to the farther mergers. This suggests that there may be some systematic change in service offering after mergers. We formalize the idea in the next section using a difference-in-difference design.

1.3 Empirical Analysis on Service Repositioning Pattern

1.3.1 Effects of Service Consolidation

An illustrative example of service consolidation is presented in Figure 1.4. We use two hospitals in the previously mentioned antitrust case (mentioned in Section 1 Footnote 1), OSF Medical Center and Memorial Rockford hospitals, as an example. These hospitals claimed they would consolidate their cardiovascular surgery and trauma services if the FTC cleared their proposed merger, and we use these two services in our illustration. The left blue box indicates the hospitals' pre-merger service volumes, and the right yellow box stands for post-merger. One possible way in which these two hospitals might consolidate their cardiovascular surgery and trauma services is by eliminating trauma at OSF Anthony Medical Center, eliminating cardiovascular surgery at Memorial Rockford, and steering eliminated service's patient volume to the other hospital. In this scenario, both the cardiovascular surgery and trauma services are consolidated and only provided by a single facility.

Consolidation like that described in the example above has two effects, one on the total number of services offered by each hospital, and the other on the number of duplicate services:

- Effect 1 (Individual Facility Concentration): At the facility level, a merging hospital pursuing service consolidation decreases its number of services offered.

- Effect 2 (Within System Differentiation): The service consolidation leads to a decrease in the number of duplicate services across the merging hospitals.

Effect 1 stems from the phenomenon that each hospital participating in the service consolidation shifts some of its services to the other merging hospital. This repositioning leads to a decrease in the number of services the hospital offers. Figure 1.5 highlights this effect for the example given in Figure 1.4, showing that after the merger, the number of services offered by each hospital decreases from two to one. In other words, Effect 1 reflects the fact that hospitals pursuing service consolidation become specialized and concentrated because they provide fewer services than before.

Meanwhile, if we choose to summarize the offering list at the service level, the service consolidation shifts the services previously spread between two facilities into a single location. Effect 2 captures this idea. The illustration example is shown in Figure 1.6, which summarizes the hospitals' service information horizontally by services. In this example, cardiovascular surgery and the trauma service are provided by both hospitals pre-merger but are available at only one facility post-merger. The merging pair therefore become more differentiated in terms of the services each provides.

These two effects depict two dimensions of service consolidation. If merging hospitals remove services but mainly remove their unique services, Effect 1 still holds but Effect 2 does not exist. On the other hand, if merging hospitals replace their duplicate services with new services that the other side of merging hospitals do not provide, then we would only observe Effect 2 but not Effect 1. In our assessment of service consolidation, we will examine both of these effects by looking at both changes in the number of services provided by each facility as well as the number of duplicate services available across facilities.

However, because the services we defined are based on aggregated procedure categories, analyses using the number of services neglect the service changes happening at the subcategory level. Moreover, while it may be organizationally difficult to remove or relocate a service entirely, hospitals may try to consolidate services in more subtle ways by redirecting patient flows in a way that concentrates volume at one facility. An example of such reshuffling is illustrated in Figure 1.7, which alters the previous example to depict service consolidation through patient volume reallocation rather than service removal. Here, OSF Anthony Medical Center keeps some cardiovascular surgery services (e.g. maze surgery), but moves the majority to Rockford Memorial Hospital. Both of the hospitals still keep cardiovascular surgery, but the volume is highly concentrated in one facility. This type of service consolidation can be described by two effects:

- Effect 1.b. (Individual Facility Concentration of Service Volume): At the facility level, a merging hospital pursuing service consolidation by reallocating patient volume experiences an increase in the concentration of volumes across services.
- Effect 2.b.(Within System Differentiation of Service Volume): For a given service, service relocation concentrates patient volumes in a single facility, increasing the volume HHI across hospitals for that consolidated service.

Effect 1.b. & 2.b. follow the same intuition as the Effect 1 & 2, but change the measurement of consolidation from the number of services to the volume of services performed. There are mainly two benefits to these analyses with the service volume. First, volume catches the change in services present in the absence of complete removal of duplicates. Second, the study with volume evaluates the magnitude of service repositioning from the utilization perspective. If the consolidated services are mainly low-volume services, they will not significantly impact the service volume concentration across services. Therefore, the service volume analysis supplements the number of services results by quantifying the impact on utilization.

However, even if we observe the hospitals dropping duplicate services, it may be that the newly merging system is shifting its service spectrum for the whole system and remove some service in every facility. This strategy leads to removal of services from both members of a merging pair, while the service consolidation results in removal in only one hospital but keeping that service in the other. To tell which mechanism drives the change of the hospital services, we analyze the number of services and service concentration of the hospital pairs.

Finally, we also study the heterogeneous effect of mergers across different geographic distance.[7] Service consolidation is feasible only if the merging hospitals are geographically close. If two hospital facilities are distant from each other, it is not realistic to combine the service volume of a given service into a single location as patients are sensitive to travel distance.[8] Thus, we decompose the effects of service consolidation by mergers of different distance groups to seek the effective distance of service consolidation.

In the following section, we detail the specifications used to examine the above effects and present results.

1.3.2 Number of Services

1.3.2.1 Effect 1

To start with, we use the following staggering difference-in-differences model to quantify Effect 1:

$$n_{it} = \alpha_i + \gamma_t + \lambda \cdot \mathbb{1}[i \in \mathcal{M}, t \geq \tau_i] + \epsilon_{it}. \tag{1.1}$$

In Equation 1.1, n_{it} denotes the number of services provided by hospital i in year t. α_i denotes hospital fixed effects. γ_t is the year fixed effect included to absorb any time trend. $\mathbb{1}[i \in \mathcal{M}, t \geq \tau_i]$ is a binary variable indicating whether hospital i is in the treatment group of merging hospitals $\mathcal{M}$ and year t is in or later than the

[7]A theoretical model to illustate the distance is important to service removal decision is in Appendix Section

[8]For instance, Gowrisankaran et al. (2015) find that a five minute increase in travel time to a hospital reduces demand between 17 and 41 percent.

treatment year τ_i. λ represents the treatment effect and it shows how the number of services changes relative to the control group.

For the baseline analysis, we only include the targets/acquirers whose closest merging counterparts are within 100 miles, and exclude all non-merging hospitals.[9] This avoids potentially biased comparison of merging and non-merging hospitals since there is likely selection into merger activity in this market. Furthermore, because service consolidation is sensitive to the distance between the merging hospitals, we decompose the mergers within 100 miles into two distance groups, a close merging group whose closest merging counterparts are located no further than 10 miles apart, and another group of hospitals involved in mergers of distances between 10-100 miles, as in Equation 1.2, where λ_g is the post-merger effect of the hospital i belongs to the distance group $\mathcal{G}_g \in \{\mathcal{G}_1, \mathcal{G}_2\}$. $\mathcal{G}_1$ stands for the hospitals with merging counterparts 0-10 miles away, and $\mathcal{G}_2$ is for those with merging counterparts 10-100 miles away.

$$n_{it} = \alpha_i + \gamma_t + \sum_g \lambda_g \cdot \mathbb{1}[t \geq \tau_i] \times \mathbb{1}[i \in \mathcal{G}_g] + \epsilon_{it}. \tag{1.2}$$

Additionally, to fully understand the evolution of service repositioning after mergers, we also conduct an event study to decompose the effect of mergers on consolidation over time as

$$n_{it} = \alpha_i + \gamma_t + \sum_{k=-5}^{3} \lambda_{k1} \cdot \mathbb{1}[t = \tau_i + k] \times \mathbb{1}[i \in \mathcal{G}_1] + \sum_{k=-5}^{3} \lambda_{k2} \cdot \mathbb{1}[t = \tau_i + k] \times \mathbb{1}[i \in \mathcal{G}_2] + \epsilon_{it}. \tag{1.3}$$

We group observations that are five or more years prior to the treatment year into $k = -5$, and $k = 3$ indicates three or more years after the merger. λ_{kg} presents the effect on service repositioning of being k years post merger for group $\mathcal{G}_g$.

[9]For the baseline regressions, we do not include mergers further than 100 miles, for the worry that the geographically closed mergers may be different from the distant out-of-market mergers. For instance, a merging hospital which has a merging partner within 10 miles may not be comparable to another hospital whose closest merging counterparts are 300 miles away.

1.3.2.2 Effect 2

We analyze the number of duplicate services of hospitals pairs to measure Effect 2. The number of duplicate services are built by pairing every two hospitals in the sample and counting the number of shared services of the hospital pairs. Specifically, we estimate the following equation

$$d_{pt} = \alpha_p + \gamma_t + \sum_g \lambda_g \cdot \mathbb{1}[p \in \mathcal{M}_g, t \geq \tau_p] + \epsilon_{pt}, \tag{1.4}$$

where p is for hospital-pair identifier, d_{pt} indicates the number of duplicate services for the hospital pair p at time t. $\mathcal{M}_g$ indicates the merging pair falls into different distance group g, where $\mathcal{G}_g \in \{$0-10 miles, 10-100 miles$\}$. τ_p stands for the merger time of hospital pair p, and $\mathbb{1}[p \in \mathcal{T}, t \geq \tau_p]$ indicates the post-merger status of hospital pair p. λ_g is the post-merger change of the duplicate services of hospital pairs belongs to group g. This heterogeneous effect parameter allows us to evaluate how the post-merger duplication change varying with the distance. Besides this specification, we also replace the dependent variable in Equation (1.4) to the total number of services of the hospital pairs. This specification helps to illuminate the motivation for the service decrease identified in the above specifications. In other words, by study the total number of services of hospital pairs, we can distinguish if the services are dropped for consolidation at one facility and kept at the adjacent facilities, or if the services are entirely removed at both hospitals.

Identification In our baseline models, we exclude non-merged hospitals in our sample. Merging decision is likely endogenous and confounded by many other factors related to repositioning decisions. This fact can also demonstrated by summary statistics in Table 1.1. As such, the non-merging hospitals may not be comparable to the merged hospitals. Instead, we only include merged hospitals. The identification of our specification comes from the variation in the timing of mergers: the later merged hospitals serve as the controls for the earlier merged hospitals, and the time trend is jointly determined by all the merged hospitals. Our model assumes a parallel pre-trend across early merged hospitals and later merged hospitals. The selection of merging time may undermine this assumption. However, due to the complexity of merger activity and involvement of antitrust authorities, hospitals do not necessarily have full control of the merger time, which mitigates the concern about selection on merger time. In Appendix A.2, we provide evidence on the internal validity of method by showing that there is no correlation between the merging time and the change in service offering pre-order.

1.3.2.3 Empirical Results

Number of Services of Individual Hospitals Table 1.2 presents the results with the post-merger effect on the number of services defined from the procedures. The regression sample is the merging hospitals that have merging counterparts within 100 miles. Columns (1) and (2) use the individual hospitals' number of services as the dependent variable. The result in Column (1) shows that for all the merging hospitals which have within-100-mile counterparts, the average number of services has a slight drop of around 1.2 services post merger. This effect is mainly driven by the service change of the close-merging hospitals (merger counterparts within 10 miles), as shown in Column (2). Merging hospitals with counterparts within 10 miles experience a drop of approximately 4.5 services among all the services they offered. In Column (3), we add the interaction term between post merger status and the distance between the merging entities and their closest counterparts. It is shown that, if the distance between the merging hospitals increases, these hospitals are less likely to drop services. The heterogeneous effect results with more narrow distance groups are shown in Table A.4 in Appendix.

The results of the event study looking at the effect of close and far mergers on the number of services provided per facility are given in the left- and right-hand panels of Figure 1.8 respectively. The parallel trend assumption holds for the analysis with the total number of services, and there is a lasting post-merger service decrease for merging hospitals in 0-10 miles, while the further merging hospitals do not see such an effect.

Number of Services of Hospital Pairs The analysis with the merging hospital pairs within 100 miles is presented in Table 1.3. For all the merging hospital pairs within 100 miles, the nearby merging hospitals remove averagely 5.1 duplicate services. Furthermore, this decrease in the number of services is mainly due to the service consolidation but not the elimination of the services by the system, because the total number of services by the merging hospital pairs within 10 miles does not have a significant reduction as exhibited in Column (2). The event study of the number of duplicate services of hospital pairs within 10 miles is presented in Figure 1.9. The effect of number of duplicate services begins in the merger year, and this effect keeps several years after mergers.

1.3.3 Service Volume

1.3.3.1 Effect 1.b.

To test Effect 1.b., we adopt a similar specification as Equation (1.1) by replacing the dependent variable with the hospital's volume HHI across services to measure the concentration of volume across services. The volume HHI across service is defined as

$$HHI_{it} = \sum_{s} (\frac{v_{sit}}{\sum_{s}^{S} v_{sit}})^2 \times 10000, \tag{1.5}$$

where for each individual hospital i, v_{sit} is the volume of service $s \in \{1, 2, ...S\}$ at time t. HHI_{it} measures the concentration across service. The DID specification we use is

$$log(HHI_{it}) = \alpha_i + \gamma_t + \eta \cdot \mathbb{1}[i \in \mathcal{M}, t \geq \tau_h] + \epsilon_{it}. \tag{1.6}$$

We still choose 100 miles as our baseline merger sample. Meanwhile, we also care about how the effect varies with the distance of hospitals. Therefore, we decompose the effect by the distance group 0-10 miles and 10-100 miles in Equation (1.7)

$$log(HHI_{it}) = \alpha_i + \gamma_t + \sum_{g} \eta_g \cdot \mathbb{1}[i \in \mathcal{G}_g, t \geq \tau_i] + \epsilon_{it}, \tag{1.7}$$

where $\mathcal{G}_g$ indicates the merging hospitals falls into group $\mathcal{G}_g \in \{\mathcal{G}_1, \mathcal{G}_2\}$, and η_g

stands for the change on HHI of group $\mathcal{G}_g$ post mergers. Similar as before, we run the event study to separately decompose the time varying effect with the mergers in different distance group.

1.3.3.2 Effect 2.b.

Specification We study the post-merger change of hospital pair HHI across services. The hospital pair HHI across services is calculated as

$$HHI_{pt} = \sum_s (\frac{v_{spt}}{\sum_s^S v_{spt}})^2 \times 10000, \tag{1.8}$$

where v_{spt} is the volume of the hospital pair p in service s at time t. The specification used to study its change is

$$log(HHI_{pt}) = \alpha_p + \gamma_t + \sum_g \zeta_g \cdot \mathbb{1}[p \in \mathcal{M}_g, t \geq \tau_p] + \epsilon_{pt}, \tag{1.9}$$

where ζ_g stands for the change of the hospital pair's HHI across services post-merger if the merging pairs belong to the distance group g. Still, this regression only includes the merging pairs within 100 miles. If we observe a significant treatment effect in this specification, it means at the system level some services are shrunk or even closed, and this could be the reason for the individual facility's concentration change in the testing of Hypothesis 1.b. On the other hand, if no significant increase in the hospital pair's HHI across services is found, then at the system level there is no significant change of service composition, which would confirm that the service repositioning is a shift of services across locations rather than a system-level service shrinkage.

Additionally, for each given service, we analyze the pair HHI of every service to examine Effect 2.b. For a given service s, the pair HHI of that given service is defined as

$$HHI_{spt} = (\frac{v_{sit}}{v_{sit} + v_{sjt}})^2 + (\frac{v_{sjt}}{v_{sit} + v_{sjt}})^2, \tag{1.10}$$

where hospital i and j are the two hospitals composing hospital pair p.

The following Equation (1.11) is conducted service by service to examine the change of volume distribution across facilities.

$$log(HHI_{spt}) = \alpha_{sp} + \gamma_t + \sum_g \eta_g \cdot \mathbb{1}[p \in \mathcal{M}_g, t \geq \tau_p] + \epsilon_{pt}. \tag{1.11}$$

In this Equation α_{sp} are the pair-service fixed effects and η_g stands for the post-merger change of the HHI of the hospital pair falls into group g in service s. Similar to before, we use only the merging pairs within 100 miles to avoid possible selection bias in the comparison between the merging and non-merging pairs. We conduct this analysis at different service service level, including all services together, by service categorization (Level 1 of CCS), and also service by service.

1.3.3.3 Empirical Results

Service Volume of Individual Hospitals The results with the hospital pairs are presented in Table 1.4. In Columns (1) and (2), the dependent variable is the Log HHI of individual hospitals across all the services offered. On average, there exists a 6% increase in HHI across services for all merging hospitals with counterparts within 100 miles. When we decompose the heterogeneous effect for mergers with different distance groups, we find that the increase of HHI is mainly due to the change for geographically close mergers (within 10 miles). For merging hospitals with a counterpart in 10 miles, there occurs a 10.7% increase in the HHI across all the services. Meanwhile, the geographically distant merging hospitals do not exhibit a significant change in the HHI. In Column (3) and (4), we change the dependent variable to the Log of HHI of individual hospitals computed using only non-removed services. The difference between the dependent variable in Column (1) & (2) with Column (3) & (4) is that the post-merger removed services are included in building the HHI in Column (1) and (2), while they are excluded in the HHI measurement use in Column (3) and (4). That is to say, while the Column (1) and (2) includes the information of both service removal and patient reshuffle, Column (3) and (4) provides the service volume change only for the services kept even after mergers. For all the merging hospitals within 100 miles, there exists a

5.3% increase of HHI of non-removed services. Moreover, the effect is particularly strong for the nearby merging hospitals (within 10 miles), as they have an 9.2% increase in the non-removed services. Therefore, for the non-removed services, there still exits repositioning in terms of the service volume reshuffle, and hospitals become more concentrated in the procedures they performed.

Figure 1.10 presents the change of the Log HHI of services decomposed by time. Panel (a) uses the specification in Table 1.4 Column (2) while Panel (b) adopts the specification in Table 1.4 Column (4). The event study graphs show that the HHI based on all service/ non-removed services both have a post-merger increase around 10%, meaning that the individual hospitals become more concentrated on service provision. We note that, in both graphs, there exists a one-year pre-trend that the increase of HHI starts one year before the merger. One possible reason is that the target hospitals of poor financial conditions may start shrinking the service spectrum they provided one year before the merger. Another potential reason is that mergers take a while to complete. Due to the complexity of merger deals and the other regulation factors, there usually exists a time gap between the merger starting and complete. The merger activity database we used provides the finishing time of the mergers, and any repositioning activity happens after the merger starting time but before the merger finish could result in the pre-trend of service repositioning.

Service Volume of Hospital Pairs Similar to the analysis with the total service number of hospital pairs, we would like to check if the increase of service concentration is because of the reshuffle of patients or is due to the service shrinking at the system level. To test this problem, we analyze the change of the service concentration of the hospital pairs. The result is presented in Table 1.5, where we do not find a significant change in service concentration. Therefore, there is no evidence indicating the service concentration occurred as the individual hospitals are triggered by the systems shifting their service concentration after mergers.

Service By Service Analysis To identify which services are consolidated, we run analysis service by service using Equation 1.11. The analyzed results at different samples of services are summarized in Table 1.6. The second to the fifth column of the table are the estimated coefficients and standard errors using Equation 1.11 by service categories (CCS Level 1). The last two columns in this table present how many services belong to that specific service category and how many of these services have observed significant increase in concentration when we run the analysis service by service. For instance, for the obstetrical procedures, one service category of CCS Level 1, there is on average 5% increase in pair HHI of all services belongs to that category for merging hospital in 10 miles, and only 0.7% in crease for further mergers. And the last two columns show that there are 10 services fall into this category, and 6 of them have significant increase (at 10% level) in their pair HHI for the 10-mile mergers. Overall, the services experiencing significant consolidation are mainly in obstetrical procedures, operations on female genital organs, and operations on cardiovascular system.[10] The last row of Table 1.6 is the regression result when all services are included in Equation 1.11. When all services are pooled together, there is a minor effect of 1.7% increase in services' pair HHI. This effect is not significant because we average the consolidation occurring only in a subset of services to all services and dissipate the effect.

Graph 1.11 shows services which have a significant increase in the pair HHI of mergers 0-10 miles but no such effect in further mergers when we estimate post-merger effects service by service. In the graph, services in different categories are indicated by different colors, and the magnitude of the horizontal axis indicates the magnitude of Log HHI change for the merging pairs within 10 miles. Overall, the services that experienced consolidation are highly concentrated in the cardiovascular system and obstetrical procedures. For instance, for the peripheral vascular bypass, there exists a 10% increase in the pair HHI for the merging pairs within 10 miles, but this effect does not hold for the further mergers. Additionally, some services in the nervous and musculoskeletal systems also experience significant

[10]These services are consistent with the claimed services to be consolidated by CEO of OSF Healthcare System when the proposed merger is challenged by FTC.

consolidation. For example, spinal fusion and laminectomy, which are two main surgical procedures to treat lower back pain, have 9.2% and 8.7% increase in the pair HHI for merging pairs within 10 miles. Table A.6 in Appendix shows the results of all services.

1.3.4 Robustness Check

1.3.4.1 Alternative Definition of Hospital Services Using Diagnoses

Instead of defining the services by the procedure codes, we can define services using the diagnosis information. The diagnoses contain information related to the symptoms and the diseases of patients, while the procedures depict the treatment patients received. To check if there exists evidence of service repositioning regarding the diseases hospitals cover, we use the ICD-9 diagnosis codes from the California Discharge data to build an alternative service measurement. Similar to before, due to the large number of ICD-9 diagnosis codes, we classify them using the Clinical Classification Software and define a service at level two of the multi-level diagnosis categories.

We implement the analysis of service numbers and volume HHI at the individual hospitals on the services defined by the diagnoses, and the result is shown in Table 1.7. When we study the effect on the number of services by diagnoses as in Column (1) and (2), no significant change is observed. Nevertheless, the study with the service volume concentration in Column (3) and (4) illustrates that the individual hospitals become more concentrated on the diagnoses they cover. The results indicate that hospitals may not be able to entirely refuse patients with certain symptoms and diseases, but that they possess some ability to steer patients based on their diseases. Figure 1.12 is the event study of the Column (4). A one-year pre-trend exists as in Figure 1.10, and could be due to the reason that targets with poor financial conditions starts repositioning early or because of the time gap between the merger starting time and finishing time.

1.3.4.2 Matched Non-merging Hospitals as Control

To check the robustness of our previous estimators, we use the matching-DID to estimate the change of the within 10-mile merging hospitals compared with the non-merging control hospitals. Specifically, we use propensity score matching to build the control group with a similar service concentration and capacity as the within-10mile merging hospitals. Similar to Heckman et al. (1998) and Smith and Todd (2005), we match on the pre-treatment history of an outcome variable, log HHI of services, and another observable, total beds of the hospitals. We set a caliper of 0.08 to eliminate the treated hospitals without similar controls. The summary statistics of the within-10-mile merging hospitals possessing proper controls and their matched controls in the beginning year (year 2002) are presented in Table 1.8. Overall, the matched sample is balanced with no significant group mean difference across the treatments and controls.

Meanwhile, we observe that the estimated post-merger effect is robust. Table 1.9 Column (1) reveals that with the matched control group, the merging hospitals within 10 miles drop approximately 6 services. In the same table, Column (2) & (3) indicates that the HHI of services (defined by procedures increase around 11%-12%, regardless of excluding the dropped services or not. Column (4) and (5) define the services by the diagnosis as in the previous robustness check. The estimated results show that the services defined based on diagnosis do not have significant removal, but there exists a subtler repositioning in terms of patient reshuffle and increase the HHI of services defined by the diagnosis around 3.3%.

Figure 1.13 is the event study of the within-10-mile merging hospitals and its matched control group (i.e., the event study for Column (2) and (3) in Table 1.9). The one-year pre-trend appear in Figure 1.10 is dismissed in this matching-DID specification, indicating that the matching process manages to select a control group of similar pre-merger outcomes with the treatments. And the parallel trend assumption also holds for other outcome variables, and their event study can be found in the Appendix.

1.3.4.3 Other Measurements of Hospital Repositioning

California Hospital Financial Reports also report the hospitals' physicians, beds, discharge numbers and discharge days based on service categories, which allows us to examine the service repositioning based on these measurements. Table 1.10 presents the results.

In Table 1.10, Column (1)'s dependent variable is the log HHI of physicians across different service categories and Column (2) uses log of HHI based on beds assigned to different service categories. The dependent variable of Column (3) and (4) are concentration measurement derived from total patient days and discharges of different service categories. We find that, except physicians, all other measurements indicate that services become more concentrated post-merger. This effect does not hold for physicians, perhaps because a large proportion of physicians are not directly hired by hospitals and are able to freely choose at which hospital they treat their patients.

1.3.5 Heterogeneous Effect of Targets and Acquirers

The change we observe above could also be motivated by the financially poor-performed targets' intention to shrink their service spectrum, which is irrelevant with the service consolidation. There is a possibility that targets are financially constrained, and they would remove services even without occurrence of mergers. Under this case, the service removal would occur for the targets, while the acquirers which are of decent financial status might absorb the target hospitals. This mechanism would result in all the services elimination only on the target side, while the service consolidation leads to a simultaneous service exchange on both the targets and acquirers due to the service consolidation. To test whether the services repositioning only occurs on targets or both sides, we turn to the national sample from the AHA Annual Survey to form a large sample to study the effect with the targets and the acquirers separately. We use the same strategy in Section 1.3.2 to evaluate the change of services at the individual hospitals and hospital pairs. Table 1.14 presents the summary statistics of the mergers and acquirers at the beginning year of the AHA sample, year 2001. On average, the acquirer hospitals are larger than the targets, offering more services and treats more patients. Meanwhile, for the targets/acquirers having merger counterpart within 10 miles, they are more likely to be in metro areas, and are of larger size compared with the hospitals with further merging partners. The services from the AHA data is listed in Table A.7 in Appendix.

