# Targeting Efficiencies? Reducing Costs Through Hospital Consolidation*

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**Abstract**

Policymakers are concerned about the effects of consolidation in the hospital industry. Much of the consolidation is driven by the expansion of multi-unit hospital "systems" that claim acquisitions generate efficiencies that are passed through to consumers. Although recent studies have confirmed the presence of merger efficiencies, there is no evidence on whether efficiencies are passed through and meaningfully reduce prices. We fill this gap using novel data on transaction prices for hospital outpatient care and detailed administrative data on hospital costs from California. We first show that system ownership generates significant price increases and cost synergies for independent hospitals but not for targets that were already organized as systems. We then develop and estimate a structural model of patient demand and hospital-insurer negotiations. We find that systems target for acquisition independent hospitals with weak bargaining power, suggesting a strategy to maximize price increases rather than maximizing merger efficiencies. We also detect significant cost savings from system ownership, of which approximately 50% is passed through to the insurers in the form of price reductions. However, since the acquired hospitals are small relative to the acquirers, the pass-through of synergies does not meaningfully affect negotiated prices.

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# 1 Introduction

The hospital industry has experienced significant consolidation over the past few decades, with multihospital firms, commonly known as "systems", steadily acquiring independent hospitals or other systems. This trend has sparked a growing debate among policymakers, economists, and the public about the effects of hospital consolidation on healthcare prices and the need for more antitrust enforcement (Brot et al. 2024). Although proponents of consolidation argue that mergers and acquisitions lead to cost savings and improved quality of care, critics highlight a troubling pattern: prices for healthcare services rise after consolidation, with little evidence that consumers see the benefits of any cost savings. Previous studies have documented the presence of cost savings after hospital mergers and acquisitions (Schmitt 2017; Andreyeva et al. 2024); however, there is little or no evidence on the transfer of such savings to consumers, which is often presented as a key justification to regulators. To our knowledge, this paper presents the first empirical evidence to fill this gap in the literature and inform this important policy debate.

A central concern in the debate is the observed increase in prices in markets with high levels of hospital concentration (Dafny 2009). Economic theory and empirical studies suggest that when hospitals consolidate, they gain market power, which softens competition and enables them to negotiate higher reimbursement rates with insurers. The increase in prices has also been noted when the merging parties do not share geographic markets (Lewis and Pflum 2017; Schmitt 2018). Other studies have shown that insurers pass on the increase in prices after consolidation to consumers in the form of higher premiums and out-of-pocket expenses (Brot-Goldberg et al. 2024). The evidence on the effects of hospital consolidation on quality of care is mixed, with some studies finding higher readmission rates, and others unable to detect any changes (Ho and Hamilton 2000; Beaulieu et al. 2020; Andreyeva et al. 2024). However, the balance of evidence strongly suggests that hospital consolidation does not improve quality of care.

Hospital systems often justify consolidation by pointing to potential cost synergies, such as economies of scale, shared administrative resources, and streamlined operations. By pooling resources and standardizing care delivery, larger hospital systems argue that they can operate more efficiently, potentially reducing the cost of providing care. In the absence of quality improvements, the key argument for a benefit to consumers from consolidation rests on whether the resulting cost synergies are passed through to insurers and help lower prices. This highlights the need to critically examine how the purported benefits of consolidation are shared between hospitals and consumers.

We inform this active debate by empirically examining the effects of hospital consolidation using novel data on hospital prices and operating costs from California. We have obtained novel proprietary hospital outpatient billing claims data, which allows us to observe detailed patient-level claims, including the negotiated prices, during 2013–2020. The data is sourced from a claims processing intermediary and, therefore, allows us to observe data from a wide sample of hospi-

tals and insurers in the state. Comparisons with the universe of hospitals in California indicate that hospitals in the claims sample are representative on key dimensions such as size, ownership type, etc. Similarly, the leading commercial insurers in California, such as Anthem, Blue Shield, and United Healthcare, are well represented in the sample. We obtain detailed data on hospital operating costs during 2013–2020 from annual reports submitted to California's Department of Health Care Access and Information (HCAI). These administrative reports are more detailed and reliable than the corresponding information in the Healthcare Cost Reporting Information System (HCRIS) reports commonly used to study hospital costs. This unique data source on costs is available only for California and motivates us to focus on this state for the empirical analysis.

We study acquisitions by hospital systems that were implemented during 2014–2017, allowing us to observe both prices and costs before and after all deals for all affected hospitals. During this period, 11 independent hospitals and 11 system-owned hospitals were acquired by systems. We proceed in two steps. We first perform a reduced form analysis using a staggered difference-in-differences research design that is standard in the previous literature on consolidation (e.g., Cooper et al. 2019; Eliason et al. 2020). This enables us to transparently present evidence on the causal effects of system acquisitions on the price and operating cost per outpatient care visit for a privately insured patient. The main finding from this step is that when systems acquire independent hospitals, it leads to both an increase in prices and a reduction in operating costs, which is consistent with recent work on the effects of system acquisitions (Andreyeva et al. 2024). In the second step, we develop and structurally estimate a model of patient demand for outpatient care and hospital-insurer price negotiations that formally links price setting to costs. We use both the model estimates and the reduced-form effect on costs to simulate counterfactual prices under alternate assumptions about market structure and hospital costs.

There are three main takeaways from the analyses. First, there is substantial heterogeneity in the effects of system ownership, depending on the nature of the target facility. When systems acquire independent hospitals, we observe a large increase in prices coupled with cost reductions; however, the increase in prices is an order of magnitude higher than the cost savings. In contrast, acquisitions of system-owned targets show no detectable effects on prices or costs. These results imply that acquisitions of system-owned hospitals do not even have the potential to improve consumer welfare through cost synergies. Previous studies have typically not examined heterogeneity in the effects of system ownership and have tended to estimate the average effect across a variety of deals (e.g., Cooper et al. 2019; Schmitt 2017). However, these results highlight the policy relevance of studying heterogeneity in the effects of consolidation.

Second, acquirers and target facilities appear to be strategically matched to obtain a large price increase for the target hospital rather than to prioritize cost reductions. This interpretation flows intuitively from both the reduced form and structural analyses. The independent hospitals acquired had low prices before acquisition in both absolute terms and relative to their acquirers.

Within three years of acquisition, the prices of the target hospitals nearly converge to those of the acquirers. This pattern is consistent with a pricing strategy of systems persuading insurers to reimburse all their member facilities at a similar rate. In contrast, the average prices of independent hospitals that did not participate in acquisitions were already high and comparable to those of acquirers at baseline, suggesting that they would not experience much of an increase. Model estimates from the structural analysis confirm that the acquired independent hospitals had low bargaining weights at baseline, implying that they negotiated poorly with insurers as independent entities and benefited from the negotiation umbrella provided by the acquirer. Furthermore, the independent hospitals acquired already had lower operating costs than their acquirers prior to the deal, suggesting little potential for large efficiency gains.

Third, we simulate prices and profits under counterfactual scenarios where we undo the cost synergies that we estimate in our reduced form analyses, as well as when we undo the effects of mergers on hospital systems' bargaining positions and bargaining power. A key assumption in the model is that systems negotiate a single price with insurers for all their member facilities. This assumption is both standard in the literature (Ho and Lee 2017), and supported by observed trends in the sample. We show that under this type of pricing strategy, the price effect of cost changes is approximately proportional to the relative size of the acquired hospital to the acquiring system, which for the acquisitions in our data is typically small. Consistent with this implication, we find that although systems pass-through around 50% of their aggregate cost savings in the form of reduced insurer reimbursements, their negotiated prices reduce by less than 1% due to cost synergies. We then perform a more comprehensive series of counterfactuals and prospectively evaluate a large number of hypothetical acquisitions of independent hospitals. However, cost synergies fail to produce meaningful price reductions across the range of proposed acquisitions, reinforcing the conclusion that system acquisitions of independent hospitals are unlikely to generate meaningful price reductions, even though the cost synergies at the acquired facility are sizable.

Our paper occupies a unique position at the intersection of three strands of the literature. The first strand examines the effects of hospital consolidation on cost efficiencies. Recent studies have documented the presence of moderate cost savings following hospital acquisitions with substantial heterogeneity depending on the context. Estimated savings at the acquired hospital are larger when a system acquires an independent hospital and are small or not detected when a system acquires or combines with another (Schmitt 2017; Gaynor et al. 2023; Andreyeva et al. 2024). Our study corroborates these findings in a new context, hospital outpatient care services. However, these studies have faced data limitations in deciphering the source of the savings, and specifically whether they are fixed or variable in nature. We leverage the granular nature of the California cost data and confirm that the savings are mainly driven by a reduction in variable costs at the acquired hospital, and within that, mainly by a reduction in employment.

The second related strand is the literature examining the effect of consolidation in healthcare on

prices. These studies have consistently found that horizontal consolidation leads to an increase in prices that typically ranges between 5–10%, depending on the context (Cooper et al. 2019; Andreyeva et al. 2024). A few studies have predicted much greater price increases (Dafny 2009; Gowrisankaran, Nevo, and Town 2015). Price increases have also been detected when the acquisitions involve facilities located in different markets (Lewis and Pflum 2017; Dafny, Ho, and Lee 2019). Finally, this phenomenon is not unique to hospitals since price increases of a similar magnitude have been detected following the consolidation of health insurers (Dafny, Duggan, and Ramanarayanan 2012). Our study examines the effect on prices in a new context, outpatient care services, which now contribute more than half of all hospital revenue. We find that systems strategically select targets that had poor bargaining ability and low prices at baseline. This tends to maximize the price increases obtained after acquisition since the system raises the targets to their prevailing price level.

Finally, we add to the small set of studies that have examined the pass through of merger efficiencies to customers. In the hospital setting, Andreyeva et al. (2024) show that system acquisition of independents leads to higher prices and cost savings at the target facility. However, they do not quantify the pass-through of the savings to insurers. To our knowledge, ours is the first to perform this exercise in the hospital setting. Our analysis confirms that a substantial share of savings is passed through to the insurer in the form of price reductions. However, our analysis also produces a novel insight that such cost savings are unlikely to meaningfully affect hospital prices because independent targets are typically very small relative to the acquiring system. Our results differ considerably from those of Miller and Weinberg (2017), who perform a case study on a merger of two large beer manufacturers and find that cost efficiencies due to reduced shipping distances are large enough to offset unilateral price increases by the merging firms.

The rest of the paper is organized as follows. Section 2 provides a brief background on the potential effects of system ownership, recent trends in hospital outpatient care, and the related literature. Section 3 describes the key data sources and sample construction. Section 4 describes the reduced form analysis on the effects of system acquisitions on prices and costs. Section 5 presents a model of patient demand for outpatient care and a Nash-in-Nash bargaining model of hospital-insurer price negotiations. Section 6 presents the model estimates and results from counterfactual simulations. Finally, Section 7 concludes.

## 2 Background

### 2.1 Hospital system ownership

Multihospital firms, colloquially known as hospital "systems", have steadily expanded their footprint in the US hospital industry over the past few decades. In 2000, systems represented nearly 60% of bed capacity among short-term general acute care hospitals. This share increased to over

80% by 2020 (Andreyeva et al. 2024). Since relatively few new hospital facilities have opened in the US during this period, most of the growth in system capacity has been inorganic, driven by the acquisition of formerly independent or standalone hospitals.

System ownership offers numerous benefits to independent hospitals. One of the most significant benefits is economies of scale, which affects nearly every aspect of operations. In theory, systems can leverage the bulk purchasing power for medical supplies, equipment, and services, significantly reducing the procurement costs for materials and equipment. Scale facilitates greater financial stability. Systems enjoy access to cheaper credit and potentially more sources of capital than standalone facilities. A lower cost of capital gives systems a competitive edge in making the necessary investments for growth. Furthermore, systems can subsidize unprofitable member units for short periods of time, allowing them to make necessary long-term investments or changes in their operations. Systems can also streamline operations by centralizing administrative functions such as billing and accounting, IT, and human resources, minimizing overhead expenses. Finally, greater scale also helps to attract and retain top clinical and managerial talent. This has important implications for reputation, patient demand, and operational efficiency.

In addition to having access to potentially higher quality staff, hospital systems may also provide better patient care due to standardized protocols that ensure consistency in quality and safety across all facilities. Shared electronic health records (EHR) further improve care coordination, especially for patients receiving treatment at multiple locations, leading to better health outcomes.

The preceding advantages of system ownership may be considered beneficial to society as a whole, as these changes improve efficiency in the hospital industry and patient care simultaneously. Transitioning an independent hospital to system ownership may therefore generate a surplus for both the hospital and payers. The latter group is diverse and consists of the federal and state governments, employers, private insurers, and self-insured consumers. However, system ownership may also lead to changes that benefit the hospital at the expense of payers. Specifically, systems may use acquisitions to increase their share of a local market and, consequently, increase their bargaining leverage in negotiations with private insurers leading to higher prices without a commensurate change in quality of care. Alternatively, systems may use their existing leverage and bargaining tactics to negotiate a higher price for the newly acquired hospital without meaningful changes to the target facility. By construction, this will result in a welfare loss for consumers and taxpayers that fund hospital care.

Although the discussion above was with reference to the effects of system ownership for an independent hospital, the same arguments also apply to the case where a system acquires another system, so long as the acquirer is larger and offers scale economy benefits to the acquired units. That is, the effects of system ownership may apply both on the extensive and intensive margins.

## 2.2 Growth of outpatient care

In general, hospitals provide two types of care services, inpatient and outpatient. Inpatient services refer to care for which patients spend at least one night in the hospital. These services are geared for more intensive procedures that require sophisticated technology or that require supervised postoperative recovery and continuous monitoring for patients. Examples of inpatient care include complex procedures such as cardiac surgery and treatment for highly acute conditions such as pneumonia. In contrast, outpatient services refer to care in which the patient returns home after the procedure without staying overnight in the hospital. Common examples include diagnostic imaging and screening tests and minor procedures such as colonoscopies. Intuitively, hospitals receive much lower reimbursement for outpatient procedures. Traditionally, the vast majority of hospital revenue was sourced from inpatient care. As a result, economists have typically focused on outcomes related to inpatient care, including patient volume, prices, and quality.

With advances in technology, more procedures that were previously considered safe only in the inpatient setting are now feasible in the outpatient setting as well. Insurers have a financial incentive to encourage hospitals to perform more procedures in the outpatient setting once the technology has been proven. A recent example is knee replacement surgery. Starting in 2018, the Centers for Medicare and Medicaid Services (CMS) allowed hospitals to perform knee replacement surgery, known as total knee arthroplasty (TKO), as an outpatient procedure for Medicare patients. Medicare payments for TKO are approximately 30% lower when it is outpatient, generating significant savings for the program.

As a result of technology and cost considerations, the volume of outpatient care has grown over time, while that of inpatient care has declined. Therefore, the share of total revenue contributed by outpatient care has also increased. Figure A1 presents the trend in the revenue share of outpatient care specifically for privately insured patients at general acute care hospitals. Panel (a) presents the trends during 1995–2019 using data from CMS' HCRIS data for a national sample of hospitals. The revenue share of outpatient care increased from 35% in 1995 to more than 50% at the end of the study. Panel (b) shows a very similar pattern for hospitals in California using more granular data, albeit over a shorter period (2003–2019). Hence, outpatient care now accounts for the majority of revenue at hospitals among privately insured patients. This pattern, coupled with the paucity of evidence on outpatient care, motivates our focus on outpatient care services in this study.

## 2.3 Related Literature

### 2.3.1 Hospital Consolidation and Cost Efficiencies

Economists have long debated whether hospital consolidation yields economies of scale and lower operating costs. Early evidence was mixed, but recent studies suggest modest cost savings. In a difference-in-differences analysis of 2000–2010 mergers, Schmitt (2017) finds that acquired hospitals experienced 4—7% reductions in operating cost per discharge following a merger or acquisi-

tion. These cost declines were statistically significant and robust to alternative controls, implying that some promised efficiencies do materialize. Andreyeva et al. (2024) examine the effects of system acquisitions over 2013–2017 and find a 5% decrease in costs when the targets are standalone hospitals but only a small and statistically insignificant effect when the target is already part of a system. Similarly, Gaynor et al. (2023) fail to detect cost savings following the merger of two large hospital systems. Overall, the recent literature suggests that hospital mergers can produce some operating cost efficiencies, although far from uniformly or dramatically. These studies have used operating cost data from the Medicare cost reports, which limited their ability to shed light on the origins of the cost reductions. Hence, there is little consensus on the mechanisms producing these efficiencies.

### 2.3.2 Hospital Consolidation and Prices

A separate body of work analyzes how hospital consolidation affects prices negotiated with private health insurers. Here the evidence is clearer: consolidation leads to higher prices on average. Gowrisankaran, Nevo, and Town (2015) develop a structural bargaining model for hospital-insurer negotiations and use it to simulate a proposed merger in northern Virginia. Their simulations predict that a within-market hospital merger would significantly raise negotiated prices absent large efficiencies, and even with assumed cost synergies, the net price effect remains positive. Using transaction price data from large insurers, Cooper et al. (2019) examine the effects of 366 hospital mergers from 2007—2011. They estimate that transactions between nearby hospitals led to price increases over 6% for the merging facilities, whereas mergers between hospitals in distant markets ($> 25$ miles) had no significant price effect. Andreyeva et al. (2024) use transaction price data from a different insurer and reach a similar conclusion. Other studies have detected price increases following hospital acquisitions that span markets. Lewis and Pflum (2017) and Dafny, Ho, and Lee (2019) document price increases even when the merging hospitals do not share a market. The latter study theorizes that the price effects arise due to the presence of a common customer, the health insurer. However, their model assumes away the possibility of cost efficiencies following a merger. In addition to market power, Lewis and Pflum (2015) hypothesize that systems obtain higher prices because they are more skilled at negotiating prices with insurers than independent hospitals. Using data from California, they show that hospital systems have much higher bargaining weights than independent hospitals at a point in time. Overall, the net increase in prices following hospital consolidation implies that cost synergies are not passed through sufficiently to offset the incentive to increase prices. The same pattern has also been detected in other sectors of healthcare. For example, Dafny, Duggan, and Ramanarayanan (2012) find that insurer consolidation led to higher premium growth.

### 2.3.3 The Pass-Through of Cost Synergies

To our knowledge, Andreyeva et al. (2024) is the only study that has examined the effects of hospital acquisitions on prices and costs together. They detect a negative correlation between the

price and cost effects when systems acquire independent hospitals. This is consistent with a pass-through of savings since deals that delivered larger cost savings also had smaller price increases. However, they cannot accurately quantify the pass-through of savings since they cannot simulate prices without cost savings holding market structure constant. Therefore, the pass-through of cost synergies in hospital acquisition remains unexplored. Beyond the hospital setting, two recent studies have examined this question empirically. Blonigen and Pierce (2016) analyze manufacturing plant data across many sectors and find that after mergers and acquisitions, average markups increase with no detectable improvements in plant productivity. In other words, mergers raised firms' pricing power more than they improved efficiency. Miller and Weinberg (2017) estimate a structural model of the beer market and show that a merger of two large manufacturers achieved cost reductions (shipping distances fell by an average of 360 miles). The cost savings were large enough to offset unilateral price increases by the merging firms. However, the study finds that prices increased on net due to price coordination among the competing firms after the merger.

## 3 Data sources and key variables

This section describes the main data sources that underpin our analyses and the construction of key variables.

