Bargaining with Private Equity: Implications for Hospital Prices and Patient Welfare

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Abstract

This paper studies how changes in hospital ownership after private equity (PE) buyouts impact hospital–insurer price negotiations and patient welfare. Estimating an empirical model with proprietary insurance claims data, I find PE buyouts lead to an 11% increase in healthcare spending, driven by higher prices at PE-owned hospitals and price spillovers to local rivals. PE's superior bargaining skills and financial engineering account for 83% of the price increase. Counterfactual simulations imply that patient-surplus gains are equivalent to 10.7% of health expenses if restricting PE ownership and that regulators might underestimate the impact of hospital mergers if ignoring PE-owned acquirers' features.

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1 Introduction

The steep rise in U.S. healthcare prices has become a source of grave concern. In 2019, total U.S. health expenditure reached 18% of GDP, making the healthcare sector larger than the manufacturing sector (11% of GDP) and the energy sector (6% of GDP) combined. At the same time, the ownership landscape of the healthcare sector has greatly changed, particularly embodied in the active involvement of private equity (PE) investors over the last decade. The PE deal values in healthcare have recorded a 10-fold increase from 2009 to 2019. But we still know very little about how the ownership shift as a result of PE buyouts affects real outcomes. Proponents of PE argue that it can improve operational efficiency, lowering health costs. Opponents claim that PE firms are tough negotiators who care only about profits and load up hospitals with debt, hence pushing up health expenses and making patients worse off. Because of the unknown consequences for patients, providers, and healthcare prices, PE involvement in the healthcare sector has raised concerns among regulators.[1]

This paper studies the rise of PE ownership in healthcare using the hospital setting. Focusing on the setting, I address the following questions: How do ownership changes affect healthcare pricing? What are the specific channels by which PE investors create and redistribute value among stakeholders? What are the implications for patient welfare and regulations? There are several key novelties of this paper in exploring these questions. First, I use new, nationwide large-scale insurance claims data to capture detailed hospitals' transaction prices. It overcomes the data challenge since hospital prices are typically negotiated between hospitals and private insurers and thus difficult to observe. Second, I apply a structural approach that exploits state-level regulation changes as PE entry shocks to quantify how the ownership change impacts negotiated prices and patient welfare. The model also demonstrates new economic mechanisms in bilateral price bargaining, which apply to other business-to-business settings beyond the hospital sector. Third, the paper has policy implications. It highlights that evaluating mergers without accounting for PE-owned acquirers' features might potentially underestimate these mergers' impacts on consumer welfare.

Despite its importance, empirical research on how the ownership change after PE buyouts affects healthcare pricing and price bargaining in a business-to-business setting is scarce. One challenge is to assemble a dataset of sufficient detail and scope to credibly identify the impact of hospital ownership changes. Typically, the outcomes of hospital–insurer price negotiations are treated as commercially sensitive and thus are largely unavailable to researchers. I introduce new insurance claims data covering over 60% of individuals with private health insurance in the United States from 2013 to 2019. My final sample includes more than 600 million claims sourced from around 5,000 hospitals. The data include hospitals' detailed transaction prices charged to private insurers during patients' visits. For PE-ownership information, I manually match claims data with a comprehensive list of PE investments in hospitals over the last two decades. The novel combination of datasets enables me to study the impact of ownership change on hospital pricing.

I begin by presenting descriptive evidence that PE ownership in hospitals leads to sharp increases in their negotiated prices with private insurers. These increases cannot be attributed to market consolidation alone. After accounting for a rich set of observables and fixed effects, I find that negotiated prices rise about

[1] For example, Congress has recently passed legislation to curb the "surprise medical billing" crisis, in which PE-owned physician staffing firms predominate.

32% within a hospital–insurer pair after PE interventions. The results hold even when I compare prices of a subset of homogeneous medical procedures—specific medical imaging procedures—contracted between a hospital and an insurer. In contrast, hospital service utilization does not change significantly; I find that the units of medical resources used to treat a patient with a given diagnosis do not change after PE buyouts. This result suggests that transition to PE ownership mainly affects prices, not quantities.

PE intervention also imposes heterogeneous spillovers on the negotiated prices of rivals in the local market. After a PE firm acquires any hospital in a region, local non-PE-owned rivals that share common insurers with the PE-owned hospital experience an average 8.1% increase in negotiated prices. No such pattern is observed among other local rivals. This contrast shows that the existence of spillover effects closely hinges on whether a rival is connected with a PE-owned hospital through a common insurer in the "bargaining network."

Motivated by these patterns in the data, I develop and structurally estimate a model of price bargaining between hospitals and insurers. The structural approach helps overcome several empirical challenges. First, the existence of heterogeneous spillovers in price bargaining implies that the stable unit treatment value assumption (SUTVA) is violated, possibly introducing bias in reduced-form potential outcomes. Second, reduced-form techniques allow measuring the direction of various channels for changes in negotiated prices. However, evaluating their magnitudes requires a model. Third, quantifying patient welfare and exploring counterfactual experiments also requires the structural model.

The model presented here features PE buyouts, leverage choices of target hospitals, bilateral hospital–insurer bargaining over prices, and hospital choices of patients. It builds on the price bargaining model in Gowrisankaran et al. (2015) and Ho and Lee (2017) to include PE investments as well as the associated financial and operational adjustments after the ownership change. On the demand side, I model patients' choices as dependent on a rich set of patient and hospital characteristics. I incorporate the impact of PE buyouts on patients' choices by including a PE-ownership indicator and its interaction terms with patient demographics in the demand model. These variables capture any impact on patients' choices due to changes in service quality after buyouts.

On the supply side, private insurers bilaterally negotiate a benchmark price with hospitals in the local market. Price negotiations are modeled as a modified Nash-in-Nash bargaining game in which all bilateral negotiations occur separately and simultaneously; renegotiations occur when the local market structure shifts due to hospital bankruptcies. In the bargaining process, PE-backed hospitals can credibly threaten bankruptcy if their expected revenues are unable to meet the debt burden. PE investors optimally choose whether to invest in a hospital. They also choose financial leverage to maximize the expected payoffs of target hospitals. In addition, the model captures spillover effects of price bargaining in the local market.