Table 1.15 implements the two-way fixed effect models only with the target hospitals and acquirer hospitals within 10 miles separately. From Table 1.15, we can observe that the service elimination happens simultaneously at the targets and acquirers, and the targets drop more services compared to the acquirers. We decompose the effect by time in the event study in Figure 1.15, where the left panel is the event study with the targets sample in Table 1.15 Column (1) and the right panel is the acquirers in Table 1.15 Column (2). For the target hospitals, we observe that the service removal happens one year before the merger. The early service reposition of the target hospitals can be driven by the possible poor financial performance of targets so that they already shrink the spectrum of services covered. However, the parallel trend assumption holds for the acquirers. Meanwhile, the acquirer hospitals, which may not face financial stress as targets do, still eliminate some services, indicating the service removal we observe are not entirely driven by the worry of financial performance. The pair analysis results is attached in the Appendix. Overall, the service repositioning identified in the California sample also holds in the national sample from the AHA data.

1.4 Implications for Service Cost and Quality

1.4.1 Post Consolidation Cost Change

Specification Having established that geographically close hospitals consolidate their services post-merger, we now look for evidence that these consolidations affect hospitals' reported costs. Similar to the analysis with hospital pairs to identify service-specific HHI change, we use only the merging hospital pairs and compare the post-merger cost saving between consolidated and non-consolidated services as

$$log(c_{pst}) = \alpha_{ps} + \gamma_t + \lambda \cdot \mathbb{1}[t \geq \tau_p] + \delta \cdot \mathbb{1}[s \in \mathcal{S}, t \geq \tau_p] + \epsilon_{pt}, \tag{1.12}$$

where c_{pst} is the per unit patient care cost for the hospital pair p's service s at time t, $\mathbb{1}[t \geq \tau_p]$ is the indicator for the post-merger status, and $\mathbb{1}[s \in \mathcal{S}, t \geq \tau_p]$ stands for the post-merger status for consolidated services. The parameter λ is for the average change of services pre and post-merger, while δ indicates the extra cost change for the consolidated services compared with non-consolidated services. This δ term is identified through the comparison between consolidated and non-consolidated services. Under the assumption that the other merger-related factors influence the standardized patient care cost per unit similarly across services, the comparison of the consolidated and non-consolidated cost would be the extra cost change related to the consolidation in the repositioned services.

For the concern that consolidated services and non-consolidated services are not comparable, we take advantage of the fact that service consolidation only occurs when merging entities are close with one another, and compare the cost change of the consolidated services across different merger distance. Specifically, we use

$$log(c_{pst}) = \alpha_{ps} + \gamma_t + \sum_g \eta_g \cdot \mathbb{1}[t \geq \tau_p] \times \mathbb{1}[p \in \mathcal{M}_g] + \epsilon_{pt} \tag{1.13}$$

where η_g is the post-merger standardized cost change when a hospital pair p belongs to the distance group $\mathcal{M}_g \in \{$0-10 miles, 10-100 miles$\}$. Equation (1.13) is implemented on the sample consolidated and non-consolidated service separately.

The primary data we use to analyze the service cost change is the California Financial Report. The financial data report at more aggregate level of service than was used in the above analyses. We reestimate the previous analysis with the hospital pair concentration service by service to identify the consolidated services. We find the cardiac and obstetric services are found to be consolidated, which is similar to before. Table A.5 in Appendix is the summary statistics of the per unit cost of the services in the California Financial Report.

1.4.1.1 Empirical Results

Table 1.11 presents the results of the cost analysis. Column (1) and (2) include the sample of services of all merging pairs within 100 miles. Column (1) shows that on average there exists an insignificant increase on the standardized cost of services post mergers. However, when comparing the consolidated and non-consolidated services in Column (2), the cost of consolidated services actually decreases by 15%. When we restrict the sample to the merging pairs within 10 miles, we observe that the difference between the consolidation is significantly larger, as the consolidated services on average drop 31% of the per unit service cost. That is to say, the adjacent merging hospitals are the entities achieved most cost savings in consolidated services. However, the event study shows that this setting does not satisfy the parallel trend assumption.

Table 1.12 shows the results of different services groups with the consolidated and non-consolidated services separately. For the consolidated services, only the merging pairs with close distance have significant drop in the service cost, as they are the hospitals effectively repositioning the consolidated services. In Column (1), the merging hospital pairs within 10 mile have a drop in cost with 20%, equivalent to approximately $277 for cardiac catheterization and $13 for the echocardiology service. When it comes to the standardized cost change to the non-consolidated services in Column (2), we do not find statistically significant differences across the close merging pairs and further merging pairs. The event study of Column (1) in Table 1.12 is presented in Figure 1.14. The figure shows that the consolidated services create long run cost-savings for close merging hospitals.

1.4.2 Impact on Patients

In the previous section, we find that hospitals' service repositioning leads to cost reductions for providers. In this section, we analyze the service repositioning implications for patients. The hospitals' service repositioning can influence patients from several aspects. First, service relocation can increase patients' travel distance, resulting in patients' travel costs increase. Second, service quality may also change due to service repositioning. For instance, concentrating patient flows in single, specialized locations might lead to better patient outcomes because of physicians' learning-by-doing. Meanwhile, mergers can harm healthcare quality due to a reduction in market competitiveness. Finally, the providers' cost reductions can be passed on to consumers in the form of lower claim prices. Due to data limitations, we do not observe the transaction prices of services. Thus, we mainly analyze the impact on patients by investigating the impact on service quality and patients' travel distance.

1.4.2.1 Service Quality

To evaluate the change of service quality for the consolidated services, we examine the readmission rate of discharges. We concentrate on patients whose primary diagnosis relating to the consolidated services (circulatory/cardiac, birth delivery, and women genital). For each patient discharge, his/her 30-day all-cause unplanned readmission record is identified following Horwitz et al. (2011). We also control for the Charlson comorbidity conditions (D'Hoore et al., 1993) to adjust the risk of patients. Specifically, we analyze the change of readmission at the discharge level using the following equation

$$q_{jit} = \alpha_i + \gamma_t + \sum_g \lambda_g \cdot \mathbb{1}[t \geq \tau_i] \times \mathbb{1}[i \in \mathcal{G}_g] + \beta X_{jt} + \epsilon_{jit} \tag{1.14}$$

where for patient j's discharge occurred in hospital i at time t, q_{jit} indicates a quality measurement, the readmission indicator, i.e. whether any unplanned readmission happens to the patient within 30 days. α_i are hospital fixed effect and γ_t are year fixed effects. $\mathbb{1}[i \in \mathcal{M}, t \geq \tau_i]$ is the indicator function showing whether hospital i is in its post-merger status. When the patient j is admitted by the hospital i in merger distance group G_i, λ_g shows the post-merger change in the readmission for the discharges that occurred in the hospital i. Similar to before, $\mathcal{G}_g \in \{\mathcal{G}_1, \mathcal{G}_2\}$. $\mathcal{G}_1$ stands for the hospitals with merging counterparts 0-10 miles away, and $\mathcal{G}_2$ is for those with merging counterparts 10-100 miles away. X_{jt} stands for the Charlson comorbidity conditions for risk adjustment. We only include patient discharges that occurred in the merging hospitals with the closest partner within 100 miles as before. Discharges with different primary diagnoses are separately analyzed.

The results are presented in Figure 1.16 and 1.17. In these figures, each row stands for a primary care diagnosis. The value along the horizontal axis shows the post-merger change of likelihood being readmitted when a patient is discharged in a 0-10 mile merging hospital. Figure 1.16 exhibits the results with discharges for circulatory diseases and Figure 1.17 shows the results for birth delivery and women genital discharges. Overall, the readmission rate remains stable after mergers for these repositioned services. We do not find evidence that the service repositioning significantly changes the readmission.

Besides the readmission rate, we also examine the service quality change using other measurements. The analysis with Centers for Medicare and Medicaid Services (CMS) Hospital Compare data's measurement about the timeliness and effectiveness care measures shows some minor improvement in quality after mergers. In summary, our study suggests that service repositioning does not impose a significant impact on service quality.

1.4.2.2 Patient Travel Distance

Service relocation can change the travel distance of patients. We establish the travel distance using patients' home address 5-digit zip code information. The travel distance is calculated as the centroid of the zip code to the geolocation of the hospital and travel time is the driving time to cover the distance under normal traffic conditions.[11] And we also concentrate on patients seeking the consolidated services in the 0-10 mile merging hospitals. We implement the analysis using the following equation

$$r_{jit} = \alpha_i + \gamma_t + \sum_g \lambda_g \cdot \mathbb{1}[t \geq \tau_i] \times \mathbb{1}[i \in \mathcal{G}_g] + \epsilon_{jit}. \tag{1.15}$$

r_{jit} is the travel distance/time of a patient j's discharge at hospital i at time t. α_i are hospital fixed effect and γ_t are year fixed effects. $\mathbb{1}[i \in \mathcal{M}, t \geq \tau_i]$ is the indicator

[11]See Weber and Péclat (2017) for details.

function showing whether hospital i is in its post-merger status and λ_g shows the post-merger average change in travel distance/time,with $\mathcal{G}_g \in \{\mathcal{G}_1, \mathcal{G}_2\}$. $\mathcal{G}_1$ stands for the hospitals with merging counterparts 0-10 miles away, and $\mathcal{G}_2$ is for those with merging counterparts 10-100 miles away.

The result is shown in Table 1.13. Column (1) takes travel time as the outcome variable and Column (2) in the table uses travel distance as the dependent variable. The analysis shows that both the travel distance and travel time have a very minor and insignificant increase. According to the estimation of Ho and Pakes (2014), the willingness to pay for one-mile travel distance is between 100-1,500 dollars. In our context, this means that the service relocation can leads to the consumer surplus decrease by around 50-750 dollars per discharge for the consolidated services.

1.5 Discussion & Conclusion

This paper finds evidence that hospitals reposition their services via a cost-saving mechanism. By employing a DID study design, we find that the geographically close merging hospitals (within 10 miles) drop around 5 duplicate services. This repositioning appears to generate a 20% cost saving for consolidated services. Our results provide systematic evidence supporting hospitals' claims that mergers can enable efficient re-organizations of services. However, these savings of service repositioning can only be applied to local mergers. When it comes to mergers between hospitals located in different markets, our analyses suggest that service consolidation is unlikely.

We also provide some evidence on how hospitals' repositioning behavior affects consumer welfare. First, service reorganization may lead to service quality change. We analyze some measurements of hospital quality and find no significant change. Second, the reallocation of patient flows can change the travel cost of patients. Our results show that service repositioning indeed leads to an increase in travel distance by around 0.5 mile.

Ultimately, anti-trust laws concern whether consumers can enjoy the benefits of the created surplus. Our paper opens up future research opportunities on whether and how cost savings after mergers are passed on to consumers in the form of lower claim prices. If cost savings generated by service repositioning is not effectively transformed into price reduction, policy interventions may help to achieve this goal. One potential option is to impose the price-cap condition on the merger terms. For instance, in the merger of Beth Israel Deaconess Medical Center and Lahey Health System in Boston, the Attorney General imposed a seven-year price cap condition. Another potential solution to extract the surplus of service repositioning without creating market power is to form operating agreement across close facilities but prohibit them from joint price bargaining. For example, Accountable Care Organizations (ACO) of geographically close hospitals may improve the service repositioning across facilities by aligning their financial incentives, and ACOs are not likely to result in price increase because hospitals are mainly paid under capitation from CMS.

Table 1.1: Summary Statistics of California OSHPD & Financial Data at Year 2002

	Merging <10 miles	Merging 10-100 miles	Merging >100 miles	Non-merging All
Number of services (by proc)	159.0	162.8	164.2	138.1
	(24.63)	(28.95)	(26.71)	(54.40)
Number of services (by diag)	130.0	131.9	132.8	125.7
	(5.866)	(4.588)	(4.892)	(15.92)
Hospital HHI across services (by proc)	1158.2	924.8	927.3	1647.9
	(592.0)	(688.7)	(428.1)	(1856.2)
Hospital HHI across services (by diag)	337.4	361.3	338.3	354.6
	(69.63)	(80.06)	(63.79)	(142.8)
Case-mix index	1.072	1.061	1.111	1.045
	(0.235)	(0.192)	(0.196)	(0.221)
Number of staffed beds	181.5	213.0	204.8	184.8
	(99.83)	(157.9)	(116.3)	(164.4)
Total discharges	8735.0	10875.0	9506.6	9018.6
	(5585.7)	(7038.1)	(5837.0)	(8762.1)
Board certified/eligible physicians	253.2	343.6	248.8	224.6
	(187.1)	(264.0)	(194.1)	(267.3)
Total discharge days (in thousand)	45.59	52.67	43.43	45.56
	(27.71)	(36.98)	(25.83)	(42.57)
Total patient care cost (in million)	95.50	129.4	107.0	123.8
	(70.75)	(102.3)	(66.28)	(161.1)
Number of Hospitals	41	60	64	190

Note: The table shows the summary statistics of hospital characteristics at the starting year of the data sample. The first to the last column describes the hospitals with their closest merging counterparts within 100 miles/10-100 miles/out of 100 miles and non-merging hospitals separately. The Case Mix Index (CMI) is the average relative DRG weight of a hospital's inpatient discharges, calculated by summing the Medicare Severity-Diagnosis Related Group (MS-DRG) weight for each discharge and dividing the total by the number of discharges. The CMI reflects the diversity, clinical complexity, and resource needs of all the patients in the hospital. A higher CMI indicates a more complex and resource-intensive case load.

Table 1.2: Post Merger Effect of Individual Hospital of Mergers within 100 miles

	(1) Number of Services	(2) Number of Services	(3) Number of Services
Post merger	-1.248		-4.498*
	(1.942)		(2.411)
Post merger 0-10 miles		-4.531*	
		(2.357)	
Post merger 10-100 miles		2.120	
		(2.365)	
Post merger × Merger distance			0.211***
			(0.068)
N	1208	1208	1208
R^2	0.95	0.95	0.95

Note: Model clusters at individual hospital level.[12] Total number of beds and for-profit status of hospitals are included in regressions. $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

Table 1.3: Post Merger Effect of Merged Pairs within 100 miles

	(1) Duplicate Services	(2) Total Services
Post merger 0-10 miles	-5.147***	-0.889
	(1.705)	(1.130)
Post merger 10-100 miles	-1.821	-0.209
	(1.443)	(0.846)
N	1475	1475
R^2	0.93	0.92
$DependentMean$	131.43	177.40
$DependentS.D.$	27.16	14.76

Note: Model clusters at hospital pair level. Total number of beds is included in regressions. $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

Table 1.4: Post Merger Effect of Individual Hospital of Mergers within 100 miles

	(1) Log HHI of All Services	(2) Log HHI of All Services	(3) Log HHI of Non-removed Srv	(4) Log HHI of Non-removed Srv
Post merger	0.054		0.046	
	(0.032)		(0.032)	
Post merger 0-10mile		0.102**		0.087*
		(0.050)		(0.049)
Post merger 10-100mile		-0.007		-0.007
		(0.037)		(0.037)
N	1208	1208	1208	1208
R^2	0.89	0.89	0.90	0.90

Note: Model clusters at individual hospital level. Total number of beds and for-profit status of hospitals are included in regressions. $*p < 0.05, \ **p < 0.01, \ ***p < 0.001$.

Table 1.5: Post Merger Effect of Log HHI of Merged Pairs within 100 miles

	(1) Log HHI of Services
Post merger 0-10 mile	-0.011
	(0.049)
Post merger 10-100 mile	0.026
	(0.033)
N	1475
R^2	0.88
$DependentMean$	-2.63
$DependentS.D.$	0.48

Note: Model clusters at hospital pair level. Total number of beds is included in regressions. $*p < 0.05, \ **p < 0.01, \ ***p < 0.001$.

Table 1.6: Summary of Service by Service Analysis

Level 1 Service Category	post 0-10 miles	se	post 10-100 miles	se	Num. of Services	Significant Service Num
Obstetrical procedures	0.050**	(0.021)	0.007	(0.013)	10	6
Op. on female genital organs	0.049***	(0.016)	0.022**	(0.010)	13	4
Op. on cardiovascular system	0.039**	(0.016)	-0.004	(0.010)	21	7
Op. on endocrine system	0.034	(0.020)	0.025	(0.019)	3	1
Op. on nervous system	0.032**	(0.015)	0.001	(0.010)	9	3
Op. on hemic & lymphatic system	0.032**	(0.012)	0.016	(0.024)	4	1
Op. on respiratory system	0.025	(0.021)	-0.0034	(0.012)	9	0
Op. on nose; mouth; and pharynx	0.020	(0.020)	0.013	(0.011)	7	1
Misc diag/therapeutic proc	0.011	(0.009)	-0.0068	(0.0070)	42	5
Op. on integumentary system	0.011	(0.012)	0.0010	(0.015)	9	0
Op. on digestive system	0.006	(0.010)	-0.009	(0.009)	31	0
Op. on urinary system	0.001	(0.013)	-0.0003	(0.011)	11	1
Op. on musculoskeletal system	0.0007	(0.017)	-0.021	(0.021)	17	3
Op. on eye	-0.027	(0.024)	-0.0072	(0.020)	9	0
Op. on ear	-0.016	(0.020)	0.019	(0.019)	5	0
Op. on male genital organs	-0.009	(0.014)	0.007	(0.016)	6	0
All Services	0.017	(.011)	-0.002	(0.009)	204	32

Note: We abbreviate "Operations" as "Op.". The last two columns present how many services belong to that specific service category (Num. of Services) and how many of these services have observed significant increase in concentration when we run the analysis service by service (Significant Service Num.). The estimated coefficients and standard errors in the second to the fifth column are from analyses using only the services belonging to the corresponding service category in the first column. Model clusters at hospital pair level. Total number of beds is included in regressions. $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

Table 1.7: Post Merger Effect of Services by Diagnosis of Merged Hospitals within 100 miles

	(1) Number of Srv.	(2) Number of Srv.	(3) Log HHI of Srv.	(4) Log HHI of Srv.
Post merger	-0.911		0.041*	
	(0.861)		(0.023)	
Post merger 0-10 miles		-0.662		0.067***
		(0.477)		(0.019)
Post merger 10-100 miles		-1.280		0.011
		(1.592)		(0.039)
N	1208	1208	1208	1208
R^2	0.78	0.78	0.80	0.80

Note: Services are defined by diagnosis classification. Model clusters at hospital pair level. Total number of beds and for-profit status are included in regressions. $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

Table 1.8: Summary Statistics of California OSHPD & Financial Data of the Matched Sample, 2002

Number of services (by proc)	160.5	155
	(24.44)	(39.46)
Number of services (by diag)	130.2	130.2
	(5.691)	(13.12)
Hospital HHI of services (by proc)	1151.6	1083.4
	(564.5)	(696.4)
Hospital HHI of services (by diag)	336.7	333.7
	(66.58)	(70.68)
Casemix index	1.099	1.010
	(0.247)	(0.139)
Number of staffed beds	182.8	169.5
	(85.30)	(111.5)
Total discharges	8616.7	9191.5
	(4439.5)	(7044.1)
Board certified/eligible physicians	245.8	224.6
	(154.5)	(227.0)
Total discharge days (in thousand)	46.55	40.93
	(24.44)	(27.94)
Total patient care cost (in million)	94.78	105.1
	(65.82)	(83.69)
Number of Hospitals	34	29

Note: Match is implemented with replacement.

Table 1.9: Within-10mile Merged Hospitals Compared with Matched Non-merged Controls

	(1) Number of Services by Proc	(2) Log HHI of All Services by Proc	(3) Log HHI of Non-removed Services by proc	(4) Number of Services by Diag	(5) Log HHI of All Services by Diag
Post merger	-6.085***	0.120**	0.113**	-0.393	0.033*
	(1.937)	(0.055)	(0.054)	(0.255)	(0.019)
N	759	759	759	759	759
R^2	0.95	0.88	0.88	0.93	0.83

Note: Model clusters at hospital level. Total number of beds and for-profit status of hospitals are included in regressions. $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

Table 1.10: Other Measurements of Service Concentration of Merged Hospitals within 100 miles

	(1) Log HHI of Physicians	(2) Log HHI of Beds	(3) Log HHI of t days Patient days	(4) Log HHI of Discharges
Post merger of 0-10mile	-0.043***	0.100***	0.077**	0.078**
	(0.014)	(0.036)	(0.034)	(0.034)
Post merger of 10-100 miles	-0.033	0.015	0.011	0.022
	(0.021)	(0.058)	(0.052)	(0.057)
N	1113	1208	1208	1208
R^2	0.78	0.87	0.89	0.83

Note: Models are clustered at individual hospital level. $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

Table 1.11: Normalized Cost per Service Unit of Merged Hospital Pairs within 100 miles

	(1) 100-mile Merged	(2) 100-mile Merged	(3) 10-mile Merged
Post merger	-0.004	0.016	0.045
	(0.017)	(0.018)	(0.040)
Post merger × Consolidated Service		-0.151***	-0.311***
		(0.033)	(0.073)
N	37692	37692	8046
R^2	0.93	0.93	0.94

Notes: Model clusters at hospital level. Year fixed effects and Hospital× Service fixed effects are included. $*p < 0.05,\ **p < 0.01,\ ***p < 0.001$.

Table 1.12: Normalized Cost per Service Unit of Merged Hospital Pairs by Distance

	(1) Consolidated Services	(2) Non-consolidated Services
Post merger 0-10 miles	-0.199***	0.013
	(0.066)	(0.038)
Post merger 10-100 miles	0.008	-0.005
	(0.035)	(0.018)
N	6025	31659
R^2	0.92	0.93

Note: Model clusters at hospital level. Year fixed effects and Hospital× Service fixed effects are controlled. $*p < 0.05,\ **p < 0.01,\ ***p < 0.001$.

Table 1.13: Post Merger Effect of Travel Distance of Merged Hospitals within 100 mile

	(1) Travel Time (min)	(2) Travel Distance (mile)
Post merger of 0-10 miles	0.433	0.517
	(0.755)	(0.795)
Post merger of 10-100 miles	-0.048	-0.015
	(0.862)	(0.926)
N	4,530,729	4,530,729
R^2	0.004	0.003

Table 1.14: Summary Statistics of AHA Data in Year 2001

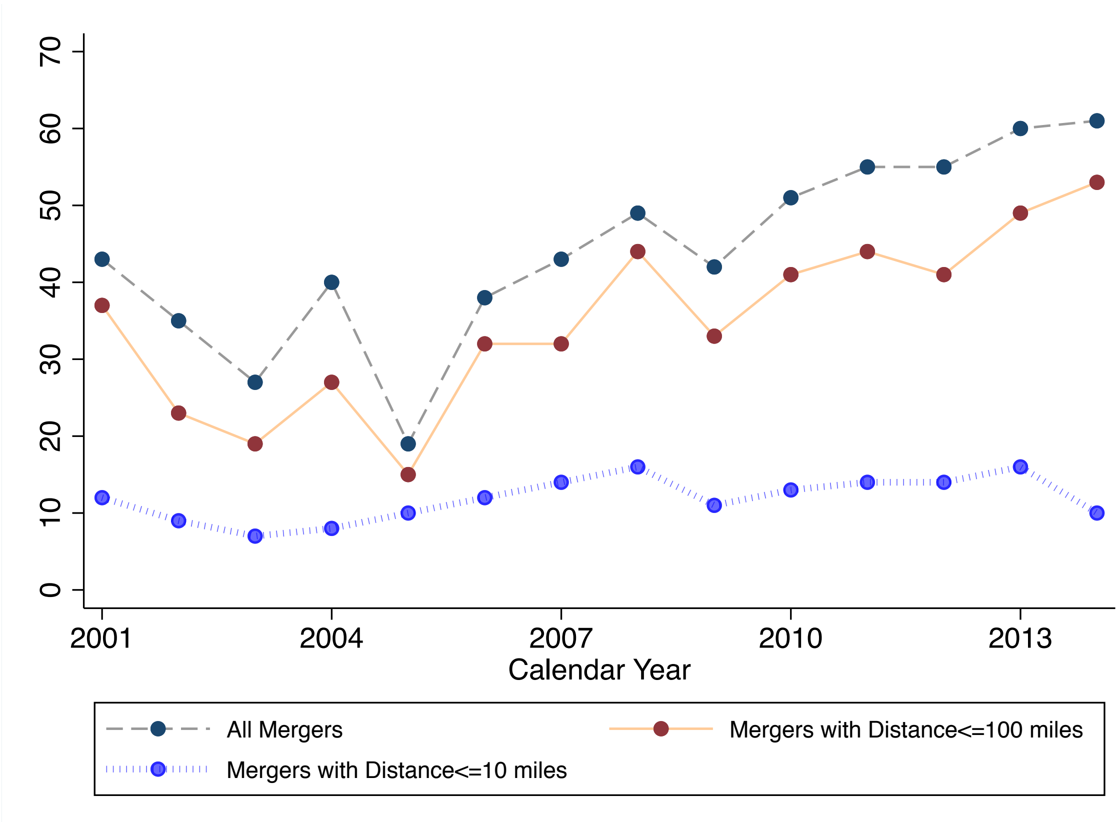
	Targets in 10 miles	All Targets	Acquirers in 10 miles	All Acquirers
Number of services	28.47	23.04	32.60	25.51
	(10.01)	(11.32)	(12.05)	(12.26)
Total staffed beds	252.3	158.9	347.8	207.1
	(138.2)	(136.0)	(267.9)	(203.5)
Total admissions	10755.3	6556.4	15883.1	9241.1
	(6819.8)	(6207.4)	(12955.9)	(9912.0)
Local sys members	3.781	2.625	3.481	3.470
	(4.308)	(3.570)	(3.689)	(3.702)
Metro	0.562	0.427	0.596	0.486
	(0.499)	(0.495)	(0.492)	(0.500)

Table 1.15: Individual Hospital Number of Services for Mergers within 10 miles

	(1)	(2)
	Targets within 10 miles	Acquirers within 10 miles
Post merger	-2.544***	-1.816**
	(0.880)	(0.787)
N	1182	1657
R^2	0.88	0.92

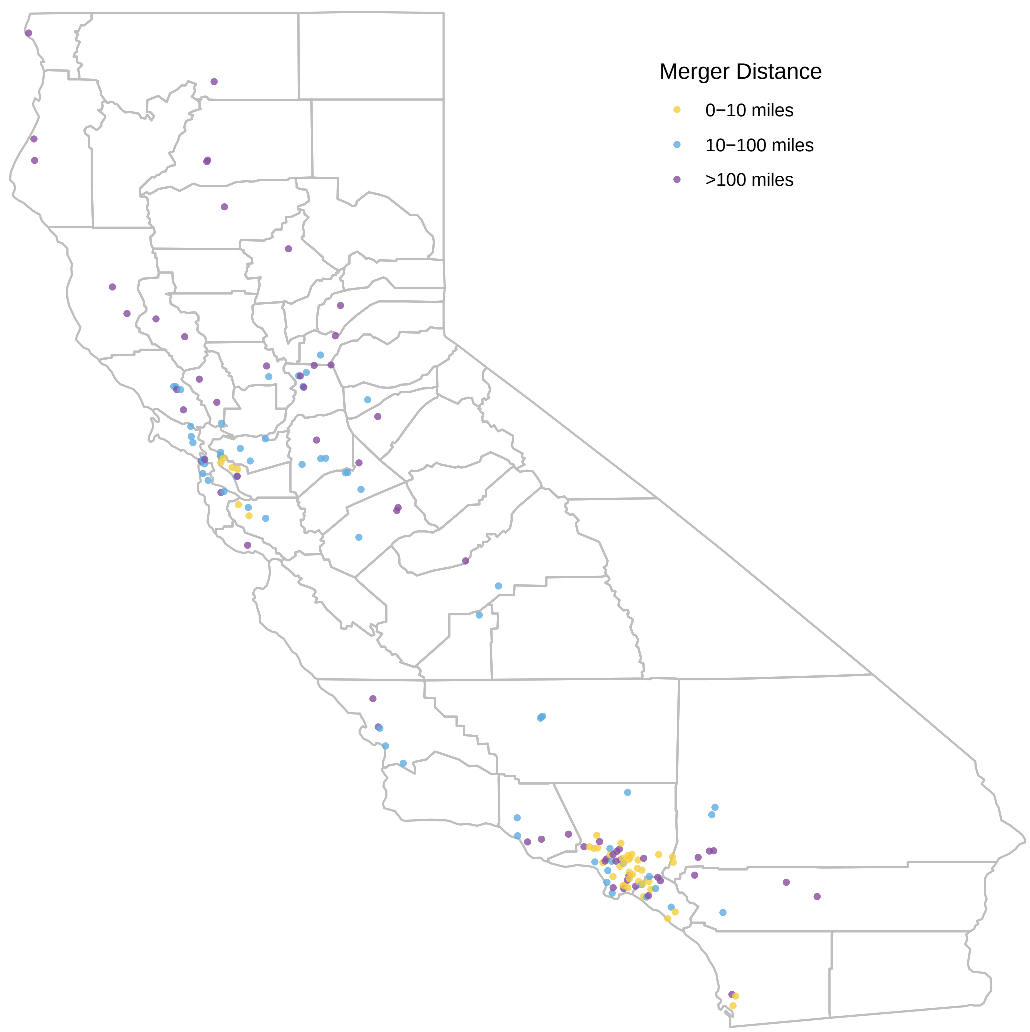
Note: Model clusters at individual hospital level. Total number of beds and for-profit status of hospitals are included in regressions. $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

Figure 1.1: National Hospital Merger Transactions, 2001-2014



Note: The figure shows the trend of the transactions of all horizontal mergers within the U.S.