### 3.1 Hospital outpatient care use and prices

We use a novel data set that allows us to observe a sample of national patient-level billing claims for outpatient hospital care during the period 2013–20. This was first used by Liu (2022) to study the pricing strategies of private equity firms in the hospital industry. This data has several important features that suit our application. First, it contains granular details about patient characteristics and the procedure(s) performed, including the ability to follow patients over time across providers. Therefore, we can carefully model the demand for outpatient care from the patient. Second, for a subset of claims, we observe transaction prices for privately insured patients negotiated between hospitals and commercial insurers. Researchers typically have not had access to transaction prices since insurers and providers have protected this information as a trade secret. As a result, much of the prior literature on hospital consolidation has relied on prices imputed from hospital revenue data reported to regulators (Dafny 2009; Lewis and Pflum 2017; Dafny, Ho, and Lee 2019). Third, since the data is sourced from a claims processing intermediary between insurers and providers, it is not limited to a single insurer, provider, or employer, and is more representative of the average prices for hospital care faced by privately insured consumers.

We limit our empirical analysis to California, since it is a large state that experienced several hospital acquisitions during this period, is covered relatively well in the claims sample, and publicly releases detailed hospital accounting information that allows us to examine changes in operating costs for commercially insured patients. With regard to the claims data, we observe 289 general

acute care hospitals in the sample, out of a maximum of 293 possible facilities.[1] Panel A of Table A1 shows that the hospitals in our sample are representative of the universe of hospitals in California on important aspects like bed size, owner type, and payer mix. Similarly, Panel B of Table A1 shows that we observe prices for the large commercial insurers in the state. We limit the sample to patients aged 18 to 64 years and further exclude patients in privately administered Medicaid and Medicare plans. The final analysis sample has 6.6 million privately insured outpatient visits over 8 years and we observe the allowed amounts (prices) for approximately 20% of them. Section B.1 describes the claims data and sample construction in more detail.

**Hospital price index**

The patient-level claims allow us to observe prices by hospital, procedure, and payer. However, retaining such rich heterogeneity in prices introduces additional complexity into the analysis. Descriptive studies of hospital prices have found that variation in prices across hospitals is much larger in magnitude than that across payers (Panhans, Rosenbaum, and Wilson 2021). Hospitals are also much more likely to be consistently high- or low- priced across insurers than vice versa (Gorman et al. 2016). Therefore, to simplify the analysis, we construct a scalar price index for each hospital year, eliminating the variation across insurers. We deflate prices by the CPI-U series so that they are expressed in 2020 dollars. We also scale observed prices by the procedure APC weight, a measure of the intensity of resource use developed by CMS to adjust Medicare payments for hospital outpatient care. Hence, the variable used in our analysis reflects a standardized price charged by a hospital for a procedure of APC weight 1. Finally, we estimate fixed effects models at the patient level that account for differences in patient demographics and health risks. Hospital-year fixed effects recovered from this estimation serve as the corresponding price indices. This approach follows previous work on the effects of hospital consolidation (Gowrisankaran, Nevo, and Town 2015; Cooper et al. 2019). Appendix B.1 describes the steps in more detail.

### 3.2 Hospital operating costs

We obtain information on operating costs from annual hospital cost reports submitted by hospitals to California during the period 2013–2020. The reports are processed by HCAI and released for public use. We prefer using these reports over the HCRIS or Medicare cost report data more commonly used in health economics research for three reasons. First, states are known to invest more in maintaining the quality of such reports than CMS, such as by performing regular audits. California reports have long been recognized as high quality and have frequently been used by researchers to study hospital operations (Duggan 2000; Ho and Lee 2017). Second, California data allow us to calculate, with reasonable assumptions, the average cost per outpatient visit for

1. Kaiser Permanente (KP) is the largest hospital system in California with 31 hospitals in 2019. This is not observed in the claims data and we do not include it in the count of hospitals in the state since it is a closed-network vertically integrated firm that offers both insurance and healthcare to its members. Hence, these hospitals do not negotiate contracts with other insurers, nor does the insurance arm purchase care from outside facilities.

privately insured patients, which is not possible using HCRIS. Third, we can disaggregate costs into more granular categories in California reports than in HCRIS. This enables examining the sources of cost synergies following system ownership.

**Outpatient cost per visit**

We briefly describe the steps to calculate the operating costs for privately insured patients, the details of which are left for Section B.3. For each hospital, we observe operating cost by granular service line (e.g., coronary care, psychiatric long-term care, etc.). We also observe the gross revenue for inpatient and outpatient care by payer type (e.g., Medicare, Medicaid, and private) for each service line. We then make two assumptions that have been used in prior research examining hospital costs. First, outpatient care contributes the same share of total cost as its share of gross revenue for a service line. In effect, we are assuming that the ratio of list prices ("charges") to costs does not vary by service line. Researchers frequently invoke this assumption when they use a hospital-wide cost-to-charge ratio to calculate patient-level costs based on charges. Second, we assume that payers contribute the same share of the total outpatient cost for a service as their share of gross outpatient revenue for that service. This effectively imposes that the cost-to-charge ratio within a service is constant across payers. Using these two assumptions, we calculate the outpatient cost by service line and payer and aggregate to the payer level. Since the report also records the number of outpatient visits by payer, we calculate the mean operating cost per visit for privately insured patients. We scale the mean cost per visit by the mean APC weight corresponding to the hospital in the claims sample and obtain a standardized mean cost per visit for a weight of 1. Finally, as with prices, we deflate the operating cost per visit to be expressed in 2020 dollars.

### 3.3 Changes in hospital ownership

A key task is to identify which hospitals and systems are involved in acquisitions. We limit the analysis to deals that were executed between 2014 and 2017. This allows us to observe prices and costs for at least one year before and three years after each deal. To identify the facilities involved in the deals, we closely follow the approach used by previous studies on hospital consolidation (e.g., Schmitt 2017; Andreyeva et al. 2024). We identify potential acquisitions by examining changes in system ownership reported in the American Hospital Association (AHA) annual hospital surveys. The AHA assigns a unique ID to each system, allowing us to track changes in hospital-system links. We detect two types of deals involving systems as acquirers. First, systems may acquire independent or standalone facilities. In this case, a previously unaffiliated hospital begins to report being a member of a specific system. Second, one system may acquire all or some facilities owned by another system. This will show in the data as a change in the system ID associated with the acquired hospitals. This exercise results in a starting list of facilities involved in acquisitions.

We enhance the list from the AHA using hospital acquisitions listed in SDC platinum, which has also been used in prior studies of hospital ownership (Liu 2022). Finally, we manually validate each deal to confirm: 1) it involves a change in ownership, not merely a partnership or affiliation of some sort; 2) the acquirer and target(s) involved; and 3) the year the deal closed as opposed to when it was announced. This process yields 11 deals in which systems acquired one independent hospital at a time and 2 deals in which one acquirer, Providence, acquired a total of 11 hospitals from other systems. Hence, a total of 22 hospitals were acquired during this period in California. Table A2 lists the acquisition systems and targets for all the deals identified during this period. A limitation of the claims data is that we do not observe price information for five independent targets prior to their acquisition.

### 3.4 Supplementary data

In addition to the key data sources described above, we use several publicly available datasets. This includes data from the American Community Survey (ACS) on population and demographic characteristics by zipcode, hospital market definitions from California HCAI, and hospital characteristics from CMS Provider of Service files. Travel time to the hospital is a key explanatory variable in the demand analysis. This is calculated using information from the proprietary API of a data provider, HERE. Specifically, we look up the average travel time between the population-weighted centroid of the patient's 3-digit zipcode and the hospital's exact location.

## 4 Effects of system ownership: Reduced form analysis

This section describes a reduced form analysis to quantify the causal effects of acquisitions by systems. The goal is to transparently test whether system ownership leads to changes in prices and operating costs for outpatient care services.

### 4.1 Research design

We follow previous studies on hospital consolidation and use a staggered difference-in-differences (D-D) research design for this exercise (e.g., Craig, Grennan, and Swanson 2021; Andreyeva et al. 2024). We begin with an approach that mirrors most prior work and estimates an average effect across all acquisitions in the sample. The design compares the trends for 17 target hospitals (6 independent and 11 system-owned) with those of a set of comparison hospitals that are not involved in any acquisition during this period. The comparison group includes hospitals that remain independent until December 2020, as well as system-owned hospitals that are neither acquirers nor targets in a deal themselves.

We estimate the model presented in Equation 1 below to quantify causal effects for the acquired

hospitals.

$$Y_{ht} = \alpha_h + \alpha_t + \beta\, 1(\text{acquired})_h \cdot 1(t \geq T)_{ht}\, [+X'_{ht}\delta]\, + \epsilon_{ht}. \tag{1}$$

We include hospital fixed effects to eliminate stable unobserved differences between hospitals and ensure that we rely only on within-hospital changes in outcomes to estimate the treatment effect. Since the most important concerns about potential omitted variables bias relate to stable factors (e.g., teaching status, weak management, etc.), this approach mitigates concerns about the endogeneity of acquisitions to a first-order. We also include year fixed effects to account for secular trends in the outcomes, such as changes in operating costs that reflect technological advances. The coefficient of interest, $\beta$, is on the interaction of an indicator for acquisition and a hospital-specific time-varying indicator that takes the value of one starting in the year of acquisition. In secondary models, we also include a vector of time-varying hospital characteristics, $X_{ht}$, such as the number of beds and the share of patients contributed by Medicare and Medicaid. This helps control for differences in attributes that may change significantly over time and affect outcomes. Reassuringly, including or excluding these covariates does not affect the coefficients of interest, mitigating concerns about omitted variables bias. $\epsilon_{ht}$ denotes all remaining unobserved idiosyncratic factors.

Under the standard parallel trends assumption, $\beta$ is unbiased and recovers the average treatment effect on treated hospitals, or the ATT. In our setting, this means assuming that the acquired and comparison hospitals would continue along their preexisting trends in the absence of acquisitions. This assumption is untestable. However, we present evidence on the dynamic treatment effects to assess the plausibility of the assumption. Equation 2 below represents these models. The coefficients $\beta_s$ from years before treatment indicate whether the acquired hospitals trended differently from the comparison hospitals even before they were acquired. A lack of differential pre-trends supports the parallel trends assumption.

$$Y_{ht} = \alpha_h + \alpha_t + \sum_{s=-5,\neq -1}^{s=4} \beta_s\, 1(\text{acquired})_h \cdot 1(t = s)_{hs}\, [+X'_{ht}\delta]\, + \epsilon_{ht}. \tag{2}$$

### 4.2 Estimation

Recent econometric studies have shown that D-D estimates obtained using conventional two-way fixed effects (TWFE) models suffer from bias in the presence of staggered treatment and heterogeneity in the treatment effect (Goodman-Bacon 2021). This threat also extends to the dynamic effects obtained by using Equation 2 (Sun and Abraham 2021). We use the estimator developed by Borusyak, Jaravel, and Spiess (2024) to circumvent this concern. This estimator is consistent for the ATT in our setting even if there is treatment effect heterogeneity and it produces unbiased

dynamic treatment effects in addition to an unbiased ATT. We use the R package "didimputation" to implement this estimator.

### 4.3 Descriptive evidence

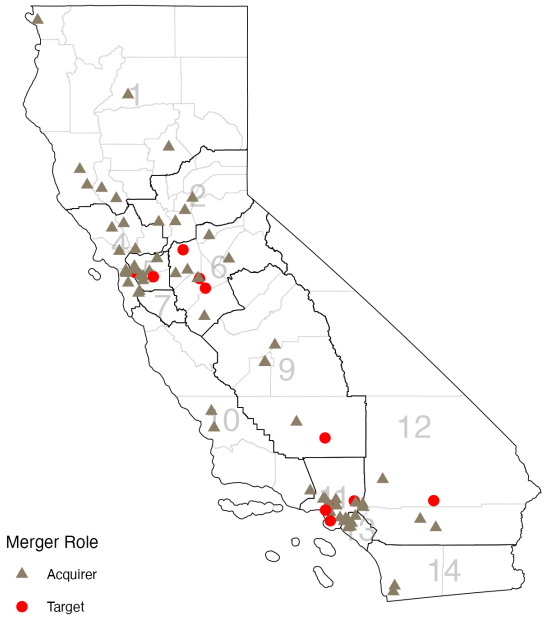
Figure 1 presents California maps to help the reader navigate the geography of hospital markets in the state and the locations of hospitals involved in the acquisitions studied here. Panel (a) depicts the hospitals involved in the acquisitions of independent targets, while Panel (b) does the same for acquisitions of system-owned facilities. We use the geographic markets delineated by HCAI based on healthcare use patterns. These are called Health Service Areas (HSA), and they consist of contiguous counties selected so that the residents of these counties are typically observed choosing hospitals within the set. These markets have previously been used by Ho and Lee (2017) to study hospital-insurer price negotiations for inpatient care services. Although the agency defines 14 markets, we combine two small markets into their larger neighbors based on the hospital choice patterns observed in the claims data sample. Our analysis therefore recognizes 12 hospital markets.[2]

For those familiar with California's geography and population distribution, the market definitions are intuitive. For example, 14 sparsely populated counties in the northern part of the state are combined to form one HSA with Redding as the main city (HSA 1). At the other extreme, Los Angeles (LA) County is coterminous with a hospital market (HSA 11).

The map also shows the locations of the hospitals involved in the acquisitions. Hospitals that were already part of the acquiring system prior to 2014 and targets are represented in triangles and circles, respectively. Intuitively, most target hospitals are located in populous counties in or near the San Francisco Bay area and LA. In our sample, acquirers have more geographic overlap with their independent targets. Nine out of the 11 independent targets share a market with at least one acquirer hospital, while only one of the 11 system-owned targets shares a market (LA) with the acquirer, Providence. Previous studies on hospital consolidation have found that the geographic proximity between merging parties is a strong predictor of price increases (Dafny 2009; Cooper et al. 2019). Furthermore, although Providence is a large chain nationwide, it owned only five hospitals in California prior to 2014 and was therefore a small player relative to other systems in the state (e.g., Sutter). Together, these patterns suggest that the price gains due to acquisition will be larger for independent targets.

2. Specifically, we combine HSA 3 (Napa, Solano, and Sonoma counties) into HSA 4 (San Francisco, Marin, and San Mateo counties) and HSA 8 (Monterey, San Benito, Santa Cruz, and San Louis Obispo) into HSA 10 (Ventura and Santa Barbara). This decision was prompted by the fact that the majority of patients in the claims data residing in the former markets choose hospitals located in the latter markets.

(a) Independent




(b) System

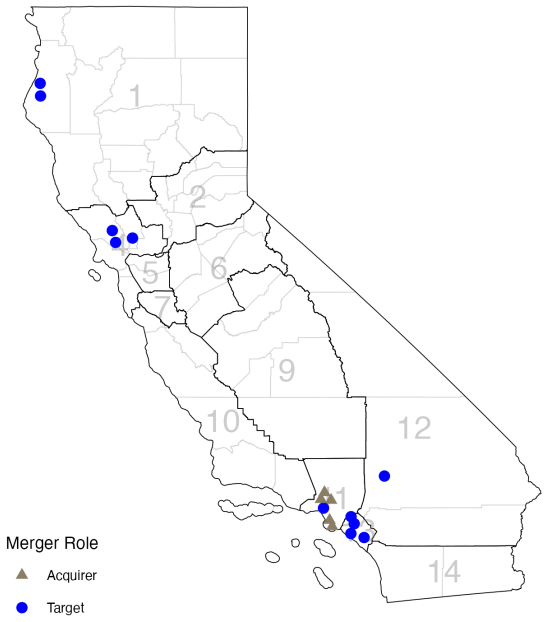



Figure 1: Hospital markets and acquisitions

Notes: This figure depicts the boundaries of the hospital markets in California used in the analysis. These markets were defined and numbered by California Health Care Access and Information (HCAI) to study healthcare markets. The maps also depict the locations of acquiring and target hospitals involved in the deals studied in the article. Panels (a) and (b) present the locations of facilities involved in acquisitions of independent and system-owned hospitals, respectively.

Table 1 presents descriptive statistics on the hospitals observed in the sample. The values represent means for the first year that we observe the hospital in the sample, which is 2013 in the case of most hospitals. Column 1 describes all hospitals in the sample. Columns 2–6 describe different subgroups of hospitals based on their system status and role in the analysis. Column 2 describes hospitals belonging to acquirers in the 13 acquisition deals during this period. These hospitals do not experience a change in ownership and are not used in the reduced form analysis. Column 3 describes the hospitals used as the comparison group for the independent targets, shown in Column 4. Column 5 describes system-owned hospitals used as the comparison group for system-owned targets, shown in Column 6.

Panel A presents hospital characteristics such as bed capacity, teaching status, share of patients on Medicaid and Medicare (including private plans such as Medicare Advantage), and the fraction of hospitals owned by for-profits. Panel B presents the mean values of the key outcome variables. This includes the standardized values of the price (allowed amount) and variable cost per outpatient visit for privately insured patients. We refer to these as standardized values since they correspond to a procedure of APC weight one. We also present the mean APC weight for privately insured patients observed in the claims sample. Finally, we also present the proportion of total operating cost that we consider to be variable in nature. Table xx lists all the cost categories observed in the cost reports and their classification into fixed and variable costs.

Columns 2 and 4 help to compare the acquirer and target independent hospitals at the beginning of the sample period. The targeted hospitals had about 15% smaller bed capacity on average, but had similar shares of patients on public insurance plans and a similar rate of for-profit ownership. The most striking difference is in the price level. The hospitals in the acquiring system enjoyed a standardized price nearly 75% higher than the independent hospitals targeted for acquisition. In contrast, variable operating costs were similar between the two groups of hospitals, implying that the acquirer enjoyed significantly higher mark-ups. Indeed, mean variable (and total) cost per visit was slightly lower at the targeted facilities. The hospitals in Column 3 constitute the comparison group for the independent targets (Column 4). The hospitals in both groups are smaller on average than the system-owned hospitals. Comparison hospitals enjoy much higher prices than the target hospitals. In fact, their price level is even higher on average than that of system hospitals. These patterns argue against the realization of cost efficiencies as the key motivation for the acquisition of independent hospitals. Instead, a pricing arbitrage opportunity is readily apparent if the acquirer could renegotiate prices for the newly acquired hospital at levels close to those enjoyed by its existing hospitals.

Table 1: Descriptive Statistics

| | All Hospitals | Acquiring System | Independent | Independent Target | System-Owned | System-Owned Target |
|---|---|---|---|---|---|---|
| No. of Hospitals | 298 | 74 | 93 | 11 | 109 | 11 |
| No. of Systems | 145 | 11 | 93 | 11 | 29 | 2 |
| Hospital Characteristics | | | | | | |
| Beds | 200.73 | 206.73 | 146.23 | 168.91 | 242.50 | 239.18 |
| Fraction Teaching | 0.06 | 0.04 | 0.02 | 0.00 | 0.11 | 0.00 |
| Medicare Share of Visits | 0.31 | 0.30 | 0.32 | 0.30 | 0.32 | 0.34 |
| Medi-Cal Share of Visits | 0.25 | 0.26 | 0.27 | 0.28 | 0.24 | 0.12 |
| Fraction For-Profit | 0.22 | 0.32 | 0.11 | 0.27 | 0.27 | 0.00 |
| Fraction Rural | 0.05 | 0.01 | 0.12 | 0.00 | 0.02 | 0.00 |
| Prices, Costs, and Service Mix | | | | | | |
| Standardized Price Per Visit | 397.53 | 306.85 | 509.77 | 196.85 | 381.42 | 449.92 |
| Standardized Cost Per Visit | 59.59 | 66.34 | 59.15 | 52.43 | 58.15 | 39.29 |
| Average APC Weight | 8.28 | 8.31 | 7.53 | 9.60 | 8.69 | 8.73 |
| Percentage Variable Costs | 60.76 | 56.64 | 63.98 | 63.95 | 60.71 | 58.45 |

Notes: This table presents descriptive statistics on the hospitals observed in the analysis sample. The values are taken from the first year a hospital is observed in the sample, which is 2013 for most hospitals. Column 1 describes all hospitals in the sample. The remaining columns describe the following subgroups: Column 2, acquirer hospitals; Column 3, independent hospitals used as a comparison group for independent targets; Column 4, independent targets; Column 5, system-owned hospitals used as a comparison group for system-owned targets; and Column 6, system-owned targets. The price and variable cost values only reflect outpatient care and are standardized for a procedure of APC weight 1. The price and cost values are expressed in 2020 dollars. The average APC weight for privately insured patients is taken from the claims sample.