PE ownership can affect bargained prices through multiple channels in the model. These channels cover key mechanisms of PE creating and redistributing value through financial, operational, and governance engineering. For example, the model recognizes that PE firms could potentially bring in new negotiating strategies and contracting expertise to improve hospitals' bargaining power; PE intervention affects hospitals' operational efficiency, non-pecuniary motives, and service quality. Importantly, the model also highlights that financial engineering of PE has direct implications: High debt loads render credible threats of bankruptcy from PE firms. On the one hand, bankruptcies of PE-owned hospitals make the outside option of insurers worse since they will have to face a more concentrated hospital sector and higher service prices charged by others. Therefore, insurers have incentives to "subsidize" hospitals and keep them competing with each other. On the other hand, bankruptcy threats make the outside option of equityholders more attractive as they can walk away if net revenues are under water. This mechanism spotlights a unique relation between financial characteristics of PE buyouts and price bargaining outcomes.

The main identification challenges in estimating the model are that PE endogenously select target hospitals, and PE-owned hospitals endogenously choose their financial leverage. I tackle the endogenous selection of target hospitals by exploiting state-level regulatory changes regarding the corporate practice of medicine doctrine (CPOM), which prohibits nonprofessional business corporations (e.g., PE firms) from practicing medicine or employing physicians to perform medical services. These changes provide exogenous variation in PE's entry costs into the hospital sector. I manually collect a series of legislative events and construct a CPOM regulation index as an instrumental variable. For the endogenous selection of leverage, I use the annual ICE BofA U.S. high yield index option-adjusted spread as the instrumental variable. The rationale for this approach is that the market price of credit risk affects PE's debt financing costs but is uncorrelated with idiosyncratic shocks to hospitals.

I use the estimated model as a laboratory to conduct a series of counterfactual analyses. First, I consider a counterfactual restriction on PE ownership in the hospital sector and its implications for negotiated prices, spending, and patient surplus. Similar policies were recently considered in several state legislatures.[2] The results show that restricting PE ownership in hospital would lead to an 11% reduction of health spending in affected regions, with savings mainly coming from a decrease of negotiated prices. While the quantities of provided services barely change in the counterfactual.

Looking at the spillover effects in the counterfactual, the results show that PE-backed hospitals would contribute 86% of the total savings if PE ownership were restricted. Another 14% would be contributed by local rivals that share common insurers with the PE-backed hospitals, while the remaining hospitals (local rivals that do not share insurers with the PE-backed ones) would contribute almost nil to the total savings. These results are largely consistent with the reduced-form evidence on the heterogeneous spillover effects. More specifically, I find that restricting PE ownership results in a 49% decrease of the quantity-weighted average prices among PE-backed hospitals and a 3.2% decrease among local rivals that share insurers with the PE-backed one.

Next, I use the model to quantify the relative contribution of various channels to the total savings. I find that superior bargaining skills of PE sponsors contribute about 43% of the savings, making it the largest contributor. There are many anecdotes of PE firms bring better negotiating expertise to their portfolio companies. I find strong empirical support for those stories in the hospital–insurer setting. Financial engineering and bankruptcy threats contribute an additional 40% of the savings, implying that the financing structure of PE buyouts can generate significant real effects in markets. Further savings come from the other two channels: changes in patient demand and the focus on social objectives, which contribute 10% and 8%, respectively. In contrast, changes in operational efficiency contribute about -1% since restricting PE would

[2]For instance, the California legislature in 2020 introduced a bill (SB-977) that aimed to rein in PE healthcare buyouts. The bill gave the state attorney general power to review and potentially block a broad range of merger deals in the healthcare sector involving private equity groups.

eliminate a gain in operational efficiency.

Finally, I quantify the impact on patient surplus in the counterfactual of restricting PE. Under the assumption that the savings on medical expenses would be passed through to patients by reducing insurance premiums, the model implies that restricting PE would bring patient-surplus gains equivalent to 10.7% of the documented health expenses in the affected regions. The gains largely come from savings in outpatient expenses, even though small reductions in service quality would negatively impact patient surplus if PE ownership were restricted.

In the second counterfactual, I use the model to evaluate policy implications for merger reviews. I consider a sample of hypothetical mergers wherein a PE-owned hospital system is randomly assigned to acquire one local rival. I assess the impacts of those mergers using the full model estimated in this paper (PE model) and a re-estimated plain model after removing PE-related features (No-PE model). I compare the two models' predictions regarding total spending, average prices, and patient surplus before and after mergers.

Both models predict an increase in total spending and average prices after mergers, however, with different magnitudes: Percentage changes in total spending and average prices predicted by the No-PE model could be 10 points lower than the PE model. The prediction gap still remains when I examine the change in patient surplus after mergers. The underestimation mainly comes from merging hospitals, among which the prediction gap in negotiated prices, for example, could be as high as 25%. For non-merging rival hospitals, the underestimation is much less severe. The results imply that regulators might potentially underestimate the impacts of proposed mergers if they disregard the unique features of PE ownership.

This work contributes to the industrial organization literature on hospital transaction prices and hospital competition. Unlike most of the literature focusing on health spending variation using Medicare claims data (e.g., Finkelstein et al., 2016 and Cutler et al., 2019), Cooper et al. (2019a) and Cooper et al. (2019b) quantify price variations within hospitals by using insurance claims data from the Health Care Cost Institute (HCCI) that cover the privately insured nationwide. This paper contributes to the discussion by introducing a national multiyear dataset of hospital transaction prices from the DRG Real World Data. It sheds light on how hospital price variations arise as a result of the ownership change after PE buyouts.