Figure 1.2: Merging Hospitals in California by Distance



Note: The figure shows location of merging hospitals in California. The yellow dots represent the hospitals with at least a merging partner within 100 miles. The blue dots are for the hospitals with their closest merging counterparts within 100-200 miles. The purple dots stand for the merging hospitals with no merging counterparts within 200 miles.

Figure 1.3: Number of Services over Time by Distance Group

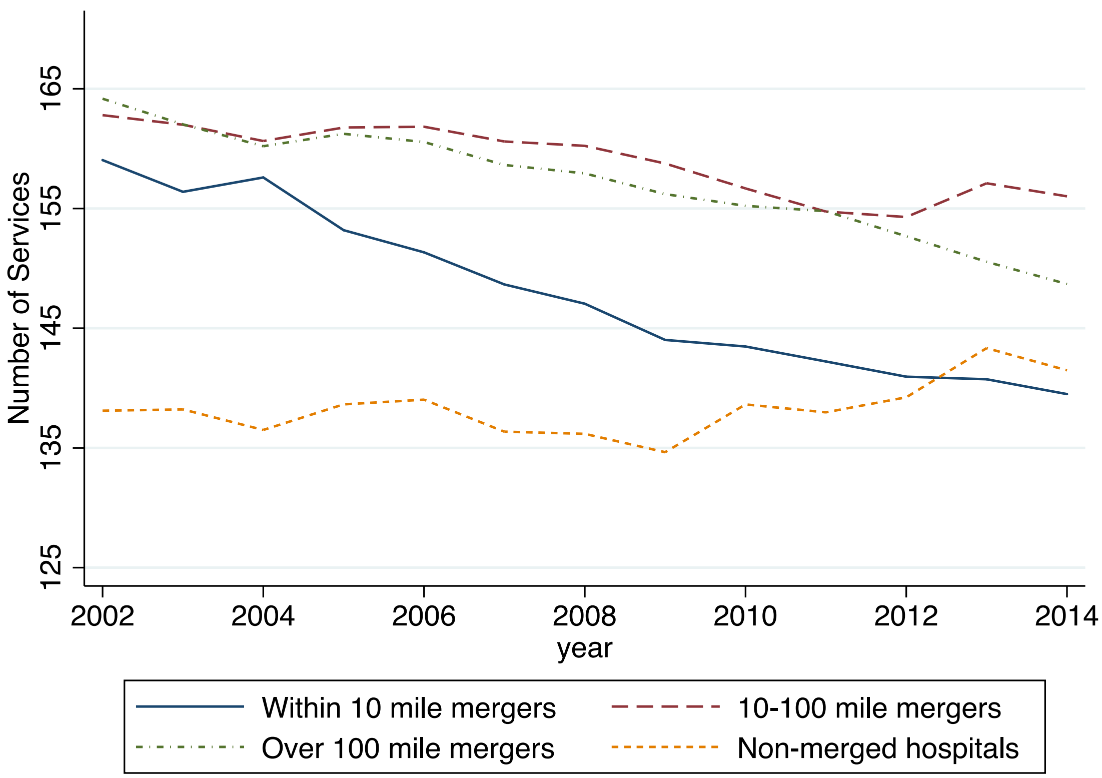


Figure 1.4: Illustrative Example of Service Consolidation with Service Removal

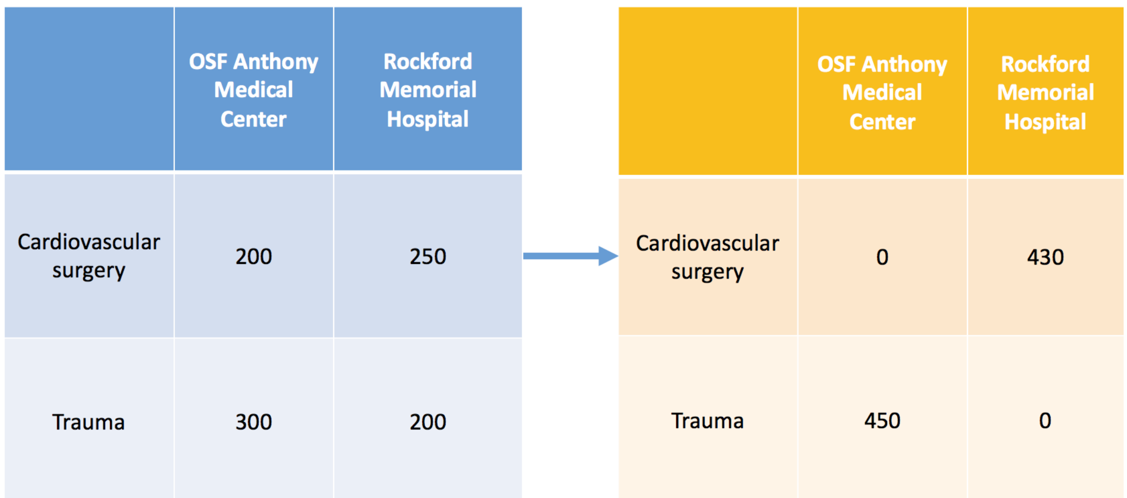


Figure 1.5: Illustration for Effect 1

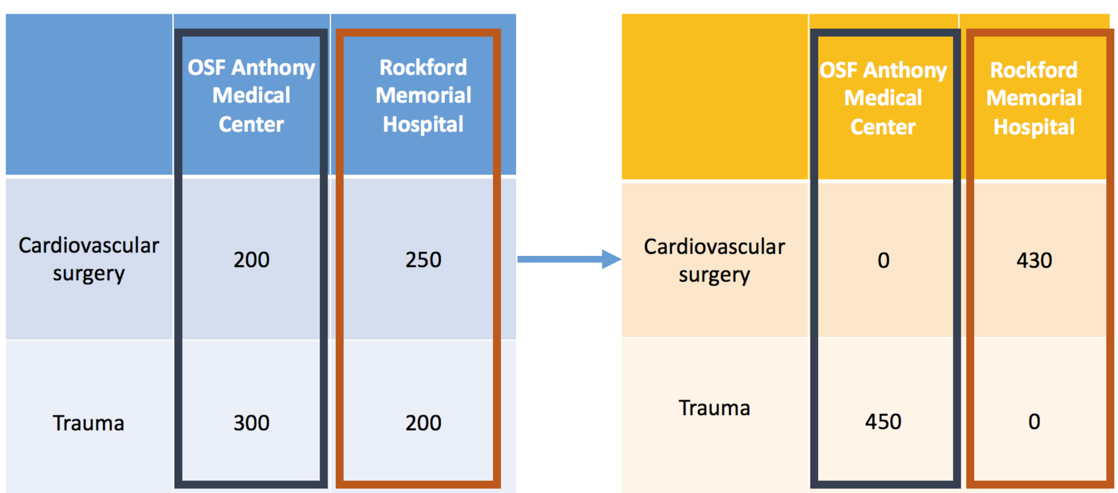


Figure 1.6: Illustration for Effect 2

	OSF Anthony Medical Center	Rockford Memorial Hospital
Cardiovascular surgery	200	250
Trauma	300	200

	OSF Anthony Medical Center	Rockford Memorial Hospital
Cardiovascular surgery	0	430
Trauma	450	0

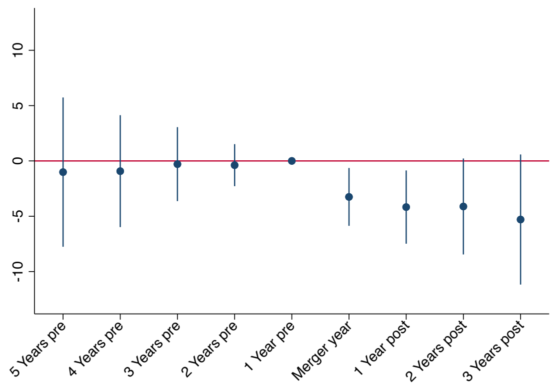
Figure 1.7: Illustrative Example of Consolidation without Service Removal

	OSF Anthony Medical Center	Rockford Memorial Hospital
Cardiovascular surgery	200	250
Trauma	300	200

	OSF Anthony Medical Center	Rockford Memorial Hospital
Cardiovascular surgery	30	400
Trauma	400	60

Figure 1.8: Event Study of Number of Services

(a) Merged in 0-10 miles



(b) Merged in 10-100 miles

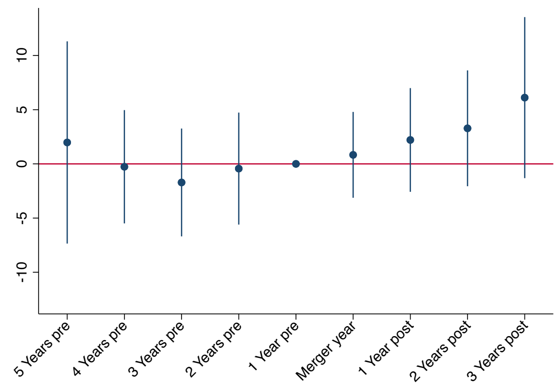


Figure 1.9: Event Study of Duplicate Services of Merging Pairs within 10 miles

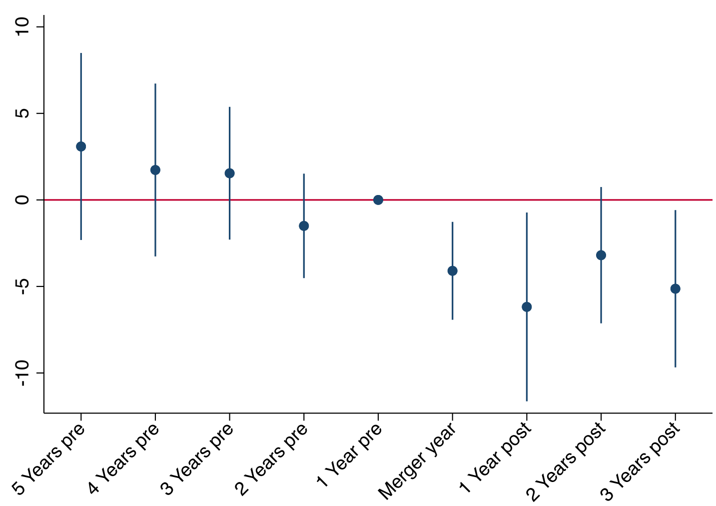
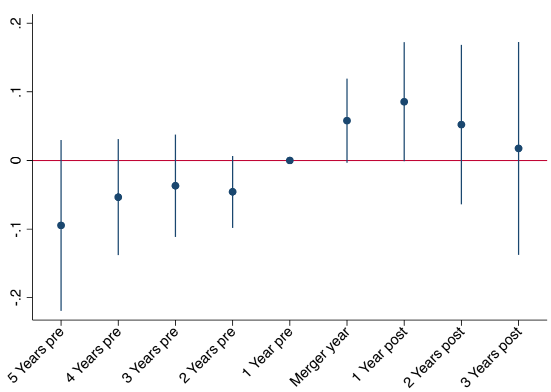


Figure 1.10: Event Study of Log HHI of Services for Hospitals with Group 0-10 miles

(a) Log HHI of All Services



(b) Log HHI of Non-removed Services

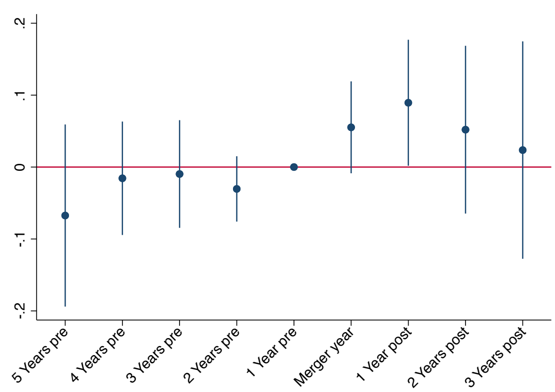


Figure 1.11: Services Consolidated for the 10-mile Merging Pairs

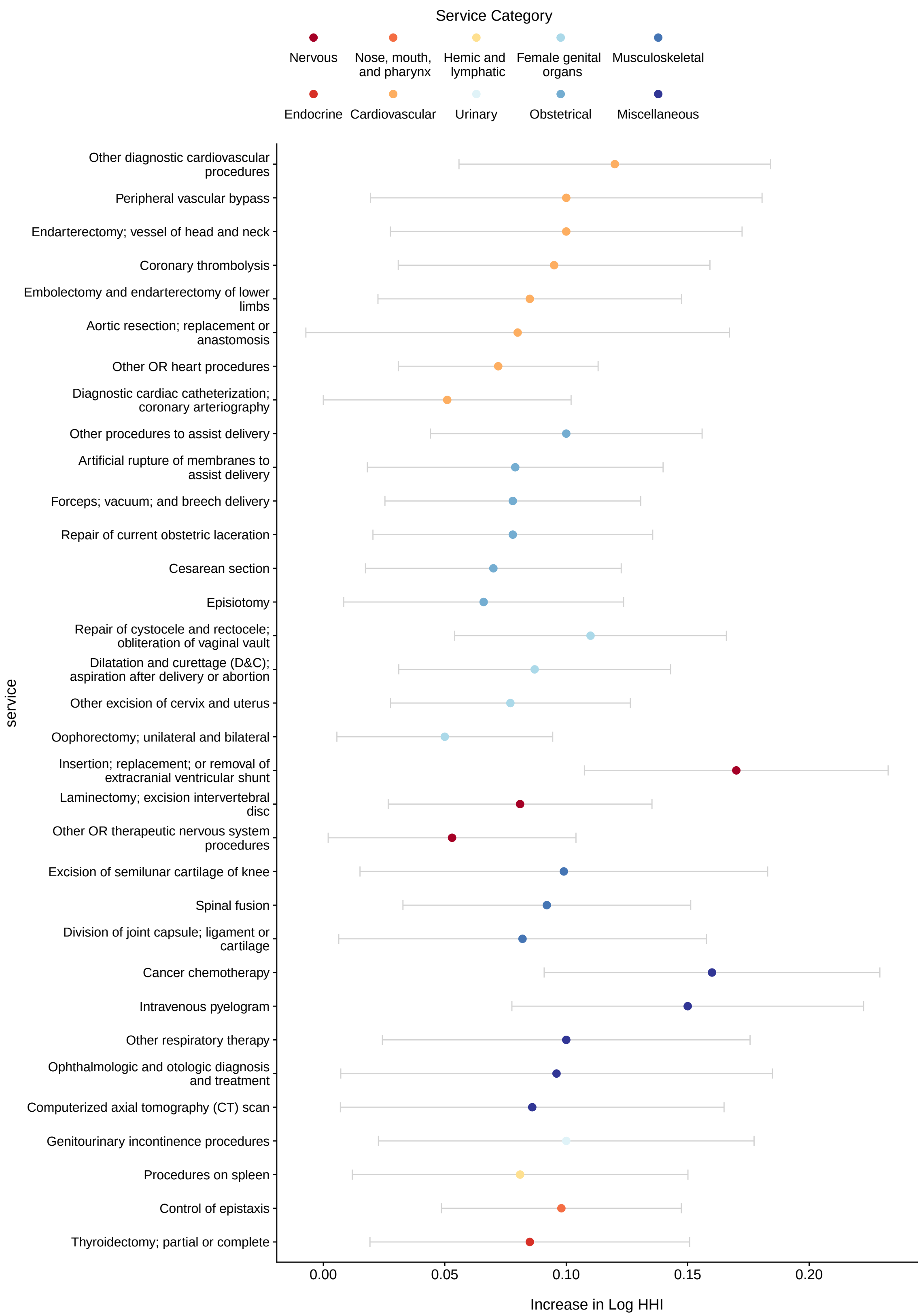


Figure 1.12: Event Study of Log HHI of Services by Diagnoses of within-10-mile Merging Hospitals

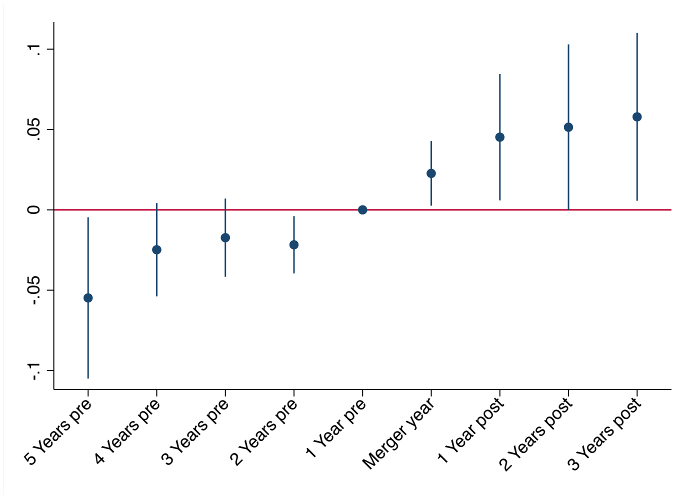
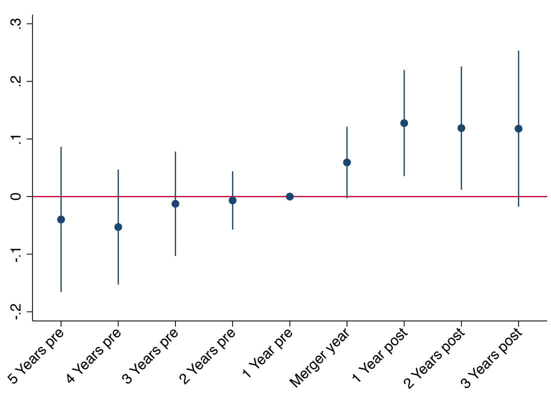


Figure 1.13: Event Study of 10-mile Merging Hospitals and Matched Non-merging Controls

(a) Log HHI of All Services



(b) Log HHI of Non-removed Services

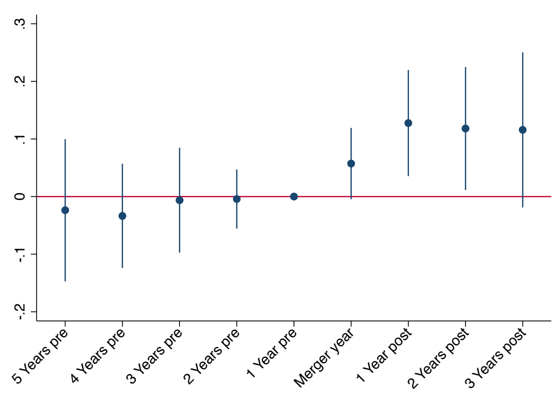


Figure 1.14: Event Study of Consolidated Service in 0-10 miles Mergers

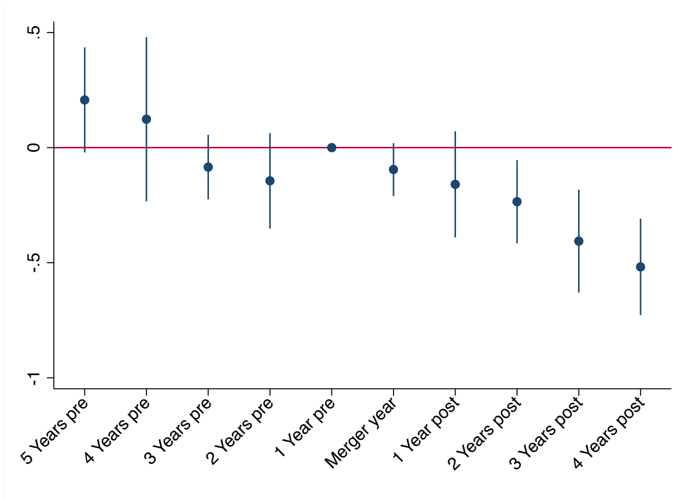
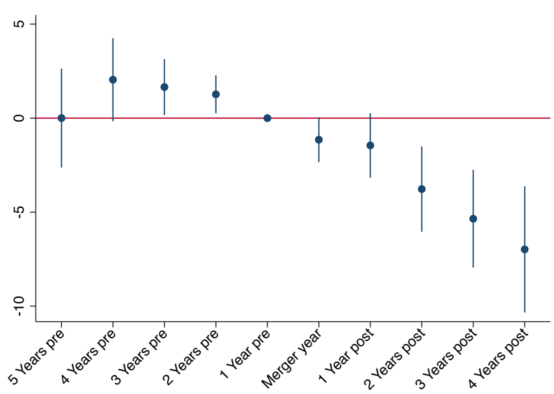


Figure 1.15: Event Study of Number of Services for Hospitals within 10-mile Mergers

(a) Targets within 10 miles



(b) Acquirers within 10 miles

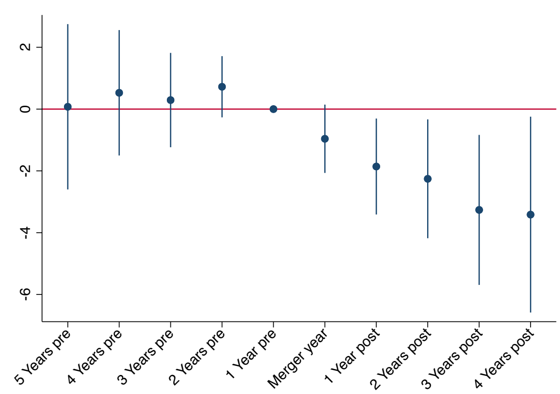


Figure 1.16: Post-Merger Change of Discharge Readmission in 0-10 mile Merging Hospitals, Discharges for Circulatory Diseases