Similarly, comparing the acquirers in Column 2 and the target hospitals in Column 6 shows that although similar in many respects, the target hospitals had much lower price levels than the acquirers at baseline. The target hospitals appear to have a lower standardized operating cost at baseline, arguing against the potential for further efficiency improvements by merging into the acquirer. Perhaps the most distinctive feature of the system target facilities is that there is no for-profit hospital among them.

## 4.4 Results

This section presents the results of the reduced form analysis. We focus on the effects on the prices and costs of outpatient care services. We also investigate the effects on specific cost categories to help explain the changes in operating costs.

### 4.4.1 Prices

Table 2 presents the effect of system acquisition on prices for outpatient care services. We present difference-in-differences estimates from three models in each panel. Column 1 presents results from a model with hospital and year fixed effects but does not include time-varying covariates or account for differences in hospital size. Column 2 weights hospitals by bed capacity in order to give more importance to larger target hospitals since they serve more patients. Column 3 also includes the time-varying hospital covariates discussed in Section 4.1. Column 3 is our preferred specification. Figure 2 presents the corresponding dynamic effects on outpatient prices estimated using Equation 2 from a model corresponding to Column 3. Panels (a), (b), and (c) present the effects on prices for all targets, independent targets, and system-owned targets, respectively.

Table 2 Panel (a) implies that system acquisitions result in an average increase of $63 per outpatient visit on a base of approximately $400. This represents a meaningful 15% increase in prices; however, the coefficient is imprecisely estimated at conventional levels of significance. Figure 2 Panel (a) shows dynamic effects consistent with a modest and imprecise increase in price.

Table 2 Panel (b) indicates that independent targets experience a sharp increase in price of approximately $225. This represents more than a 100% increase in the baseline price level at the targeted hospitals before acquisition. The choice of specification does not qualitatively affect this conclusion. Figure 2 Panel (b) confirms this interpretation. There is no evidence of differential trends before acquisition and a continuous increase in price in each year of system ownership, which appears to stabilize by the fourth year after the deal. A large increase in price at independent targets due to system ownership is also consistent with unadjusted trends in the price index, as seen in Table A3. The table shows that the mean prices at the acquired hospitals rose approximately $230 from the year before the acquisition to 3 years after the acquisition. The patterns suggest a convergence of price levels between the acquirer and the acquired facilities. The mean prices at the acquired hospitals were 46% (163 vs. 356) that of their acquirers in the year of acquisition.

However, in the third year after the transaction, prices at the acquired hospitals had risen to 93% (359 vs. 386)) of the mean price at the acquirer hospitals.

Table 2 Panel (c) shows that system-owned targets experience a decrease in price after acquisition, although the coefficient is imprecisely estimated. Figure 2 Panel (c) shows a downward trend in price after acquisition, however it is not consistently trending down. Overall, we interpret these patterns as representing an ambiguous effect on the target's price index.

The results highlight the heterogeneity in the treatment effects of system acquisition depending on the state of the target hospital. Much of the previous literature has overlooked this heterogeneity and estimated the average effect of hospital consolidation (e.g., Cooper et al. 2019). However, our estimates imply that the consolidation of independent hospitals has a much bigger impact on price levels than changes in ownership of hospitals that are already owned by a system.

Table 2: Difference-in-Differences Estimates on Prices

| | No Controls, Unweighted | No Controls, Weighted | Controls, Weighted |
|---|---|---|---|
| Acquired x Post | −0.05 | 53.94 | 62.77 |
| | (35.36) | (61.57) | (56.79) |
| No. Obs. | 1001 | 983 | 981 |
| Mean Price Per Visit, Pre-Acquisition | 354.64 | 353.19 | 353.19 |

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

(a) All Targets

| | No Controls, Unweighted | No Controls, Weighted | Controls, Weighted |
|---|---|---|---|
| Acquired x Post | 245.73*** | 278.78*** | 226.28*** |
| | (59.29) | (53.23) | (50.34) |
| No. Obs. | 482 | 482 | 482 |
| Mean Price Per Visit, Pre-Acquisition | 145.33 | 145.33 | 145.33 |

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

(b) Independent Targets

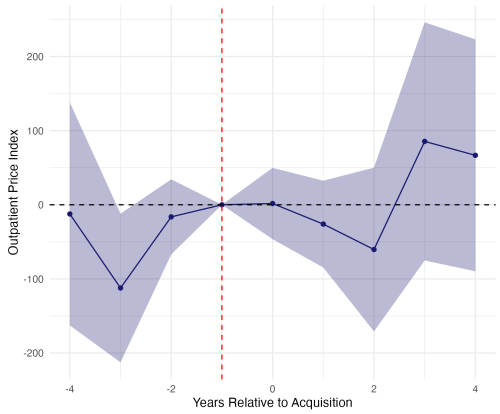
| | No Controls, Unweighted | No Controls, Weighted | Controls, Weighted |
|---|---|---|---|
| Acquired x Post | −107.74*** | −63.57 | −70.86 |
| | (37.58) | (75.21) | (85.49) |
| No. Obs. | 519 | 501 | 499 |
| Mean Price Per Visit, Pre-Acquisition | 397.95 | 397.73 | 397.73 |

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

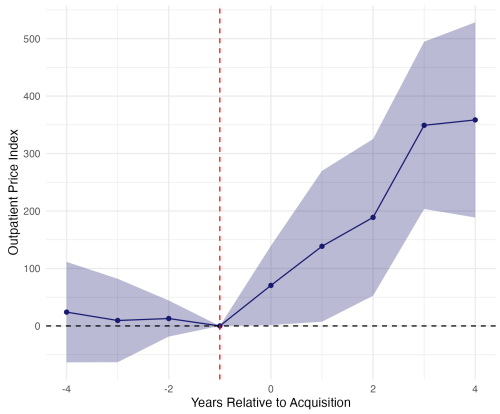
(c) System-owned Targets

Notes: This table presents difference-in-differences estimates of the effect of system acquisition on prices for the acquired hospitals. Panels (a), (b), and (c) present the average effect for all targets, independent targets, and system-owned targets, respectively. We present results from three specifications in each panel. Column 1 presents the results using a model without hospital covariates and no weighting to account for differences in hospital size. Column 2 presents results from a model in which observations are weighted by the number of beds to account for differences in size. Column 3 presents results from a model which includes both covariates and weighting. Standard errors are clustered by hospital. Prices are deflated to 2020 dollars. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

(a) All targets




(b) Independent targets




(c) System-owned targets

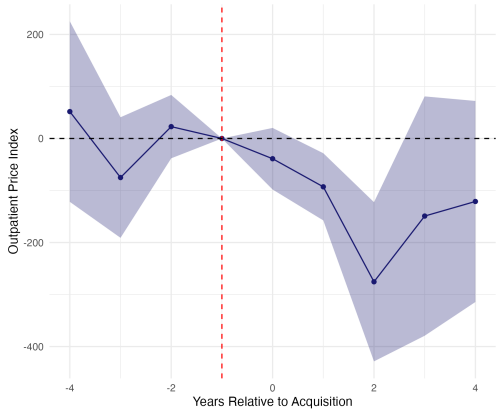



Figure 2: Dynamic Effects on Hospital-Level Outpatient Prices

Notes: This figure presents event study estimates of the effect of a system acquisition on hospital outpatient prices. Panels (a), (b), and (c) present the estimates for all targets, independent targets, and system-owned targets, respectively. The outpatient price index is adjusted for severity, demographics, and payer composition, as described in the appendix. The models include time-varying controls such as the Medicare share of visits, the number of beds, and the percentage elderly population in the hospital's HRR. The shaded region indicates 95% confidence intervals. Standard errors are clustered by hospital.

### 4.4.2 Operating cost

Table 3 below presents the corresponding difference-in-differences estimates on variable operating cost at the acquired hospital following system acquisition. It is identical in format to Table 2 that examined the effects on prices. Similarly, Figure 3 presents the corresponding dynamic effects of system acquisition on operating costs at the targeted hospitals.

Table 3 Panel (a) reports a modest decrease in operating cost per visit of $4. This represents a decrease of approximately 6% relative to the baseline cost at the target hospitals. However, the coefficients are statistically insignificant across all models. Panel (a) of Figure 3 similarly suggests that there is no significant change in costs after acquisition. However, this is the average effect across all targets and masks considerable heterogeneity.

When we disaggregate the results by the ownership type of the target hospital, we detect a precisely estimated meaningful reduction in operating cost at independent targets but cannot reject the null of no change in costs at system-owned target hospitals. The coefficients in Table 3 Panel (b) indicate a reduction of about $15 per visit, approximately 22% of the baseline operating cost level. The coefficient remains similar in magnitude across models, but precision improves when we weight hospitals according to bed capacity. Figure 3 Panel (b) presents the corresponding dynamic effects, which corroborate the DD estimate. The figure shows no evidence of differential trends at the targeted facilities before acquisition and a sharp trend break toward a reduction in costs after system ownership.

Table 3: Difference-in-Differences Estimates on Costs

| | No Controls, Unweighted | No Controls, Weighted | Controls, Weighted |
|---|---|---|---|
| Acquired x Post | $-6.88$ | $-4.32$ | $-5.28$ |
| | $(4.92)$ | $(3.77)$ | $(4.25)$ |
| No. Obs. | 1354 | 1353 | 1353 |
| Mean Cost Per Visit, Pre-Acquisition | 35.25 | 35.25 | 35.25 |

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

(a) All Targets

| | No Controls, Unweighted | No Controls, Weighted | Controls, Weighted |
|---|---|---|---|
| Acquired x Post | $-15.64^{*}$ | $-13.38^{**}$ | $-15.82^{**}$ |
| | $(9.35)$ | $(6.05)$ | $(7.28)$ |
| No. Obs. | 674 | 673 | 673 |
| Mean Cost Per Visit, Pre-Acquisition | 52.38 | 52.38 | 52.38 |

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

(b) Independent Targets

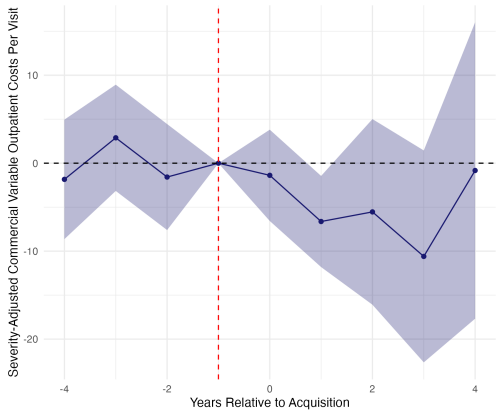
| | No Controls, Unweighted | No Controls, Weighted | Controls, Weighted |
|---|---|---|---|
| Acquired x Post | 0.32 | 5.84 | 1.23 |
| | $(6.31)$ | $(4.67)$ | $(5.79)$ |
| No. Obs. | 680 | 680 | 680 |
| Mean Cost Per Visit, Pre-Acquisition | 30.97 | 30.97 | 30.97 |

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

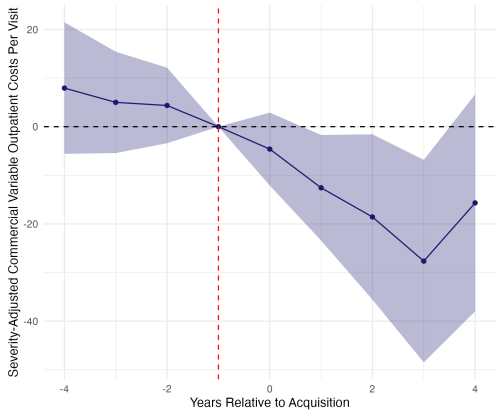
(c) System-Owned Targets

Notes: This table presents difference-in-differences estimates of the effect of system acquisition on operating cost at the acquired hospitals. Panels (a), (b), and (c) present the average effect for all targets, independent targets, and system-owned targets, respectively. We present results from three specifications in each panel. Column 1 presents the results using a model without hospital covariates and no weighting to account for differences in hospital size. Column 2 presents results from a model in which observations are weighted by the number of beds to account for differences in size. Column 3 presents results from a model which includes both covariates and weighting. Standard errors are clustered by hospital. Costs are deflated to 2020 dollars. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

(a) All targets




(b) Independent targets




(c) System-owned targets

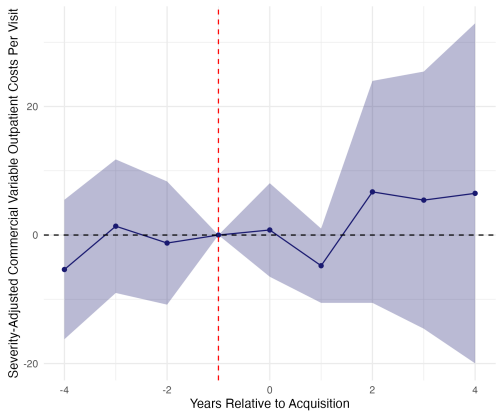



Figure 3: Dynamic Effects on Hospital-Level Outpatient Cost Per Visit

Notes: This figure presents event study estimates of the effect of a system acquisition on hospital outpatient cost per visit. Panels (a), (b), and (c) present the estimates for all targets, independent targets, and system-owned targets, respectively. The models include time-varying controls such as the Medicare share of visits, the number of beds, and the percentage elderly population in the hospital's HRR. The shaded region indicates 95% confidence intervals. Standard errors are clustered by hospital.

Finally, the point estimates in Table 3 Panel (c) imply a modest *increase* in operating cost at system-owned targets after acquisition. However, the coefficient in our preferred specification is close to zero and is not statistically significant. As in the case of prices, these results highlight the importance of heterogeneity in the effects of system acquisitions. The consolidation of independent hospitals appears to generate meaningful cost savings.

The previous analysis focused only on variable operating costs. We further investigate the reduction in costs at independent targets by examining the effect on different categories of total operating costs. Figure 4 below presents dynamic effects on four mutually exclusive and collectively exhaustive groupings of costs at independent targets. The top two panels present the effects on labor expenses assigned to fixed and variable costs, respectively. The bottom two panels present the effect on nonlabor expenses similarly bifurcated into fixed and variable. The panels clearly show that the main reduction in operating cost is driven by the variable labor category. Table A4 presents the corresponding D-D estimates for the effects on each category. Consistent with the event study plots, it shows that the effects on fixed costs are small and are imprecisely estimated. In contrast, we detect much larger and precise reductions in variables costs. The total reduction in variable costs is approximately $17 per visit, more than three times the total estimated reduction in fixed costs and disproportionate to their respective contributions to the total cost base.

Figure A2 presents event study plots showing the dynamic effects on more granular categories of variable costs at independent targets.

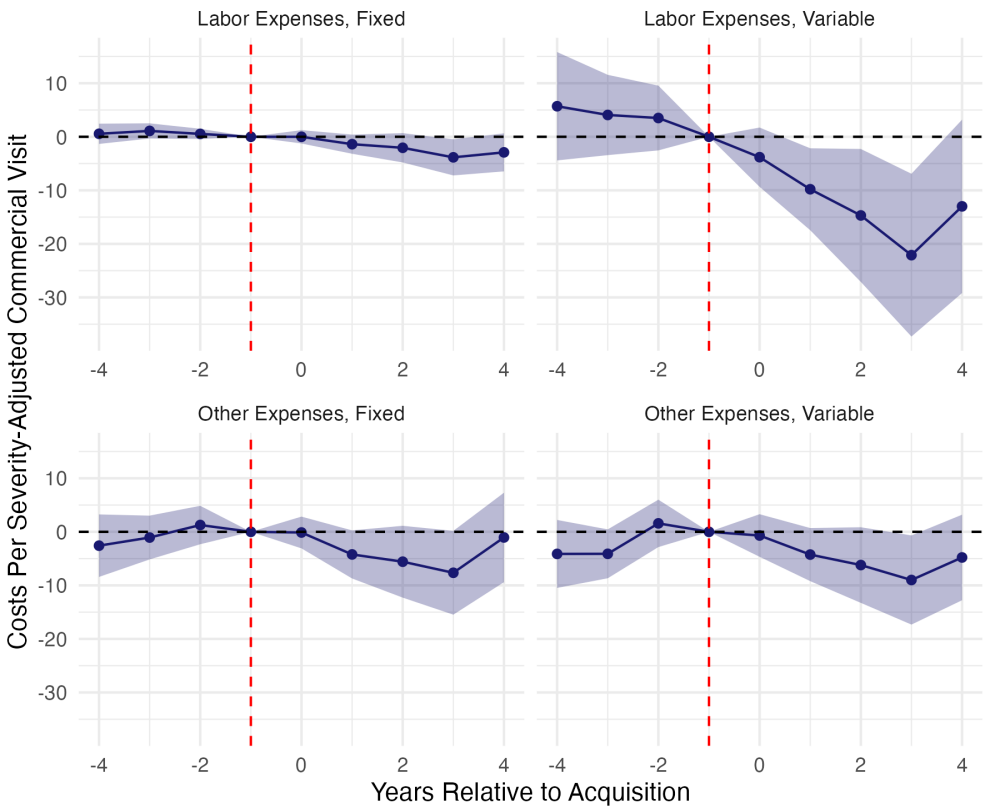



Figure 4: Dynamic Effects on Cost Per Visit, Independent Targets

Notes: This figure presents event study estimates of the effect of a system acquisition on four mutually exclusive collectively exhaustive components of operating cost at independent target hospitals. The models include time-varying covariates as described in Section 4.1. The shaded area represents 95% confidence intervals. Standard errors are clustered by hospital.

Next, we develop an economic model of insurer and hospital price negotiations and estimate the parameters of the model so that we can simulate counterfactual scenarios and quantify the fraction of these savings that are passed to insurers in the form of lower prices.

# 5 Model and estimation

## 5.1 Model

This section describes our model of the market for private hospital outpatient care. The model features the negotiations between hospital systems and insurers as well as patients' choices over providers. We use this model to quantify how provider reimbursements are determined in equilibrium. Furthermore, we use the model to decompose how reimbursements change after a hospital system makes an acquisition, where we allow for changes in bargaining weights, and bargaining positions (as in Lewis and Pflum (2017)) and, importantly for our research question, quantify the

pass-through of the cost synergies that we document in our reduced form evidence in the previous sections.

The model consists of two stages. In the first stage, insurers negotiate with the hospitals in their networks over the reimbursement rates for outpatient care. In the second stage, patients requiring outpatient care choose a hospital within their insurer's network. We describe the components of the model by starting with the second stage and then working backward to the first.

### 5.1.1 Patient demand

In each market year, there exists a set of patients $n = 1, \cdots, N$ (we omit market year subscripts for notational convenience). Patients are covered by a set of insurers $i = 1, \cdots, I$; where applicable, we denote patient $n$'s insurer as $i(n)$. Each insurer offers a network of covered outpatient hospitals $\mathcal{G}_i$, which is a subset of the total set of hospitals operating in the market $h = 1, \cdots, H$.