My analysis relates to the empirical literature on bargaining in health care and other markets. In a survey paper, Gaynor et al. (2015) introduce the general framework to study the impact of hospital–insurer price bargaining on medical spending. Handel and Ho (2021), Grennan and Swanson (2022), and Lee et al. (2021) discuss the most recent developments in the literature. Due to the difficulty in data access, the empirical literature in this area is still relatively small. Previous studies have focused on the relationships between insurers and providers (Ho, 2009, Lewis and Pflum, 2015, Dafny et al., 2019, Brown, 2019, and Tilipman, 2022), insurers and employers (Dafny, 2010 and Ho and Lee, 2019), hospitals and medical suppliers (Grennan, 2013, Grennan, 2014, and Grennan and Swanson, 2020), pharmaceutical companies and the government (Dubois et al., 2022), conglomerates of channels and distributors (Crawford and Yurukoglu, 2012).[3] This paper builds on the models of bargaining and competition between hospitals and insurers from Gowrisankaran

[3]There is a strand of literature discussing how debts affect bargaining outcomes. Towner (2020) finds that hospitals with more debt negotiate higher reimbursement rates with insurers. Brown et al. (2009) exhibit that leveraged buyouts strengthen the bargaining positions of portfolio companies when facing their suppliers.

et al. (2015) and Ho and Lee (2017). It examines a different question and uncovers new channels, in particular the financing side of PE buyouts, that impact hospital price bargaining. It also demonstrates how ownership changes could potentially affect consumer surplus due to changes in price negotiation strategies in an important context.

It also contributes to the empirical literature on the effects of PE ownership, both in health care and more generally.[4] In health care, previous studies (e.g., Stevenson and Grabowski, 2008, Pradhan et al., 2014, Huang and Bowblis, 2019, Gondi and Song, 2019, Bruch et al., 2020, Gandhi et al., 2020, Bruch et al., 2021, Cerullo et al., 2021, Offodile et al., 2021, and Gupta et al., 2021) primarily examine medical service quality and facility profitability after PE buyouts. In recent work, Cerullo et al. (2022) use the CMS data to investigate how PE acquisitions affect patient outcomes and spending in short-term acute care hospitals among Medicare beneficiaries. Gao et al. (2021) examine facility-level employment and patient outcomes at hospitals acquired by PE. My paper adds to this literature by exploring how PE ownership impacts bargained prices and consumer surplus. It decomposes PE's real effects into operational versus financial channels, which brings new insights on why and how PE creates and redistributes value in the market. In contrast to the prior literature, I show that PE's financial engineering has significant real impacts on market prices. I also document that PE ownership has heterogeneous spillovers to the price negotiation of local hospitals.

More broadly, this paper contributes to the literature on firm ownership and its implications for organizational behavior and consumer welfare (Hansmann, 1980; Lichtenberg et al., 1987). Focusing on the hospital setting,[5] Duggan (2000) uses a plausibly exogenous change in hospital financing to test three competing theories of firm ownership. He finds that different types of ownership respond to financial incentives differently. Eliason et al. (2020) use rich data from the dialysis industry and find that ownership transfer after acquisitions produces significant changes in provider behavior and patient outcomes. In my setting, I show that changes in ownership types lead hospitals to alter their strategies and practices in price negotiations with insurers. These changes are closely tied to PE firms' unique features and have important implications for patient welfare.

2 Data and Summary Statistics

2.1 Data

The main data used in the paper are from the proprietary database DRG Real World Data Product (RWD Product). The raw RWD data contain over 26 billion claims, track more than 300 million longitudinal patient lives in the United States. One contribution of this paper is to use the DRG RWD data in healthcare economics. The Online Appendix compares RWD data to other prominent insurance claims data, including

[4] Kaplan and Stromberg (2009) and Jenkinson et al. (2021) provide nice surveys on the economics of leverage buyout and PE. A number of papers have examined the effects of PE ownership on firm productivity and growth (e.g., Kaplan, 1989, and Boucly et al., 2011), firm employment (e.g., Davis et al., 2014 and Davis et al., 2019), industry performance (e.g., Bernstein et al., 2017), financial stability (e.g., Bernstein et al., 2019 and Johnston Ross et al., 2021), workplace safety (e.g., Cohn et al., 2021), restaurant quality (e.g., Bernstein and Sheen, 2016), student outcomes (e.g., Eaton et al., 2020), and product prices (e.g., Fracassi et al., 2022).

[5] There is a literature in finance using the hospital context to study how firms of different ownership types respond to financial shocks, including Adelino et al. (2015), Adelino et al. (2022), and Aghamolla et al. (2021).

the IBM MarketScan and Health Care Cost Institute (HCCI) databases.

The RWD Product includes a unique provider identifier, a patient identifier, a payer identifier, the date services were provided, the date payments were processed, the hospital's charges and negotiated prices (sum of the payer paid amounts and patient paid amount), and a detailed decomposition of the patient's payments such as deductibles, coinsurance, and copayments. In addition, the data contain full diagnosis information in terms of International Classification of Disease (ICD) codes; medical procedures in terms of Healthcare Common Procedure Coding System (HCPCS) codes; patients' demographic information such as 3-digit zip code prefix of their residency, gender, and age; insurer's identity if they are commercial, Medicare, or Medicaid; and types of patients' insurance plans. One advantage of the RWD data is the ability to identify payers, which enables comparison of price variations within hospital–insurer pairs and makes it possible to study the impacts of PE ownership on price bargaining outcomes given a hospital–insurer pair.

For the purpose of this analysis, I focus on a sample of outpatient hospital claims of private insurers in the RWD data. The detailed method for identifying outpatient claims is provided in the Online Appendix, which yields a sample of over 600 million commercial insurance claims in hospital outpatient settings. In the main analysis, I group claim lines to each patient visit. To identify the *Disease* category for each patient visit, I follow previous literature (e.g., Shepard, 2016) to group ICD-10 (or ICD-9) diagnosis codes in medical claims into 285 mutually exclusive Clinical Classification Software (CCS) single-level categories. The sample contains 78,742,811 patient visits. I drop any observations of patient visits to federal government-owned hospitals (e.g., army, veterans) and the Kaiser Foundation's hospital system. Any patient visits with missing information on patient age, gender, CCS category, payer identification, and total paid amounts are dropped. Patient visits with negative paid amounts are excluded as well. Lastly, I require that a hospital has at least 10 patient visits a year in the sample. Applying all these filters leads to a final sample of 72,663,354 patient visits between 2013 and 2019.