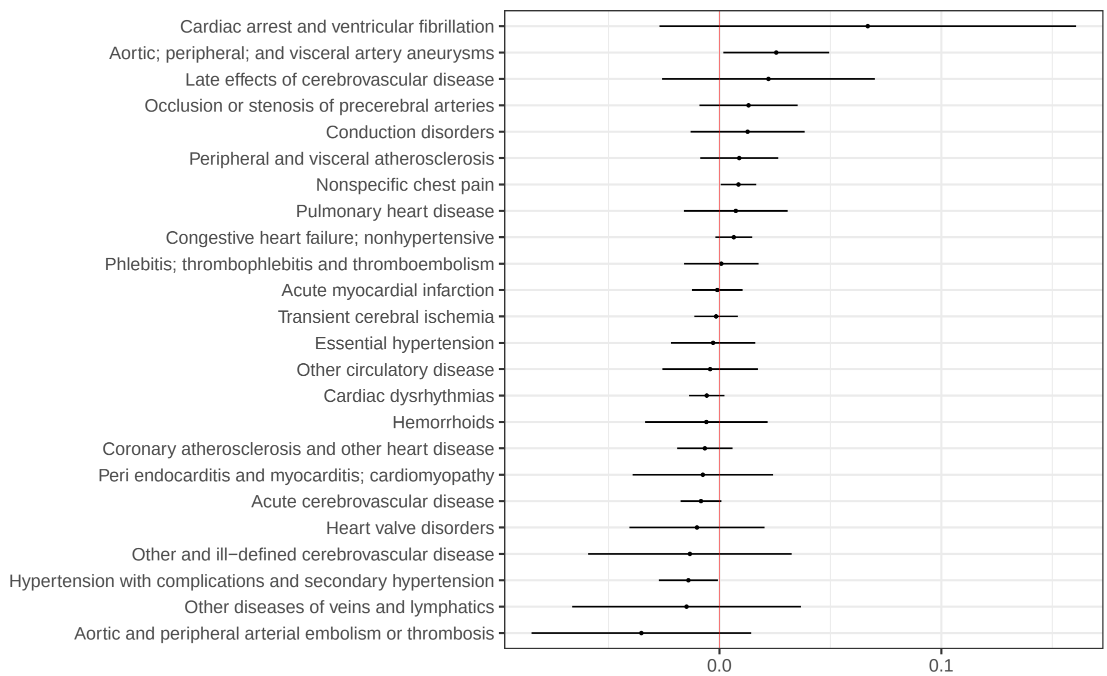
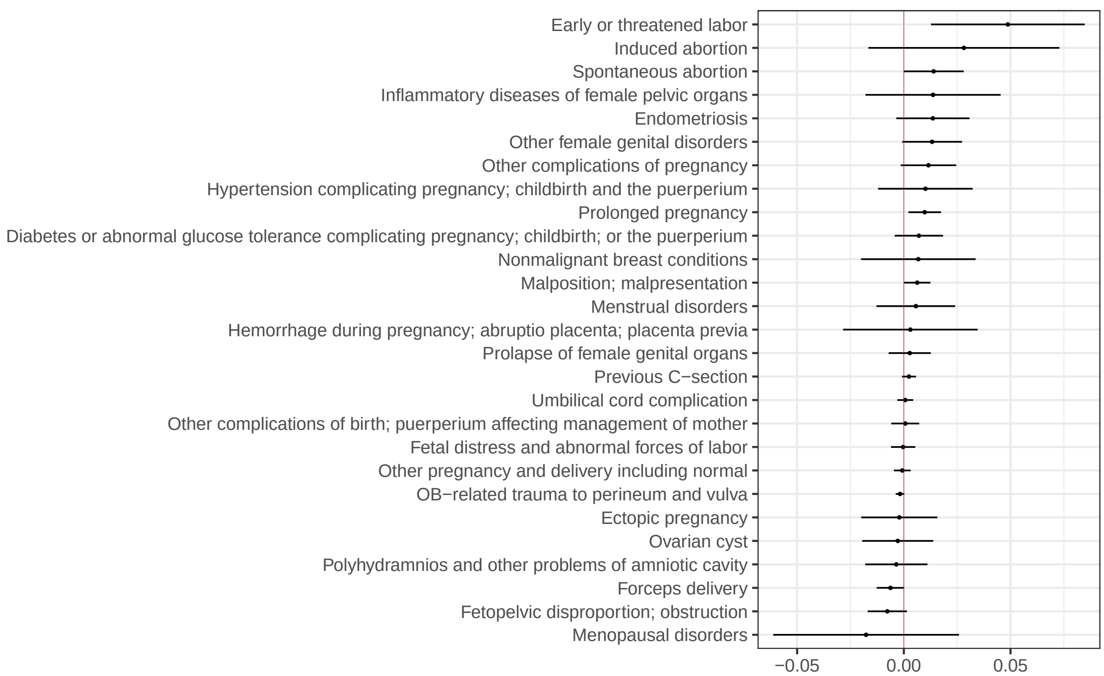


Figure 1.17: Post-Merger Change of Discharge Readmission in 0-10 mile Merging Hospitals, Patients for Birth Delivery and Female Genital



Chapter 2

Financial Incentives and Physician Treatment Decisions: Evidence from Lower Back Pain

with Chenyuan Liu

2.1 Introduction

Health care spending accounts for a large and increasing share of gross domestic product in the United States. In response, some payers deviate from the traditional fee-for-service payment model and have adopted the capitated payment model. Under capitation, physicians are compensated based on the number of patients they treat rather than the volume of services they prescribe. Payers who have adopted capitation payments claim that it can reduce the use of medical services and the provision of low-value care—two factors contributing to the high cost of health care. For instance, Shrank et al. (2019) estimated that the annual cost of overtreatment rose from about $75.7 billion in 2012 to $101.2 billion in 2019. The literature also documents a range of potentially low-value care.[1] Essentially, the capitated payment contract transfers all or part of the financial risk to the physicians, encouraging them to be accountable for the quantity and quality of services they provide. The recently established accountable care organizations in Medicare and private insurers are an example of a capitation payment model.

It can be challenging to assess whether capitated contracts lead to cost savings because there is selection into which providers and payers use capitation. For example, capitation contracts are more common in managed care plans such as health maintenance organizations (HMOs), and these plans may attract patients with lower medical needs rather than truly reduce unnecessary care. Understanding the source of any potential cost differences driven by capitation contracts is important in evaluating whether such incentives should be implemented more widely.

In this paper, we empirically examine the effects of capitated payment models on physicians' prescribing decisions. The movement toward managed care in the 1990s and early 2000s led to the growing popularity of capitation contracts in many places.[2] This historical movement toward capitation contracts provides an opportunity to study the issue. We focus on the treatment of lower back pain (LBP). The disease is economically significant: about 80% of the US population is affected by lower back pain at some point, and people with this condition spend more than $50 billion annually on treatment. More importantly, the treatment varies greatly across patients and providers (Smith, 2011). For example, using surgeries to treat lower back pain is costly, and the effects are unclear for most people (Mirza and Deyo, 2007; Goodney et al., 2015). However, more than 1.2 million spinal surgeries are performed each year, and the number of elective lumbar fusion surgeries increased by 62.3% from 2004 to 2015 (Martin et al., 2019). This raises the question of the efficacy of the treatment, and whether the capitated payment model helps reduce the overuse of surgery for treating lower back pain.

[1] Examples include treatment of marginally-ill patients (Currie and Slusky 2020; Alalouf et al. 2019), long-term care (Einav et al., 2018), heart disease treatment (Chandra and Staiger, 2017), and C-section (Jacobson et al., 2013).

[2] For example, Ho and Pakes (2014) document that in 2003 74% of primary care physicians in California were paid under capitation.

To collect data for the period 2003–2006, we use Truven MarketScan, a large commercial insurance claim data set based on the working-age US population. We construct and identify around 80,000 episodes treating lower back pain. For each episode, we identify the primary care physicians who refer patients to subsequent care. We directly observe from the data whether these physicians are paid under capitation, and we use this information as the key independent variable.[3] For each episode, we also construct a treatment intensity measure based on the weighted sum of the procedures performed. We construct the weights using a hedonic regression, where we regress price on procedure code dummy variables, patient age, and gender using noncapitated contracts, and we predict the average price for each procedure code. By taking this step, price variation is removed from the data and we are able to focus only on variation in utilization.

We use a fixed-effects model to control for patient and physician selection into a capitation payment arrangement. First, patients who are treated by a primary care physician under a capitated plan may differ from other patients. To address this selection problem, we control for patient demographic information and chronic conditions generated from past claims. We also identify patients who stay in the same set of plans over the sample period and control for the plan-group fixed effects. Variation in capitation within a plan-group can be generated either from a plan contracting with multiple providers with different capitation contracts or from employers switching plans—for example, from a traditional plan to a managed care plan—over time. This procedure allows us to control for unobserved patient selection into capitated plans. We also control for physician fixed effects to account for physician selection into capitated contracts. This leverages the variation of within-physician capitation arrangements, because the same physician may contract with multiple plans and the capitation contracts are bargained separately.

We find that patients referred by primary care physicians in a capitated plan experience a moderate reduction in their overall treatment intensity. The overall

[3]We use the capitation status of the primary care physician as the measure of capitation. Given that patients are often treated by multiple physicians and capitation status of these physicians is correlated, we interpret our results as identifying the effects of capitated episodes rather than the capitated primary care physician alone.

treatment intensity is 25% lower for patients in a capitated model than for other patients under no control, and the difference dropped to 4% to 10% when controlling for patient individual characteristics and different fixed effects. The treatment difference is mainly driven by the utilization of diagnostic testing (21%), therapy (14%), and drugs (13%). There is almost no difference in the use of surgery.

We also find that the differences in treatment lead to very little difference in the subsequent likelihood of LBP-related claims. For a fraction of patients in our benchmark sample who we were able to track over the next four years after the end of their episodes, we find that those in a capitated system have a very similar likelihood of having another LBP-related episode one to four years after the end of their last episode. This finding suggests that capitation is effective in reducing the use of treatment in LBP episodes without causing negative treatment outcomes.

This paper contributes to the growing literature studying whether the capitated payment model reduces unnecessary care. Researchers have found mixed evidence on the impact of capitated contracts on the cost and quality of health care. Some studies provide evidence that capitation leads to lower costs (Gaynor et al., 2004; Ho and Pakes, 2014; Andoh-Adjei et al., 2018), while others show a limited effect of capitation in controlling total health care expenditure or improving health care quality (Altman et al., 2003; Duggan, 2004; Kontopantelis et al., 2015; Zhang and Sweetman, 2018). Many studies examine the effects of capitated arrangements using cross-plan or cross-insurer variation (e.g., Altman et al. 2003, Ho and Pakes 2014). The problem with such an approach is that capitation often exists along with other cost-control methods, such as a narrow network, utilization authorization, and selected covered benefits (Glied and Zivin, 2002). We offer new insights by leveraging episode-level variation in capitation and use plan-year fixed effects to separate the effects of capitated contracts from other cost-control methods. This study also contributes to the literature by considering employer-sponsored plans of a large-scale national sample, as opposed to plans only in a specific state (Ho and Pakes, 2014) or only Medicare/Medicaid plans (Duggan, 2004).

More broadly, our work advances the literature exploring physician behaviors and the organization of care. Recent research finds that physicians respond strongly to financial incentives, including payments from drug firms (Carey et al., 2020), reimbursement from Medicaid (Alexander and Schnell, 2019) and Medicare (Einav et al. 2018; Maclean et al. 2018), physician ownership of practices (Howard et al., 2017), and episode-based payment (Carroll et al., 2018), etc. Our results indicate that physicians respond to the capitated compensation model in the treatment of lower back pain.

The rest of the chapter is organized as follows. Section 2.2 provides background information on lower back pain and capitation contracts. Section 2.3 presents the empirical strategy. The results are presented in Section 2.4. Section 2.5 concludes.

2.2 Background

2.2.1 Lower Back Pain

Lower back pain (LBP) is defined as "pain in the area on the posterior aspect of the body from the lower margin of the twelfth ribs to the lower gluteal folds with or without pain referred into one or both lower limbs that lasts for at least one day" (Deyo et al., 2015). LBP affects most adults, causes disability for some, and is a common reason for seeking healthcare (Deyo et al., 2015). According to the estimation of Luckhaupt et al. (2019), 26.4% of US workers have LBP, 8.1% have frequent and severe LBP, and 5.6% have work-related LBP.

Despite the prevalence of LBP, generally accepted guidelines for treating LBP are absent (Koes et al., 2010). The diagnostic methods include medical history and physical exam and imaging tests. When combined with clinical evaluations, imaging tests may help diagnose spinal problems. However, imaging tests are not always associated with clinically meaningful benefits, and they can even be harmful. In addition, many imaging tests poorly predict which patients will benefit from surgery (Chou et al., 2011; Goodney et al., 2015). Nevertheless, the utilization of imaging tests is high in the United States. For instance, Schwartz et al. (2014) estimated that annual Medicare spending on imaging for uncomplicated LBP ranges from $82 million to $226 million, which does not include costs associated with follow-up testing and care due to the results.

There is no consensus on the best way to treat LBP. Treatments for lower back pain include medications, noninterventional treatments such as physical therapy and exercise programs, and interventional spine surgeries and procedures. Surgical procedures range from well-established approaches for discectomies and spinal canal decompression to multiple means of addressing segmental fusion using several different approaches, materials, instruments, and indications. However, medical researchers find limited evidence to support the use of many interventional surgical procedures (See Friedly et al. (2010) for a review of the literature.) Meanwhile, the utilization of LBP surgeries continues to increase. For instance, the rate of spinal fusion operations for stenosis increased 67%, from 31.6 per 100,000 Medicare beneficiaries in 2001 to 52.7 per 100,000 Medicare beneficiaries in 2011 (Goodney et al., 2015). Disagreement also exists regarding the benefits of physical therapy, and "international guidelines contain conflicting recommendations for manipulation and exercise therapy" (Koes et al., 2001; Chou et al., 2007). Fritz et al. (2012) and Fritz et al. (2015) find a large variation among physicians about whether to use and when to use physical therapies.

In summary, due to LBP's proliferation and wide variation in the treatment choices, we concentrate on LBP to examine how the capitation arrangement influences the treatment decisions of physicians.

2.2.2 Capitation

To control health care expenditures, payers may replace a fee-for-service payment model with a capitated payment model by paying physicians based on the number of patients they treat instead of the volume of services they prescribe. Capitation contracts are most common with HMO plans and are less common with preferred provider organization plans. But even among HMO plans, there is large variation in whether capitation contracts are used. For instance, according to Zuvekas and Cohen (2010), only 15%–33% of physician office visits for private HMO plan enrollees are under a capitation arrangement.

The forms of capitation payments can vary. One extreme is the global capitation payment system, which bundles all providers and covers the cost of all services received by patients, including inpatient hospital stays. At the other extreme is payment that covers only the services provided by the primary care physician or physician group. The latter type is almost always accompanied by "shared risk arrangements," under which a target is set for total spending. Cost savings or overruns relative to the target are shared between the primary care physicians and the insurers. Overall, the capitation payment system deviates from the traditional pay-for-volume model and generates incentives for physicians to share the financial risk of a patient's entire treatment episode.[4]

The capitation payment model appeared in the 1980s and thrived with the proliferation of HMOs. The rate of capitation payment among physicians has decreased since the early 2000s (Zuvekas and Cohen, 2010). Recent years have seen new reforms toward a bundled payment model and Medicare accountable care organization initiatives; these variations of the capitation idea are intended to create financial incentives for physicians to curb medical expenditures (Friedberg et al., 2015).

2.3 Empirical Strategy

2.3.1 Data and Sample

The data for this study are from the Truven MarketScan Commercial Claims and Encounter Data from 2003 to 2006.[5] It is a large commercial insurance claim data set based on the working-age US population. For each claim record, the data set provides diagnosis and procedure codes and detailed payment information. We can directly observe whether a claim is paid under capitation, which allows us to compare the effect of capitation payment on treatment intensity. Because the Truven MarketScan data also track enrollees over time, we can observe an

[4]See Ho and Pakes (2014) for details about capitation arrangements.

[5]2003 is the first year the capitation measure is reported. Starting in 2007, few observations are under capitation.

individual's full history of medical service use. We also observe other demographic and socioeconomic characteristics, including age, gender, and employment status.

We construct a sample of patients with nonemergency LBP-related episodes. To build this sample, we identify a patient's claim encounters with LBP-related diagnoses and assign these encounters into episodes by time.[6] An LBP episode starts from a patient's earliest LBP encounter, followed by subsequent encounters with a time gap shorter than 180 days. An episode ends if there is no additional LBP encounter within 180 days of the last record. Two consecutive LBP encounters that occur more than 180 days apart are designated as two separate episodes.[7] We then keep only episodes that initiated from a primary care office visit.[8] Finally, we remove from the data set pregnant women, people under age 18 or over age 65, and people with severe chronic diseases.[9] We also exclude episodes involving emergency care or out-of-network encounters, because we want to focus on the non-urgent development of treatment.[10] In total, the sample includes 82,156 episodes from 76,407 patients.

The key independent variable of capitation is defined based on the payment arrangement of a patient's primary care physician. We choose primary care physicians because they play a critical role in deciding different treatment options. They are also most frequently targeted by capitation arrangements. When a capitation

[6]We follow Cherkin et al. (1992) to define the LBP diagnosis. The specific International Classification of Diseases (ICD-9) diagnosis codes for lower back pain are presented in Table B.4 in the Appendix.

[7]Most individuals have one episode during the sample period. Table B.3 in the Appendix displays the robustness of our main results using episodes defined based on a 90-day window rather than a 180-day window.

[8]Episodes that begin with surgical treatment or urgent care may be different from episodes that begin with primary care physicians. Such episodes might be more acute, or part of the episode might not be included in the data set.

[9]The chronic conditions we rule out include colorectal cancer, lung cancer, female/male breast cancer, endometrial cancer, prostate cancer, Alzheimer's disease and related disorders or senile dementia, heart failure, acute myocardial infarction, stroke/transient ischemic attack, and hip/pelvic fracture.

[10]Occasionally, in-network physicians may refer patients to out-of-network facilities or providers. But patients might also use out-of-network facilities without referral, which we want to rule out. Since we cannot distinguish the actual referral pattern in the data, we drop from the sample all out-of-network episodes.

arrangement is set up, insurers often remunerate primary care physicians through fixed monthly payments per patient to cover the cost of patient services. Primary care physicians can also be rewarded for savings from the entire episode. Therefore, the capitation arrangement generates a financial incentive for primary care physicians to save on patient treatment.[11] Even though the process by which a patient receives medical treatment involves multiple players, primary care physicians can influence the treatment intensity of the entire episode. A primary care physician under a capitation arrangement can decrease the treatment intensity for patients (for example, prescribing fewer physical therapy sessions), or the physician can refer patients to specialists who are less likely to prescribe expensive treatments, or who charge lower price for the same service.[12]

Patients in capitated plans seem to be healthier. The sample defined above includes 10,274 capitated LBP episodes and 71,882 noncapitated episodes. In Table 2.1 we compare the patient individual characteristics of capitated and noncapitated episodes. The patients in capitated plans are slightly younger than their counterparts receiving treatment in a noncapitated system, and they are less likely to have chronic conditions. We also find that patients who receive care in a capitation arrangement are more likely than others to be paid hourly and to work part-time.

2.3.2 Treatment Intensity Measures

We construct the overall treatment intensity measure for medical services based on the procedures used in each episode. In our sample, we observe a primary procedure code associated with each medical claim. An episode often contains tens to hundreds of medical claims and procedure codes. To aggregate all procedures at the episode level, we calculate the weighted sum of all the procedures performed

[11]In our data, we do not observe the specific financial terms of the capitation arrangements; rather, we observe whether a claim is paid under capitation. The capitation status may represent different types of capitation contracts.

[12]The capitation status of primary care physicians and downstream providers (such as radiologists, surgeons, and therapists) is positively correlated in our data. One should think of the treatment effects as not only from the capitated primary care physician but as representing the capitation status of the entire episode.

in that episode, where the weights are the expected average price of each procedure $\bar{p}_z$:

$$t = \sum_z \bar{p}_z f_z, \tag{2.1}$$

where f_z is the quantity of each procedure code z, and $\bar{p}_z$ is the weight.

For each medical claim, we observe the price p as the sum of the insurer payment to the provider, including consumer cost-sharing. This price represents the overall resources used for each procedure and captures price variation among insurers and providers. Since our focus is on understanding utilization patterns, we want the measure of treatment intensity to reflect only differences in service utilization but not differences in prices for services across different contracts. To eliminate the role of prices, we calculate the average price of each procedure by regressing price on the patient's age, gender, and chronic conditions. We control for these patient characteristics because they might affect the resources used. In this estimation step, we only use the claims from noncapitated claims, because the price is often not accurately reported for capitation contracts. We then predict the price for all claims with that procedure code to get $\bar{p}_z$.

The treatment intensity measure has a bimodal distribution and is highly skewed. Most people receive minimum or no treatment, while some patients receive very intensive treatment. To account for the skewness of the data, we transform the raw treatment intensity measure into log scale using the inverse hyperbolic sine transformation:

$$IHS(t) = log(t + \sqrt{t^2 + 1}).$$

The inverse hyperbolic sine transformation behaves similar to log and preserves zero as zero. As shown in Table B.1 in the Appendix, the main results are robust using the raw value.

For each episode, we can also construct the treatment intensity measure for different medical services. We classify LBP-related medical claims into five categories: office visit, diagnostic testing, therapy session, surgeries directly related to LBP treatment, and other surgeries.[13] We also construct a dummy variable indicating whether each type of service is used at all in an episode. Every observation will have an office visit, but some may not have other services.

Table 2.2 shows the summary statistics of the outcome variables. The average treatment intensity for all services within an LBP episode for patients in a capitation system is around \$438, while that of patients in other types of plans is \$590. The average treatment intensity is significantly higher for patients in noncapitated plans for nearly all categories of service except for back surgery. Meanwhile, the out-of-pocket expenditures of patients in noncapitated plans are also significantly higher regardless of the category of service they receive.

For 75% of the episodes in our baseline sample, we observe whether there is any drug use, and the related drug claims. For these episodes, we identify LBP-related drug prescriptions and all subsequent refills for these prescriptions. We then construct a similar treatment measure for overall drug use, and also for the two most common types of drugs: opioids and muscle relaxants. To do so, we group drug claims by a national drug code. We then calculate the average per-day price for each drug by year. Finally, we multiply the average price by the number of days of supply to determine the per-drug spending. The episode-level total drug usage is the sum of the spending on all drugs. This usage measure takes the same price for a specific drug across different plans and insurers and reflects only usage difference, not price differences.

2.3.3 Regression Model

As noted in Section 2.3.1, selection is a potentially large problem in our data. As a first way to address the problem, we control for patient characteristics X, including age, gender, employment status, and the existence of chronic conditions:

$$y_{it} = \alpha + \beta_1 CAP_{it} + X_{it}\beta_X + t + \epsilon_{it}, \tag{2.2}$$

[13]We define LBP surgery based on Cherkin et al. (1992).

where y_{it} is either the log treatment intensity measure or a dummy variable indicating whether a certain service is used. CAP_{it} is a dummy variable indicating whether the patient is referred by a primary care physician under a capitation system. A time trend t controls for aggregate movement in treatment style over time.[14]

One important channel where selection might happen is when different patients choose different plans. For example, capitation contracts are more common in HMOs than in preferred provider organizations. The former also impose other cost-control tools, such as a narrower network. So variation in capitation status may reflect patients' selection into these different insurance plans. To address this concern, we want to control for plan fixed effects. To do so, we first classify patients as in the same group if they enroll in the same set of plans over the sample period. For example, if patient 1 chooses plan A in year 1 and plan B in year 2, patient 2 chooses plan A in year 1 and plan B in year 2, and patient 3 chooses plan C in year 1 and plan B in year 2, then only patients 1 and 2 will be classified in the same group, and patient 3 will be in another group. The plan group classification is hereafter referred to as plan fixed effects. We estimate the following equation:

$$y_{it} = \alpha + \beta_2 CAP_{it} + X_{it}\beta_X + \gamma_g + t + \epsilon_{it}, \tag{2.3}$$

where y_{it} is either the log treatment intensity measure or a dummy variable indicating whether a certain service is used. CAP_{it} is a dummy variable indicating whether the patient is referred by a primary care physician under capitation. X_{it} represents patients' demographic characteristics, γ_g are dummy variables for different plan groups, and t is the linear time trend. The estimated β_2 captures the treatment difference for patients in both capitated and noncapitated plans who have similar demographic characteristics and who are enrolled in the same set of plans over time.

The coefficient of capitation within a plan group, β_2, is identified based on two types of variations. First, a plan often covers multiple physician groups with differ-

[14]Time is included as a continuous variable because some episodes span multiple years.

ent capitation status. However, patients are less likely to actively select physicians in a capitation system based on their health status, because patients often cannot observe the specific capitation arrangement of a physician within a plan. Second, employers may switch plan types over time. For example, an employer might offer an HMO in year 1 and switch to a preferred provider organization in year 2, while the same set of employees remain in the risk pool. Controlling for plan fixed effects in this case is similar to controlling for individual fixed effects over time, where individuals remain in the same plans over time. Under the assumption that both sources of variation are not affected by active patient selection, β_2 will identify the true treatment effects of a capitation arrangement on physicians' treatment decisions.

We further decompose the treatment effects estimated in equation (2.3) into the cross-section variation (based on the first source of variation) and cross-time variation (based on the second source of variation) in the following two models:

$$y_{it} = \alpha + \beta_{21} CAP_{it} + X_{it}\beta_X + \gamma_{gt} + \epsilon_{it}. \tag{2.4}$$

$$y_{it} = \alpha + \beta_{22} CAP_{gt} + X_{it}\beta_X + \gamma_g + t + \epsilon_{it}. \tag{2.5}$$

Model (2.4) controls for plan-year fixed effects, so the variation in capitation is due only to the contract differences within a plan-year, and there is no cross-time variation. One benefit of this model is that it also separates the effects of capitation from other cost-control methods that vary at the plan level. Often capitation happens along with other supply-side cost-control methods, such as utilization authorization and referral restriction. These measures, however, usually vary across plans and are the same within a plan-year. By controlling for plan-year fixed effects, we can hold fixed the variation of other supply-side cost-control measures and identify the net effects of capitation.

Model (2.5) calculates the average capitation rates within a plan-year, CAP_{gt}, and we use this as the new independent variable. Since we control for plan fixed effects, the coefficient of CAP_{gt} reflects the change in capitation of a specific plan over time.