Patient $n$'s indirect utility from receiving care at hospital $h$ is specified as

$$u_{nhi} = \alpha_0 \cdot d_{nh} + \alpha_1 \cdot d_{nh}^2 + \alpha_2 \cdot \mathbf{X}_{ni}^1 \cdot \mathbf{Y}_h^1 + \alpha_3 \cdot \mathbf{X}_n^2 \cdot \mathbf{Y}_h^2 + \eta_h + \varepsilon_{nhi}. \tag{3}$$

This specification is similar to that used in Liu (2022), with the notable difference that we do not include indicators for hospital ownership by private equity firms, which is a central focus of his paper. Our specification is also similar to Prager and Tilipman (2020). Here, $d_{nh}$ measures the travel time (in hours) between patient $n$'s residence and hospital facility $h$'s location. The term $\mathbf{X}_{ni}^1 \cdot \mathbf{Y}_h^1$ captures interactions between patient observables and hospital characteristics. $\mathbf{X_i^1}$ includes the average income in patients' ZIP code, travel time, relative service-mix weights, patient gender, an indicator for whether the patient visited any hospital in the past year, and indicators for insurance coverage by either UnitedHealth, Anthem, or CA Blue Shield. $\mathbf{Y}_h^1$ includes the number of hospital beds, for-profit status, and teaching status. Similarly, $\mathbf{X}_n^2 \cdot \mathbf{Y}_h^2$ captures additional interaction terms. $\mathbf{X}_n^2$ includes all variables in $\mathbf{X}_{ni}^1$ except those relating to insurance carriers. $\mathbf{Y}_h^2$ includes indicators for the presence of catheterization laboratories, magnetic resonance imaging services, neurological services, or neonatal intensive care units in a hospital. The term $\eta_h$ represents hospital fixed effects, while $\varepsilon_{nhi}$ is assumed to be independently and identically distributed, following the Type 1 Extreme Value distribution.

We model patient choices among hospitals in their local market that are within their insurance's network. The outside option corresponds to seeking care at a hospital outside of the market.[3] We assign the outside option a mean utility of zero.

Let $\delta_{nhi} = u_{nhi} - \varepsilon_{nhi}$, where $\delta_{nhi}$ represents patient $n$'s mean utility. Conditional on requiring treatment, the probability that patient $n$ goes to hospital $h$ (among in-network hospitals) is given

3. Our sample only consists of patients that live in California and receive outpatient hospital care in California.

by the standard logit choice probability:

$$S_{nhi}(\mathcal{G}_i) = \frac{\exp(\delta_{nhi})}{1 + \sum_{\mathcal{G}_i} \exp(\delta_{nhi'})}. \tag{4}$$

Aggregating across enrollees, the total demand from insurer $i$ for hospital $h$ is

$$D_{hi} = \sum_{\{n:i(n)=i\}} \gamma_{vn}\gamma_{dn}S_{nhi}, \tag{5}$$

where $\gamma_{vn}$ is the probability that patient $n$ will need outpatient care within the year, and $\gamma_{dn}$ is the diagnosis probability, conditional on having a visit. Both probabilities are allowed to vary across patients.

The expected utility that patient $n$ derives from their insurer's network $\mathcal{G}_i$ plays an important role in the bargaining model (as in Gowrisankaran, Nevo, and Town (2015) and Lewis and Pflum (2015)). It is given by

$$W_{ni}(\mathcal{G}_i) = \gamma_{vn}\gamma_{dn} \log\left(\sum_{h\in\mathcal{G}_i} \exp(\delta_{nhi})\right). \tag{6}$$

### 5.1.2 Bargaining model

In each market-year pair, every hospital $h$ belongs to a system denoted by the set $\mathcal{H}_h$ (for independent hospitals, this set is a singleton).[4] Each insurer $i$ operating in the market negotiates reimbursement rates $p_{hi}$ for every hospitals $h$ in its network $\mathcal{G}_i$.

The payoff to hospital $h$ for being part of insurer $i$'s network is given by

$$\Pi_{hi}(\mathcal{G}_i) = (p_{hi} - c_h)D_{hi}(\mathcal{G}_i), \tag{7}$$

where $D_{hi}(\mathcal{G}_i)$ represents the demand for hospital $h$ from enrollees of insurer $i$, which depends on insurer $i$'s entire network ($\mathcal{G}_i$). Demand tends to be increasing in the size of the network.

Following Gowrisankaran, Nevo, and Town (2015) and Lewis and Pflum (2015), the payoff to insurer $i$ from offering network $\mathcal{G}_i$ is characterized as

$$V_i(\mathcal{G}_i) = \beta \sum_{\{n:i(n)=i\}} W_{ni}(\mathcal{G}_i) - \sum_{h\in\mathcal{G}_i} p_{hi}D_{hi}(\mathcal{G}_i). \tag{8}$$

The first term on the right-hand side represents the dollar value of the aggregate expected utility of insurer $i$'s enrollees under network $\mathcal{G}_i$, where $\beta$ reflects the weight insurers place on their enrollees'

4. Under this notation, if $h$ and $h'$ belong to the same hospital system, then the sets $\mathcal{H}_h$ and $\mathcal{H}_{h'}$ are identical.

expected utility from their network. The second term measures the outlays that insurer $i$ must pay to hospitals in network $\mathcal{G}_i$.

We assume that the negotiation over reimbursement rate $p_{hi}$ between hospital $h$ and insurer $i$ follows the Nash-in-Nash bargaining framework.[5] Under this framework, reimbursements are determined by solving

$$\max_{p_{hi}} [\Pi_{hi}(\mathcal{G}_i)]^{\alpha_h} [V_i(\mathcal{G}_i) - V_i(\mathcal{G}_i \setminus h)]^{1-\alpha_h} \tag{9}$$

where $\alpha_h$ is hospital $h$'s bargaining weight.

We define the following differences to measure the effects of losing a hospital from the network:

$$\Delta W_{ni}(\mathcal{G}_i, h) := W_{ni}(\mathcal{G}_i) - W_{ni}(\mathcal{G}_i \setminus h),$$

which captures the reduction in expected utility for patient $n$ when hospital $h$ is removed from the network, and

$$\Delta D_{h'i}(\mathcal{G}_i, h) := D_{h'i}(\mathcal{G}_i) - D_{h'i}(\mathcal{G}_i \setminus h),$$

which reflects the change in demand for hospital $h'$ when hospital $h$ is excluded from insurer $i$'s network. The solution to the Nash-in-Nash bargaining problem is characterized by a set of first-order conditions (FOCs). The FOC for hospital $h$ and insurer $i$ is

$$\Pi_{hi}(\mathcal{G}_i) = \alpha_h \left( \beta \sum_{\{n:i(n)=i\}} \Delta W_{ni}(\mathcal{G}_i, h) - \sum_{h' \neq h} p_{h'i} \Delta D_{h'i}(\mathcal{G}_i, h) - c_h D_{hi}(\mathcal{G}_i) \right). \tag{10}$$

This condition is standard in the literature.[6] It states that under Nash-in-Nash bargaining, hospital $h$'s gains from trade are equal to its bargaining-weighted share of the joint surplus gains (relative to disagreement payoffs). This occurs because negotiated reimbursements are used to transfer any gains from trade between the two parties.

## 5.2 Estimation

### 5.2.1 Demand Estimation

We use Maximum Likelihood Estimation (MLE) to estimate the patient demand model specified in Equation 3. The model is estimated separately for each market-year pair, allowing all coefficients to vary across market-year pairs. This approach ensures a high degree of flexibility in our demand estimation. For example, patients in Los Angeles may exhibit a different aversion to travel time than those in San Francisco or the Central Valley. Similarly, patient demographics can interact

5. If $h$ belongs to a hospital system $\mathcal{H}$, the entire system simultaneously negotiates with insurer $i$. This case is discussed in Appendix C.1.

6. See, for example, Grennan (2013) or Gowrisankaran, Nevo, and Town (2015).

differently with hospital teaching status across market-year pairs.

Patients' aversion to travel time and their preferences for hospital characteristics are important determinants of the value they place on broader insurer networks. Following the literature, we assume that hospital-specific taste shocks are uncorrelated with hospital characteristics. This assumption eliminates the need for instrumental variables to estimate the coefficient on distance (e.g., Ho and Lee (2017) and Gowrisankaran, Nevo, and Town (2015). Under this assumption, patients' aversion to travel time is identified using within-market variation in patients' ZIP codes of residence, which generates variation in travel times and hospital choice probabilities.

To calculate how hospital demand depends on insurer networks, we estimate two additional probabilities showing up in Equation 5. These probabilities are estimated "offline." Specifically, $\gamma_{vn}$ is derived from Census data, while $\gamma_{dn}$ is estimated using a combination of Census data and our claims data. Further details on these estimations are provided in Appendix C.2.

#### 5.2.2 Supply: A Sufficient Condition for Aggregating Over Insurers

Our hospital price data are measured at the hospital level, which prevents us from directly estimating Equation 10, which uses hospital insurer level price data. To overcome this data limitation, we aggregate the FOCs in Equation 10 across insurers, following the approach in Lewis and Pflum (2015).

Suppose that we had hospital-by-insurer prices. We could still sum Equation 10 over insurers to derive an aggregate FOC that serves as the basis for estimation:

(11)

$$\sum_{\{i:h\in\mathcal{G}_i\}} \Pi_{hi}(\mathcal{G}_i) = \alpha_h \left( \beta \sum_{\{i:h\in\mathcal{G}_i\}} \sum_{\{n:i(n)=i\}} \Delta W_{ni}(\mathcal{G}_i, h) - \sum_{\{i:h\in\mathcal{G}_i\}} \sum_{h'\neq h} p_{h'i} \Delta D_{h'i}(\mathcal{G}_i, h) - c_h \sum_{\{i:h\in\mathcal{G}_i\}} D_{hi}(\mathcal{G}_i) \right).$$

The only difference between Equation 11 and Equation 10 is that here, all terms are summed across insurers whose networks include hospital $h$.

Now consider the implications of having only hospital prices (rather than hospital-by-insurer prices). For estimation, we use the following modified FOC:

(12)

$$\sum_{\{i:h\in\mathcal{G}_i\}} \Pi_{hi}(\mathcal{G}_i) =$$

$$\alpha_h \left( \beta \sum_{\{i:h\in\mathcal{G}_i\}} \sum_{\{n:i(n)=i\}} \Delta W_{ni}(\mathcal{G}_i, h) - \sum_{\{i:h\in\mathcal{G}_i\}} \sum_{h'\neq h} p_{h'} \Delta D_{h'i}(\mathcal{G}_i, h) - c_h \sum_{\{i:h\in\mathcal{G}_i\}} D_{hi}(\mathcal{G}_i) \right).$$

We clarify, for the first time to our knowledge, a sufficient condition under which estimation using Equation 12 recovers the same parameters as estimation using Equation 11 or Equation 10. Comparing Equations 12 and 11, it is clear that the middle term in parentheses on the right-hand side of Equation 11 is critical. The other terms do not include hospital prices and aggregate in a straight forward manner.

*Proposition. In the Nash-in-Nash bargaining model specified in Section 5.1.2, estimation using the aggregate FOC (equation 12) and average hospital prices recovers the same parameters as estimation based on the standard Nash-in-Nash FOCs (equation 10) if*

$$\frac{D_{h'j}(\mathcal{G}_j)}{\sum_{\{i:h'\in\mathcal{G}_i\}} D_{h'i}(\mathcal{G}_i)} = \frac{D_{h'j}(\mathcal{G}_j \setminus h)}{\sum_{\{i:h'\in\mathcal{G}_i\}} D_{h'i}(\mathcal{G}_i \setminus h)} \quad \text{for all } h' \neq h \text{ and for all insurers } j. \tag{13}$$

*Proof. See Appendix C.3.*

The most important aspect of this proposition is that it is empirically testable, as all terms in Equation 13 can be computed using estimates from our patient demand model. In Appendix C.4, we quantify the empirical analogs of the left- and right-hand sides of Equation 13. In our application, the correlation between the two exceeds $0.99$. Additionally, we show in Appendix C.4 that with different coefficients, our demand model can generate substantial deviations from Equation 13, ensuring that the high correlation we obtain is not merely mechanical.

### 5.2.3 Supply Estimation

Given that the condition in Equation 13 appears to hold in our context, we proceed to use Equation 12 to estimate the bargaining weights and the weight that insurers place on enrollee utility.

Following Lewis and Pflum (2015) and Liu (2022), we parametrize hospital bargaining weights as a funtion of hospital characteristics:

$$\alpha_h = \omega \mathbf{X}_{ht} + \nu_{ht} \tag{14}$$

where $\mathbf{X}^3_{ht}$ are time-varying covariates (including time subscripts) that leverage the panel nature of our data.

Let $GFT^h_t$ denote hospital $h$'s gains from trade in its negotiations, corresponding to the left-hand side of Equation 12. Let $GFT^T_t(\beta)$ denote the total aggregate gains from trade for negotiations involving hospital $h$, corresponding to the parenthetical term on the right-hand side of Equation

12.[7] Combining Equations 12 and 14 yields

$$\nu_{ht} = \frac{GFT_t^h}{GFT_t^T(\beta)} - \omega \mathbf{X}_{ht}. \tag{15}$$

We estimate $\omega$ and $\beta$ using the Genralized Method of Moments, which makes the sample analogs of our moment conditions align closely with the data. Our first set of moments takes the form:

$$\mathbb{E}[\nu_{ht}\mathbf{X}_{ht}] = 0 \tag{16}$$

where we assume that hospital characteristics in the model are exogenous to the error terms in the bargaining weight specification. These moment conditions provide as many equations as there are terms in $\omega$. Importantly, while the model is described using independent hospitals for clarity, we appropriately account for hospital systems; the relevant equations are detailed in Appendix C.1.

To estimate the remaining parameter, $\beta$, which captures the weight insurers place on their enrollees' expected utility, we introduce an additional moment condition. This condition equates the medical loss ratios (MLRs) implied by our model with observed MLR data from California.

$$\mathbb{E}\left[MLR_t - \sum_i \gamma_{it} \frac{\sum_{\{h:h\in\mathcal{G}_i\}} p_{ht} D_{hit}}{\beta \sum_{\{n:i(n)=i\}} W_{nit(\mathcal{G}_{it})}}\right] = 0, \tag{17}$$

which is similar to the MLR condition in Ho and Lee (2017). Notably, this last moment condition does not depend on the parameter $\omega$. This independence allows us to estimate the model sequentially: first, we use Equation 17 to pin down $\beta$, and then, with the estimate of $\beta$ in hand, we estimate $\omega$ using Equation 16.

# 6 Results

This section reports our results. We first describe the estimates from our demand model. Then we discuss our bargaining model estimates. Last, we describe counterfactuals where we quantify pass-through of cost synergies from horizontal mergers.

## 6.1 Demand Estimates

We estimate our demand model separately for 96 HSA-year pairs. This gives our demand model substantial flexibility as the parameters are allowed to vary across both HSAs and years. To illustrate our demand estimates, Figure 5 plots the distribution of mean demand elasticities with respect to travel time at the HSA-year level. Our results indicate that demand elasticities with

7. Our notation emphasizes the fact that this term depends on $\beta$, a parameter to be estimated.

respect to travel time are negative in over 80% of HSA-year markets. The average elasticity across all HSA-years is $-0.17$, implying that a hospital located twice as far from a patient's home has a 17% lower probability of being chosen. Our estimates suggest that patient demand for outpatient hospital services is generally inelastic with respect to travel time.

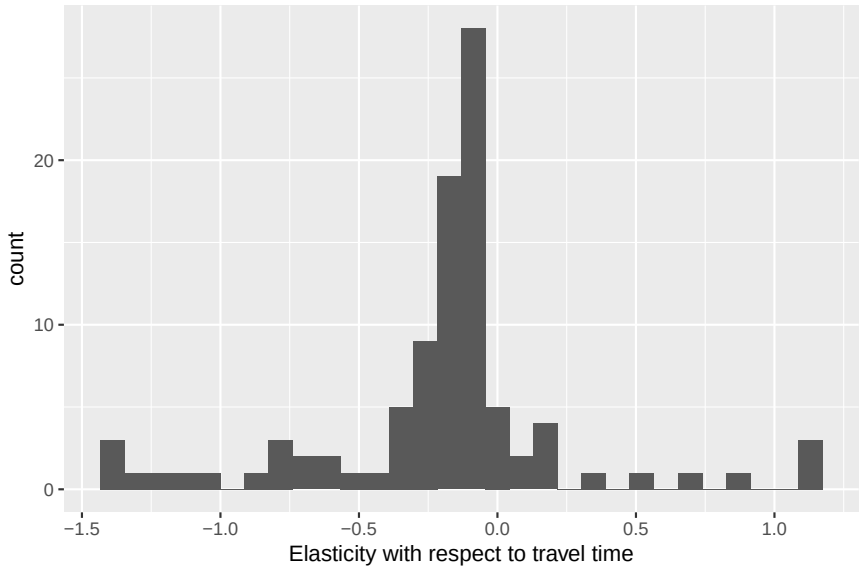



Figure 5: Demand Elasticity with Respect to Travel Time

Notes: This figures presents the distribution of mean demand elasticities with respect to travel time (at the HSA-year level). We calculate elasticities at the individual level using the regular logit expression based on our demand model specified in Equation 3.

## 6.2 Bargaining Model Estimates

Table 4 reports the estimated coefficients from our bargaining model, along with standard errors obtained by bootstrapping the estimation procedure 100 times. The average bargaining weight in our samples is 0.70, which is similar in magnitude to the mean hospital bargaining weights reported in Lewis and Pflum (2015), which ranged from 0.59 to 0.70.[8] Teaching hospitals have substantially larger bargaining weights relative to non-teaching hospitals. Additionally, acquiring hospital systems have greater bargaining weights than non-acquiring systems, while acquired hospitals demonstrate lower bargaining weights relative to non-acquired independent hospitals.

8. Lewis and Pflum (2015) also examine hospitals in California but focus on inpatient hospitals in 2007 and 2008, so the results may not line up closely.

Table 4: Bargaining Model Results

| | Bargaining Weight |
|---|---|
| Intercept | $0.83^{***}$ |
| | $(0.22)$ |
| Teaching | $0.37^{***}$ |
| | $(0.11)$ |
| Physician Group | $-0.08^{**}$ |
| | $(0.04)$ |
| For-Profit | $-0.16^{***}$ |
| | $(0.05)$ |
| Rural | $-0.02$ |
| | $(0.07)$ |
| Medicare Share | $-0.17$ |
| | $(0.27)$ |
| Medicaid Share of Visits | $-0.14$ |
| | $(0.22)$ |
| Independent Hospital | $0.06$ |
| | $(0.06)$ |
| Non-Acquiring System | $-0.14^{**}$ |
| | $(0.06)$ |
| Target Hospital | $-0.31^{**}$ |
| | $(0.13)$ |
| $\beta$ | $755.08^{**}$ |
| | $(335.05)$ |
| No. Obs. | 648 |
| R-squared | 0.16 |
| Mean Dep. Var. | 0.70 |
| HSA Fixed Effects? | Y |
| Year Fixed Effects? | Y |

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Notes: This table presents the results from the estimation of the bargaining model according to Equation 15). Standards errors are calculated using 100 boostrapped resamples of hospitals.

Figure 6 plots a histogram showing the distribution of our estimated bargaining weights. These bargaining weights are *raw*, meaning they correspond to $\alpha_h$ from Equation 14. In contrast, we refer to the fitted values from Equation 14 as the *fitted* bargaining weights ($\hat{\alpha} = \hat{\omega}\mathbf{X}_{ht}$). The vast majority of our estimated raw bargaining weights lie in the unit interval, although we do not impose this restriction during estimation. We find that a hospital system can have a negative raw bargaining weight if its profits are negative. Conversely, we estimate a raw bargaining weight greater than 1 when a hospital system's profits exceed the total joint surplus from its negotiations with insurers.