I manually match claims data to PE ownership information. The data on PE deals are from four proprietary sources: PitchBook, Preqin, Capital IQ, and SDC Platinum. I tap the AHA annual survey sample to obtain characteristics of hospitals. To match AHA survey data to RWD claims, I follow Cooper et al. (2019b) and use the NPI codes in both datasets to link them (Online Appendix). I also use the Healthcare Cost Report Information System (HCRIS) to complement the AHA survey data. To evaluate the quality information of hospitals, I leverage the quality scores from various CMS-managed quality programs. Other supplemental data used include the APC and RVU code files from CMS to compute the relative service-mix weights, HRR and HSA files from the Dartmouth Atlas, and hospital mergers and acquisitions (M&As) data from the Irving Levin Associates' healthcare services acquisition reports.

2.2 Summary Statistics

For the sample of PE hospital buyouts from 2006 to 2019, Table OA.1 in the Online Appendix reports key features of the deals. It records a total of 243 deals. Panel A classifies them into six categories based on deal types. A total of 838 hospital facilities were ever involved in these PE deals. Panel B of Table OA.1 tabulates descriptive statistics of these hospitals' characteristics. The majority of target hospitals are located in urban areas and do not have teaching or critical access statuses. Panel C reports hospital ownership types prior to PE buyouts. About one-third of hospitals were not-for-profit prior to PE investments. These not-for-profit hospitals must abruptly transform their ownership types from not-for-profit to for-profit after buyouts because only for-profit entities are allowed to distribute profits to their shareholders.

For the insurance-claim sample, Table OA.2 in the Online Appendix reports summary statistics in the full sample as well as the "Never Treated" and "Ever Treated" subsamples. The "Ever Treated" group contains hospitals that were ever targeted by PE or received PE investment during the sample period. The remaining hospitals are in the "Never Treated" group. Panel A of Table OA.2 shows the mean age of patients is 46. A typical visit requires a 42-minute drive, which is calculated between the centroid of a patient's 3-digit zip code prefix and the location of the hospital under normal traffic conditions using the *HERE API*. The full sample mean of *relative service-mix weights*, a variable measuring how much medical services or resources are used to treat a disease during a patient's visit, is 6.5.[6] In terms of hospital prices, the mean listing price for a typical visit is around \$2,675 (dollars in 2019 adjusted by GDP deflators). In contrast, the average negotiated payment per visit is \$814, of which insurers cover about 82%. Panel B of Table OA.2 reports variables at the hospital-year level. Panels C and D of Table OA.2 summarize variables at the local region level.

3 Descriptive Evidence

3.1 Empirical Specification

To explore the impacts of PE ownership, I adopt the following specification:

$$Y_{i(m)jdt} = \alpha_1 \mathrm{PE}_{jt} + \alpha_2 \mathbf{x}_{it} + \alpha_3 \mathbf{y}_{jt} + \mathrm{FEs} + \varepsilon_{i(m)jdt} \tag{1}$$

in which $Y_{i(m)jdt}$ is an outcome variable in a visit for patient i to hospital j with disease d at time t, and $i(m)$ represents that patient i enrolled in a health plan provided by carrier m. The dependent variable includes the natural logarithm of patients' out-of-pocket costs, payer paid amounts, and total paid amounts (negotiated prices between hospitals and insurers) defined as the sum of the previous two variables.[7] All dependent variables are winsorized at the 1st and 99th percentiles within each CCS category. PE_{jt} is a dummy equal to one if facility j is owned by PE firms at time t. $\mathbf{x}_{it}$ is a vector of patient characteristics, including their gender, ages, plan types (HMO, PPO, etc.), and relative service-mix weights. $\mathbf{y}_{jt}$ is a vector of facility characteristics, including total number of beds, for-profit status, teaching school status, fraction of total admission days of Medicare patients, and fraction of total admission days of Medicaid patients. FEs are a

[6] The detailed procedure to assign the relative service-mix weights to each patient visit is depicted in the Online Appendix. The weights play an important role in pricing services for both public (e.g., Medicare) and private insurance. For example, in the Medicare Hospital Outpatient/Inpatient Prospective Payment System (PPS), hospitals are reimbursed based on a benchmark price set by CMS and the relative weights of incurred services. The benchmark price is equivalent to the price per unit of service weights. Of course, the final payments for individual services will also adjust by a conversion factor and other factors to take into account the geographic differences in input prices. So, a lot of private insurers follow similar pricing schemes by negotiating a benchmark price with providers and setting the payments using the relative service-mix weights. The structural model would adopt this assumption, which has been extensively used in previous literature (e.g., Gowrisankaran et al., 2015 and Ho and Lee, 2017).

[7] I use the logarithm of the outcomes plus one dollar to ensure there are no zeros in the dependent variable, which are otherwise quite frequent in, for example, patients' out-of-pocket payments (Cuesta et al., 2019). The results are robust when using the inverse hyperbolic sine transformation of the dependent variable, $\tilde{y} = \ln(y + \sqrt{y^2+1})$, which is recommended by Burbidge et al. (1988) and has been widely adopted in the literature (e.g., Browning et al., 1994 and Kale et al., 2009). The results are displayed in the Online Appendix.

set of fixed effects to control for unobserved time-invariant characteristics, which include $Disease \times Year$ FEs, $\gamma_d \times \tau_t$, to isolate variations within a given disease and a year, and most importantly, $Hospital \times Insurer$ FEs, $\mu_j \times \eta_m$, to compare negotiated prices within a hospital–insurer pair before and after PE investments. Standard errors are clustered at the hospital level.

The coefficient of interest, α_1, captures the difference of negotiated service prices between PE- and non-PE-owned hospitals for patients of identical disease complications (and hence who required the same treatment) in a given period. In addition, these patients are supposed to have insurance plans from an identical insurer. In a separate set of tests, I use the natural logarithm of the relative service-mix weights of each visit as the dependent variable to investigate how PE buyouts affect the medical resource utilization, given patients stricken by the same disease. I discuss regression results in the following section.