The second source of selection comes from the physician side. Physicians may have different preferences toward capitated arrangements and treatment philosophies, and they may actively select into capitation contracts based on their treatment style. For example, physicians who prescribe less intense treatment on average may be more willing to join a capitation contract. To address this type of selection, we control for physician fixed effects:

$$y_{it} = \alpha + \beta_3 CAP_{it} + X_{it}\beta_X + \delta_s + t + \epsilon_{it}, \tag{2.6}$$

where y is either the log treatment intensity measure $IHS(t)$ or a dummy variable indicating whether a certain service is used, and δ_s are dummy variables for different providers. β_3 will then capture the difference in treatment decisions for patients in both capitated and noncapitated arrangements who are treated by the same provider.

Similar to the plan fixed effects model, the coefficient of capitation for a physician, β_3, is identified based on two types of variation. First, the same physician may enter different contracts with different plans in the same year. Controlling for physician fixed effects in this case will remove the concern that a physician's treatment style is correlated with her or his decision to enter a capitation arrangement, because we compare the treatment within a year. Second, physicians may switch capitation arrangements over time. Controlling for physician fixed effects in this case will remove time-invariant physician characteristics correlated with treatment and capitation choice. Under the assumption that there is no change in treatment philosophy that is correlated with the decision to switch between capitation contracts, the model will identify the true treatment effects.

We further decompose the treatment effects we estimated in equation (2.6) into the cross-section variation (based on the first source of variation) and cross-time variation (based on the second source of variation) in the following two models:

$$y_{it} = \alpha + \beta_{31} CAP_{it} + X_{it}\beta_X + \delta_{st} + \epsilon_{it}. \tag{2.7}$$

$$y_{it} = \alpha + \beta_{32} CAP_{st} + X_{it}\beta_X + \delta_s + t + \epsilon_{it}. \tag{2.8}$$

In model (2.7), β_{31} identifies differences in the same physician's treatment decisions in the same year; it does not identify the effects if a physician switches from no capitation to treating only patients in a capitated plan. Anecdotal evidence indicates that physicians may not be able to vary their treatment decision among patients with different underlying reimbursement contracts in the same year. To the extent that this is true, a null effect in this model might not indicate that the true treatment effect is zero. Model (2.8) identifies how the treatment decision will change over time when physicians move from fewer patients in capitated contracts to more patients in capitated contracts.

Finally, we include both plan fixed effects and physician fixed effects in the same regression:

$$y_{it} = \alpha + \beta_4 CAP_{it} + X_{it}\beta_X + \delta_s + \gamma_g + t + \epsilon_{it}. \tag{2.9}$$

$$y_{it} = \alpha + \beta_5 CAP_{it} + X_{it}\beta_X + \delta_s\gamma_g + t + \epsilon_{it}. \tag{2.10}$$

Controlling for physician fixed effects removes the impact of time-invariant physician characteristics on capitation, and plan fixed effects removes the impact of time-invariant plan characteristics on capitation. Equation (2.9) controls for both of these effects separately in the same equation. Under the assumption that physician fixed effects are similar across different plans conditional on all other variables, this model controls both physician and patient selection. β_4 represents the treatment effects for similar patients treated by the same physician. In equation (2.10), we control the interactive term of plan fixed effects and provider fixed effects. Since there is no variation of capitation status for a plan-provider pair in the same year, β_5 identifies the effects of capitation using cross-time variation within a plan-provider pair.

Even though we cannot directly examine whether these fixed effects models remove all selection concerns, we can at least show that they reduce selection on observable patient characteristics. Figure 2.1 offers a comparison of the likelihood of having chronic conditions among patients in capitated and noncapitated plans. The first panel on the left contains the raw mean differences. Patients in a capitation system are less likely to have most of the chronic conditions without controls. Controlling for plan and provider fixed effects reduces the differences to almost zero for almost all chronic conditions. For example, patients under capitation are 7.5% less likely to have high blood fat (hyperlipidemia) than patients in other types of plans under no controls. The estimated difference for hyperlipidemia decreases to 4% once we add plan or provider fixed effects separately, and the difference is 2.6% when we include both plan and provider fixed effects. If unobservables are of a similar nature to observables, then our fixed effects model will account for the selection problem.

Anther way to assess whether plan and provider fixed effects removed the selection concerns is to estimate a model without controlling for individual characteristics:

$$y_{it} = \alpha + \beta_6 CAP_{it} + \delta_s + \gamma_g + t + \epsilon_{it}. \tag{2.11}$$

If β_6 is similar to β_4, then the fixed effects model is effective in removing selection concerns.

2.4 Results

2.4.1 Treatment

In this section, we present the results of treatment decisions for medical services and drugs.

Using Any Medical Services Figure 2.2 presents the impact of capitation status on the likelihood of patients using a certain category of service. The dependent variables are the dummy variables of using therapy (panel 1), back surgery(panel 2), other surgeries (panel 3), and diagnostic (panel 4) during a lower back pain (LBP) episode.[15] Each panel lists, from bottom to top, six specifications: raw difference without any controls ("no control"); controlling for patient characteristics and time trend ("individual"); controlling for time trend, patient characteristics, and plan fixed effects ("plan"); controlling for time trend, patient characteristics, and provider fixed effects ("provider"); controlling for year, patient characteristics, plan, and provider fixed effects ("provider, plan"); controlling for year, patient characteristics, and provider times plan fixed effects ("provider $\times$ plan").

Patients who are experiencing LBP episodes and treated by capitated physicians are less likely to have therapy and diagnosis testing. We observe that with no control variables, the patients in a capitated plan are 4.1% less likely to use any therapy treatment. Controlling for patient characteristics, this difference is 3.3%. When we further add plan fixed effects, the difference in likelihood decreases to 2%. When we include provider fixed effects instead of plan fixed effects, the difference changes to 1.6%. Further, there exists a 2.1% difference in the likelihood of using therapy between capitated and noncapitated patients if we control for provider and plan fixed effects at the same time. Finally, when we control for provider $\times$ plan fixed effects, there exists a difference at 1.3%.

For diagnostic testing, controlling for the provider and plan fixed effects leads to a difference of around 4% between capitated and noncapitated arrangements. Medical literature suggests that diagnostic testing has low value for most patients. Our findings indicates that capitation contracts are effective in reducing the usage of such services.

On the other hand, we do not observe that capitation status significantly influences the utilization of back surgery or other surgeries. This might be due to the fact that the surgeries are used mainly for very severe cases of LBP and are not excessive treatments that could be removed.

Treatment Intensity of Medical Services Table 2.3 shows the results with the treatment intensity of all services. The outcome variable is the inverse hyperbolic

[15]We do not include the office visit category here because every episode by definition contains an initial office visit to a primary care physician.

sine transformation of treatment intensity of all services. Column (1) shows that, with no controls, the patients in a capitation system utilize 25.2% fewer medical resources than patients in noncapitated plans. Column (2) addresses the concern that healthy patients may endogenously select into capitated plans by controlling for patient individual characteristics. Under this specification, we find that treatment intensity is 16.4% lower with capitated episodes. Further controlling for the plan fixed effects in Column (3) shows that capitation results in a difference of 10.2% in overall treatment intensity. In Column (4), we control for provider fixed effects and patient characteristics. The difference in treatment intensity between capitated and noncapitated plans is 4.4%. Column (5) simultaneously addresses the concern of patient selection and provider selection by controlling plan fixed effects and provider fixed effects. We find that capitation reduces treatment intensity by 9.4%. One way to evaluate whether the fixed effects model is effective in controlling for selection is to remove patient characteristics from the regression and see whether the results are similar. As shown in Column (6), removing patient characteristics yields very similar estimates, which means provider and plan-group fixed effects are adequate to absorb the impact of individual-level observable differences. Finally, Column (7) shows the effects of capitation based on cross-time variation within a provider-plan pair. For this specification, we are not able to use all the observations in the sample and the standard errors are larger, yet we still find a modest (though not significant) reduction in treatment intensity.

Figure 2.3 shows the results with treatment intensity by medical service categories. The dependent variables are the inverse hyperbolic sine transformation of treatment intensity for certain service categories. When we compare the raw differences with no control variables, capitation is related to significant decreases in treatment intensity, ranging from 4.5% to 30.0%. However, when patient individual characteristics, provider, and plan fixed effects are jointly controlled, the results indicate that primary care physicians' capitation status does not significantly influence the intensity of office visits, back surgery, and other surgeries. Capitation mainly impacts the utilization of therapy and diagnostic testing, decreasing the treatment intensity by 13.5% and 20.6%, respectively.

Table 2.4 and 2.5 display the effect of capitation on the treatment intensity of all services by cross-sectional and cross-time variation. Table 2.4 show separate results of capitation variation within a plan with cross-section variation and with cross-time variation. Column (1) uses the same specification as Column (3) in Table 2.3, controlling for time trend, patient characteristics, and plan fixed effects. In Column (2), we absorb the cross-time variation of the insurance plan's capitation arrangement by controlling the plan $\times$ year fixed effects. This specification shows that the treatment intensity of patients treated by capitated physicians is 9.6% lower than that of patients treated by noncapitated physicians. This difference is solely driven by capitation status and is not driven by any other supply-side cost-control methods varying between but not within a plan year.

In Column (3), we replace the capitation status of an episode by the average capitation rate of a plan within a year. This specification leads to all patients in the same plan-year getting the same capitation status and takes the plans' variation across years to identify the effect of capitation. The result indicates that a plan change from 0% of capitation to 100% capitation would lead to a 32.1% reduction in treatment intensity. Column (4) changes the plan-year's average capitation rate to a dummy variable indicating whether a plan-year has any capitation arrangement. This specification shows that having capitation with some physicians in a plan leads to a 10.4% reduction in the treatment intensity of all services relative to a plan with no capitated patients.

Similar to Table 2.4, Table 2.5 analyzes the effect of capitation using providers' cross-sectional and cross-time variation. Column (1) examines each episode's capitation status and controls for the provider fixed effects, time trend, and patient characteristics (similar to Column (4) in Table 2.3). The cross-time variation in providers' capitation status is shown in Column (2) by adding the provider $\times$ year fixed effect. This specification does not find a significant effect of capitation on treatment intensity. This may suggest that physicians are not able to vary treatment based on patients' insurance status within a year. Column (3) uses the cross-time variation of a provider's capitation status by using the provider-year's average capitation rate as the regressor. Under this specification, capitation on average results in a 10.7% reduction in treatment intensity. Finally, when we replace the average capitation rate in Column (3) with whether a provider-year has any capitated arrangement as in Column (4), the adoption of capitation status on average reduces the treatment intensity of all services by 9.2%.

Drug Utilization Figure 2.4 shows the results with drug utilization. Panel A analyzes the effect of capitation on whether an episode includes any LBP-related drug claims. The three specifications, from bottom to top, are the differences with no controls, controlling for individual characteristics, and simultaneously controlling for individual characteristics and plan fixed effects. We find that when controlling for patient individual characteristics, time trend, and plan fixed effects, the patients receiving care under a capitation arrangement are 2% less likely to use any drugs, 2.3% less likely to use opioids, and 3% less likely to use muscle relaxants.[16]

Panel B analyzes the impact of capitation on treatment intensity related to the use of drugs. After controlling for patient individual characteristics, time trend, and plan fixed effects, capitation results in an 11.9% reduction in the use of all drugs. Capitation also reduces the use of opioids and muscle relaxants by 2.6% and 10%, respectively.

2.4.2 Placebo Test: Emergency Room Visits

The previous results provide evidence that the capitation status of providers leads to reductions in the intensity of treatment for lower back pain. In this section, we use emergency room (ER) visits as a placebo test. We analyze ER visits that are unrelated to patients' LBP conditions.[17] Unlike LBP episodes, ER visits are typically initiated by patients with urgent conditions needing immediate care. The treatment patients receive during a visit to the ER should be less affected by primary care physicians.

[16]We do not control for provider fixed effects for the smaller drug sample because there are not enough observations to accurately identify capitation effects within a provider.

[17]Patients with LBP ER visits are excluded from our sample, as mentioned in Section 2.3.1.

For the same patient episodes identified in our baseline analysis, we construct several measures on the ER services utilization. First, we construct a dummy variable indicating whether a patient has at least one ER visit during the episode. The procedure codes related to ER visits also document the severity of the illness and the urgency for care (in five levels). We thus construct a measure for any ER visits, or any ER visits with the most severe conditions (Level 5). To reflect the overall utilization intensity, we also calculate the number of days with ER visits for all ER visits and ER visits with the most severe conditions, respectively. Finally, we construct a measure of the overall ER visit treatment intensity based on a weighted average of the number of procedures performed, where weights are calculated by average payment.

As shown in Figure 2.6, the capitation status of a patient's primary care physician has almost no impact on the patient's utilization of ER services. Patients with a primary care physician in a capitated plan are slightly less like to use any ER services (1%) under no controls, indicating selection into these services is much smaller, consistent with the nature of this type of utilization. After controlling for patient individual characteristics, the coefficients are almost zero, though the standard errors are larger when we control for provider fixed effects. The effects are even closer to zero using ER visits with severe conditions as dependent variables. The treatment intensity measures are more noisy with larger confidence intervals. But again, none of the coefficients are significant. These results show that our benchmark results are not driven by confounding factors that might affect the treatment intensity for all services.

2.4.3 Financial Outcome: Out-of-Pocket Expenditures

We examine the effects of capitated contracts on patients' expenditure by comparing the out-of-pocket spending of patients treated by capitated physicians or not. The difference in out-of-pocket spending can come from three sources: difference in treatment decisions, differences in the price insurers paid to providers, and the difference in consumer cost-sharing. Capitated contracts may involve less treatment.

As a result, insurers may pay less to the providers overall. Insurers may also pass a higher proportion of the cost savings to consumers. In fact, literature has argued that supply-side cost control methods like capitation are often substitutes for demand-side cost-sharing (Ellis and Zhu 2015). So consumers under capitated plans may face even lower spending as a result of more generous coverage.

Unfortunately, capitated claims often do not record the price insurers paid. This is because in nature capitated physicians are compensated based on multiple services and may share their payments with others, and it is difficult to map the true compensation into itemized services. As such, we are not able to accurately measure the price effects. Instead, we focus on the difference in out-of-pocket spending as these measures are accurately documented. For each episode, we aggregate consumer payment towards deductible, copayments and coinsurance. We also separate them into different categories. Finally, we take the inverse hyperbolic sine transformation of the out-of-pocket spending.

Table 2.6 presents the results with the out-of-pocket expenditures for all services. Column (1) shows that capitation patients' out-of-pocket payments are 73.1% lower compared with noncapitated patients. Column (2) addresses the observable patient heterogeneity by controlling for the patient individual characteristics and shows that capitation patients pay 64.9% less in their out-of-pocket expenditures. When we further control the plan level unobservables by adding plan fixed effects in Column (3), we observe a 19.4% difference between capitated and noncapitated patients. In column (4), patient characteristics and provider fixed effects are controlled, and the within-provider capitation status difference leads to a 59.3% decrease in the out-of-pocket expenditures. In Column (5), we use patient individual characteristics, plan fixed effects, and provider fixed effects. It indicates that the capitation of primary care physicians leads to a 32.5% decrease in the out-of-pocket expenditures for all services. Compared with Column (5) in Table 2.3, capitation's savings on out-of-pocket expenditures are larger than the savings on treatment intensity by more than 20%. This suggests that given the same treatment intensity, capitated patients pay less compared to patients in noncapitated plans.

Figure 2.5 shows the estimated results by service categories. When no patient and provider heterogeneity are controlled, the out-of-pocket expenditures are significantly lower for capitated patients, regardless of service categories. However, when patient individual characteristics, plan fixed effects, and provider fixed effects are included, the capitation status of primary care physicians mainly influences office out-of-pocket expenditures on office visits by decreasing 27.2%. We do not observe significant differences in other categories. The reason could be that the largest fraction of out-of-pocket expenditures is spent on physician office visits.

2.4.4 Readmission Rates

The previous sections describe modest treatment differences between patients who are being treated by a physician in a capitated plan and those receiving treatment by a physician under a noncapitated arrangement, especially for therapy and diagnostic testing. A natural question is whether this treatment difference represents a reduction in overtreatment or indicates undertreatment by capitated physicians. Understanding the question is important for understanding the welfare implication of the capitated payment model.

One way to measure the quality of care is to compare the readmission rates for lower back pain. If a reduction in treatment for patients in a capitation system leads to readmission for lower back pain, then the differences may reflect underuse of valuable care. On the other hand, if we find that patients in a capitated plan have similar likelihood of having a lower back pain diagnosis in the future, then this indicates that capitation might reduce overtreatment.

We construct readmission measures by tracking patients in our sample over time. We are able to track about 65% of the baseline sample over the next four years. We examine whether these patients have any LBP-related diagnosis in the four years after the end of their episodes. We then run a regression of this readmission measure on their original capitation status with other controls and fixed effects specified in Section 2.3.3.

Figure 2.7 shows the results of our analysis. In general, after controlling for individual characteristics and plan fixed effects, patients receiving treatment under a capitation arrangement are either slightly less likely to be readmitted for LBP, or the differences are not significant.

2.5 Conclusion

This paper explores the effect of capitated payment models on the treatment of lower back pain in employer-sponsored health insurance plans. We find that patients who are referred by primary care physicians under capitated contracts receive significantly less treatment. The overall treatment intensity is 10% lower. Capitation contracts reduce the utilization of therapy, diagnostic imaging, and drugs such as muscle relaxants, but capitation contracts have almost no effect on surgeries or the prescription of opioids. Our identification relies on the panel feature of the claim data. Although patients rarely have multiple LBP episodes, we identify a group of people who are enrolled in the same plan over time and control for the plan and group fixed effects. We also control for physician fixed effects to further isolate selection from true treatment effects.

We choose to study patients with lower back pain because evidence from the medical literature indicates that many of the services used to treat this condition have low value to patients. We find that capitation leads to differential treatment for otherwise similar patients, suggesting inefficiency in care from either undertreatment of patients under a capitated arrangement or overtreatment of patients in a noncapitated plan. More detailed data are needed to evaluate whether capitation moves treatment closer to the optimal level.

In our data, we do not observe the specific capitation arrangement details. Specifically, we do not observe how the incentives are shared among different physicians in a group, and whether they face dynamic incentives over time. Our sample period is one characterized by the declining popularity of capitation payment contracts. Physicians might not respond to the incentive if they did not stay in this type of contract for the following period, especially if some of the contracts offer dynamic incentives. The current movement toward value-based care may suffer from the same concern. More research is needed to understand the incentives of different capitation contracts, and how they affect patients' long-term health status.

Using only within-provider-year variation to identify the effects of capitation on treatment yields almost zero treatment effects, suggesting that physicians do not differentiate care for patients with different insurance plans in the same period. The treatment effects solely come from variations in the average capitation rates a physician faces over time. These findings are consistent with other empirical works providing evidence that treatment is homogeneous within a physician practice in the same year, even though the patients are from both fee-for-service plans and managed care plans (Glied and Zivin, 2002). Most physician groups in the United States contract with multiple insurers and face variation in their compensation incentives within the practice. However, the pattern is changing due to the recent trend toward fully integrated systems. For example, providers in certain vertically integrated health care systems, such as Kaiser, almost exclusively treat managed care patients from their own system. A natural next step is to study whether and to what extent fully integrated systems change physician behaviors relative to a simple capitation model.

Table 2.1: Summary Statistics of Capitated/Non-capitated Patients, Patient Characteristics

	Capitated		Non-capitated		Difference	
	mean	sd	mean	sd	mean	se
Demographics						
Female (%)	56.61	49.56	55.92	49.65	0.68	0.52
Age	43.79	10.94	44.85	10.93	-1.07	0.12
Health Status (%)						
Acquired Hypothyroidism	5.54	22.87	7.74	26.72	-2.20	0.25
Anemia	4.20	20.05	5.91	23.59	-1.72	0.22
Cataract	2.62	15.97	3.40	18.13	-0.79	0.17
Obstructive Pulmonary / Bronchiectasis	5.67	23.14	7.25	25.93	-1.58	0.25
Chronic Kidney Disease	1.90	13.65	1.89	13.63	0.00	0.14
Diabetes	7.97	27.09	9.35	29.12	-1.38	0.29
Hyperlipidemia	20.75	40.55	28.40	45.10	-7.65	0.43
Depression	8.32	27.62	9.47	29.28	-1.15	0.29
Hypertension	19.28	39.45	26.60	44.19	-7.32	0.42
Glaucoma	2.64	16.03	3.53	18.45	-0.89	0.17
Ischemic Heart Disease	3.70	18.87	5.36	22.51	-1.66	0.20
Atrial Fibrillation	0.59	7.68	0.80	8.88	-0.20	0.08
Asthma	5.99	23.72	5.97	23.68	0.02	0.25
Benign Prostatic Hyperplasia	1.51	12.19	2.61	15.96	-1.11	0.13
Rheumatoid Arthritis/ Osteoarthritis	14.12	34.83	18.57	38.89	-4.45	0.37
Osteoporosis	2.84	16.62	2.94	16.90	-0.10	0.18
Compensation Classification (%)						
Salary Non-union	2.99	17.03	11.67	32.11	-8.69	0.21
Salary Union	0.18	4.18	0.88	9.31	-0.70	0.05
Salary Other	0.05	2.21	1.02	10.03	-0.97	0.04
Hourly Non-union	1.35	11.55	8.49	27.87	-7.14	0.15
Hourly Union	4.33	20.36	7.20	25.85	-2.87	0.22
Hourly Other	0.02	1.40	1.06	10.22	-1.04	0.04
Non-union	3.39	18.09	7.73	26.71	-4.35	0.20
Union	0.15	3.82	1.56	12.40	-1.41	0.06
Unkown	87.55	33.02	60.39	48.91	27.16	0.37
Employment Status (%)						
Active Full Time	17.88	38.32	45.66	49.81	-27.78	0.42
Active Part Time or Seasonal	0.13	3.56	1.33	11.44	-1.20	0.06
Early Retiree	1.42	11.84	5.43	22.67	-4.01	0.14
Medicare Eligible Retiree	0.10	3.12	0.49	6.99	-0.39	0.04
Retiree (status unknown)	0.19	4.41	0.19	4.38	0.00	0.05
COBRA Continuee	0.07	2.61	0.53	7.26	-0.46	0.04
Long Term Disability	0.05	2.21	0.32	5.61	-0.27	0.03
Surviving Spouse/Depend	0.00	0.00	0.20	4.44	-0.20	0.02
Other/Unknown	80.16	39.88	45.85	49.83	34.31	0.44
Observations	10274		71882			

Note: The table shows the summary statistics of patient characteristics for capitated/non-capitated patients separately.

Table 2.2: Summary Statistics of Capitated/Non-capitated Patients, Outcome

	Capitated		Non-capitated		Difference	
	mean	sd	mean	sd	mean	se
Treatment Intensity						
all	438.08	1507.88	590.00	1586.65	-151.92	16.01
office visit	151.62	220.17	171.46	234.91	-19.84	2.34
therapy	49.21	262.10	97.95	404.82	-48.74	2.99
back surgery	81.91	981.26	97.37	968.28	-15.46	10.33
other surgery	67.44	485.61	101.54	583.88	-34.10	5.26
diagnostics	81.14	294.93	113.23	317.87	-32.09	3.14
Out of Pocket Expenditure						
all	45.95	148.22	129.70	376.75	-83.75	2.03
office visit	25.08	39.41	47.91	81.60	-22.84	0.49
therapy	7.53	50.78	23.36	107.03	-15.84	0.64
back surgery	4.65	92.34	13.08	242.57	-8.44	1.28
other surgery	3.50	32.50	15.53	108.24	-12.02	0.52
diagnostics	4.18	21.20	22.86	130.14	-18.68	0.53
Observations	10274		71882			

Note: The table shows the summary statistics of outcome variables for capitated/non-capitated patients separately.