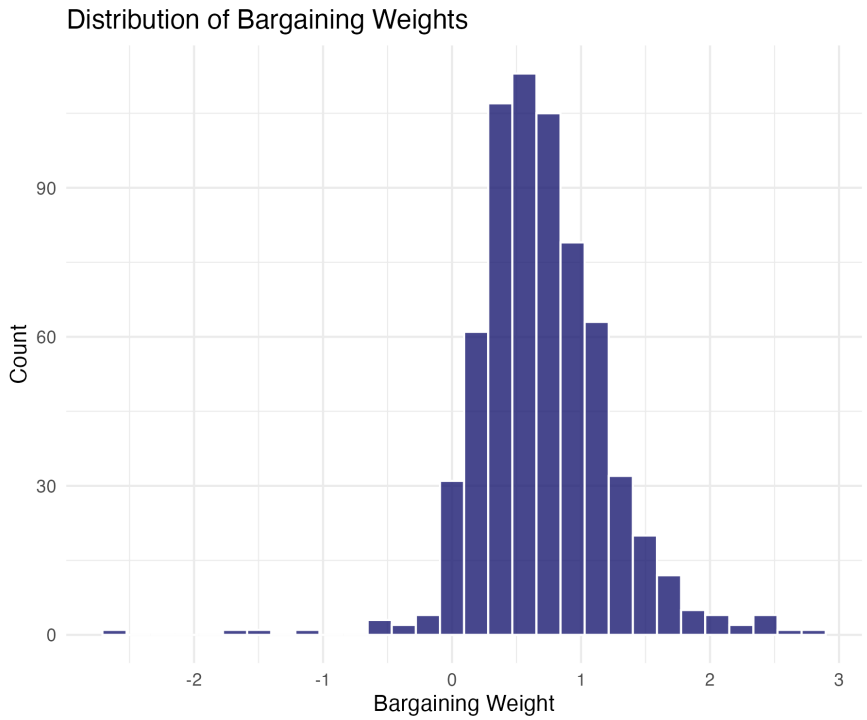



Figure 6: Raw Bargaining Weight Distribution

Notes: This figures presents the distribution of our estimated bargaining weights. We plot the raw bargaining weight, which corresponds to $\alpha_h$ from Equation 14 and is estimated as $GFT_t^h/GFT_t^T(\hat{\beta})$. Bargaining weights outside the unit interval when a hospital systems' profits are negative or when its profits exceed the total joint surplus from its deals with insurers.

We estimate our Nash-in-Nash bargaining model for each hospital system in every year.[9] Figure 7 plots the estimated bargaining weights against time for a mutually exclusive and exhaustive partition of hospitals in our data: independent acquired hospitals, acquiring hospitals, independent hospitals that remain independent, and non-acquiring systems. This figure illustrates the heterogeneity in both the level and trends of bargaining weights across different hospital types. In terms of central tendency, acquired independent hospitals exhibit noticeably lower bargaining weights compared to other hospitals. In contrast, independent hospitals that remain independent throughout our sample period have the highest bargaining weights among all groups. It appears that acquiring systems tend to target independent hospitals with lower bargaining power when negotiating with insurers.[10] We caution against over-interpreting the convergence in bargaining weights between acquired and acquiring hospitals. This convergence is mechanical, as we estimate bargaining weights at the system level, and post-acquisition, both acquired and acquiring hospitals necessarily share identical bargaining weights.

9. Independent hospitals are treated as singleton systems.

10. The mergers in our data should be viewed as matches between two parties, and it is unclear whether the selection is driven primarily by the acquirer's or the target's motives.

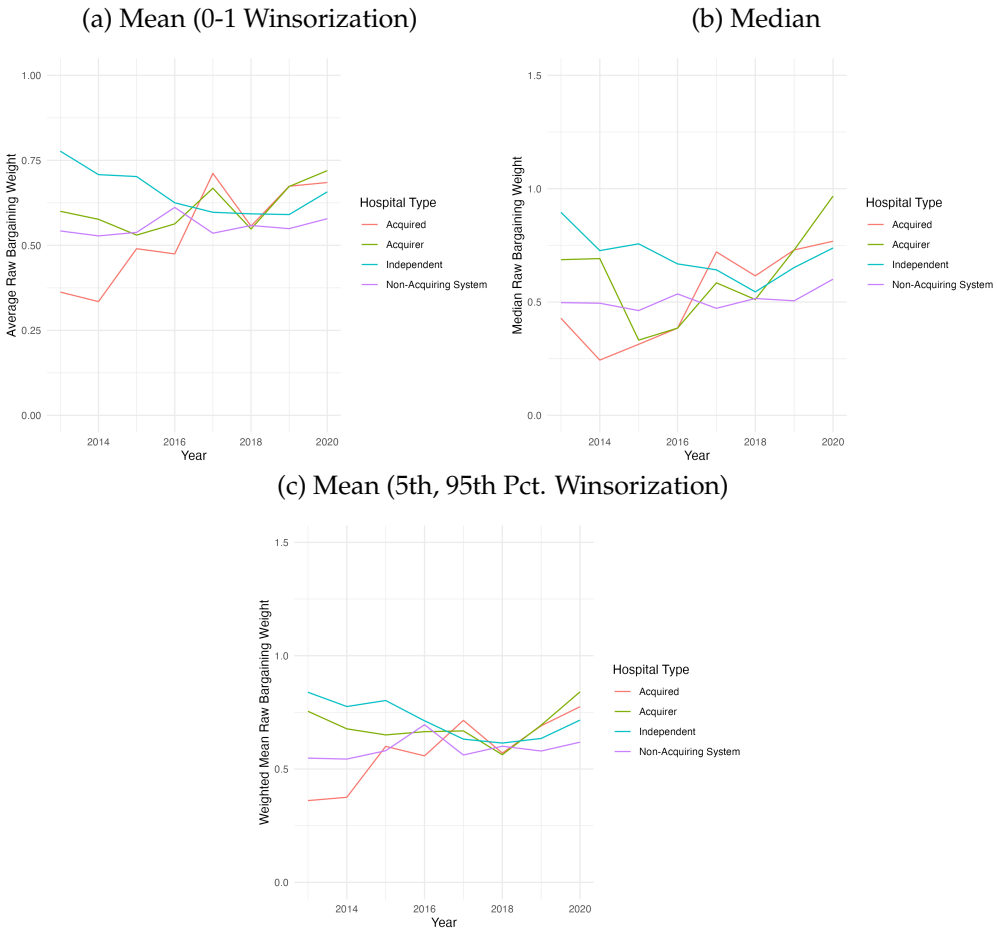



Figure 7: Bargaining Weights Over Time

Notes: This figures presents trends in estimated bargaining weights for a mutually exclusive and exhaustive partition of hospitals in our data. The $y$–axis plots the mean of our raw bargaining weight, which corresponds to $\alpha_h$ from Equation 14. We report several measures of central tendency that are robust to outliers. Panel (a) plots mean raw bargaining weights after winsorizing values outside the unit interval. Panel (b) plots median raw bargaining weights. Panel (c) plots mean raw bargaining weights after winsorizing values below the 5th percentile or above the 95th percentile.

## 6.3 Counterfactuals

We use our model to quantify the extent to which hospital prices decrease after mergers due to cost synergies that are passed through to insurers. In addition, we use our model to quantify the overall price effect of mergers and to decompose its sources.

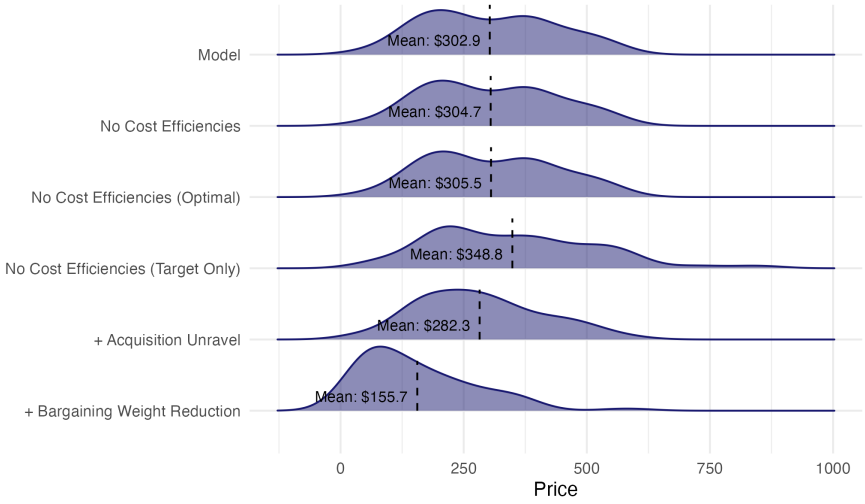
Figure 8 presents the results from our main counterfactual exercise. In both panels, we plot kernel density estimates of the distribution of counterfactual prices. Panel (a) shows prices for acquired hospitals, while Panel (b) shows prices for acquiring hospitals. In both panels, separate columns correspond to distinct counterfactual scenarios. Counterfactual prices are calculated using Equation 12, the same equation we used to estimate the bargaining model. Here, we treat our estimated

bargaining weights as data and use them to calculate prices.

Focusing on Panel (a), row 2 shows the predicted prices from our model under the status quo, where the merger occurred and costs fell as observed in our data. Our model predicts lower prices than we observe in the data (row 1) because we winsorize bargaining weights to ensure they remain within the unit interval. This approach helps prevent our counterfactuals from being unduly influenced by hospitals systems with outlier bargaining weights. Row 3 shows prices in a counterfactual where we restore the costs of acquired systems to the pre-merger levels (by adding back the reduced-form average treatment effect on costs). We find almost no effect of cost synergies on hospital system prices for either the acquired or the acquiring hospitals. In row 4, we allocate cost savings from mergers in the way that is most favorable for identifying price effects, yet we still find only modest effects.[11] The results in rows 3 and 4 might be surprising, given that we found operating cost reductions of around 22% for acquired independent hospitals; we offer an explanation for this finding below. Row 5 reports prices when we unwind mergers. In this counterfactual, independent hospitals negotiate separately from their acquiring system, but still use the bargaining power of the acquiring system. Under this scenario, prices are 7% lower for acquired hospitals and 2% lower for acquiring hospitals. In the final counterfactual, we revert bargaining powers back to pre-merger levels. We do this in the same way we revert cost synergies from mergers, by subtracting the reduced-form average treatment effect on bargaining weights. This counterfactual has the largest effect on prices, with prices falling by 49% for acquired hospitals and 2% for acquiring hospitals.

11. We describe how we perform this allocation below.

(a) All Acquired Hospitals




(b) All Acquirer Hospitals

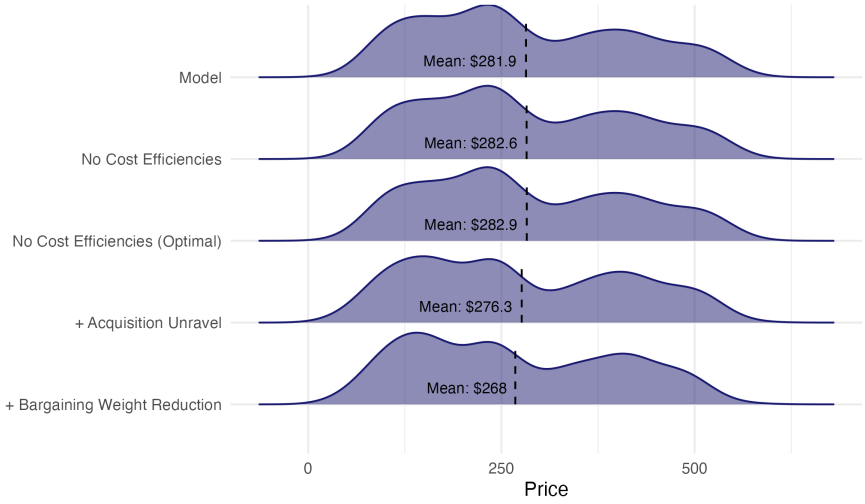



Figure 8: Counterfactuals

Notes: This figure presents the prices in each counterfactual scenario, along with the observed prices on the far left as a benchmark. All dots are hospital-year observations. Panel (a) presents the results for acquired hospitals, and panel (b) presents the results for hospitals which are members of acquiring systems. The "Model" column presents the simulated prices predicted by the bargaining model, holding bargaining weights, ownership, and costs fixed. Bargaining weights are winsorized at 0 and 1. The "No Cost Efficiencies" column reverses the cost efficiencies according to the reduced-form average treatment effect on costs. The next column allocates cost efficiencies in order to maximize their effect on prices. The penultimate column unravels all acquisitions, but keeps bargaining weights the same for formerly acquired hospitals. The final column changes bargaining weights for the acquired hospitals to their pre-acquisition levels.

We now explain why reductions in operating costs translate into modest price effects in our counterfactuals. By implicitly differentiating the hospital system version of the Nash-in-Nash FOC (in Appendix C.1), we derive $\partial p_s / \partial c_h$, the effect of a cost change at hospital $h$ on the system price. Ig-

noring equilibrium effects of cost changes on other hospital systems' prices provides the following approximation:[12]

$$\frac{\partial p_s}{\partial c_h} \approx \frac{\sum_{\{i:h\in\mathcal{G}_i\}} D_{hi}(\mathcal{G}_i)}{\sum_{h'\in\mathcal{H}_h}\sum_{\{i:h\in\mathcal{G}_i\}} D_{h'i}(\mathcal{G}_i)}(1-\alpha_s) \tag{18}$$

This equation says that system prices are more sensitive to hospital cost changes when: (1) the hospital experiencing the cost change accounts for a larger proportion of system demand (as captured by the fraction on the right-hand side), and (2) the hospital system has lower bargaining power (reflected by $1-\alpha_s$).

These conditions align with intuition. When a hospital with a substantial share of system demand experiences a cost change, it has a greater impact on the joint surplus of the negotiating parties, thereby influencing prices more significantly. Additionally, in the limit, if hospitals have no bargaining power (il.e., $\alpha_s = 0$), insurers place hospitals at their disagreement payoff, meaning that all cost changes are fully passed through to prices.

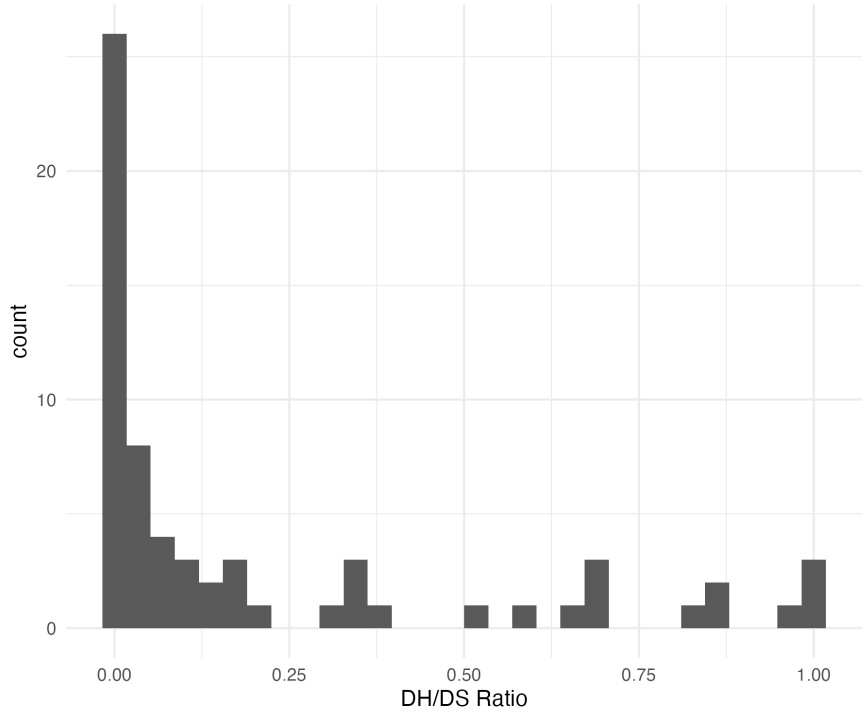



Figure 9: DH/DS Distribution of Acquired Hospitals

Notes: This figure presents the distribution of the fraction on the right hand side of Equation 18. An observation is a hospital year pair and we use data for acquired independent hospitals ost acquisition. A ratio of one corresponds to an out–of–market acquisition, where the acquiring system had no presence in the pre–period.

12. This is an approximation as it neglects equilibrium price effects.

Equation 18 provide a useful framework for understanding the modest price effects observed in counterfactuals that undo cost synergies. Figure 9 plots the empirical distribution of the fraction on the right-hand side of Equation 18. In our data, acquired hospitals are typically small relative to their acquiring system, which empirically explains the limited price effects we observe. Equation 18 is also important for calculating the counterfactuals in column 4 of figure 8. To undo cost synergies in a manner most favorable to identifying the price effects, we allocate cost changes proportionally based on Equation 18.

(a) Profit Change After Cost Efficiencies

(b) Pass-Through of Cost Efficiencies to Hospital Profits

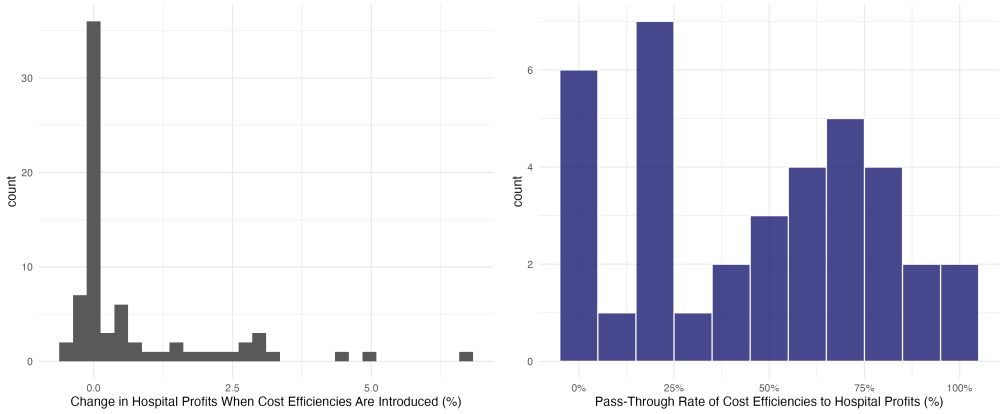



Figure 10: Pass–Through by Profits

Notes: This figure presents three measures of the pass-through of cost efficiencies to consumers by hospitals. All three compare hospital profits and costs between the "Model" and "No Cost Efficiencies" counterfactual scenarios. Bargaining weights are winsorized at 0 and 1. All observations are at the system-year level, and all system-years are for acquiring systems post-acquisition. Panel (a) shows how much system profits increase when cost efficiencies are introduced relative to the no cost efficiencies scenario. Panel (b) compares the (log) change in total costs to the (log) change in total profits when cost efficiencies are introduced. Panel (c) plots one minus the ratio, in percentage terms, of the change in hospital profits to the change in hospital costs.

The final set of calculations in this section quantifies the pass-through of cost synergies using an alternative approach. Instead of examining the effect of cost synergies on negotiated prices, we look at how the implied reductions in total costs translate into changes in hospital system profits, and ultimately, into changes in insurer reimbursements. The results are presented in Figure 10. Our focus is on acquiring systems post-acquisition, including the acquired hospitals in the calculations.

Panel (a) of Figure 10 shows the distribution of changes in hospital system profits under the counterfactual with cost synergies relative to the counterfactual without cost synergies. While a substantial number of hospital systems experience no change in profits at the system level post-acquisition, some systems see profit increases of 2.5% or even 5%.