3.2 Impacts of PE Buyouts on Negotiated Prices

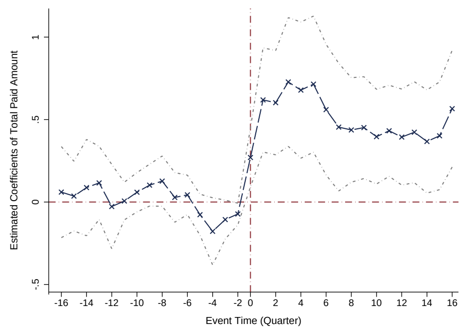
The OLS regression results are exhibited in Table 1. Column (1) of Table 1 uses the log of total paid amounts as the dependent variable. The coefficient on PE is positive and statistically significant at the 5% level. It suggests that after PE buyouts, negotiated prices between a hospital and an insurer increase by 32%. Columns (2) and (3) of Table 1 report the regression results using the log of patient/insurer paid amounts. Most of the price increase is covered by insurers: the payer paid amounts increase by 28% after PE buyouts, while patient paid amounts slightly increase by only about 4% and the coefficient is insignificant for most specifications. Instead of paid amounts, I use the log of relative service-mix weights of each visit as the dependent variable and re-estimate the model. It shows that PE ownership has no impacts on service utilization given the same diagnosed disease, which contrasts with the significant increase in negotiated prices observed in the data.

Table 1: Impacts of PE Ownership

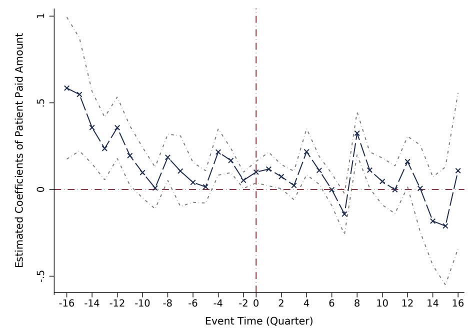
This table reports the results of Regression (1) for the full sample of patient visits between 2013 and 2019. Columns (1) to (4) examine the impacts of PE ownership on the natural logarithm of the total paid amounts, patient paid amounts, payer paid amounts, and relative service-mix weights. All columns contain hospital×payer fixed effects, diagnosis×year fixed effects as well as patient controls, including *gender*, *age group*, *insurance type*, and *relative service-mix weights* (except in Column (4)), and hospital controls, including *hospital bed numbers*, *teaching status*, *rural status*, *for-profit status*, *ratio of Medicare patients*, and *ratio of Medicaid patients*. Standard errors are clustered at the hospital level. t-statistics are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Log(total paid)	**Log(patient paid)**	**Log(payer paid)**	**Log(service weight)**
PE	0.319**	0.046*	0.280**	0.019
	(2.340)	(1.681)	(2.053)	(0.720)
Hospital Controls	Y	Y	Y	Y
Patient Controls	Y	Y	Y	Y
Diagnosis×Year FE	Y	Y	Y	Y
Hospital×Payer FE	Y	Y	Y	Y
Adj. R^2	0.308	0.352	0.183	0.305
Observations	70,861,542	70,852,700	70,861,113	70,861,542

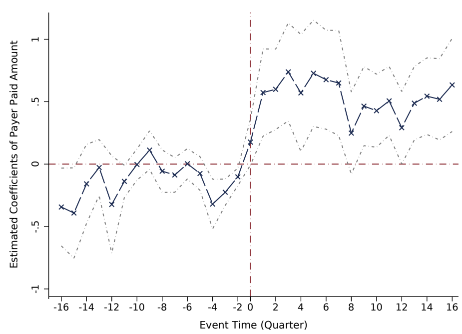
Figure 1: Dynamic Effects of PE Intervention



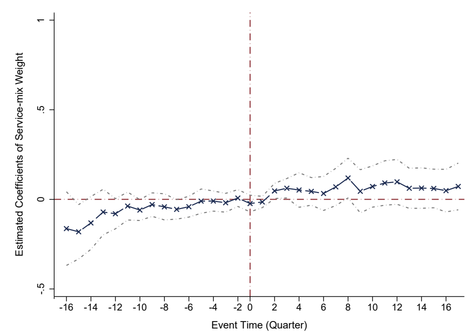
(a) Log of Total Paid Amounts



(b) Log of Patient Paid Amounts



(c) Log of Payer Paid Amounts



(d) Log of Service-mix Weights

This figure presents the dynamic treatment effects of PE buyouts in event studies. It plots the OLS coefficients α_τ from the following regression:

$$Y_{i(m)jdt} = \sum_{\tau=-16,\tau\neq-1}^{16} \alpha_\tau \mathrm{PE}_{j,\{t-t_0=\tau\}} + \mathrm{Controls} + \mathrm{FEs} + \varepsilon_{i(m)jdt},$$

wherein t_0 denotes the first quarter when $\mathrm{PE}_j = 1$ for hospital j. The coefficient with $\tau = -1$ is excluded as a benchmark category. Any quarters beyond 16 (-16) are binned into the 16th (-16th) quarter. All standard errors are clustered at the hospital level. Gray dotted lines represent 95% confidence intervals.