Table 2.3: Treatment Intensity of All Services

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
capitated	-0.252***	-0.164***	-0.102***	-0.044	-0.094**	-0.088**	-0.053
	(0.029)	(0.036)	(0.036)	(0.041)	(0.037)	(0.037)	(0.058)
Observations	82,156	82,156	81,058	61,370	60,206	60,206	36,477
R-squared	0.004	0.042	0.073	0.326	0.352	0.335	0.403
Prov FE				×	×	×	
Plan FE			×		×	×	
Prov × Plan FE							×
Individual Characteristics		×	×	×	×		×

Note: The table shows the regression results comparing the treatment intensity of capitated/non-capitated patients. The dependent variable is the inverse hyperbolic sine transformation of treatment intensity of all services. Column (1) has no control variable. Column (2) controls for individual characteristics (chronic condition, employment status etc.). Column (3) controls for year, patient characteristics, and plan fixed effects. Column (4) controls for year, patient characteristics, and provider fixed effects. Column (5) controls for year, patient characteristics, plan and provider fixed effects separately. Column (6) controls for year, plan and provider fixed effects separately. Column (7) controls for year, patient characteristics, plan and provider fixed effects interactively. Standard errors are clustered at the data contributor level. *** p<0.01, ** p<0.05, * p<0.1

Table 2.4: Cross-sectional & Cross-time Plan Capitation Variation on Overall Treatment Intensity

	(1)	(2)	(3)	(4)
capitated	-0.102***	-0.096***		
	(0.036)	(0.035)		
average capitation rate of plan-year			-0.321**	
			(0.158)	
any capitated within plan-year				-0.104**
				(0.044)
Observations	81,058	79,849	81,058	81,058
R-squared	0.073	0.087	0.073	0.073
Plan FE	$\times$		$\times$	$\times$
Plan $\times$ Year FE		$\times$		

Note: The table examines the cross-sectional and cross-time variation of plan's capitation status change on the overall treatment intensity. The dependent variable is the inverse hyperbolic sine transformation of treatment intensity of all services. Column (1) controls for year, patient characteristics, and plan fixed effects. Column (2) controls for patient characteristics and plan $\times$ year fixed effects. Column (3) uses the similar specification as Column (1), but replaces the capitation status of each episode with the average capitation rate of the plan-year which the episode belongs to. Column (4) replaces the plan-year's average rate of capitation in Column (3) to the dummy that whether a plan-year has any capitation or not. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 2.5: Cross-sectional & Cross-time Provider Variation on Overall Treatment Intensity

	(1)	(2)	(3)	(4)
capitated	-0.044	0.007		
	(0.041)	(0.052)		
average capitation rate of prov-year			-0.107	
			(0.067)	
any capitated within prov-year				-0.092**
				(0.044)
Observations	61,370	47,094	61,370	61,370
R-squared	0.326	0.368	0.326	0.326
Prov FE	×		×	×
Prov × Year FE		×		

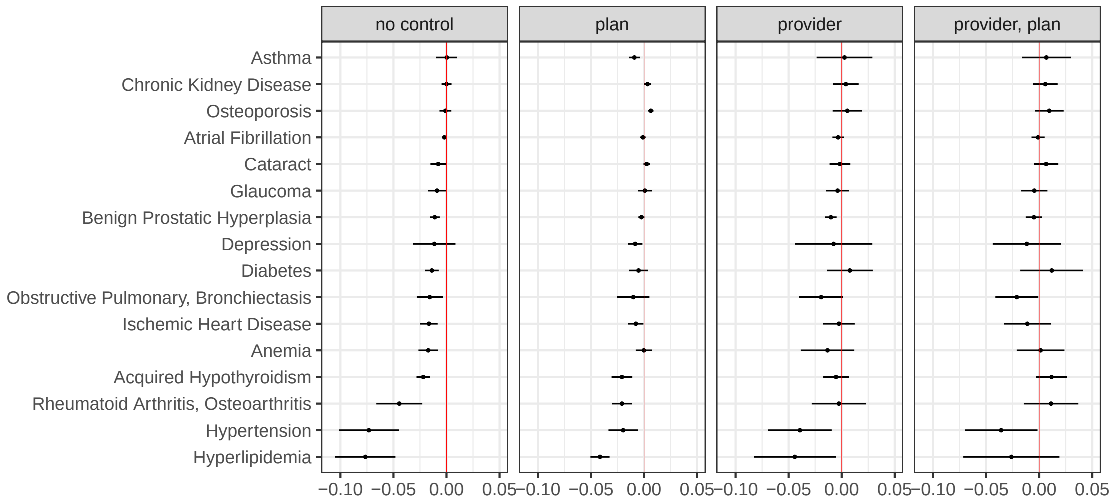
Note: The table examines the cross-sectional and cross-time variation of provider's capitation status change on the overall treatment intensity. The dependent variable is the inverse hyperbolic sine transformation of treatment intensity of all services. Column (1) controls for year, patient characteristics, and provider fixed effects. Column (2) controls for patient characteristics and provider × year fixed effects. Column (3) uses the similar specification as Column (1), but replaces the capitation status of each episode with the average capitation rate of the provider-year which the episode belongs to. Column (4) replaces the provider-year's average rate of capitation in Column (3) to the dummy that whether a plan-year has any capitation or not. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 2.6: Out-of-Pocket Expenditures of All Services

	(1)	(2)	(3)	(4)	(5)
capitated	-0.731***	-0.649***	-0.194***	-0.593***	-0.325***
	(0.136)	(0.177)	(0.060)	(0.103)	(0.102)
Observations	82,156	82,156	81,058	61,370	60,206
R-squared	0.023	0.049	0.205	0.365	0.432
Prov FE				×	×
Plan FE			×		×
Individual Characteristics		×	×	×	×

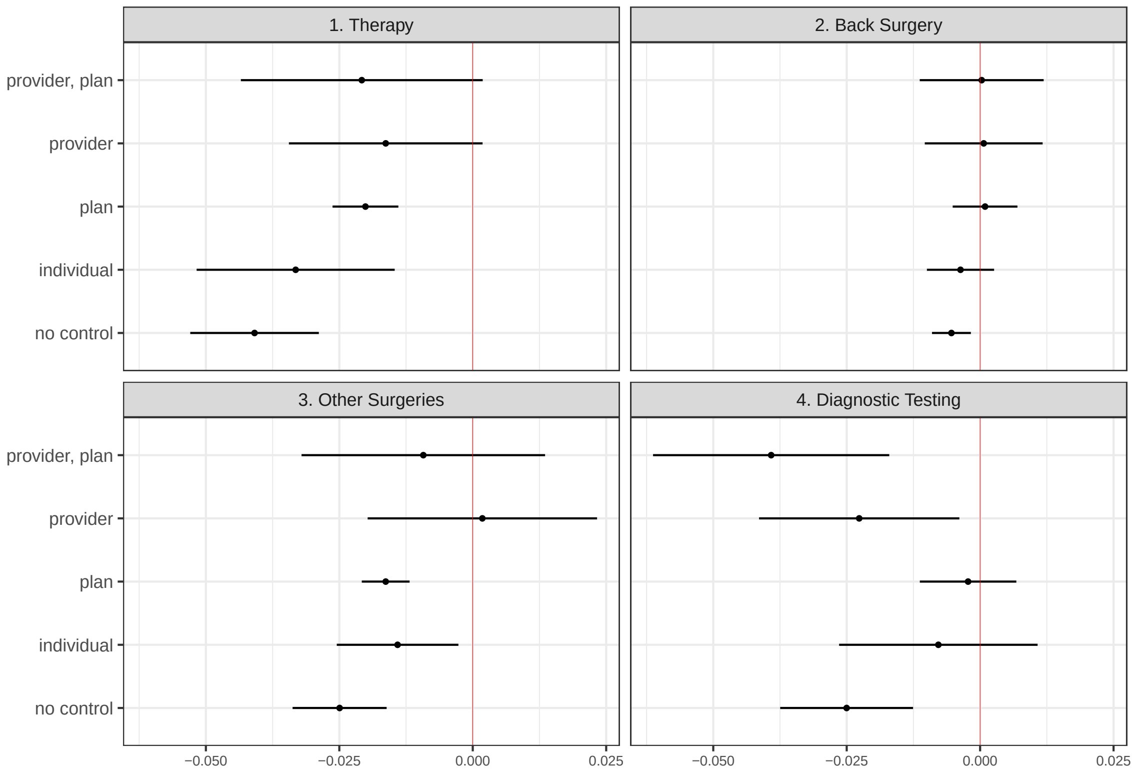
Notes: The table shows the regression results comparing the out-of-pocket expenditures of capitated/non-capitated patients. The dependent variable is the inverse hyperbolic sine transformation of out-of-pocket expenditures of all services. Column (1) has no control variable. Column (2) controls for individual characteristics (chronic condition, employment status etc.). Column (3) controls for year, patient characteristics, and plan fixed effects. Column (4) controls for year, patient characteristics, and provider fixed effects. Column (5) controls for year, patient characteristics, plan and provider fixed effects. Standard errors are clustered at the data contributor level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Figure 2.1: Chronic Condition Rate Differences between Capitated/Non-capitated Patients



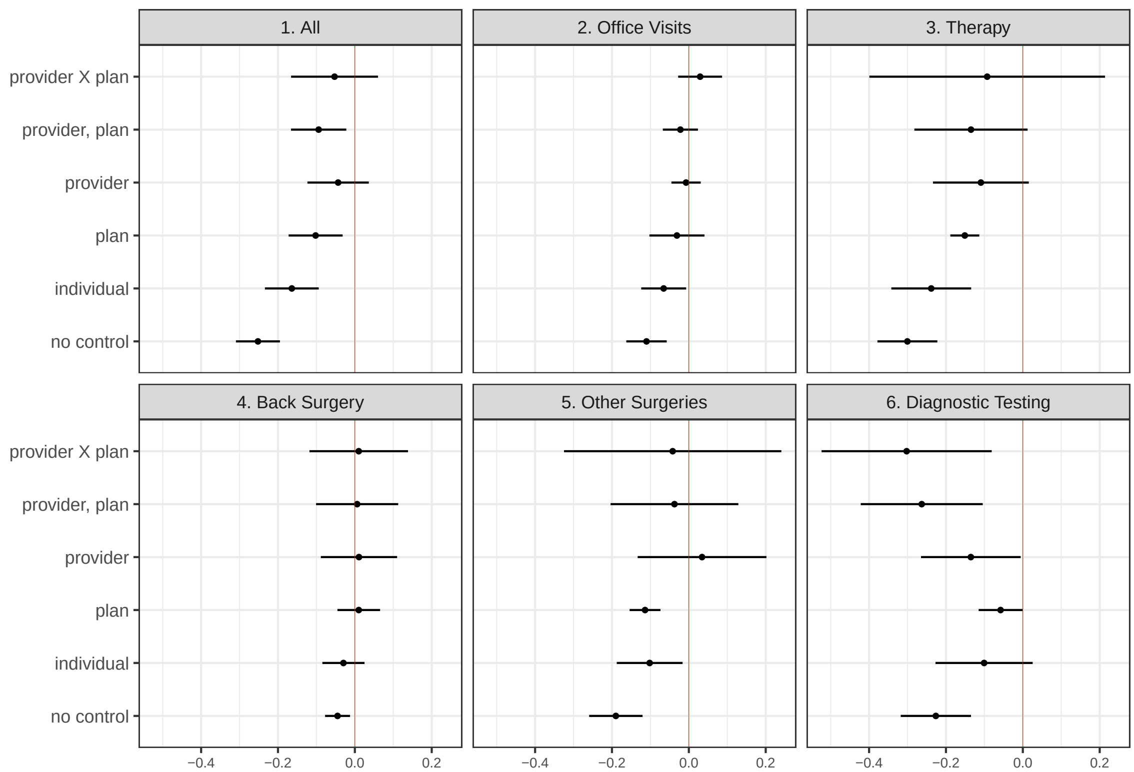
Notes: The figure shows the differences of chronic condition rates between capitated/non-capitated patients. The four panels from left to right indicates no controls, controlling for year, age and plan fixed effects, controlling for year, age and provider fixed effects, and controlling for year, age, plan and provider fixed effects.

Figure 2.2: Extensive Margin: Using Any Medical Services



Notes: The figure shows the estimated results that whether capitated patients use certain type of services compared to non-capitated patients. The dependent variables are the indicators of using any services of certain types. Panel 1 to 4 examines the usage of therapy services, back surgery, other surgeries, and diagnostic testing. Standard errors are clustered at data contributor level.

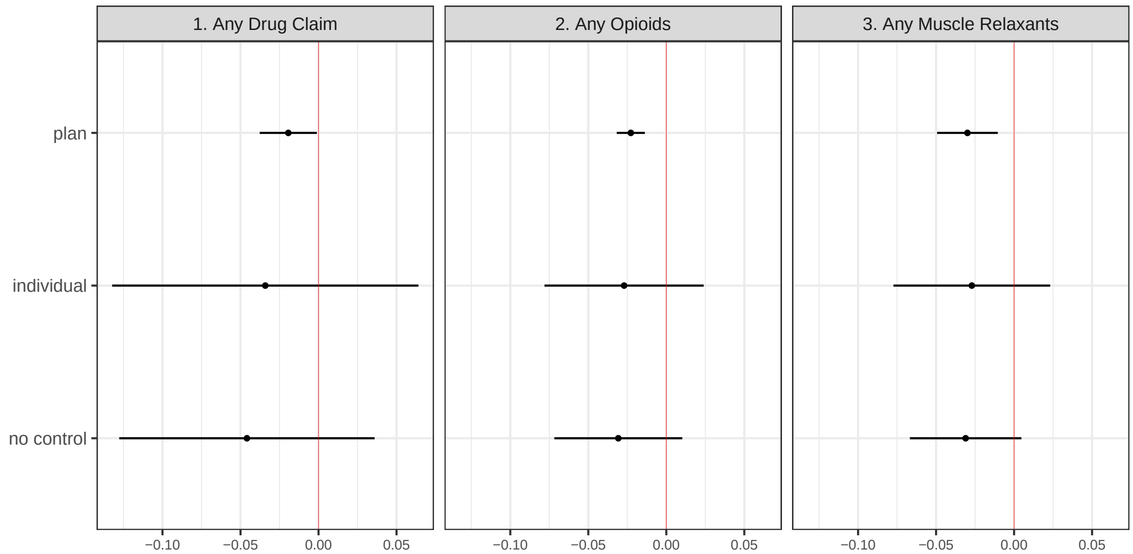
Figure 2.3: Treatment Intensity of Medical Services



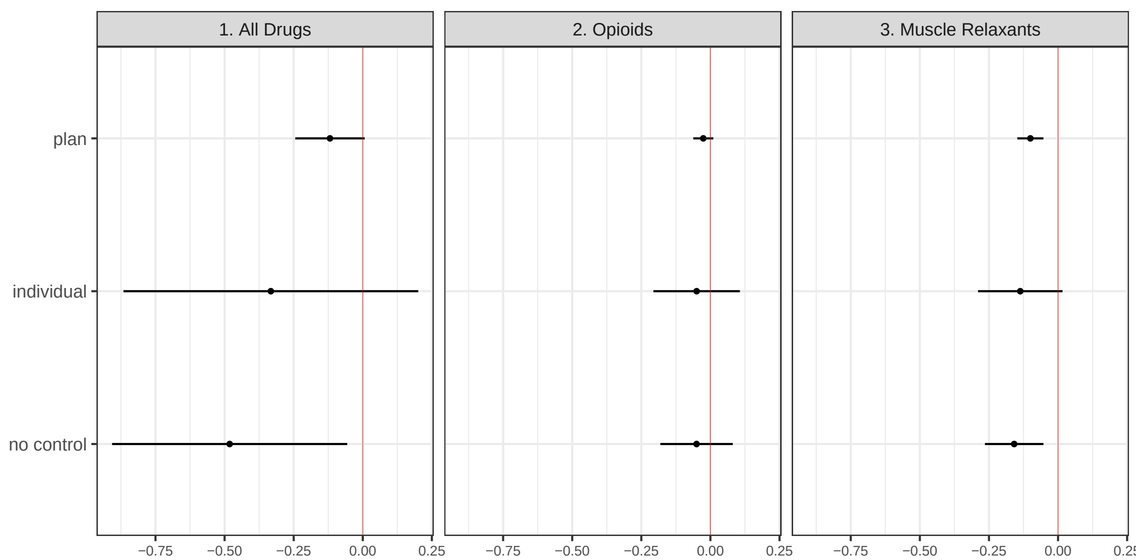
Notes: The figure shows the estimated results studying the treatment intensity differences of capitated and non-capitated patients. The dependent variables are the inverse hyperbolic sine transformation of treatment intensity. Panel 1 to 6 examines the effects with all medical services, office visits, therapy, back surgery, other surgeries, and diagnostic testing separately. Standard errors are clustered at data contributor level.

Figure 2.4: Drug Usage Intensity

Panel A: Any Drug Claim

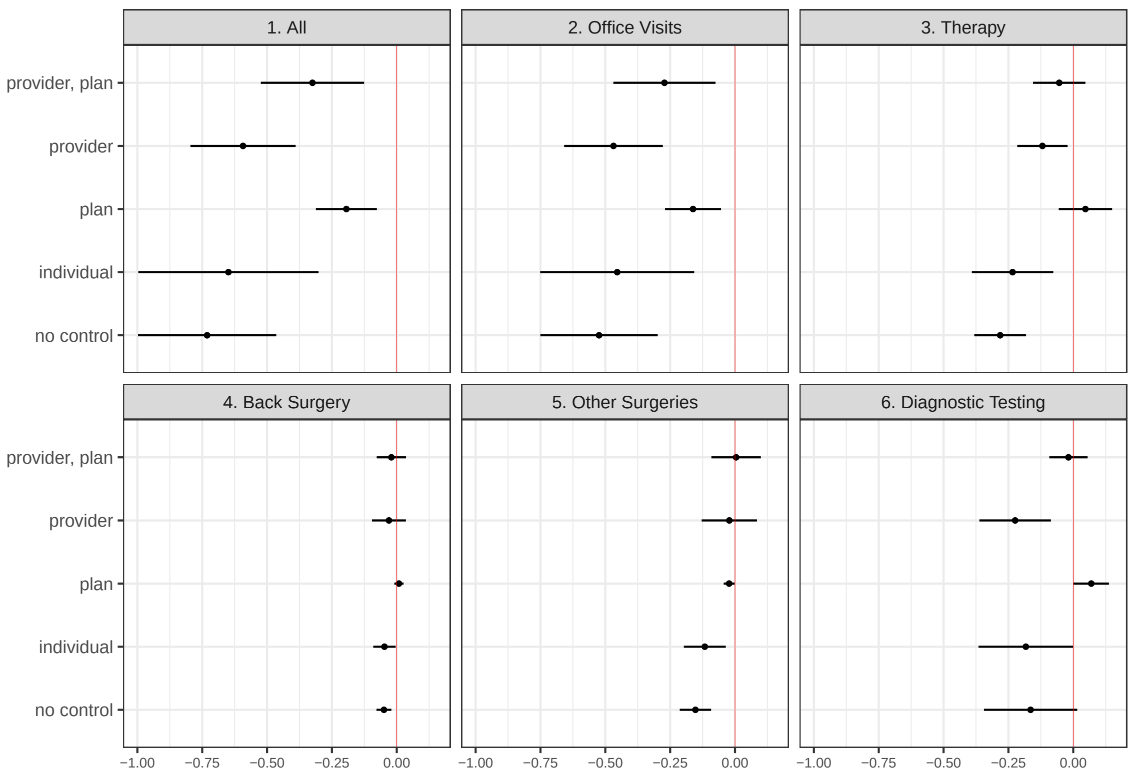


Panel B: Drug Usage Intensity



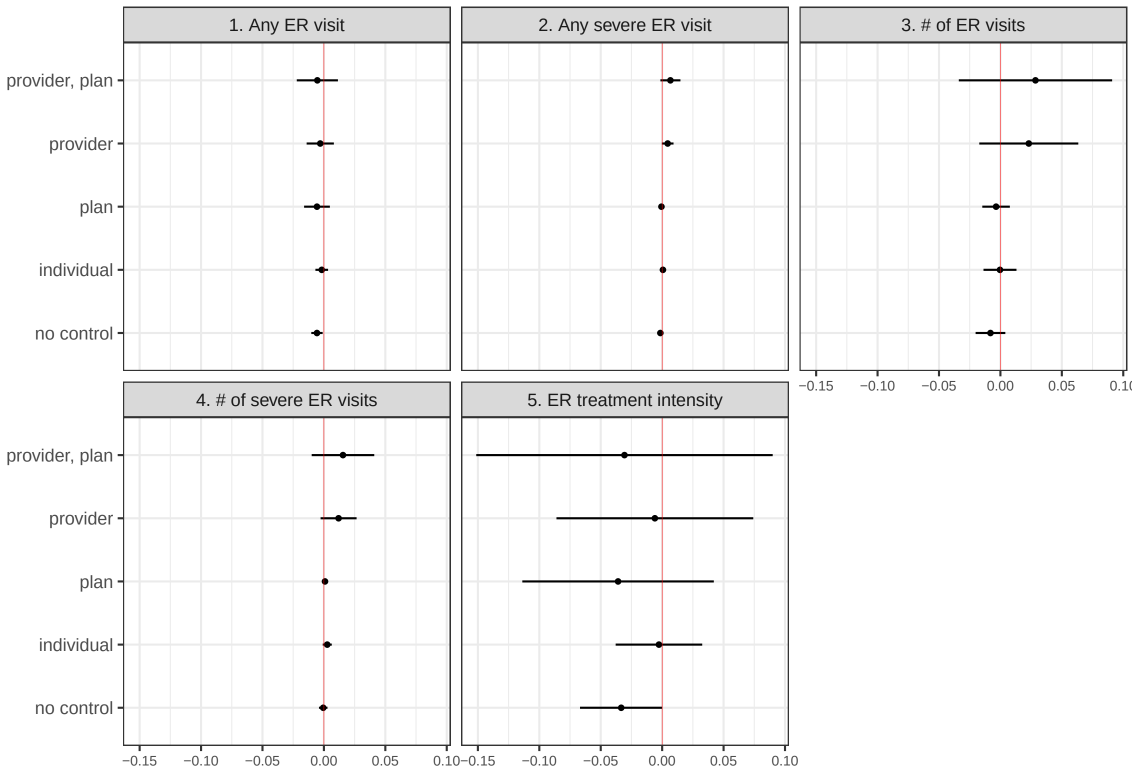
Notes: The figure shows the coefficient estimates of capitation and the 95% confidence interval. In Panel A, the dependent variable is whether there is any claim. In Panel B, the dependent variables are the inverse hyperbolic sine transformation of treatment intensity. Sub-panel 1 to 3 examines the effects with all drugs, opioids, and muscle relaxants. Standard errors are clustered at data contributor level.

Figure 2.5: Out-of-Pocket Expenditures



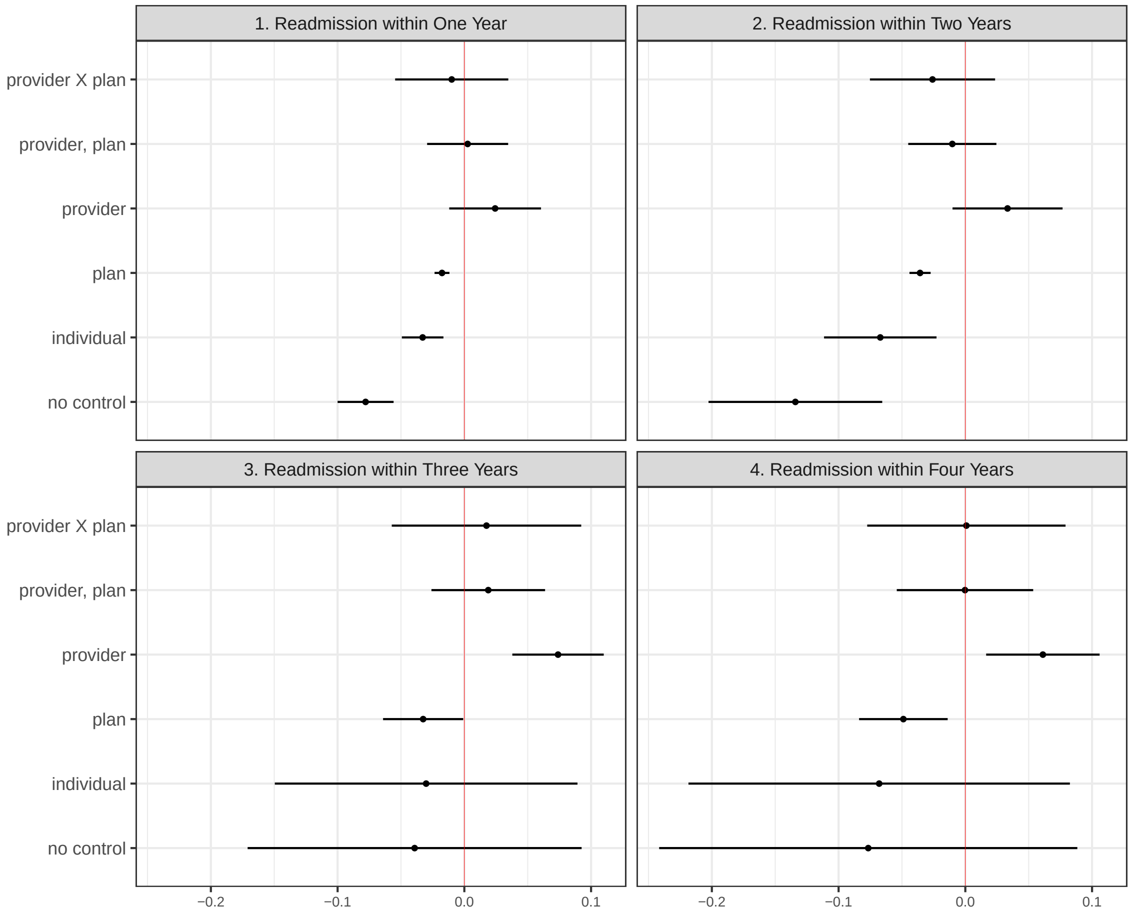
Notes: The figure shows the estimated results studying the out-of-pocket expenditure differences of capitated and non-capitated patients. The dependent variables are the inverse hyperbolic sine transformation of out-of-pocket expenditures. Panel 1 to 6 examines the effects with all medical services, office visits, therapy, back surgery, other surgeries, and diagnostic testing separately. Standard errors are clustered at data contributor level.

Figure 2.6: Placebo Test: Emergence Room Visits



Notes: The figure shows the treatment intensity differences for ER visits of capitated and non-capitated patients. The dependent variable in panel 1 is a dummy variable indicating whether there is any ER visit. The dependent variable in panel 2 is a dummy variable indicating whether there is any ER visit associated with severe conditions. The dependent variable in panel 3 is the number of ER visits. The dependent variable in panel 4 is the number of ER visits with a severe condition.

Figure 2.7: Readmission Rates



Notes: The figure shows the differences in readmission rates of lower back pain for capitated and non-capitated patients. The dependent variables are a dummy variable indicating whether there is any lower back pain related claims within a certain period of the end of the episode. Each line represents a different specification: "no control" represents no control variable; "individual" controls for patient characteristics; "plan" controls for plan fixed effects; "provider" controls for provider fixed effects; "provider, plan" controls for both plan and provider fixed effects separately; "provider X plan" controls for plan and provider fixed effects interactively. Standard errors are clustered at data contributor level.

Appendix A

Supplementary Materials for the First Chapter

A.1 Illustrative Example

This section shows an illustrative example where hospitals have incentives to remove their duplicate services and how the distance between merging hospitals matters. We use a spatial differentiation model similar to Salop (1971)'s circular city. We assume a case with four hospitals $\{A, B, C, D\}$ evenly distributed on a circle, as in Figure A.1. Each hospital offers two medical services (s^1, s^2). For simplicity, we assume these hospitals are identical to consumers except their locations. For service s^i, hospitals have $mc^i = c^i$ for treating each unit of patients and fixed cost of entry f^i. For the consumers, they are distributed uniformly on a circle with circumference 1 and they can only travel on the circle. There are equally amounts of consumers separately seeking service s^1 and s^2 and we assume both type is of mass 1. For consumers seeking service s^i, consumers have unit demands and enjoy utility $V^i - xt - P^i$ if they decide to go to a hospital with x distance away and charge a price P^i. Additionally, we assume there are no other health providers could enter this market.