Panel (b) plots the distribution 100% minus the ratio of change in profits (from panel (a)) to change in costs. If hospitals systems retained all cost savings as profits, this measure would equal 0%. Higher values indicate that a greater share of cost savings is passed through to insurers via lower reimbursements. The histogram reveals a somewhat bimodal distribution: a sizable portion of hospital systems pass through less than 25% of their cost savings, while many others pass through more than 50% at the other end of the distribution. On average, the pass-through rate is 46%, with a median of 51%.

## 7 Discussion and Conclusion

This paper uses novel data and structural analysis to shed light on the pass-through of cost synergies generated from hospital consolidation to insurers in the form of lower prices. In the absence of quality improvements, potential price reductions due to cost synergies are the main benefit of consolidation for consumers. Hence, the division of these synergies between hospitals and consumers is a necessary input for policymakers concerned about the negative impacts of consolidation.

We examine the effects of acquisitions of independent and system-owned hospitals by systems in California during 2014–17. We find that when systems acquire independent hospitals, it generates cost savings as well as price increases. Subsequent simulations of counterfactual prices using model estimates show that, although systems pass through approximately 50% of the cost savings to insurers in the form of reduced prices, system prices hardly budge. This occurs because the acquired independent hospitals tend to be small relative to the acquiring systems and savings from the acquired facility are diluted to be negligibly small when spread across all hospitals of the acquirer. Overall, our results imply that the trend of increasing consolidation of independent hospitals is unlikely to benefit consumers even though it generates substantial cost savings for the acquired facilities.

Although this was a first step in understanding the importance of synergies in system acquisitions, there are several directions for future work. Researchers should consider examining these effects on a larger sample of deals, ideally covering other states, to obtain a nationally representative set of estimates.

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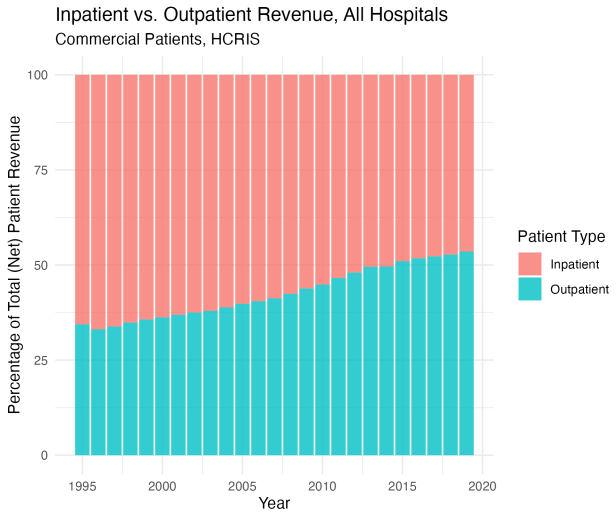
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# A Appendix Figures

(a) All states




(b) California

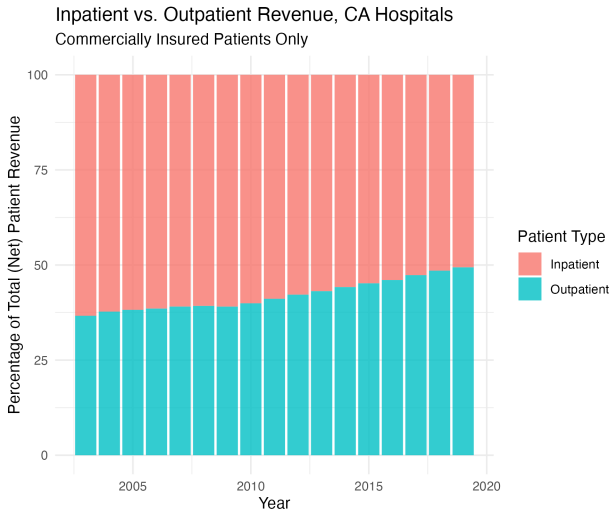



Figure A1: Inpatient Vs. Outpatient Commercial Revenue

Notes: The figure presents the trend in share of hospital revenue from commercial payers attributed to inpatient and outpatient care. Panel (a) presents the trend across all short-term general acute care (GAC) hospitals, as reported in the Medicare cost reports (HCRIS). Panel (b) presents the corresponding trend among GAC California hospitals only. Long-term care revenue is excluded.

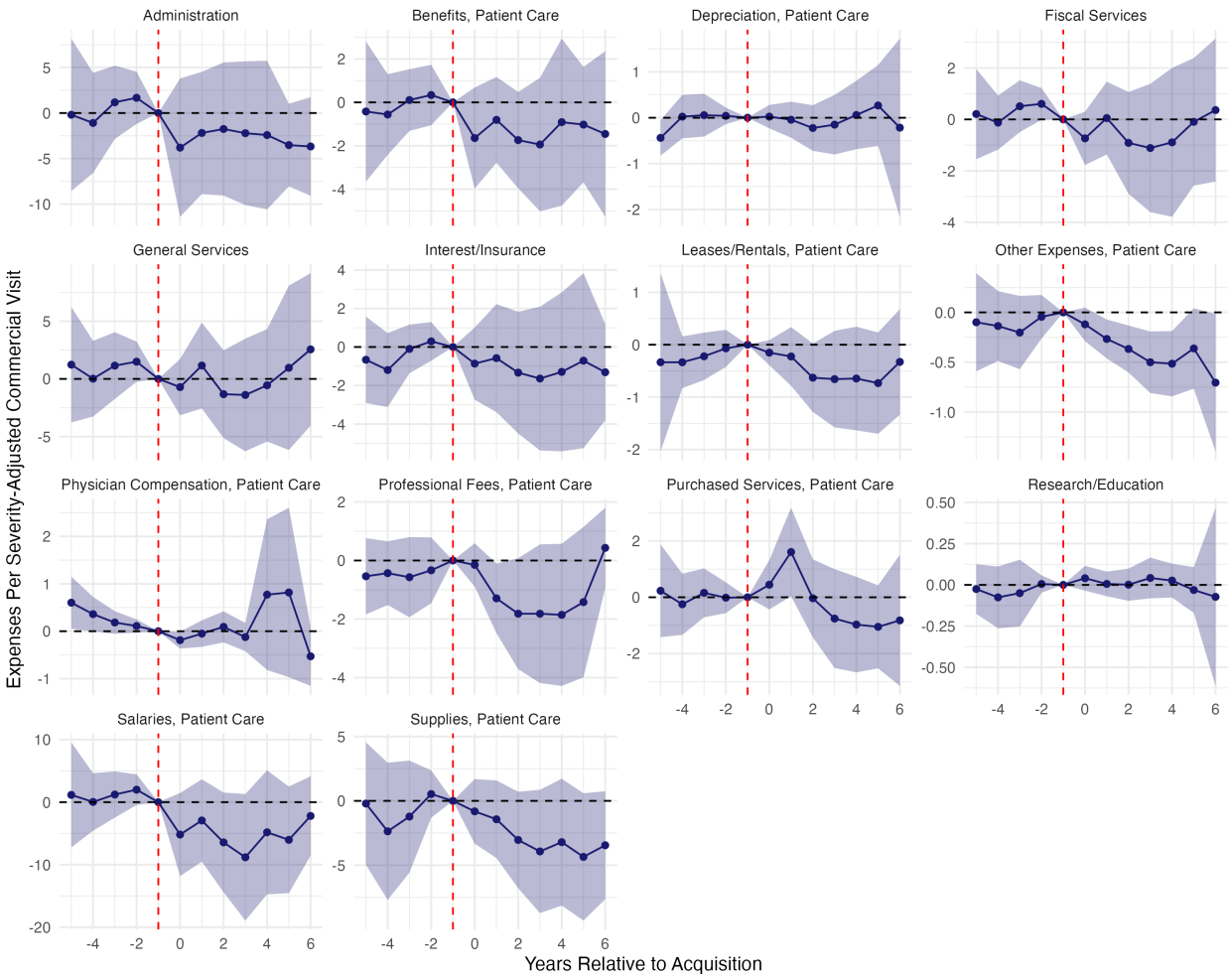
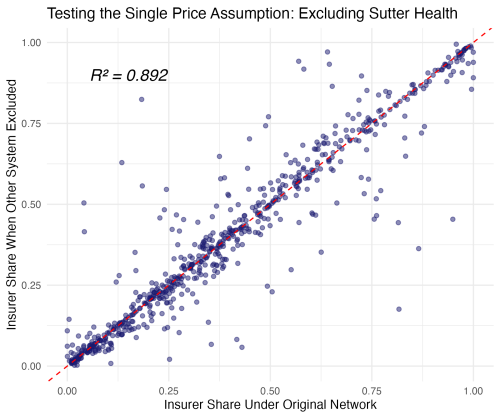



Figure A2: Dynamic Effects on Detailed Cost Categories Per Visit, Independent targets

Notes: This figure presents event study estimates of the effect of a system acquisition on the various categories of hospital variable operating costs for independent targets. The models include time-varying covariates as described in Section 4.1. The gray shaded areas denote 95% confidence intervals. Standard errors are clustered by hospital.

(a) No Multiplier




(b) Payer Effects Multiplied By 10

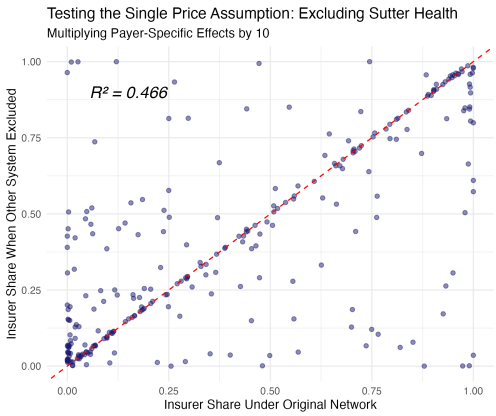
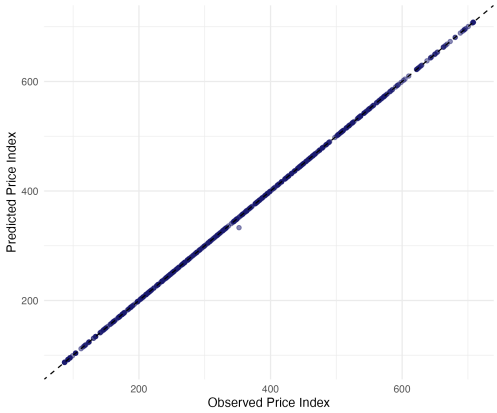



Figure A3: Testing the sufficiency condition

Notes: This figure presents a test of Equation 32, limited to excluding a single system, Sutter Health. All of the demand quantities in Equation 32 can be predicted with our data and demand estimates. In both panels, the $x$–axis corresponds to the left hand side of Equation 32 and the $y$–axis corresponds to the right hand side. Panel (a) uses our actual demand estimates. Panel (b) scales our payer-specific demand parameters by 10 before predicting demand.

(a) No Winsorization




(b) Winsorized at 0 and 1

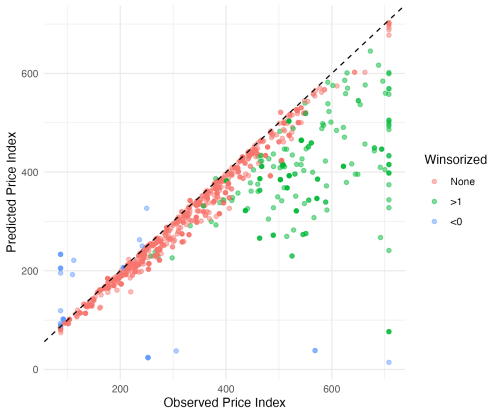



Figure A4: Bargaining Model Goodness-of-Fit

Table A1: Representativeness of the Claims Sample

**Panel A: Hospital Characteristics**

| | Claims Sample | Full Sample | Diff | t-value |
|---|---|---|---|---|
| Beds | 209.686 | 206.868 | -2.819 | (-0.58) |
| Fraction Teaching | 0.059 | 0.058 | -0.001 | (-0.12) |
| Fraction For-Profit | 0.207 | 0.211 | 0.003 | (0.26) |
| Medicare Share of Visits | 0.465 | 0.465 | -0.000 | (-0.08) |
| Medi-Cal Share of Visits | 0.278 | 0.274 | -0.004 | (-0.92) |

**Panel B: Payer Share**

| Payer | Share (%) |
|---|---|
| Anthem | 27.10 |
| Blue Shield | 13.53 |
| United | 26.66 |
| Others | 32.71 |

Notes: This table compares the characteristics of hospitals in our claims sample with those of the full sample of California short-term general acute care hospitals from 2014 to 2020.

Table A2: Hospitals involved in acquisitions

| Target Name | Acquirer Name | Year of Acquisition | No. Beds | In-Market |
|---|---|---|---|---|
| Independent Targets | | | | |
| Alameda Hospital | Alameda Health System | 2014 | 246 | 1 |
| Olympia Medical Center | Alecto Healthcare | 2014 | 204 | 0 |
| Glendora Community Hospital | Prime Healthcare Services | 2014 | 118 | 1 |
| Emanuel Medical Center | TENET Healthcare Corporation | 2014 | 209 | 1 |
| Lodi Memorial Hospital | Adventist Health | 2015 | 190 | 1 |
| Stanford Health Care - ValleyCare | Stanford Health Care | 2015 | 207 | 0 |
| Marina Del Rey Hospital | Cedars-Sinai Health System | 2015 | 145 | 1 |
| Hi-Desert Medical Center | TENET Healthcare Corporation | 2015 | 179 | 1 |
| Stanislaus Surgical Hospital | Sutter Health | 2016 | 23 | 1 |
| Adventist Health Medical Center - Tehachapi Valley | Adventist Health | 2016 | 24 | 1 |
| Torrance Memorial Medical Center | Cedars-Sinai Health System | 2017 | 444 | 1 |
| System-Owned Targets | | | | |
| Saint John's Health Center | Providence Health & Services | 2014 | 234 | 1 |
| St. Mary Medical Center | Providence St. Joseph Health | 2016 | 212 | 0 |
| St. Joseph Hospital | Providence St. Joseph Health | 2016 | 153 | 0 |
| Santa Rosa Memorial Hospital | Providence St. Joseph Health | 2016 | 278 | 0 |
| St. Jude Medical Center | Providence St. Joseph Health | 2016 | 320 | 0 |
| Mission Hospital | Providence St. Joseph Health | 2016 | 249 | 0 |
| Queen of the Valley Medical Center | Providence St. Joseph Health | 2016 | 120 | 0 |
| Hoag Memorial Hospital Presbyterian | Providence St. Joseph Health | 2016 | 470 | 0 |
| St. Joseph Hospital | Providence St. Joseph Health | 2016 | 379 | 0 |
| Petaluma Valley Hospital | Providence St. Joseph Health | 2016 | 51 | 0 |
| Redwood Memorial Hospital | Providence St. Joseph Health | 2016 | 25 | 0 |

Notes: This table presents details on the hospitals involved in the deals studied in the analysis. For each deal we present the names of the acquiring system and acquired hospitals, the year the deal was executed, whether the target shares a market with at least one member of the acquiring system, and the number of beds of the target.

Table A3: Mean Prices, Pre- and Post-Acquisition

| | 1 Year Pre-Acquisition | Acquisition Year | 3 Years Post-Acquisition |
|---|---|---|---|
| Acquired Hospitals | \$131.73 | \$163.49 | \$359.02 |
| Acquiring Hospitals | \$300.51 | \$356.45 | \$386.89 |
| N. Obs. | 55 | 72 | 89 |

Notes: This table presents mean values of hospital outpatient prices for the hospitals involved in the acquisition of independent targets. All values are deflated to be in 2020 dollars.

Table A4: Difference-in-Differences Estimates on Cost Categories

| | Labor, Fixed | Labor, Variable | Other, Fixed | Other, Variable |
|---|---|---|---|---|
| Acquired x Post | $-2.11^{*}$ | $-12.74^{**}$ | $-3.59$ | $-4.91^{*}$ |
| | (1.12) | (5.27) | (2.86) | (2.93) |
| No. Obs. | 681 | 681 | 681 | 681 |
| Mean Dep. Var. | 9.59 | 48.84 | 20.39 | 23.55 |

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Notes: This table presents difference-in-differences estimates of the effect of a system acquisition on four mutually exclusive collectively exhaustive components of operating cost at independent target hospitals. Column 1 presents results for a model with fixed labor costs as the dependent variable, while Column 2 presents results for variable labor costs. Columns 3 and 4 present results for other (non-labor) fixed and variable costs, respectively. All models include covariates and are weighted by hospital outpatient volume. Standard errors are clustered by hospital. Costs are deflated to 2020 dollars. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table A5: Pre-Treatment Cross-Sectional Bargaining Weight Regression

| | Raw Weight |
|---|---|
| Acquirer | $0.322^{**}$ |
| | (0.160) |
| Independent | $0.441^{***}$ |
| | (0.131) |
| Non-Acquiring System | $0.301^{**}$ |
| | (0.138) |
| Year FEs | Y |
| HSA FEs | Y |
| Controls | Y |
| $R^2$ | 0.41 |
| N | 130 |

Table A6: Difference-in-Difference Estimates Using a Matched Sample

| | Costs, Baseline | Costs, Matched Sample | Prices, Baseline | Prices, Matched Sample |
|---|---|---|---|---|
| Acquired x Post | $-15.82^{**}$ | $-15.96^{**}$ | $226.28^{***}$ | $226.52^{***}$ |
| | (7.28) | (7.31) | (50.34) | (50.78) |
| No. Obs. | 673 | 591 | 482 | 423 |
| Mean Dep. Var., Pre-Acquisition | 52.38 | 52.38 | 145.33 | 145.33 |

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

(a) Independent Targets

| | Costs, Baseline | Costs, Matched Sample | Prices, Baseline | Prices, Matched Sample |
|---|---|---|---|---|
| Acquired x Post | 1.23 | $-1.00$ | $-70.86$ | $-59.94$ |
| | (5.79) | (5.65) | (85.49) | (86.64) |
| No. Obs. | 680 | 563 | 499 | 421 |
| Mean Dep. Var., Pre-Acquisition | 30.97 | 29.92 | 397.73 | 397.73 |

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

(b) System-Owned Targets

Notes: This table presents difference-in-differences estimates of the effect of a system acquisition on costs and prices, comparing our baseline specification with a matched sample. Columns 1 and 2 have costs as the dependent variable, while Columns 3 and 4 have prices as the dependent variable. Columns 1 and 3 use our baseline sample, while Columns 2 and 4 use a matched sample. The matched sample is created by matching acquired hospitals with never- and not-yet-treated hospitals in the control group along three variables: for-profit status, rural status, and the number of beds (discretized into three categories). All models include covariates and are weighted by hospital outpatient volume. Standard errors are clustered by hospital. Costs and prices are deflated to 2020 dollars. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table A7: Difference-in-Difference Estimates on Employment and Wages

| | Admin FTEs | RN FTEs | Admin Wages | RN Wages |
|---|---|---|---|---|
| Acquired x Post | −4.28 | −2.34 | −1.26 | −0.72 |
| | (34.48) | (35.35) | (1.06) | (2.30) |
| No. Obs. | 1388 | 1388 | 1388 | 1388 |
| Mean Dep. Var., Pre-Acquisition | 219.07 | 290.98 | 43.59 | 64.74 |

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

(a) All Targets

| | Admin FTEs | RN FTEs | Admin Wages | RN Wages |
|---|---|---|---|---|
| Acquired x Post | −105.43*** | −99.74*** | 0.94 | 3.90 |
| | (16.41) | (14.32) | (1.39) | (6.85) |
| No. Obs. | 707 | 707 | 707 | 707 |
| Mean Dep. Var., Pre-Acquisition | 342.27 | 403.70 | 38.62 | 60.65 |