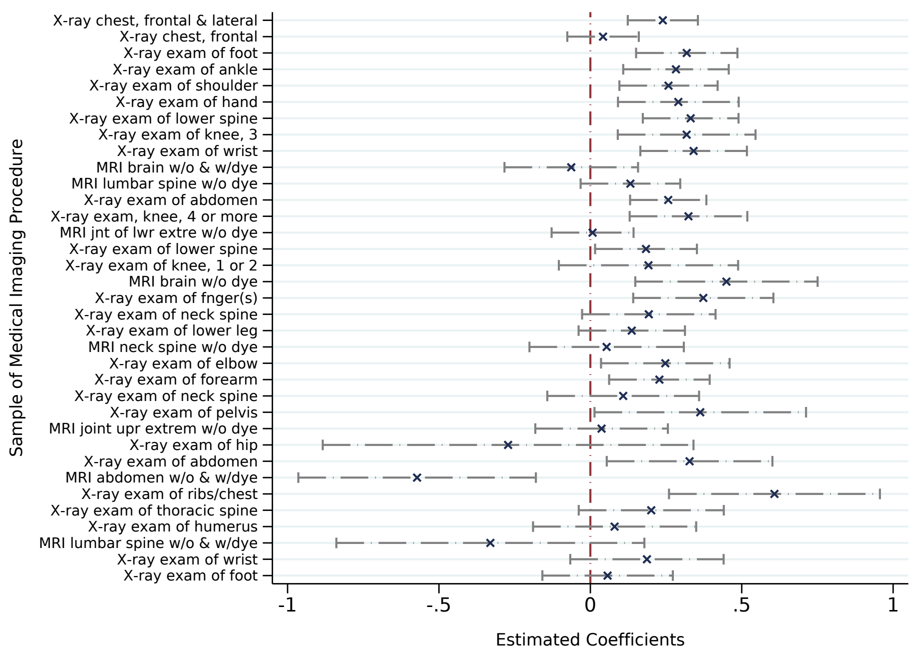
To explore the dynamics of these effects, I conduct an event study based on a matched sample.[8] I implement it at the quarterly frequency. Specifically, I match each PE-owned hospital to three control hospitals using the optimal Mahalanobis matching based on five variables in the year before PE buyouts: ratio of Medicare patients, ratio of Medicaid patients, number of hospital beds, for-profit status, and the average benchmark price. I also require that the control hospital share the same metro status, be in the same census division, and have the same service code. The estimated model is similar to Regression (1), except I include 16-quarter leads and lags of PE. Following the literature, I exclude the quarter right before the event time as a benchmark. Results are displayed in Figure 1. For all dependent variables, there are no significant coefficients in the 16 quarters leading up to the event, indicating no anticipation effects or pre-trends. After completion of PE deals, the top-left and bottom-left panels of Figure 1 witness a spike in the total paid amounts and insurer paid amounts. The effects are significantly positive and persistent for the

[8]Recent econometric literature points out several potential concerns regarding the conventional dynamic diff-in-diff design with staggered treatment timing, such as under-identification, negative weighting, and so on (e.g., Abraham and Sun, 2021 and Borusyak et al., 2021). However, as discussed in Borusyak et al. (2021), these concerns largely disappear with a large never-treated group, which is the case in this paper.

following quarters. Such pattern is not observed for the patient paid amounts[9] or the relative service-mix weights of each visit as shown in the top-right and bottom-right panels. Main results are robust if I pool matched sample and rerun Regression (1), as shown in Table OA.6 of the Online Appendix.

One potential concern of examining outcomes at the patient-visit level in the above regressions is that PE intervention might lead to a change in service quality and hence impact negotiated prices. I address this concern by focusing on a subset of medical procedures—specific medical imaging procedures, which are widely considered as the least differentiated healthcare service (Chernew et al., 2021). I follow Brown (2019) to run the main regression within each specific procedure of the top 35 X-ray and MRI scans ranked by total usage in the sample. Estimates are collected in Figure 2. For most imaging procedures, the figure supports the conclusion that after PE investments, negotiated prices between hospitals and insurers increase significantly. Results still hold when pooling X-ray and MRI scan procedures together, as demonstrated in Table OA.7 of the Online Appendix.

Figure 2: Regression Coefficients for Medical Imaging Procedures



This figure exhibits the estimated coefficients of the PE dummy in Regression (1) for the subsamples of the top 35 medical imaging procedures. The y-axis denotes the names of medical imaging procedures. All standard errors are clustered at the hospital level. Capped spikes represent 95% confidence intervals.

3.3 Spillover Effects

PE investment in hospitals not only impacts their own negotiated prices with insurers, but also imposes spillover effects on negotiated prices of local rivals via insurers' "bargaining network." I use a variant of Regression (1) and test the spillover effects by examining two separate subsamples of hospitals: (1) a subset

[9] I further decompose patient paid amounts into copayments and coinsurance, and explore the dynamic effects of PE buyouts on them. Results are shown in Figure OA.2 of the Online Appendix.

of non-PE-backed hospitals that share at least one insurer with the PE-backed facilities in the same local markets and (2) a subset of non-PE-backed hospitals that do not share any. In both subsets, I check how their negotiated prices respond to PE buyouts of other hospitals in the local market. In these tests, the PE dummy is turned on if there is any PE-backed hospital in the local market in a given year. Results are reported in Table 2.

Table 2: Evidence of Spillover Effects within HRRs

This table shows the heterogeneous spillover effects of PE intervention in the local market. Column (1) examines a subsample of non-PE-backed hospitals which share common insurers with the PE-backed one in an HRR. Column (2) examines a subsample of non-PE-backed hospitals which do not share any insurer with the PE-backed one. The dependent variable is the natural logarithm of the total paid amounts. The independent variable, PE_{jt}, is an indicator for whether the HRR where hospital j is located has any PE-backed hospitals in year t. Standard errors are clustered at the hospital level. t-statistics are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Non-PE-backed Hospitals Share an Insurer with PE-backed	Non-PE-backed Hospitals Not Share Any Insurer with PE-backed
PE	0.081**	−0.033
	(2.338)	(−0.923)
Hospital Controls	Y	Y
Patient Controls	Y	Y
Diagnosis×Year FE	Y	Y
Hospital×Payer FE	Y	Y
Adj. R^2	0.283	0.352
Observations	22,608,229	21,195,762

Column (1) documents strong positive spillover effects for the first sample. It implies that after PE buyouts, local rivals that share an insurer with the PE-backed one increase their negotiated prices by 8.1% on average, which is statistically significant at 5% level. For local rivals that do not share any insurer with the PE-backed one, column (2) reports insignificant effects on prices and the estimated magnitude is close to zero. The results reveal that PE investment imposes spillover effects heterogeneously across the "bargaining network" in the local market. The magnitude of spillover effects closely hinges on the hospital's position in the "bargaining network" of insurers. This, in fact, poses a threat to the traditional reduced-form approach to evaluate the impacts of PE ownership on healthcare prices. I will discuss its implications in Section 3.5.

3.4 Potential Channels

Some might attribute the increase in negotiated prices after PE buyouts to the market consolidation effect. In this section, I compare PE deals to typical M&As and argue that the observed effects of PE buyouts are unique. I then explore several potential channels associated with PE intervention.