Before merger, four hospitals are competitors and do not share common ownership. By symmetricity, we have

$$P_A^1 = P_B^1 = P_C^1 = P_D^1 = \frac{t}{4} + c^1$$
$$Q_A^1 = Q_B^1 = Q_C^1 = Q_D^1 = \frac{1}{4}$$

Similarly, for s^2, we can solve that

$$P_A^2 = P_B^2 = P_C^2 = P_D^2 = \frac{t}{4} + c^2$$
$$Q_A^2 = Q_B^2 = Q_C^2 = Q_D^2 = \frac{1}{4}$$

Now we assume two adjacent hospitals, hospital A & B merged together. The newly merging hospital have two choices: 1) It can continue offer two services in both branches; 2) It could let two branches specialize in only one service. In the former case, the profit of the hospital is equal to:

$$\pi^{noRel} = [(\frac{t}{4} + c^1 - c^1)\frac{1}{4} + (\frac{t}{4} + c^2 - c^2)\frac{1}{4} - f^1 - f^2] * 2 = \frac{t}{4} - 2(f^1 + f^2)$$

If it chooses to specialize. Without loss of generosity, we suppose hospital A only offers s^1 while B only offers s^2. Solving this equilibrium, we have

$$P_A^1 = P_C^1 = \frac{7t}{20} + c^1, \quad P_D^1 = \frac{3t}{10} + c^1$$
$$Q_A^1 = Q_C^1 = \frac{7}{20}, \quad Q_D^1 = \frac{3}{10}$$

and for s^2, we can solve that

$$P_B^2 = P_D^2 = \frac{7t}{20} + c^2, \quad P_C^2 = \frac{3t}{10} + c^2$$
$$Q_B^2 = Q_D^2 = \frac{7}{20}, \quad Q_C^2 = \frac{3}{10}$$

As a result, the profit after relocating services is:

$$\pi^{Rel} = (\frac{7t}{20} + c^1 - c^1)\frac{7}{20} - f^1 + (\frac{7t}{20} + c^2 - c^2)\frac{7}{20} - f^2 = \frac{49t}{200} - (f^1 + f^2)$$

Therefore, when $f^1 + f^2 > \frac{t}{4} - \frac{49t}{200} = \frac{t}{200}$, the merged firm benefits from relocating services between two branches.

However, when it comes to the case that distant hospitals merged, for instance, hospital A & C merged together, they may not cut any service at all because they are competing with B and D. As A & C's close competitors offer both services, the decision of service removal depends on the trade-off between the cost savings from removing services and the loss of profit due to consumers shifting away. The further the distance of merging hospitals, the larger the loss they have, because the consumers are more likely to choose competing substitutes.

A.2 Internal Validity Check

The main threat to our identification strategy is the selection of merger time. In other words, if there exists a correlation between the merger time and the time-path of the service change of hospitals, our results may bias. In this part, we present evidence to address the internal validity concern.

First, we check the summary statistics of hospitals across different merger time. We categorize the merger time into 3 groups, before (and includes) year 2005, year 2006-2010, and after (and includes) year 2011. Table A.1 and Table A.2 show the summary statistics of hospitals in the starting year by their merger time group. Table A.1 shows the summary statistics of all merging hospitals with counterparts no further than 100 miles, and Table A.2 shows the hospitals within merging counterparts within 10 miles. For both samples, we do not observe significant differences across the hospital characteristics.

Second, we conduct the validity test as De Janvry et al. (2015) to examine the correlation between merger time and the pre-merger service changes. We use a regression of pre-merger changes of the number of services on the indicators for the merger years

$$\Delta n_{it} = \gamma_t + \sum_{k \geq t} \delta_k \cdot \mathbb{1}[\text{Merger Year}_i = k] + \epsilon_{it}, \quad \forall\, t \leq \text{Merger Year}_i \tag{A.1}$$

The dependent variable Δn_{it} is the number of services of hospital i, $n_{it} - n_{it-1}$ and γ_t stands for the year fixed effects. The parameter of interest is δ_k, which shows the relationship between the merger time (year k) and the change of the number of services with year fixed effects controlled. The joint significance of the merger time effects would imply that pre-merger service change is related to the merger time. Table A.3 shows the results of this analysis. Column (1) uses the indicators of merger time group as the key independent variables and Column (2) adopts the indicators of merger years. In both settings, the year of mergers do not significantly explain the pre-merger change of services.

A.3 Supplement Results with the AHA data

A.3.1 Robustness Check with the Propensity Score Matching Control

To deal with the pre-trend problem in the event study of the target hospitals in the AHA data, we run a robustness check using the unmerging control group built from the propensity score matching. Similar to Section 1.3.4.2, we match on the pre-merger outcome variable, the number of services of individual hospitals, and other hospital characteristics and market characteristics. The hospital characteristics include the number of beds, the number of annual admissions, and the number of hospitals affiliated with the hospital's system in the local market. Furthermore, the market characteristics we matched on are the number of hospitals in the local market, the metro status of the market, and the market HHI based on the hospitals' number of beds. Targets and acquirers are separately matched. Similar to before, we use a propensity score matching with a caliper to exclude the treatment hospitals without proper controls. Table A.8 presents the summary statistics of the targets/acquirers within 10 miles and their matched controls of the beginning year in the sample. Compared to the targets' matched controls, the controls matched to acquirers are larger hospitals with more services, bed and admissions, and are more likely to be in the metro areas.

Table A.9 shows the results of the Diff-in-Diff analysis of within 10-mile targets/acquirers and their controls and the event study graph is presented in Figure A.2. With the matched non-merging controls, the target hospitals remove approximately 3.5 services while the acquirers averagely decrease 2 services. Graph A.2 shows the dynamic of the merger effect with time. For both targets and acquirers, the effect of service repositioning holds in both the short-run and long-run after mergers.

A.3.2 Hospital Pair Analysis

This section presents the analysis with the merging hospitals in the AHA data. Similar to before, we pair every two hospitals within the same market (Defined as Hospital Referral Region) and analysis the change of the total/duplicate services of the merging hospital pairs. The result is presented in Table A.10. The sample still includes all the merging hospital pairs within 100 miles, and we estimate the heterogeneous effect of the same sample across different geographic distance group.

Column (1) in Table A.10 presents the results with the hospital pairs' total number of services. The hospital pairs keep the similar number of services before and post mergers. However, in Column (2), the merging hospitals pairs within 10 miles have a statistically significant drop of the duplicate services, indicating the occurrence of service repositioning for the merging hospital pairs in the close distance. We also conduct the event study of the merging hospital pairs within 10 miles in Figure A.3. The analysis with the duplicate services does not reject the parallel pre-trend assumption, meanwhile, the decrease of duplicate services begins at the merger year and becomes larger as the time grows post merger.

A.4 Tables and Figures

Table A.1: Summary Statistics of 100-mile Merging Hospitals by Merging Time

	2002-2005	2006-2010	2010-2014
Number of procedure classes provided	163.3	163.2	154.1
	(26.54)	(23.25)	(33.06)
Number of diagnosis classes provided	131.3	131.4	130.4
	(5.341)	(5.062)	(5.349)
Hospital HHI of procedures	837.3	1115.4	1266.6
	(425.5)	(654.9)	(923.0)
Hospital HHI of diagnoses	350.1	339.0	371.5
	(71.15)	(55.85)	(106.4)
Casemix index	1.077	1.062	1.049
	(0.187)	(0.171)	(0.297)
Number of staffed beds	204.8	204.5	183.1
	(159.3)	(117.1)	(116.7)
Total discharges	10796.1	9509.2	8995.0
	(7230.7)	(5147.4)	(6855.1)
Total discharge days (in thousand)	50.44	50.55	47.04
	(36.51)	(28.29)	(35.07)
Total patient care cost (in million)	127.1	101.3	111.1
	(106.0)	(68.96)	(88.79)

Table A.2: Summary Statistics of 10-mile Merging Hospitals by Merging Time

	2002-2005	2006-2010	2010-2014
Number of procedure classes provided	156.1	160.0	158.8
	(26.45)	(22.51)	(30.07)
Number of diagnosis classes provided	129.1	130.5	129.5
	(6.122)	(5.493)	(6.933)
Hospital HHI of procedures	1117.5	1178.9	1136.8
	(479.6)	(591.9)	(700.5)
Hospital HHI of diagnoses	346.0	335.9	335.5
	(56.24)	(57.97)	(101.7)
Casemix index	1.069	1.050	1.124
	(0.259)	(0.177)	(0.335)
Number of staffed beds	167.7	173.4	208.9
	(76.66)	(85.54)	(140.2)
Total discharges	9189.7	8109.2	9868.2
	(5444.9)	(4085.5)	(8405.7)
Total discharge days (in thousand)	46.90	41.93	53.06
	(26.45)	(20.51)	(41.22)
Total patient care cost (in million)	90.67	83.66	125.5
	(69.86)	(52.88)	(100.1)

Table A.3: Relationship between Merger Time & Pre-merger Service Change

	(1)	(2)
	Δ Number of Services	Δ Number of Services
Before 2005	-	
2006-2009	-0.199	
	(0.989)	
After 2010	0.307	
	(1.119)	
Merger year=2003		-
		-
Merger year=2004		-0.590
		(3.274)
Merger year=2005		-2.073
		(2.550)
Merger year=2006		-2.510
		(3.115)
Merger year=2007		-1.525
		(3.086)
Merger year=2008		-0.669
		(3.094)
Merger year=2009		-0.251
		(2.955)
Merger year=2010		-1.230
		(3.049)
Merger year=2011		0.049
		(2.811)
Merger year=2012		-2.809
		(3.116)
Merger year=2013		-0.165
		(2.986)
Merger year=2014		0.163
		(3.174)
N	514	514
R^2	0.02	0.04

Table A.4: Post Merger Effect of Services across Merged Hospitals within 100 mile

	(1) Number of Services	(2) Number of Duplicate Srv	(3) Log HHI of Services	(4) Log HHI Non-removed Srv
Post merger of 0-10 miles	-4.733**	-6.774***	0.103**	0.088*
	(2.024)	(2.012)	(0.049)	(0.050)
Post merger of 10-40 miles	0.453	-5.480**	-0.034	-0.044
	(3.278)	(2.407)	(0.050)	(0.050)
Post merger of 40-70 miles	7.045**	3.393	0.016	0.033
	(3.399)	(6.558)	(0.055)	(0.055)
Post merger of 70-100 miles	6.072	5.887	0.067	0.078
	(5.741)	(4.803)	(0.111)	(0.111)
N	1208	1208	1208	1208
R^2	0.95	0.98	0.89	0.90

Notes: Dependent variable in Column (1) is the total number of services of individual hospitals. Dependent variable in Column (2) is the number of duplicate services shared by hospitals and their closest merged counterparts Dependent variable in Column (3) is the log HHI of service volumes, and in (4) is the log HHI of services kept after mergers. Model clusters at individual hospital level. $*p < 0.05$, $**p < 0.01$, $***p < 0.001$

Table A.5: Summary Statistics of California Per Unit Cost by Services

Service	Mean	Standard Deviation
Electromyography	70.32	(96.19)
Electroencephalography	152.7	(101.9)
Radiology - Diagnostic	80.71	(47.24)
Radiology - Therapeutic	166.0	(161.6)
Nuclear Medicine	261.5	(191.0)
Magnetic Resonance Imaging	244.8	(158.7)
Ultrasonography	71.60	(33.32)
Computed Tomographic Scanner	80.12	(42.54)
Respiratory Therapy	56.93	(28.42)
Pulmonary Function Services	45.92	(48.76)
Outpatient Chemical Dependency Services	89.38	(82.16)
Coronary Care	1475.6	(480.9)
Neonatal Intensive Care	1328.6	(518.3)
Burn Care	834.1	(157.3)
Definitive Observation	696.0	(269.3)
Medical/Surgical Acute	683.7	(293.9)
Pediatric Acute	1131.1	(613.4)
Psychiatric Acute - Adult	601.3	(235.3)
Psychiatric Acute - Adolescent and Child	392.9	(84.05)
Obstetrics Acute	561.9	(232.9)
Alternate Birthing Center	2118.0	(1156.2)
Partial Hospitalization - Psychiatric	352.9	(1586.6)
Skilled Nursing Care	370.2	(151.1)
Residential Care	33.44	(6.376)
Emergency Services	230.2	(119.7)
Psychiatric Emergency Rooms	793.4	(228.2)
Hospice - Outpatient Services	182.6	(62.84)
Labor and Delivery Services	2274.7	(1083.7)
Surgery and Recovery Services	16.11	(6.574)

Continued on next page

Table A.5: Summary Statistics of California Per Unit Cost by Services

Ambulatory Surgery Services	21.62	(35.36)
Anesthesiology	1.669	(1.706)
Clinical Laboratory Services	11.78	(3.594)
Pathological Laboratory Services	35.05	(20.57)
Blood Bank	191.5	(83.19)
Echocardiology	67.14	(61.51)
Cardiac Catheterization Services	1386.1	(1669.0)
Cardiology Services	41.36	(31.18)
Clinics	156.2	(135.2)
Renal Dialysis	199.3	(244.4)
Lithotripsy	1308.8	(623.8)
Gastro-Intestinal Services	325.0	(208.6)
Physical Therapy	31.59	(18.33)
Speech-Language Pathology	54.18	(37.58)
Occupational Therapy	28.39	(15.07)
Psychiatric/Psychological Testing	125.7	(353.6)
Psychiatric Individual/Group Therapy	64.64	(52.65)
Organ Acquisition	52323.0	(27302.6)
Medical/Surgical Intensive Care	1544.9	(574.0)
Observation Care	45.05	(37.60)
Chemical Dependency Services	464.2	(273.8)
Physical Rehabilitation Care	685.6	(231.1)
Hospice - Inpatient Services	549.7	(98.54)
Other Acute Care	504.7	(88.14)
Nursery Acute	354.7	(207.0)
Sub-Acute Care	398.3	(108.6)

Table A.6: Service by Service Results with All Services

Service	Post Merger <10	S.E.	Post Merger 10-100	S.E.	N	Adjusted R^2
Insertion; replacement; or removal of extracranial ventricular shunt	0.17***	(0.038)	0.035	(0.033)	965	0.541
Cancer chemotherapy	0.16***	(0.042)	-0.016	(0.025)	1,219	0.649
Intravenous pyelogram	0.15***	(0.044)	0.015	(0.035)	1,114	0.283
Bone marrow transplant	0.15	(0.13)	0.12	(0.12)	31	0.331
Other diagnostic cardiovascular procedures	0.12***	(0.039)	0.012	(0.023)	1,251	0.509
Repair of cystocele and rectocele; obliteration of vaginal vault	0.11***	(0.034)	0.038	(0.028)	1,436	0.627
Laparoscopy	0.11***	(0.031)	0.055*	(0.031)	1,470	0.434
Other procedures to assist delivery	0.100***	(0.034)	0.021	(0.017)	1,379	0.829
Genitourinary incontinence procedures	0.10**	(0.047)	0.039	(0.031)	1,400	0.526
Other respiratory therapy	0.10**	(0.046)	0.0080	(0.039)	1,402	0.209
Peripheral vascular bypass	0.10**	(0.049)	-0.015	(0.023)	1,367	0.589
Endarterectomy; vessel of head and neck	0.10**	(0.044)	0.014	(0.025)	1,341	0.628
Excision of semilunar cartilage of knee	0.099*	(0.051)	-0.00015	(0.037)	1,269	0.249
Control of epistaxis	0.098***	(0.030)	0.027	(0.026)	1,459	0.389
Ophthalmologic and otologic diagnosis and treatment	0.096*	(0.054)	-0.0080	(0.025)	707	0.356
Coronary thrombolysis	0.095**	(0.039)	0.0054	(0.024)	637	0.418
Spinal fusion	0.092**	(0.036)	0.033	(0.027)	1,261	0.565
Other non-OR therapeutic procedures; female organs	0.091**	(0.040)	0.047**	(0.023)	1,443	0.427

Continued on next page

Table A.6: Service by Service Results with All Services

Dilatation and curettage (D&C); aspiration after delivery or abortion	0.087**	(0.034)	0.0022	(0.018)	1,465	0.710
Injections and aspirations of muscles; tendons; bursa; joints and soft tissue	0.086	(0.055)	0.025	(0.034)	1,263	0.311
Computerized axial tomography (CT) scan	0.086*	(0.048)	-0.027	(0.041)	1,422	0.290
Thyroidectomy; partial or complete	0.085**	(0.040)	-0.010	(0.033)	1,439	0.559
Embolectomy and endarterectomy of lower limbs	0.085**	(0.038)	0.035	(0.026)	1,351	0.553
Division of joint capsule; ligament or cartilage	0.082*	(0.046)	0.014	(0.042)	1,252	0.317
Laminectomy; excision intervertebral disc	0.081**	(0.033)	0.022	(0.026)	1,346	0.586
Procedures on spleen	0.081*	(0.042)	-0.0043	(0.026)	1,325	0.396
Aortic resection; replacement or anastomosis	0.080	(0.053)	0.017	(0.027)	1,169	0.573
Artificial rupture of membranes to assist delivery	0.079**	(0.037)	0.014	(0.035)	1,338	0.649
Forceps; vacuum; and breech delivery	0.078**	(0.032)	-0.013	(0.016)	1,361	0.816
Repair of current obstetric laceration	0.078**	(0.035)	-0.0077	(0.016)	1,362	0.870
Other excision of cervix and uterus	0.077**	(0.030)	0.024	(0.028)	1,454	0.594
Decompression peripheral nerve	0.076	(0.047)	-0.079*	(0.041)	1,231	0.272
Other OR heart procedures	0.072***	(0.025)	0.022	(0.025)	1,268	0.693
Cesarean section	0.070**	(0.032)	-0.00083	(0.014)	1,376	0.864
Diagnostic ultrasound	0.068	(0.052)	0.012	(0.044)	1,471	0.448
Episiotomy	0.066*	(0.035)	-0.0031	(0.016)	1,357	0.835
Electroencephalogram (EEG)	0.061	(0.049)	-0.031	(0.032)	1,183	0.364
Other operations on fallopian tubes	0.059	(0.040)	0.0076	(0.025)	1,455	0.484

Continued on next page

Table A.6: Service by Service Results with All Services

Other OR therapeutic procedures; female organs	0.055	(0.034)	0.051**	(0.023)	1,472	0.532
Diagnostic dilatation and curettage (D&C)	0.055	(0.037)	0.085***	(0.028)	1,461	0.468
Intraoperative cholangiogram	0.054	(0.049)	0.027	(0.027)	1,462	0.518
Other OR therapeutic nervous system procedures	0.053*	(0.031)	0.017	(0.026)	1,404	0.628
Other bowel diagnostic procedures	0.052	(0.044)	-0.047*	(0.028)	1,367	0.319
Ligation of fallopian tubes	0.051	(0.034)	-0.035	(0.023)	1,344	0.806
Diagnostic cardiac catheterization; coronary arteriography	0.051*	(0.031)	-0.0034	(0.021)	1,164	0.856
Other diagnostic procedures of urinary tract	0.050	(0.033)	0.010	(0.028)	1,410	0.415
Oophorectomy; unilateral and bilateral	0.050*	(0.027)	0.027	(0.021)	1,474	0.675
Fetal monitoring	0.050	(0.038)	-0.0019	(0.036)	1,362	0.570
Radioisotope scan	0.050	(0.045)	0.085**	(0.040)	1,224	0.394
Other diagnostic procedures on skin and subcutaneous tissue	0.047	(0.040)	0.029	(0.029)	1,435	0.373
Myelogram	0.046	(0.041)	0.018	(0.033)	832	0.354
Lobectomy or pneumonectomy	0.046	(0.034)	-0.032	(0.028)	1,358	0.540
Debridement of wound; infection or burn	0.045*	(0.026)	0.023	(0.021)	1,475	0.572
Other OR therapeutic procedures of urinary tract	0.044	(0.038)	0.047*	(0.027)	1,467	0.513
Other operations on ovary	0.044	(0.029)	-0.010	(0.021)	1,475	0.647
Diagnostic bronchoscopy and biopsy of bronchus	0.044*	(0.024)	0.035	(0.023)	1,471	0.802
Excision; lysis peritoneal adhesions	0.044*	(0.023)	-0.0015	(0.021)	1,475	0.725
Other diagnostic procedures of respiratory tract and mediastinum	0.043	(0.031)	-0.0049	(0.030)	1,452	0.489

Continued on next page

Table A.6: Service by Service Results with All Services

Tracheoscopy and laryngoscopy with biopsy	0.041	(0.036)	0.015	(0.024)	1,424	0.519
Other diagnostic nervous system procedures	0.040	(0.058)	0.047	(0.039)	974	0.393
Gastrectomy; partial and total	0.040	(0.033)	0.065**	(0.032)	1,402	0.391
Other non-OR therapeutic cardiovascular procedures	0.039	(0.029)	-0.019	(0.023)	1,471	0.818
Other non-OR therapeutic procedures on skin and breast	0.038	(0.025)	0.040*	(0.021)	1,475	0.620
Cerebral arteriogram	0.038	(0.062)	-0.035	(0.043)	1,249	0.468
Corneal transplant	0.038	(0.033)	0.099	(0.082)	133	0.038
Other non-OR therapeutic procedures on respiratory system	0.038	(0.034)	0.0021	(0.025)	1,468	0.597
Diagnostic endocrine procedures	0.037	(0.042)	0.028	(0.030)	1,227	0.289
Other OR procedures on vessels other than head and neck	0.037	(0.035)	-0.023	(0.023)	1,475	0.731
Hysterectomy; abdominal and vaginal	0.036	(0.031)	0.0035	(0.022)	1,473	0.719
Excision of skin lesion	0.036	(0.031)	-0.028	(0.033)	1,475	0.486
Swan-Ganz catheterization for monitoring	0.036	(0.049)	-0.021	(0.029)	1,277	0.535
Circumcision	0.035	(0.028)	0.040**	(0.019)	1,318	0.699
Diagnostic procedures; male genital	0.034	(0.067)	0.0081	(0.045)	1,133	0.247
Diagnostic procedures on eye	0.033	(0.055)	-0.058	(0.060)	317	-0.021
Diagnostic procedures on nose; mouth and pharynx	0.033	(0.053)	-0.013	(0.037)	1,363	0.365
Other OR gastrointestinal therapeutic procedures	0.033*	(0.018)	0.0019	(0.019)	1,475	0.722
Skin graft	0.032	(0.030)	-0.088***	(0.030)	1,463	0.555
Amputation of lower extremity	0.031	(0.026)	0.027	(0.021)	1,473	0.647
Bone marrow biopsy	0.031	(0.027)	0.046**	(0.021)	1,463	0.528

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Table A.6: Service by Service Results with All Services

Other non-OR or closed therapeutic nervous system procedures	0.030	(0.049)	-0.016	(0.036)	1,433	0.336
Other therapeutic procedures on eyelids; conjunctiva; cornea	0.030	(0.037)	0.018	(0.028)	1,442	0.344
Other therapeutic procedures; hemic and lymphatic system	0.030	(0.034)	-0.0093	(0.020)	1,470	0.613
Other OR therapeutic procedures on respiratory system	0.029	(0.027)	-0.027	(0.023)	1,449	0.576
Other OR therapeutic procedures on bone	0.028	(0.033)	-0.057**	(0.023)	1,452	0.600
Contrast arteriogram of femoral and lower extremity arteries	0.028	(0.044)	0.015	(0.037)	1,377	0.646
Tonsillectomy and/or adenoidectomy	0.028	(0.033)	0.046	(0.038)	1,123	0.432
Other OR upper GI therapeutic procedures	0.028	(0.040)	0.034	(0.035)	1,472	0.514
Proctoscopy and anorectal biopsy	0.028	(0.027)	-0.030	(0.018)	1,473	0.568
Blood transfusion	0.025	(0.028)	0.043	(0.028)	1,475	0.575
Tracheostomy; temporary and permanent	0.025	(0.024)	-0.021	(0.023)	1,453	0.713
Therapeutic procedures on the esophagus	0.025	(0.042)	0.030	(0.031)	1,460	0.326
Other diagnostic procedures on musculoskeletal system	0.024	(0.048)	-0.030	(0.026)	1,456	0.504
Other therapeutic procedures	0.024	(0.033)	0.0040	(0.025)	1,475	0.631
Other OR therapeutic procedures on nose; mouth and pharynx	0.024	(0.033)	-0.032	(0.029)	1,427	0.519
Other non-OR lower GI therapeutic procedures	0.024	(0.030)	0.018	(0.021)	1,472	0.624
Other gastrointestinal diagnostic procedures	0.024	(0.036)	0.017	(0.028)	1,469	0.523

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Table A.6: Service by Service Results with All Services