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

(b) Independent Targets

| | Admin FTEs | RN FTEs | Admin Wages | RN Wages |
|---|---|---|---|---|
| Acquired x Post | −4.28 | −2.34 | −1.26 | −0.72 |
| | (34.48) | (35.35) | (1.06) | (2.30) |
| No. Obs. | 681 | 681 | 681 | 681 |
| Mean Dep. Var., Pre-Acquisition | 159.62 | 236.59 | 45.99 | 66.72 |

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

(c) System-Owned Targets

Notes: This table presents difference-in-differences estimates of the effect of a system acquisition on employment and wages. Columns 1 and 2 have employment of administrators and registered nurses (in FTEs) as the dependent variable, while Columns 3 and 4 have the respective hourly wages as the dependent variable. All models include covariates and are weighted by hospital outpatient volume. Standard errors are clustered by hospital. Costs and prices are deflated to 2020 dollars. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table A8: Change in Composition of Insurer

| | **DV: Inclusion of Insurer** | | |
|---|---|---|---|
| | **Combined Sample** | **Acquired Independent** | **Acquired System** |
| | (1) | (2) | (3) |
| $Acquired \times Post$ | 0.02 | -0.16 | 0.09 |
| | (0.51) | (-1.55) | (1.62) |
| *Hospital×Payer FE* | Y | Y | Y |
| *Year FE* | Y | Y | Y |
| *Controls* | Y | Y | Y |
| *N* | 2,667 | 1,219 | 1,448 |
| *adj-*$R^2$ | 0.34 | 0.34 | 0.34 |

Notes: This table presents difference-in-differences estimates of the effect of acquisitions on hospitals' insurer composition. Column 1 presents results for a combined sample including both acquired independent hospitals as well as their controls and acquired hospital systems with their controls, while Column 2 presents results for the sample of acquired independent hospitals plus their controls. Columns 3 presents results for the sample of acquired hospital systems and their controls. The dependent variable, *Inclusion of Insurer*, is an indicator equal to one if there is any claims with nonmissing payment information between a hospital facility and a payer (we classify payers into four categories: Anthem, United, Blue Shield, and others). All models include covariates. Standard errors are clustered by hospital system. Fixed effects are indicated at the bottom of the table. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

# B Data appendix

## B.1 Outpatient Insurance Claims Data

Our insurance claims data are sourced from the Clarivate Real-World Data (RWD) Product, previously known as Decision Resources Group Real-World Data. This dataset covers over 300 million longitudinal patient records in the United States, drawing from multiple payer sources and encompassing a variety of insurance plans, with records dating back to 2013. The data captures claims submitted through billing software used by healthcare providers, including hospitals, physician offices, long-term care facilities, etc. The open-network structure of this dataset allows for the tracking of patients over time and across different providers, even when patients switch carriers within the observation period. This dataset has previously been used in economic, finance, and health policy research, such as Liu (2022).

The raw claims data are composed of two primary components: submission claims (837s) and remittance claims (835s). Submission claims are records submitted by healthcare organizations and providers to clearinghouses, detailing diagnoses, medical procedures or services rendered, patient demographics, and specifics regarding service dates, locations, charges, and provider and payer information. Once these claims pass through clearinghouses, they are sent to payers, who then return remittance claims back to the providers. Remittance claims provide critical information on remittances, denials, and adjustments, including elements such as allowed amounts, deductibles, and copayments. Only a subset of submission claims can be directly linked to corresponding remittance claims via a linkage table in the dataset.

In the submission data, each claim contains a unique provider identifier (National Provider Identifier or NPI), patient identifier, payer ID, date of service, diagnosis information in the form of International Classification of Disease (ICD) codes, medical procedures in terms of the Healthcare Common Procedure Coding System (HCPCS) codes, patient demographics including the 3-digit ZIP code prefix of residence, gender, and age, payer type (e.g., commercial, Medicare, or Medicaid), and type of insurance plan held by the patient. By matching claims based on the claim payment number, submission claims can link to remittance claims, enabling the identification of hospital charges, negotiated prices (the sum of payer and patient payments), and a detailed breakdown of patient payment components, such as deductibles, coinsurance, and copayments.

Our study focuses on a sample of California hospital outpatient claims from commercial payers between 2014 and 2020. Starting with the submission claims, we follow Liu (2022) in identifying commercial outpatient claims in hospitals. We exclude duplicate claims and claims denied, pended, or suspended by payers. We also exclude any Medicare or Medicaid claims and claims paid by VA Fee Basis Programs in the sample. Additionally, to avoid including Medicare Advantage patient visits, we limit our sample to claims for patients between 18 and 64 years old at the time of medical service. We also exclude some major payers which have large footprints in Med-

icaid Advantage programs, including Centene, Molina, LA Care, Health Plan of San Joaquin and Health Plan of San Mateo.

To incorporate hospital characteristics, we match submission claims data with the American Hospital Association (AHA) annual survey data from 2014 to 2020, using a crosswalk between the National Provider Identifiers (NPIs) and AHA hospital IDs as described in Liu (2022). Our analysis focuses solely on non-governmental, general acute care hospitals within California.

For payer identity, we manually aggregate payer IDs from the submission claims data to align with the National Association of Insurance Commissioners (NAIC) Insurance Holding Company Codes. Each insurance company is assigned a Payer ID, and a single company may have multiple payer IDs. For instance, UnitedHealth is associated with payer IDs such as 87726, 06111, 81400, etc. We categorize payers into four groups based on submission claim volume in California: UnitedHealth, Anthem, CA Blue Shield (the top three payers), and an "other" group that includes all other payer IDs with relatively smaller volumes in the sample.

In our main analysis, we group claim lines to each patient visit. To measure disease severity and resource utilization per visit, following Liu (2022), we assign a relative service-mix weight (or APC weight) for each outpatient visit in the sample. The Ambulatory Payment Classification (APC) system, a fundamental element of the Hospital Outpatient Prospective Payment System (OPPS) developed by CMS, provides the basis for constructing the relative service-mix weights, which are calculated primarily using CPT/HCPCS codes associated with each claim. All APC weights are updated to the 2020Q2 version of the CMS addendum D.

We exclude any patient visits with missing claim numbers, payer ID, patient ID, age, gender, 3-digit ZIP code, service date, or APC weight. Our final sample for patient visits in the submission claims data includes 6,565,412 hospital outpatient visits in California between 2014 and 2020. Of these, 1,344,935 outpatient visits are matched with remittance claims data, containing non-missing and positive payment information.

### B.2 Constructing Hospital Price Index

In this section, we describe how we derive the hospital price index—an average negotiated price with private insurers—using patient claims data.

Given the sample of hospital outpatient claims, we aggregate the total allowed amounts (or total paid amounts) $Y_{ijmt}$ in a patient visit (claim encounter) for patient $i$ from insurer $m$ visiting hospital $j$ in year $t$. We obtain the average price per unit of service-mix weight in a visity by dividing $Y_{ijmt}$ by the relative service-mix weights, $w_i$, which measures the unit of medical resources used

to treat patient $i$ during his visit. Then we run the following model:

$$\frac{Y_{ijmt}}{w_i} = \gamma_{jt} + \beta X_{it} + \delta_{anthem} + \delta_{bs} + \delta_{united} + \varepsilon_{ijmt}$$

where $\gamma_{jt}$ is the hospital-year fixed effects, $X_{it}$ is a vector of patient characteristics including patients' gender and the natural logarithm of their age, $\delta_m$ for $m \in \{\text{anthem, bs, united}\}$ is an indicator variable equal to one if the insurer is Anthem, Blue Cross, and UnitedHealth (other insurers as a control group), and $\varepsilon_{ijmt}$ is the stochastic error term.

To obtain the hospital price, we first recover the vector of hospital-year fixed effects $\hat{\gamma}_{jt}$. We then evaluate the fitted value of patient characteristics and insurer indicators at the sample means, i.e., $\hat{\beta}\bar{X}$ and $\bar{\delta}_m$, with $m \in \{\text{anthem, bs, united}\}$ for each year. Combining all terms give us the average negotiated price per unit of service for hospital $j$ in year $t$:

$$p_{jt} = \hat{\gamma}_{jt} + \hat{\beta}\bar{X} + \bar{\delta}_{anthem} + \bar{\delta}_{bs} + \bar{\delta}_{united}.$$

In the analysis, we adjust hospital prices $p_{jt}$ to 2020 dollars using the annualized Consumer Price Index (CPI).

### B.3 California Cost Report Data

We use annual cost reports from the California Department of Health Care Access and Information (HCAI, formerly OSHPD) for data on hospital outpatient volume, revenue, and costs. These cost reports are referred to as the Hospital Annual Financial Disclosure Reports, and are publicly available going as far back as 1976. Data from these reports has been used in several previous papers on hospital competition (Lewis & Pflum, 2015; Ho & Lee, 2017). While many states collect and publish similar reports, those available at HCAI are among the most detailed.

There are essentially five types of data included in the reports: 1) basic hospital information, 2) detailed utilization data, 3) the hospital's balance sheet, 4) detailed revenue data, and 5) detailed cost data. We mainly rely on the utilization, revenue, and cost data in this paper. These data are also the most reliable, as the balance sheet data are sometimes reported at the system level with little indication as to when this is being done.

Since the annual reports are required to be submitted by law, coverage is near-complete across general and specialty care hospitals in California. However, until recently, Kaiser hospitals did not submit independent reports and are not comparable with other hospitals in the state. Because of Kaiser's vertically integrated structure and lack of involvement in hospital mergers during our sample period, we exclude them from our sample when estimating cost efficiencies and bargaining weights. Thus, the Kaiser reporting issue is immaterial to our results.

The primary benefit of the California data relative to other states is that each type of data (uti-

lization, revenue, and costs) is broken down into detailed categories, which we will refer to as "service lines." Furthermore, these service lines are the same across different sections of the report, enabling the researcher to combine and manipulate all of the reported data at a very detailed level. Examples of service lines include coronary care, psychiatric long-term care, and nuclear medicine. Working at the service level provides two primary advantages for this paper: 1) it allows us to exclude portions of hospital operations that are irrelevant to our objectives, such as long-term care, and 2) it enables us to measure heterogeneity in the cost structure across payers, since commercially insured patients may use a different mixture of services compared to Medicare-insured patients.

In this section, we describe the cleaning process for the California cost report data, along with the construction of several key variables used in the paper. These variables include the number of outpatient visits (total and by payer), outpatient fixed and variable costs (total and by payer), and net inpatient and outpatient revenue (total and by payer).

### B.4 Cleaning

The main cleaning task required to properly format the California cost report data in a panel structure is to calendarize the data. Hospitals often report their financial data using inconsistent reporting periods. While some hospitals report in January-December intervals, others report using a July-June schedule or any other 12-month schedule. More problematically, some hospitals change their reporting period partway through the sample, which means they have a transitional report that covers less than 12 months. Particularly because most of our variables of interest are flows, these reporting periods need to be standardized.

The basic idea is to aggregate information from the various reports corresponding to a particular calendar year using a weighted sum. Whether those weights need to sum to one or some other number depends upon whether the variable of interest is a stock or a flow. Weights must sum to one for stock variables, but the flow weights may sum to some other number depending upon the length of the reporting periods.

To clarify, consider a hospital in calendar year 2012 with two reporting periods that cover the year: one from January 2012 to June 2012, and another from July 2012 to June 2013. Consider a stock variable such as the number of beds at the hospital during a reporting period, and a flow variable such as the number of discharges. A reasonable procedure for the number of beds would be to calculate a weighted average of the first and second reports, perhaps using weights of 0.5 and 0.5 since each report covers half the year. But this wouldn't make sense for the number of discharges: the first report discharges correspond to only a six-month period, so averaging them with the twelve-month second report would result in a downward-biased estimate. Instead we could sum the total discharges from the first report with half of the second report discharges.

We propose a weighting scheme that accomplishes both of these goals in an intuitive way. Start with a year of interest $y$, which has begin date $t_y^b$ and end date $t_y^e$. Call the reporting period $p = (t_p, t_p + T_p)$, where $t_p$ is the begin date and $T_p$ is the period length in days. Here we only focus on reporting periods that overlap with $y$, where the set of such periods is called $P_y$. We first calculate the following two weights:

$$\nu_p^A = \begin{cases} \frac{t_p + T_p - t_y^b}{T_p} & \text{if } t_p < t_y^b \\ \min\left\{\frac{t_y^e - t_p}{T_p}, 1\right\} & \text{if } t_p > t_y^b, \end{cases}$$

$$\nu_p^B = \begin{cases} \frac{T_p}{365} & \text{if } t_p \geq t_y^b, t_p + T_p \leq t_y^e \\ \frac{t_p + T_p - t_y^b}{365} & \text{if } t_p < t_y^b, t_p + T_p \leq t_y^e \\ \frac{t_y^e - t_p}{365} & \text{if } t_p \geq t_y^b, t_p + T_p > t_y^e \end{cases}$$

Weights $A$ calculate the proportion of the reporting period that falls within year $y$. Weights $B$ calculate the size of the within-$y$ portion of the reporting period relative to the length of a year. Then, the stock and flow weights are as follows:

$$\omega_p^{stock} = \frac{\nu_p^B}{\sum_{p' \in P_y} \nu_{p'}^B}$$

$$\omega_p^{flow} = \frac{\nu_p^A}{\sum_{p' \in P_y} \nu_{p'}^B}$$

The intuition here is that for the stocks, the main concern is weighting observations according to how much of the year they account for. Thus we focus on the $B$ weights, adjusted by the sum of the weights to account for the possibility that a portion of the year is missing and so the weights must still sum to one. For the flows, we want to keep track of how much of each report corresponds to the year in concern, so we use the $A$ weights. Still, we adjust using the sum of the $B$ weights to account for missing portions of the year. Note that the flow weights need not sum to one.

Then, the calendarized data points are calculated as follows:

$$x_y^{stock} = \sum_{p \in P_y} \omega_p^{stock} x_p^{stock}$$

$$x_y^{flow} = \sum_{p \in P_y} \omega_p^{flow} x_p^{flow}$$

To implement this process, we begin with the raw complete data sets for each year during our sample period. These files are in long format, with each row corresponding to a hospital-reporting period-report entry, and report entries are characterized by a page number, column number, and line number. We classify every report entry as either a stock or a flow[A1]. In the data, examples of

A1. Some entries, such as the hospital's street address, are placed into a third category called "attributes." Since these

stocks are assets, liabilities, and number of beds. Examples of flows are visits, revenues, and costs. We then implement the calendarization process as described above to create the hospital-calendar year-report entry panel.

### B.5 Constructing the Revenue Variables

Now that the data is calendarized, we construct the relevant variables for our analysis (insofar as they are not reported directly). On the revenue side, this means obtaining net inpatient and outpatient revenue, both total and by payer. By payer, we do not mean specific insurance companies (UnitedHealth, Aetna, etc.), at which level the data is not reported. Rather, "payer" here refers to categories such as Medicare, Medi-Cal (the California version of Medicaid), and commercial payers.

The primary obstacle to obtaining inpatient and outpatient net revenue by payer is that while gross patient revenue is reported separately by payer and inpatient/outpatient, deductions are not always reported separately for inpatient and outpatient care. The same problem exists for capitation premium revenue. So to convert gross patient revenue to net patient revenue, we have to split the deductions and capitation revenue across inpatient and outpatient care. The method we use for this is described below.

In the following, $j$ refers to a payer, $s$ refers to a service line (e.g. pediatric acute), $R$ refers to gross revenue, $D$ refers to deductions, and $G$ refers to capitation revenue. $\tilde{R}$ refers to net revenue. $S$ is the set of all service lines, while $S' \subset S$ refers to the set of service lines that we include in our analysis (we exclude long-term care service lines). Inpatient/outpatient status will be denoted using superscripts $i$ and $o$, while payers and services lines will be denoted using subscripts.

The formulae for net inpatient and outpatient revenue for a payer $j$ where inpatient and outpatient deductions are reported separately are as follows:

$$\tilde{R}_j^i = \left(1 - \frac{D_j^i}{R_j^i}\right)\left(\sum_{s \in S'} R_{js}^i\right)$$
$$\tilde{R}_j^o = \left(1 - \frac{D_j^o}{R_j^o}\right)\left(\sum_{s \in S'} R_{js}^o\right)$$

If capitation revenue exists, the formulae are as follows:

$$\tilde{R}_j^i = \left(1 - \frac{D_j^i - G_j^i}{R_j^i}\right)\left(\sum_{s \in S'} R_{js}^i\right)$$

cannot be averaged, we assign the value coming from the reporting period that covers the most time in the calendar year. If this is ambiguous, we take the earliest report that covers part of the calendar year.

$$\tilde{R}_j^o = \left(1 - \frac{D_j^o - G_j^o}{R_j^o}\right)\left(\sum_{s \in S'} R_{js}^o\right)$$

In the case of managed care payers and Medi-Cal, we only observe total deductions. So the formulae become:

$$\tilde{R}_j^i = \left(1 - \frac{D_j}{R_j^i + R_j^o}\right)\left(\sum_{s \in S'} R_{js}^i\right)$$
$$\tilde{R}_j^o = \left(1 - \frac{D_j}{R_j^i + R_j^o}\right)\left(\sum_{s \in S'} R_{js}^o\right)$$

And if capitation revenue exists:

$$\tilde{R}_j^i = \left(1 - \frac{D_j - G_j}{R_j^i + R_j^o}\right)\left(\sum_{s \in S'} R_{js}^i\right)$$
$$\tilde{R}_j^o = \left(1 - \frac{D_j - G_j}{R_j^i + R_j^o}\right)\left(\sum_{s \in S'} R_{js}^o\right)$$

The idea of these formulae is to calculate net inpatient/outpatient revenue overall as a proportion of gross inpatient/outpatient revenue, and apply this proportion to impute net inpatient/outpatient revenue for the specific services in which we are interested.

In the reports, payers are categorized at a slightly more detailed level than we need. For instance, commercial payers are separated into managed care and traditional insurers. We finish the revenue variable construction by aggregating the calculated net patient revenue to the level of payer category we use.

### B.6 Constructing the Cost Variables

The next set of variables we derive from the cost reports are inpatient and outpatient costs, both total and by payer. We additionally allocate these costs to fixed and variable categories, of which we focus on the variable component in order to avoid fixed costs contaminating our measure of average costs. We also separate the costs into other broad categories, such as administrative costs and clinical labor costs, mainly for descriptive purposes.

The cost reports neither allocate costs by payer nor by inpatient and outpatient care. However, the cost reports do allocate cost by service line, $C_s$. We use this breakdown, along with the proportions of gross revenue for each service line by payer, to estimate inpatient and outpatient costs by payer. The underlying assumption is that within each service line, inpatient and outpatient charges by payer differ in proportion to the costs of providing care.

We will demonstrate the formula for estimating inpatient and outpatient costs by payer for the

inpatient case, though the same calculations apply for the outpatient case. First, we calculate the proportion of gross revenue corresponding to inpatient admissions for service line $s$:

$$\alpha_s^i = \frac{\sum_{j \in J} R_{js}^i}{\sum_{j \in J} R_{js}^i + \sum_{j \in J} R_{js}^o}$$

Next, we compute the proportion of gross inpatient revenues in service line $s$ that can be attributed to payer $j$:

$$\gamma_{js}^i = \frac{R_{js}^i}{\sum_{k \in J} R_{ks}^i}$$

Finally, we adjust costs per service line by these two proportions and sum across all the service lines of interest to form our estimate of inpatient costs by payer:

$$C_j^i = \sum_{s \in S'} \gamma_{js}^i \alpha_s^i C_s$$

Following this approach gives us our estimates of total inpatient and outpatient costs by payer. However, these total costs include fixed costs and variables costs, because the costs for each service line $C_s$ include both fixed and variable costs. To separate fixed and variable costs, we need to adjust each service line cost.