Table 3: Compare with Merger and Acquisition (M&A) Deals

This table compares the effect of PE intervention with that of M&As. The sample includes insurance claims of hospitals that ever experienced M&As or received PE investments between 2013 and 2019. The dependent variable is the natural logarithm of the total paid amounts. The independent variable, $M\&A_{jt}$, is an indicator for whether hospital j experienced any M&As by year t. $M\&A \times PE_{jt}$ equals one if hospital j is under PE ownership in year t. All columns contain hospital×payer fixed effects. Columns (2) to (4) include diagnosis×year fixed effects. Patient controls are added in columns (3) and (4). Hospital controls are added in column (4). Standard errors are clustered at the hospital level. t-statistics are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent variable:			
	Logarithm of total paid amount			
	(1)	(2)	(3)	(4)
$M\&A \times PE$	0.295**	0.314**	0.320**	0.330**
	(2.002)	(2.251)	(2.352)	(2.423)
$M\&A$	0.030*	-0.036	-0.038	-0.036
	(1.680)	(-1.581)	(-1.633)	(-1.577)
Hospital Controls	N	N	N	Y
Patient Controls	N	N	Y	Y
Diagnosis×Year FE	N	Y	Y	Y
Hospital×Payer FE	Y	Y	Y	Y
Adj. R^2	0.232	0.293	0.318	0.318
Observations	30,357,358	30,357,338	30,357,338	30,357,338

Table 3 compares the impact of PE to that of M&As. The sample only includes hospitals that ever experienced M&As or received PE investments. Key regressors are $M\&A$, an indicator equal one if a hospital was acquired or merged with another hospital before a given year, and $M\&A \times PE$, an indicator equal one if the deal involved any PE investors. The coefficient of $M\&A \times PE$ would pick up any effects of PE buyouts on negotiated prices that cannot be ascribed to M&As. Columns 1 to 4 show that all estimates of $M\&A \times PE$ are statistically significant and the economic magnitude is comparable to that in column (1) of Table 1, indicating that the impacts of PE are unique. I explore several novel channels that might explain the observed price increases after PE intervention.

Financial Engineering

One of the most prominent features in PE buyouts is the heavy use of debt (so-called financial engineering) (e.g., Kaplan and Stromberg, 2009). Higher leverage dictates higher probability of bankruptcy, which could enhance the firm's bargaining position. Panel A of Table OA.8 in the Online Appendix examines how a hospital's financial leverage changes after PE investment, in which leverage is defined by the ratio of total long-term liabilities to total assets. I winsorize it at the 1st and 99th percentiles. Column 4 shows that after PE buyouts, the leverage of a hospital increases by 10% on average. This is a nontrivial increase in debt levels given that the mean leverage in the sample is 13.7%.

To explore how leverage affects negotiated prices of a PE-owned hospital, in Panel B of Table OA.8 I include the leverage and its interaction term with PE as regressors. Two things are worth noting: First, estimates of $PE \times Leverage$ suggest a significantly positive effect: A 10 percentage point increase of leverage of a PE-owned hospital is associated with a 65 basis point increase of negotiated prices. Second, the coefficient of *Leverage* itself is insignificant and has a negligible effect on prices, which suggests that an increase in leverage for non-PE-owned hospitals does not affect price negotiations. This supports the idea that the financial engineering channel is unique to PE-owned hospitals, consistent with anecdotal evidence that PE investors have a reputation for closing down distressed facilities and are able to credibly follow through on the threat of bankrupting hospitals by taking up debt loads.

Non-pecuniary Motive

Another feature of PE firms is that they are profit-centered due to their fiduciary duty to investors (e.g., Shleifer and Summers, 1988). This contrasts with the ownership type of many not-for-profit hospitals. After a not-for-profit hospital is bought out by PE, it must transition to a for-profit entity with less focus on social objectives. This could potentially boost the negotiated prices of PE-owned hospitals. To test this channel, I compare price changes of PE-target hospitals which were previously for-profit to those that were previously not-for-profit. In the estimation, I extend Regression (1) by including an interaction term $PE \times$ Previously For-profit, an indicator whether the PE-owned hospital was previously for-profit. The prediction is that they will experience a smaller price increase after PE investment, and the coefficient of $PE \times$ Previously For-profit is expected to be negative.

Estimation results of Table OA.10 in the Online Appendix support the prediction: The estimate of $PE \times$ Previously For-profit is indeed significantly negative, indicating that previously for-profit hospitals, compared to other types of entities, experience smaller price increases after PE investment. Summing estimates of $PE \times$ Previously For-profit and PE, it suggests that their negotiated prices on average increase by only 8.5%, which is smaller than the average price increases in Table 1.

Operational Efficiency

Previous literature documents that PE improves operational efficiency of its portfolio companies, commonly translating into lower marginal operation costs (e.g., Davis et al., 2014). Lower marginal costs are theoretically associated with lower prices, which can be another channel affecting negotiated prices. I therefore check how PE buyouts affect the operational costs of hospitals by exploiting the measure of total cost per adjusted discharge proposed by Schmitt (2017), defined as

$$\text{AC}_{it} = \frac{\text{TC}_{it}}{D_{it} \times (1 + \frac{R_{it}^O}{R_{it}^I})},$$

in which AC_{it} is the cost per adjusted discharge for hospital i in fiscal year t, TC_{it} is the total costs of hospital i during the year, D_{it} is the number of inpatient discharges, R_{it}^O is the outpatient charges, and R_{it}^I is the inpatient charges.

I depict the average cost dynamics before and after PE investment in Figure OA.3 in the Online Appendix. It shows that the average costs significantly trend down two years after PE buyouts.

Service Quality and Patients' WTP

Patients' willingness-to-pay (WTP) is another determinant of a hospital's bargaining position, and it is typically correlated with the service quality provided by the hospital. If one hospital is believed to provide good services and hence patients assign high WTP to it, the hospital is able to bargain a relatively high price compared to other local providers. As a potential channel, PE might affect hospitals' bargaining positions by adjusting service quality.

To explore this channel, I use 42 different quality measures from CMS to evaluate how they change after PE intervention, including 30-day mortality rates, 30-day readmission rates, patient safety indicators, outpatient imaging efficiency, and consumer assessment scores. Results are exhibited in Figure OA.4 in the Online Appendix. Quality implications after PE buyouts are mixed: Generally there is no significant difference in service quality before and after PE buyouts. For some measures, hospitals perform better after PE buyouts. However, patient satisfaction significantly worsens after PE investments, indicating that ancillary-service quality worsens.