Nephrotomy and nephrostomy	0.022	(0.023)	-0.021	(0.020)	1,409	0.589
Procedures on the breast	0.020	(0.041)	-0.016	(0.022)	1,467	0.495
Biopsy of liver	0.020	(0.035)	-0.020	(0.030)	1,463	0.523
Arterio or venogram (not heart and head)	0.019	(0.050)	0.0024	(0.038)	1,438	0.530
Insertion; revision; replacement; removal of cardiac pacemaker or cardioverter/defibrillator	0.019	(0.027)	0.0037	(0.021)	1,458	0.711
Other diagnostic procedures; female organs	0.018	(0.039)	0.048	(0.031)	1,421	0.409
Contrast aortogram	0.018	(0.055)	-0.012	(0.033)	1,339	0.606
Abdominal paracentesis	0.017	(0.021)	0.012	(0.017)	1,474	0.740
Extracorporeal circulation auxiliary to open heart procedures	0.016	(0.014)	-0.00082	(0.014)	831	0.897
Arthroscopy	0.015	(0.044)	-0.063**	(0.031)	1,358	0.345
Incision of pleura; thoracentesis; chest drainage	0.015	(0.020)	-0.024	(0.017)	1,474	0.798
Other extraocular muscle and orbit therapeutic procedures	0.014	(0.056)	-0.025	(0.043)	911	0.244
Other non-OR upper GI therapeutic procedures	0.014	(0.027)	-0.020	(0.018)	1,473	0.704
Conversion of cardiac rhythm	0.013	(0.027)	-0.0055	(0.026)	1,475	0.611
Percutaneous transluminal coronary angioplasty (PTCA)	0.013	(0.016)	0.0035	(0.012)	956	0.923
Other non-OR therapeutic procedures; male genital	0.012	(0.045)	0.0013	(0.033)	1,437	0.221
Incision and drainage; skin and subcutaneous tissue	0.012	(0.023)	-0.0071	(0.015)	1,474	0.642
Other OR therapeutic procedures on skin and breast	0.012	(0.033)	0.019	(0.030)	1,450	0.397
Psychological and psychiatric evaluation and therapy	0.010	(0.029)	0.012	(0.031)	534	0.338
Alcohol and drug rehabilitation/ detoxification	0.0095	(0.040)	-0.019	(0.029)	1,188	0.288

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Table A.6: Service by Service Results with All Services

Other therapeutic endocrine procedures	0.0089	(0.036)	0.020	(0.032)	1,316	0.536
Other non-OR therapeutic procedures on nose; mouth and pharynx	0.0079	(0.046)	-0.028	(0.029)	1,431	0.330
Respiratory intubation and mechanical ventilation	0.0076	(0.022)	0.024	(0.017)	1,475	0.794
Creation; revision and removal of arteriovenous fistula or vessel-to-vessel cannula for dialysis	0.0068	(0.033)	-0.025	(0.030)	1,465	0.630
Coronary artery bypass graft (CABG)	0.0067	(0.010)	0.00069	(0.0092)	726	0.955
Gastrostomy; temporary and permanent	0.0059	(0.022)	-0.0089	(0.018)	1,474	0.774
Removal of ectopic pregnancy	0.0037	(0.029)	-0.024	(0.021)	1,452	0.544
Repair of retinal tear; detachment	0.0024	(0.015)	-0.051	(0.044)	357	0.446
Other OR therapeutic procedures on musculoskeletal system	0.0021	(0.049)	0.049	(0.034)	1,444	0.319
Procedures on the urethra	0.0019	(0.043)	0.045*	(0.023)	1,462	0.504
Colostomy; temporary and permanent	0.00094	(0.022)	-0.036**	(0.018)	1,462	0.572
Other vascular bypass and shunt; not heart	0.00082	(0.053)	-0.0044	(0.035)	844	0.461
Heart valve procedures	0.00024	(0.016)	-0.0080	(0.012)	679	0.950
Cardiac stress tests	-0.00038	(0.043)	0.021	(0.036)	1,252	0.402
Incision and excision of CNS	-0.00053	(0.036)	-0.012	(0.028)	1,086	0.742
Partial excision bone	-0.0017	(0.036)	-0.066***	(0.024)	1,468	0.625
Endoscopic retrograde cannulation of pancreas (ERCP)	-0.0017	(0.035)	0.021	(0.029)	1,456	0.598
Hemodialysis	-0.0018	(0.021)	-0.018	(0.016)	1,471	0.826
Other OR therapeutic procedures on joints	-0.0022	(0.037)	-0.065***	(0.024)	1,456	0.537

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Table A.6: Service by Service Results with All Services

Tympanoplasty	-0.0022	(0.053)	-0.075	(0.065)	435	0.147
Treatment of fracture or dislocation	-0.0030	(0.024)	-0.038**	(0.017)	1,465	0.773
Arthroplasty	-0.0033	(0.044)	-0.088**	(0.038)	1,453	0.619
Other hernia repair	-0.0036	(0.023)	-0.023	(0.022)	1,475	0.636
Colorectal resection	-0.0037	(0.019)	-0.054***	(0.016)	1,472	0.777
Inguinal and femoral hernia repair	-0.0056	(0.031)	-0.018	(0.020)	1,469	0.566
Hemorrhoid procedures	-0.0063	(0.037)	-0.045	(0.034)	1,422	0.283
Peritoneal dialysis	-0.0063	(0.033)	-0.027	(0.031)	1,382	0.461
Nasogastric tube	-0.0083	(0.049)	0.044	(0.036)	1,416	0.200
Other therapeutic obstetrical procedures	-0.011	(0.034)	-0.0095	(0.025)	1,341	0.741
Arthrocentesis	-0.011	(0.029)	-0.0041	(0.024)	1,470	0.626
Microscopic examination (bacterial smear; culture; toxicology)	-0.012	(0.044)	-0.0083	(0.036)	768	0.235
Upper gastrointestinal X-ray	-0.012	(0.049)	-0.045	(0.034)	686	0.203
Other OR lower GI therapeutic procedures	-0.012	(0.027)	-0.054**	(0.022)	1,474	0.714
Prophylactic vaccinations and inoculations	-0.013	(0.035)	-0.014	(0.042)	1,411	0.376
Colonoscopy and biopsy	-0.013	(0.026)	-0.013	(0.017)	1,475	0.694
Diagnostic spinal tap	-0.016	(0.023)	0.00081	(0.018)	1,475	0.675
Other OR therapeutic procedures; male genital	-0.017	(0.038)	0.0089	(0.026)	1,457	0.405
Other vascular catheterization; not heart	-0.017	(0.026)	-0.013	(0.022)	1,475	0.793
Exploratory laparotomy	-0.019	(0.041)	-0.035	(0.030)	1,456	0.264
Appendectomy	-0.020	(0.018)	-0.028**	(0.011)	1,474	0.814
Nonoperative urinary system measurements	-0.021	(0.043)	0.044	(0.068)	403	0.361
Therapeutic radiology	-0.021	(0.043)	-0.010	(0.032)	913	0.629
Upper gastrointestinal endoscopy; biopsy	-0.021	(0.024)	-0.019	(0.015)	1,475	0.770

Continued on next page

Table A.6: Service by Service Results with All Services

Other therapeutic procedures on muscles and tendons	-0.022	(0.038)	-0.11***	(0.029)	1,472	0.619
Other therapeutic ear procedures	-0.022	(0.038)	0.058*	(0.035)	1,363	0.240
Other non-OR gastrointestinal therapeutic procedures	-0.022	(0.026)	0.0082	(0.023)	1,471	0.766
Small bowel resection	-0.022	(0.022)	-0.045***	(0.017)	1,471	0.623
Myringotomy	-0.024	(0.047)	0.059	(0.058)	683	0.267
Other diagnostic procedures on lung and bronchus	-0.024	(0.051)	-0.046	(0.035)	1,213	0.411
Cystoscopy and other transurethral procedures	-0.027	(0.034)	-0.015	(0.020)	1,473	0.678
Mastoidectomy	-0.028	(0.062)	0.033	(0.069)	493	0.118
Open prostatectomy	-0.029	(0.036)	-0.0099	(0.024)	1,262	0.614
Diagnostic amniocentesis	-0.032	(0.065)	0.032	(0.046)	632	0.316
Ileostomy and other enterostomy	-0.032	(0.028)	-0.064***	(0.022)	1,458	0.505
Enteral and parenteral nutrition	-0.034	(0.053)	0.034	(0.036)	1,469	0.363
Other diagnostic radiology and related techniques	-0.035	(0.044)	0.019	(0.031)	1,471	0.501
Nephrectomy; partial or complete	-0.036	(0.041)	-0.038*	(0.022)	1,286	0.552
Transurethral resection of prostate (TURP)	-0.036	(0.048)	0.059**	(0.029)	1,451	0.510
Other non-OR therapeutic procedures on musculoskeletal system	-0.036	(0.038)	-0.059**	(0.026)	1,428	0.455
Suture of skin and subcutaneous tissue	-0.036	(0.027)	-0.049***	(0.018)	1,473	0.624
Physical therapy	-0.038	(0.042)	0.0026	(0.029)	1,474	0.486
Other diagnostic procedures (interview; evaluation; consultation)	-0.039	(0.034)	-0.072**	(0.032)	1,457	0.473
Cholecystectomy and common duct exploration	-0.039*	(0.022)	-0.043***	(0.015)	1,475	0.771
Electrocardiogram	-0.041	(0.048)	-0.0095	(0.036)	442	-0.029

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Table A.6: Service by Service Results with All Services

Nonoperative removal of foreign body	-0.045	(0.029)	-0.047***	(0.018)	1,460	0.355
Lens and cataract procedures	-0.045	(0.044)	-0.12**	(0.046)	691	0.173
Other OR procedures on vessels of head and neck	-0.045	(0.042)	-0.045	(0.031)	1,041	0.439
Dental procedures	-0.047	(0.031)	-0.0081	(0.033)	1,084	0.460
Other non-OR therapeutic procedures of urinary tract	-0.051	(0.041)	0.0044	(0.027)	1,473	0.502
Diagnostic procedures on ear	-0.054	(0.058)	-0.067	(0.046)	299	-0.139
Lower gastrointestinal X-ray	-0.056	(0.046)	-0.043	(0.041)	385	0.206
Abortion (termination of pregnancy)	-0.057	(0.042)	-0.019	(0.040)	712	0.103
Mammography	-0.057	(0.034)	-0.030	(0.024)	417	0.134
Varicose vein stripping; lower limb	-0.059	(0.064)	-0.077	(0.070)	555	0.106
Plastic procedures on nose	-0.060	(0.043)	-0.026	(0.038)	1,306	0.309
Arterial blood gases	-0.062	(0.067)	0.00047	(0.034)	537	0.038
Insertion of catheter or spinal stimulator and injection into spinal canal	-0.065*	(0.035)	-0.023	(0.028)	1,431	0.503
Extracorporeal lithotripsy; urinary	-0.075*	(0.040)	-0.0053	(0.032)	1,262	0.432
Glaucoma procedures	-0.077	(0.057)	-0.086	(0.098)	159	0.237
Indwelling catheter	-0.081	(0.051)	-0.12***	(0.033)	1,435	0.316
Bunionectomy or repair of toe deformities	-0.096	(0.060)	-0.082*	(0.043)	908	0.232
Other intraocular therapeutic procedures	-0.11*	(0.058)	-0.042	(0.056)	834	0.252
Destruction of lesion of retina and choroid	-0.12	(0.087)	0.065	(0.10)	339	0.319
Local excision of large intestine lesion (not endoscopic)	-0.12	(0.074)	-0.13***	(0.040)	857	0.322
Magnetic resonance imaging	-0.14***	(0.047)	-0.21***	(0.044)	1,196	0.326
Electrographic cardiac monitoring	-0.29***	(0.054)	-0.042	(0.027)	408	0.177

Table A.7: AHA Service List

Psychiatric education services	Hemodialysis Services
General medical and surgical care (pediatric)	HIV-AIDS services
Obstetrics care	Home health services
Medical/surgical intensive care	Hospital-base outpatient care center/services
Cardiac intensive care	Indigent care clinic
Neonatal intensive care	Linguistic/translation services
Neonatal intermediate care	Meals on wheels
Pediatric intensive care	Mobile Health Services
Burn care	Neurological services
Other special care	Nutrition programs
Other intensive care	Occupational health services
Physical Rehabilitation care	Oncology services
Alcohol/drug abuse or dependency inpatient care	Orthopedic services
Psychiatric care	Outpatient surgery
Skilled nursing care	Patient Controlled Analgesia
Intermediate nursing care	Patient education center
Acute long term care	Patient representative services
Other long-term care	Physical rehabilitation outpatient services
Other care	Primary care department
Adult day care program	Psychiatric child/adolescent services
Airborne infection isolation room	Psychiatric consultation/liaison services
Alcohol/drug abuse or dependency outpatient services	Psychiatric emergency services
Alzheimer Center	Psychiatric geriatric services
Ambulance services	Psychiatric outpatient services
Ambulatory surgery center	Psychiatric partial hospitalization program
Arthritis treatment center	Radiology therapeutic
Assisted living services	Image-guided radiation therapy

Continued on next page

Table A.7: AHA Service List

Auxiliary	Intensity-Modulated Radiation Therapy (IMRT)
Bariatric/weight control services	Shaped beam Radiation System
Birthing room/LDR room/LDRP room	Stereotactic radiosurgery
Blood Donor Center Hospital	Computed-tomography (CT) scanner
Breast cancer screening/mammograms	Diagnostic radioisotope facility
Adult diagnostic/invasive catheterization	Electron Beam Computed Tomography (EBCT)
Pediatric diagnostic/invasive catheterization	Full-field digital mammography
Adult interventional cardiac catheterization	Magnetic resonance imaging (MRI)
Pediatric interventional cardiac catheterization	Multislice spiral computed tomography <64 slice
Adult cardiac surgery	Multi-slice spiral computed tomography 64 + slice
Pediatric cardiac surgery	Positron emission tomography (PET)
Cardiac Rehabilitation	Positron emission tomography/CT (PET/CT)
Case Management	Single photon emission computerized tomography (SPECT)
Chaplaincy/pastoral care services	Ultrasound
Chemotherapy	Fertility Clinic
Children wellness program	Genetic testing/counseling
Chiropractic services	Retirement housing
Community outreach	Robotic surgery
Complementary medicine services	Sleep Center
Computer assisted orthopedic surgery	Social work services
Crisis prevention	Sports medicine
Dental services	Support groups
Emergency Department	Swing bed services
Freestanding/Satellite Emergency Department	Teen outreach services
Certified trauma center	Tobacco Treatment Services

Continued on next page

Table A.7: AHA Service List

Level of trauma center	Bone Marrow transplant services
Enabling Services	Heart transplant
Hospice	Kidney transplant
Pain Management Program	Liver transplant
Palliative Care Program	Lung transplant
Enrollment Assistance Program	Tissue transplant
Extracorporeal shock-wave lithotripter (ESWL)	Other Transplant
Fitness center	Transportation to health services
Freestanding outpatient center	Urgent care center
Geriatric services	Virtual colonoscopy
Health Fair	Volunteer services department
Health information center	Women's health center/services
Health screenings	Wound Management Services

Table A.8: Summary Statistics of Macthed Sample from AHA Data

	Targets		Acquirers	
	Within 10miles	Matched Control	Within 10 miles	Matched Controls
Number of services	28.59	25.26	32.32	28.02
	(10.08)	(14.82)	(11.72)	(14.95)
Total staffed beds	258.5	202.8	331.3	237.4
	(140.8)	(169.4)	(250.9)	(194.5)
Total admissions	11107.8	9515	15723.3	10023.0
	(6985.2)	(9024.4)	(13229.1)	(9224.5)
Local sys members	3.568	3.324	3.086	2.808
	(3.857)	(4.002)	(2.314)	(3.973)
Metro	0.630	0.559	0.664	0.587
	(0.486)	(0.500)	(0.474)	(0.495)

Table A.9: Number of Services of Merged Hsopitals within 10 miles & Matched Controls

	(1)	(2)
	Targets within 10 miles	Acquirers within 10 miles
Post merger	-3.517***	-1.894*
	(1.340)	(1.059)
N	1789	2738
R^2	0.82	0.81

Table A.10: Change of Total/Duplicative Services of Hospital Merged Pairs within 100 miles

	(1) Number of total services	(2) Number of duplicate services
Post merger of 0-10mile	-0.561	-2.496***
	(1.311)	(0.788)
Post merger of 10-40mile	-0.022	-0.095
	(0.581)	(0.439)
Post merger of 40-70mile	-1.690**	-0.047
	(0.709)	(0.496)
Post merger of 70-100mile	-0.999	-1.157**
	(1.044)	(0.558)
N	7467	7467
R^2	0.94	0.92

Figure A.1: Illustration of Hospital Distribution

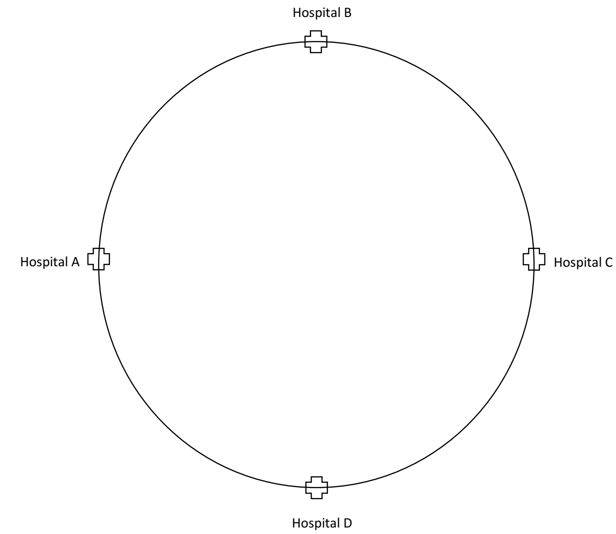


Figure A.2: Event Study of Targets/Acquirers within 10 miles & Matched Controls

(a) Targets

(b) Acquirers

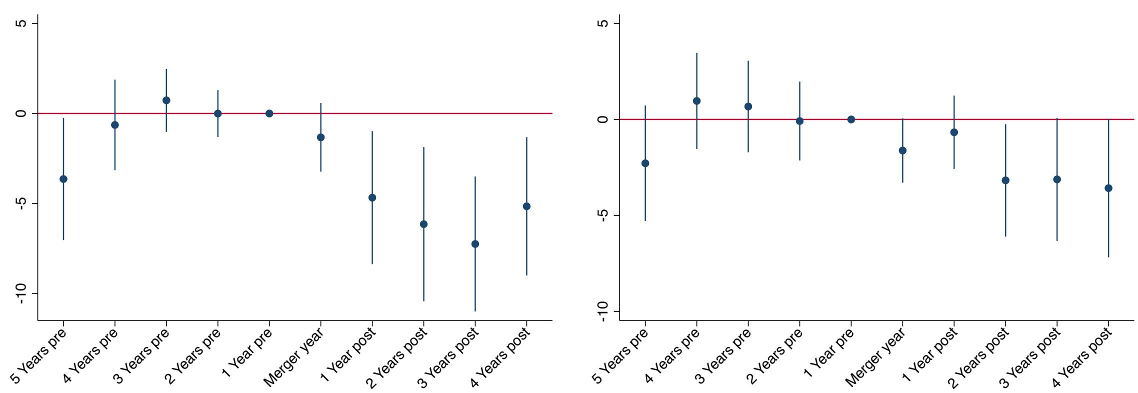
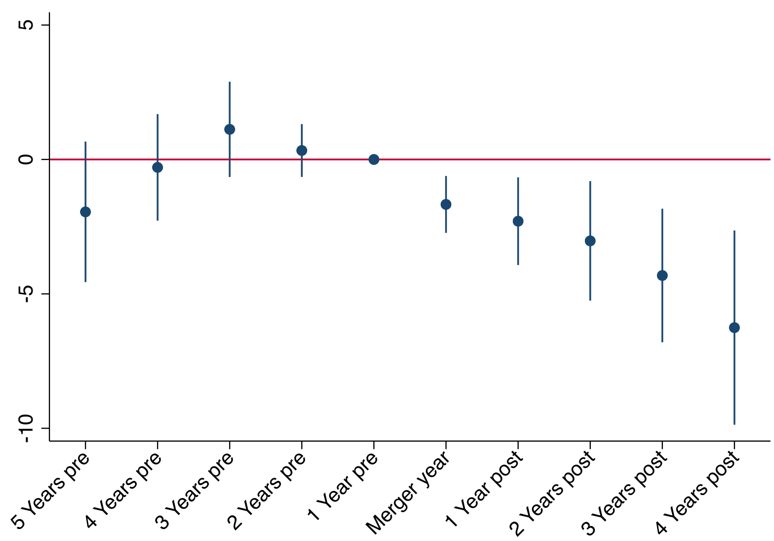


Figure A.3: Event Study of Merging Hospital Pairs within 10 miles in AHA Data



Appendix B

Supplementary Materials for the Second Chapter

B.1 Appendix Tables

Table B.1: Treatment Intensity of All Services, Raw Values

	(1)	(2)	(3)	(4)	(5)
capitated	-151.922***	-81.797**	-23.777	38.640	13.230
	(30.112)	(35.733)	(27.304)	(80.469)	(77.402)
Observations	82,156	82,156	81,058	61,370	60,206
R-squared	0.001	0.028	0.054	0.262	0.289
Prov FE				×	×
Plan FE			×		×
Individual Characteristics		×	×	×	×

Notes: The table shows the regression results comparing the treatment intensity of capitated/non-capitated patients. The dependent variable is the treatment intensity of all services. Column (1) has no control variables other than capitation. Column (2) controls for year and patient individual characteristics. Column (3) controls for year, patient individual characteristics, and plan fixed effects. Column (4) controls for year, patient individual characteristics, and provider fixed effects. Column (5) controls for year, patient individual characteristics, plan and provider fixed effects. Standard errors are clustered at the data contributor level. *** p<0.01, ** p<0.05, * p<0.1.

Table B.2: Out-of-Pocket Expenditures of All Services, Raw Values

	(1)	(2)	(3)	(4)	(5)
capitated	-83.748***	-78.962***	-8.171***	-43.085***	-3.513
	(11.911)	(17.711)	(1.786)	(9.678)	(5.742)
Observations	82,156	82,156	81,058	61,370	60,206
R-squared	0.006	0.018	0.060	0.258	0.291
Prov FE				×	×
Plan FE			×		×
Individual Characteristics		×	×	×	×

Notes: The table shows the regression results comparing the out-of-pocket expenditures of capitated/non-capitated patients. The dependent variable is the out-of-pocket expenditures of all services. Column (1) has no control variables other than capitation. Column (2) controls for year and patient individual characteristics. Column (3) controls for year, patient individual characteristics, and plan fixed effects. Column (4) controls for year, patient individual characteristics, and provider fixed effects. Column (5) controls for year, patient individual characteristics, plan and provider fixed effects. Standard errors are clustered at the data contributor level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table B.3: Robustness: Treatment Intensity of All Services with 90-Day Episode Definition

	(1)	(2)	(3)	(4)	(5)
capitated	-0.223***	-0.146***	-0.085***	-0.024	-0.055*
	(0.027)	(0.030)	(0.023)	(0.033)	(0.030)
Observations	87,838	87,838	86,790	67,833	66,784
R-squared	0.003	0.030	0.062	0.308	0.335
Prov FE				×	×
Plan FE			×		×
Individual Characteristics		×	×	×	×

Notes: The table shows the regression results comparing the treatment intensity of capitated/non-capitated patients. Each observation is an episode. For a patient, an LBP episode starts from his/her earliest LBP encounter, followed by subsequent encounters with a time gap shorter than 90 days. An episode ends if there is no additional LBP encounters within 90 days of the last record. Two consecutive LBP encounters with larger than 90-day gaps are designated to two separate episodes. The dependent variable is the inverse hyperbolic sine transformation of treatment intensity of all services. Column (1) has no control variable. Column (2) controls for individual characteristics (chronic condition, employment status etc.). Column (3) controls for year, patient characteristics, and plan fixed effects. Column (4) controls for year, patient characteristics, and provider fixed effects. Column (5) controls for year, patient characteristics, plan and provider fixed effects. Standard errors are clustered at the data contributor level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table B.4: Diagnoses for Lower Back Pain

ICD-9	Diagnosis
721.3	Lumbosacral spondylosis without myelopathy
721.42	Spondylogenic compression of lumbar spinal cord
721.9	Spondylosis of unspecified site without myelopathy
721.91	Spondylogenic compression of spinal cord, not specified
722.1	Displacement of thoracic or lumbar disc without myelopathy
722.1	Displacement of lumbar disc without myelopathy
722.2	Displacement of unspecified disc without myelopathy
722.52	Degeneration of lumbar or lumbosacral disc
722.6	Degeneration of disc, site unspecified
722.7	Disc disorder with myelopathy, site unspecified
722.73	Lumbar disc disorder with myelopathy
722.8	Postlaminectomy syndrome, unspecified region
722.83	Postlaminectomy syndrome, lumbar
722.9	Other and unspecified disc disorder, site unspecified
722.93	Other and unspecified lumbar disc disorder
724	Spinal stenosis, unspecified site (not cervical)
724.02	Lumbar stenosis
724.09	Spinal stenosis, other
724.2	Lumbago
724.3	Sciatica
724.4	Thoracic or lumbosacral neuritis or radiculitis, unspecified
724.5	Backache, unspecified
724.6	Disorders of sacrum (including lumbosacral joint instability)
724.8	Other symptoms referable to back
724.9	Other unspecified back disorders
738.4	Acquired spondylolisthesis
739.3	Nonallopathic lesions, lumbar region
739.4	Nonallopathic lesions, sacral region
756.11	Spondylolysis, lumbosacral region
756.12	Spondylolisthesis
847.2	Sprains and strains, lumbar
847.3	Sprains and strains, sacral
847.9	Sprains and strains, unspecified region
307.89*	Psychogenic backache
721.5-8*	Unique or unusual forms of spondylosis
722.30*	Schmorl's nodes, unspecified region
722.32*	Lumbar Schmorl's nodes
737.10-737.30*	Idiopathic scoliosis
738.5*	Other acquired deformity of back or spine
756.10*	Anomaly of spine, unspecified
756.13-756.19*	Various congenital anomalies
805.4*	Lumbar fracture
805.6*	Sacral or coccygeal fracture
805.8*	Vertebral fracture of unspecified site
846.0-9	Sprains and strains, sacroiliac
996.4	Mechanical complication of internal orthopedic device, implant and graft

Notes: This table exhibites the ICD-9 diagnosis codes related to LBP (Cherkin et al., 1992). * refers to diagnoses applicable only to nonsurgical cases.

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