To adjust each service line cost, we use the cost allocations described in the cost reports. We list the categories in Table A1.

In Table A1, we also show whether we treat each category as fixed or variable. These decisions are based on the intuition that capital costs and administrative costs are primarily fixed costs. Additionally, research and education are less relevant to patient care expenses, so we treat them as fixed costs. We assume the remainder of the expenditures are at least primarily variable costs. Summing the fixed and variable cost categories within each service line, we obtain fixed costs by service line $C_s^f$ and variable costs by service line $C_s^v$. Then, we reapply our inpatient and payer proportions to obtain fixed and variable inpatient costs by payer:

$$C_j^{if} = \sum_{s \in S'} \gamma_{js}^i \alpha_s^i C_s^f$$
$$C_j^{iv} = \sum_{s \in S'} \gamma_{js}^i \alpha_s^i C_s^v$$

These measures can then be divided by the number of outpatient visits (by payer) to obtain our measure of average costs per visit. Figure A1 shows the proportion of fixed and variable costs, by inpatient and outpatient care and by payer (all payers vs. commercial payers only). Overall, variable costs are about 63% of total costs, with little variation across the different payers and care

Table B1: Cost Categories

| **Cost Category** | **Fixed or Variable?** |
|---|---|
| Direct Expenses | |
| Salaries and Wages | Variable |
| Employee Benefits | Variable |
| Physician/Student Compensation | Variable |
| Professional Fees | Variable |
| Supplies | Variable |
| Purchased Services | Variable |
| Depreciation | Fixed |
| Leases and Rentals | Fixed |
| Other Direct Expenses | Variable |
| | |
| Allocated Expenses | |
| Capital-Related Expenses | Fixed |
| Administrative | Fixed |
| Personnel Costs | Variable |
| Purchasing | Variable |
| Housekeeping | Variable |
| Grounds | Fixed |
| Dietary | Variable |
| Laundry and Linen | Variable |
| Medical Records and Data | Variable |
| Outpatient Registration | Variable |
| Nursing Administration | Fixed |
| Central Services and Supplies | Variable |
| Pharmacy | Variable |
| Research Administration | Fixed |
| Education Administration | Fixed |
| Nursing School | Fixed |
| Other Education | Fixed |
| Medical Postgraduate Education | Fixed |
| Transfers for Operating Costs | Variable |

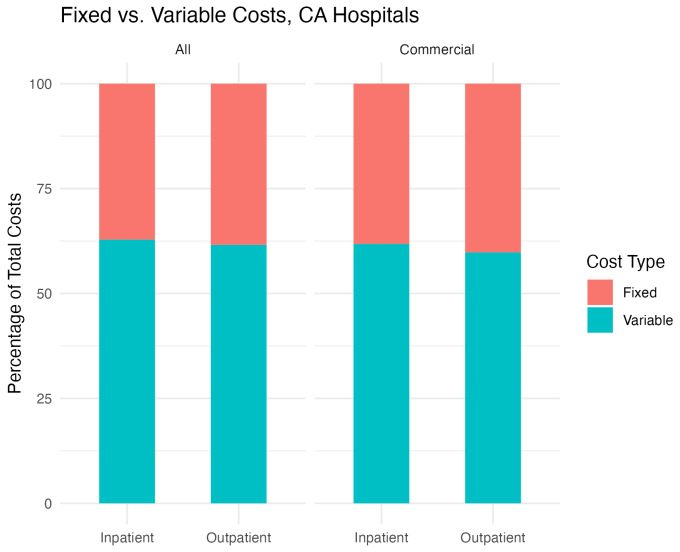



Figure B1: Fixed + Variable Cost Proportions

types.

## B.7 Constructing the Visits and Average Costs

To estimate average costs, we need to have a measure of total outpatient visits by payer to put in the denominator. For this, we take the measure provided in the cost report as given. Total outpatient visits in the cost reports include several types of visits: emergency services, clinic visits, observation care, psychiatric care, home health care, outpatient hospice care, outpatient surgeries, referred patients, and other visits. We sum all these visits to obtain our measure of outpatient visits. These visits are also reported by payer, and we perform the usual aggregation of adding the traditional and managed care categories within each payer type. This produces our measures of total outpatient visits, $v$, and total outpatient visits by payer, $v_j$. Average outpatient costs for payer $j$ are therefore:

$$c_j^o = \frac{C_j^o}{v_j}$$

# C Model Appendix

## C.1 Hospital Systems

In the main text, for expositional clarity, we wrote our Nash–in–Nash bargaining model for an independent hospital (equivalently a singleton hospital system). Here, we write down the analogous equations for a hospital system.

The first, place where the model differs for hospital systems relative to independent hospitals is Equation 9. Suppose that hospital system $\mathcal{H}$ and insurer $i$ negotiate over hospital prices.[A2]

The system version of Equation 9 is

$$\max_{\{p_{hi}:h\in\mathcal{H}\}} \left[\sum_{h\in\mathcal{H}} \Pi_{hi}(\mathcal{G}_i)\right]^{\alpha_{\mathcal{H}}} [V_i(\mathcal{G}_i) - V_i(\mathcal{G}_i \setminus \mathcal{H})]^{1-\alpha_{\mathcal{H}}}, \tag{19}$$

where $\alpha_{\mathcal{H}}$ is the bargaining weight for hospital system $\mathcal{H}$. Here we maintain the standard assumption in the literature that if system $\mathcal{H}$ and insurer $i$ disagree, then $i$ will have to drop all of the hospitals in $\mathcal{H}$ from its network, so its resulting network will be $\mathcal{G}_i \setminus \mathcal{H}$.

Using the $\Delta$ notation introduced in the main text, the Nash–in–Nash FOC is

$$\sum_{h\in\mathcal{H}} \Pi_{hi}(\mathcal{G}_i) = \alpha_{\mathcal{H}} \left(\beta \sum_{\{n:i(n)=i\}} \Delta W_{ni}(\mathcal{G}_i, \mathcal{H}) - \sum_{h'\notin\mathcal{H}} p_{h'i} \Delta D_{h'i}(\mathcal{G}_i, \mathcal{H}) - \sum_{h\in\mathcal{H}} c_h D_{hi}(\mathcal{G}_i)\right). \tag{20}$$

As in Ho and Lee (2017), this FOC is the same for every hospital $h \in \mathcal{H}$ (see their Equation A.3) and its preceding text). So, we impose a single system wide price $p_{\mathcal{H}i}$ for every hospital in $\mathcal{H}$.

We aggregate hospital system level Nash–in–Nash FOCs over insurers in the same way as we aggregate independent hospitals (described in the main text).

## C.2 Visit and Diagnosis Probabilities

While our estimated demand model alone implies choice probabilities for each hospital, translating these probabilities into market shares and volume requires estimates of market size and patient demographics. We follow Ho and Lee (2017) by using visit and diagnosis probabilities to convert Census statistics on total population by market to the population of individuals who are actively choosing a hospital for outpatient care.

We use the 1-year American Community Survey (ACS) for our Census estimates. First restricting to all respondents in California, we then filter our sample to only those who had commercial health

A2. Here we omit any subscript labeling the system, e.g., if $h, h' \in \mathcal{H}$, then according to the notation in the main text, the system could also be referred to by $\mathcal{H}_h$ or equivalently $\mathcal{H}_{h'}$.

insurance and were adults below the age of 65. This matches our claims data sample. We then calculate the total commercially insured population each year by gender and age group, where age groups are the following four groups: ages 20-34, ages 35-44, ages 45-54, and ages 55-64. Call these population statistics $N_t(\text{age}, \text{gender})$.

We then compute the corresponding statistics by age group, gender, and year using the claims data. Call these statistics $C_t(\text{age}, \text{gender})$. We then estimate the probability of an individual needing hospital outpatient care using the following frequency estimator:

$$\hat{\gamma}_{vnt} = \frac{C_t(\text{age}_n, \text{gender}_n)}{N_t(\text{age}_n, \text{gender}_n)}.$$

The diagnosis probability $\gamma_{dn}$ is a conditional probability of an APC weight given that a patient is seeking hospital outpatient care. Though the APC weight is a continuous variable, for ease of estimation we discretize its distribution to deciles and use a frequency estimator to calculate the diagnosis probabilities.

Similar to the visit probabilities, we calculate the probability of an APC weight being in a particular decile conditional on gender and age group. This allows different types of patients to require treatment at different severity levels. If we consider diagnosis $d$ to represent the average APC weight within a particular decile of the distribution, our estimator is as follows:

$$\hat{\gamma}_{dn} = \frac{C(\text{age}_n, \text{gender}_n, \text{decile}_d)}{C(\text{age}_n, \text{gender}_n)},$$

where $C(\cdot)$ is the number of claims in the respective group.

Once we have these probabilities, we simulate a set of patients in California that we use to estimate patient demand in all counterfactual scenarios. Within each market-year, our set of patients represents all combinations of the categorical variables and discretized APC weight distribution used in the demand model. We then assign each patient a weight, according to the combination of the shares of each of their attributes in the claims data and the population in the Census data. Then we adjust that weight using the visit and diagnosis probabilities. The total demand for a hospital in all counterfactual scenarios is therefore a weighted sum of its choice probability for each of these simulated patients.

### C.3 Proving Sufficiency of Equation 12

Assume

$$\frac{D_{h'j}(\mathcal{G}_j)}{\sum_{\{i:h'\in\mathcal{G}_i\}} D_{h'i}(\mathcal{G}_i)} = \frac{D_{h'j}(\mathcal{G}_j \setminus h)}{\sum_{\{i:h'\in\mathcal{G}_i\}} D_{h'i}(\mathcal{G}_i \setminus h)} \quad \text{for all } h' \neq h \text{ and for all } j. \tag{21}$$

We want to show that this implies

$$\sum_{\{i:h\in\mathcal{G}_i\}}\sum_{h'\neq h} p_{h'i}\Delta D_{h'i}(\mathcal{G}_i,h) = \sum_{\{i:h\in\mathcal{G}_i\}}\sum_{h'\neq h} p_{h'}\Delta D_{h'i}(\mathcal{G}_i,h), \tag{22}$$

which allows us to estimate the Nash–in–Nash bargaining model that we specify in section 5.1.2 using data on mean hospital prices (average over insurers within a hospital).

Swapping the order of summation on both sides of Equation 22, it is sufficient for us to show that

$$\sum_{h'\neq h} a_{h'i} = \sum_{\{i:h'\in\mathcal{G}_i\}} p_{h'i}\Delta D_{h'i}(\mathcal{G}_i,h) = \sum_{h'\neq h}\sum_{\{i:h'\in\mathcal{G}_i\}} p_{h'}\Delta D_{h'i}(\mathcal{G}_i,h) = \sum_{h'\neq h} b_{h'i} \tag{23}$$

We prove that if we assume Equation 21 holds, then $a_{h'i} = b_{h'i}$ for all $h'$ and $i$, which completes the proof.

For each $h' \neq h$, by definition

$$a_{h'i} = \sum_{\{i:h'\in\mathcal{G}_i\}} p_{h'i}\Delta D_{h'i}(\mathcal{G}_i,h) = \sum_{\{i:h'\in\mathcal{G}_i\}} p_{h'i}(D_{h'i}(\mathcal{G}_i) - D_{h'i}(\mathcal{G}_i\setminus h)) \tag{24}$$

Note that for any insurer $i$ we can write

$$p_{h'}\sum_{\{i:h'\in\mathcal{G}_i\}} D_{h'i}(\mathcal{G}_i) = p_{h'i}D_{h'i}(\mathcal{G}_i) + \sum_{j\neq i} p_{h'j}D_{h'j}(\mathcal{G}_j) \tag{25}$$

because the left hand side is the total revenue for hospital $h'$ (it's mean price multiplied by it's total demand across all insurers that cover it) and the right hand side is the sum of insurer–specific revenues for hospital $h'$ (split out between $i$ and the rest — $j' \neq i$).

The previous equation can be rearranged to give

$$p_{h'i} = \frac{p_{h'}\sum_{\{i:h'\in\mathcal{G}_i\}} D_{h'i}(\mathcal{G}_i) - \sum_{j\neq i} p_{h'j}D_{h'j}(\mathcal{G}_j)}{D_{h'i}(\mathcal{G}_i)} \tag{26}$$

Substituting Equation 26 into Equation 24 gives (for any $h'$ and any $i$)

$$\begin{aligned} a_{h'i} &= \sum_{\{i:h'\in\mathcal{G}_i\}} p_{h'i}(D_{h'i}(\mathcal{G}_i) - D_{h'i}(\mathcal{G}_i\setminus h)) \\ &= \sum_{\{i:h\in\mathcal{G}_i\}} \left(\frac{p_{h'}\sum_{\{i:h'\in\mathcal{G}_i\}} D_{h'i}(\mathcal{G}_i)}{D_{h'i}(\mathcal{G}_i)} D_{h'i}(\mathcal{G}_i) - \frac{\sum_{j\neq i} p_{h'j}D_{h'j}(\mathcal{G}_j)}{D_{h'i}(\mathcal{G}_i)} D_{h'i}(\mathcal{G}_j)\right) - \\ &\qquad \sum_{\{i:h'\in\mathcal{G}_i\}} \left(\frac{p_{h'}\sum_{\{i:h'\in\mathcal{G}_i\}} D_{h'i}(\mathcal{G}_i)}{D_{h'i}(\mathcal{G}_i)} D_{h'i}(\mathcal{G}_i\setminus h) + \frac{\sum_{j\neq i} p_{h'j}D_{h'j}(\mathcal{G}_j)}{D_{h'i}(\mathcal{G}_i)} D_{h'i}(\mathcal{G}_i\setminus h)\right) \end{aligned} \tag{27}$$

$$= b_{h'i} + \sum_{\{i:h' \in \mathcal{G}_i\}} \frac{\sum_{j \neq i}(p_{h'j} - p_{h'})D_{h'j}(\mathcal{G}_j)}{D_{h'i}(\mathcal{G}_i)} D_{h'i(\mathcal{G}_i)}(\mathcal{G}_i \setminus h)$$
$$= b_{h'i} + B.$$

All that remains is to show $B$ is zero. The mean hospital price for $h'$ is

$$p_{h'} = \frac{\sum_{\{i:h' \in \mathcal{G}_i\}} p_{h'i} D_{h'i}}{\sum_{\{i:h' \in \mathcal{G}_i\}} D_{h'i}}. \tag{28}$$

Substituting for $p_{h'}$ in $B$ and rearranging gives

$$B = \frac{1}{\sum_{\{i:h' \in \mathcal{G}_i\}} D_{h'i}(\mathcal{G}_i)} \sum_{\{i:h' \in \mathcal{G}_i\}} \frac{D_{h'i(\mathcal{G}_i)}(\mathcal{G}_i \setminus h)}{D_{h'i}(\mathcal{G}_i)} \sum_{j \neq i} D_{h'j}(\mathcal{G}_j) \sum_{k \neq j} (p_{h'j} - p_{h'k}) D_{h'k}(\mathcal{G}_k). \tag{29}$$

After a lot of simplification, we reach

$$B = \frac{1}{\sum_{\{i:h' \in \mathcal{G}_i\}} D_{h'i}(\mathcal{G}_i)} \sum_{\{i:h' \in \mathcal{G}_i\}} \sum_{j > i} (p_{h'j} - p_{h'k})(D_{h'j}(\mathcal{G}_j) D_{h'k}(\mathcal{G}_j \setminus h) - D_{h'k}(\mathcal{G}_k) D_{h'j}(\mathcal{G}_j \setminus h)). \tag{30}$$

Clearly, if there is no variation in the prices that $h'$ receives across insurers, then $B$ is zero, the proof is finished and we can aggregate as we wish.

Alternatively, $B$ is zero if

$$\frac{D_{h'j}(\mathcal{G}_j)}{D_{h'k}(\mathcal{G}_k)} = \frac{D_{h'j}(\mathcal{G}_j \setminus h)}{D_{h'k}(\mathcal{G}_k \setminus h)}, \tag{31}$$

but this equation is implied by the assumption in Equation 21.

### C.4 Aggregation Assumption

Here, we empirically investigate support for the following equation

$$\frac{D_{h'j}(\mathcal{G}_j)}{\sum_{\{i:h' \in \mathcal{G}_i\}} D_{h'i}(\mathcal{G}_i)} = \frac{D_{h'j}(\mathcal{G}_j \setminus h)}{\sum_{\{i:h' \in \mathcal{G}_i\}} D_{h'i}(\mathcal{G}_i \setminus h)} \quad \text{for all } h' \neq h \text{ and for all } j, \tag{32}$$

which would allow us to aggregate our Nash–in–Nash FOCs and to use a hospital–level price for estimation.

Each quantity in Equation 32 can be calculated with our data and demand estimates. To proceed, we predict demand for every hospital insurer year triple taking using our observed networks. Then, we predict demand again for every hospital insurer year triple, but excluding a hospital system from each insurers' network. Each time we exclude a system, we can calculate the ratios

on both sides of Equation 32.

Figure C1 presents the results. Panel (a) uses our actual demand estimates. The $x$–axis corresponds to the left hand side of Equation 32 and the $y$–axis corresponds to the right hand side. The $R$–squared exceeds 0.99. Panel (b) repeats this exercise, but we multiply our demand estimates by 10 before predicting hospital system demand. The figure shows that with different demand estimates, there is a weaker relationship between the two ratios.

Our takeaway is that Equation 32 presents an empirically testable condition that rationalizes aggregating the FOCs from our Nash–in–Nash model and using a mean hospital prices (as done previously by Lewis and Pflum (2015)).

(a) Actual Demand Estimate (b) Multiply Demand Estimates by 10

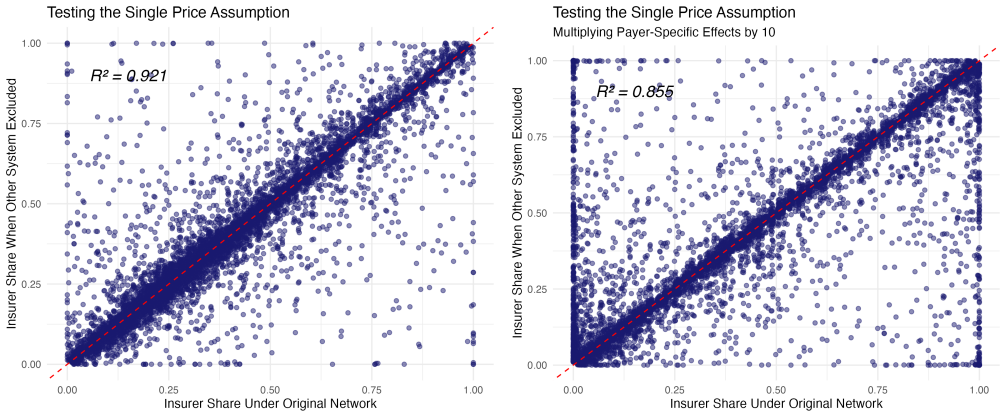



Figure C1: Testing Equation 13

Notes: This figure presents a test of Equation 32. All of the demand quantities in Equation 32 can be predicted with our data and demand estimates. In both panels, the $x$–axis corresponds to the left hand side of Equation 32 and the $y$–axis corresponds to the right hand side. Panel (a) uses our actual demand estimates. Panel (b) scales our payer-specific demand parameters by 10 before predicting demand.