3.5 Challenges of the Reduced-form Approach

Though the reduced-form regression is a transparent way to examine the impacts of PE ownership, there are a couple of challenges to that analysis that support a structural approach. First, as shown in Section 3.3, PE investment exhibits heterogeneous spillover effects. This violates the SUTVA assumption embedded in the reduced-form approach. So, more structural assumptions are needed to accommodate the spillover effects. Second, it is challenging to use the reduced-form approach to quantify the relative contribution of various channels on price bargaining outcomes. In addition, some potential channels are difficult to find proxies for and to isolate using the reduced-form techniques. On the contrary, the structural approach can serve the purpose with the help of bargaining theory to isolate the associated impacts. Third, a structural model is an indispensable tool if we would like to quantify patient surplus and explore counterfactuals. As a laboratory, the counterfactual analyses also shed light on relevant policy debates.

4 Structural Approach

4.1 Model Specification

I extend a bargaining model in the style of Gowrisankaran et al. (2015) and Ho and Lee (2017) wherein I detail the interaction between PE firms, hospitals, insurance companies, and patients in three stages, as depicted in Figure 4.1. In the first stage, PE firms pick target hospitals to invest in and choose an optimal debt leverage to finance the deal. Next, hospitals in the local market engage in bilateral bargaining to determine benchmark prices with insurers. Finally, patients select hospitals to visit when they become sick. I discuss each stage in reverse order.

PE Buys Hospital j $\xrightarrow{\text{choose}}$ **Debt Leverage** l_j — Stage 1

Hospital j **& Insurer** m $\xrightarrow{\text{negotiate}}$ **Price** p_{mj} — Stage 2 — **Hospital** j **Declares Bankruptcy**

Patient i **Picks** $\xrightarrow{\text{visit}}$ **Hospital** $j' \in N_m$ — Stage 3

4.1.1 Patient Hospital Choice

Within an HRR, which is deemed as a local market, there is a set of hospitals indexed by $j = 1, \cdots, J$, and a set of insurance companies indexed by $m = 1, \cdots, M$. The hospitals are partitioned into $S \leq J$ systems. Let J_s denote the set of hospitals in system s.[10] There is a set of enrollees denoted by $i = 1, \cdots, I$, each of which has a health insurance plan issued by a particular insurer. Let $m(i)$ denote enrollee i of insurer m. The subset of hospitals that insurer m agrees to contract with in their network is denoted by N_m. Each insurer m and hospital system s negotiate a benchmark price p_{ms} in the price bargaining stage. $\mathbf{p}_m$ denotes the vector of all negotiated prices for insurer m.

Enrollee $m(i)$ who is stricken by illness $d = 0, 1, \cdots, D$, where $d = 0$ represents the status of no illness, picks a hospital in the network to visit. Following the common pricing practice with the notion of severity weights, w_d represents the relative service-mix weights of illness d, which measures the intensity of resources used to treat the disease, and $w_0 = 0$. So, the total price paid for treatment of disease d at hospital $j \in J_s$ by insurer m is $w_d p_{ms}$, that is, the base price multiplied by the relative service-mix weights. For each illness $d = 1, \cdots, D$, the patient seeks hospital care at the hospital that gives them the highest utility. The ex post utility of patient i insured by insurer m receiving care from hospital $j \in N_m$ is given by

$$U_{ijmd} = \underbrace{\beta_1(\mathbf{X_{id}}) \cdot d_{ij} + \beta_2(\mathbf{Y_j}) \cdot d_{ij} + \beta_3 \cdot d_{ij}^2}_{\text{Distance}} + \underbrace{\gamma_1(\mathbf{X_{id}}) \cdot \mathbf{Y_j} + \gamma_2 \text{PastPatient}_{ij} + \eta_j w_d}_{\text{Hospital Characteristics} \times \text{Patient Observables}} + \underbrace{\gamma_3(\mathbf{X_{id}}) \cdot \text{PE}_j}_{\text{PE Owned} \times \text{Patient Observables}} + \eta_j + e_{ij}. \quad (2)$$

This specification encompasses different models used in the literature (e.g., Capps et al., 2003, Gowrisankaran et al., 2015, and Ho and Lee, 2017) to account for preference heterogeneity. The main covariates include travel time (in minutes) between patient i's residence and hospital j's location, d_{ij}, and travel time squared, d_{ij}^2, as well as interacted terms with a vector of patient observables $\mathbf{X_{id}}$ (e.g., patient age, gender, and relative service-mix weights), and various hospital characteristics $\mathbf{Y_j}$ (e.g., number of hospital beds, for-profit status, and teaching status). In addition to travel time, the indirect utility depends on other hospital characteristics interacted with patient observables such as major diagnoses dummies interacted with hospital-provided services[11] and relative service-mix weights interacted with hospital dummies. Following Shepard (2016), the

[10] If a single hospital in the local market does not share a system with any other local hospitals, I treat it as a single-hospital system. Hereafter, hospital system s is sometimes abbreviated to hospital s in the main text.

[11] These interaction terms potentially capture the impact on patients' utility from changes in hospitals' service lines after buyouts. For example, as shown by Eliason et al. (2020) in the dialysis industry, the change in procedures provided to patients is an important margin for patient welfare. However, I examine 95 categories of hospital service to provide descriptive evidence that PE investors do not dramatically change lines of service within a hospital after buyouts, as exhibited in Figure OA.5 in the Online Appendix.

indirect utility specification also includes the past outpatient status, PastPatient_{ij}, to capture relationships between patients and a hospital's physicians. Note that, following previous literature (e.g., Ho and Lee, 2017), I exclude out-of-pocket costs in the utility function. This simplifying assumption is consistent with (1) limited cost-sharing faced by patients and (2) empirical evidence of Section 3.4 indicating negligible impacts of PE intervention on patient paid amounts. I will add out-of-pocket costs back when inferring implications for patient surplus.

I include the PE-owned indicator to account for the effects of PE buyouts on patients' hospital choices as a result of changes in service quality and patient experience, as documented in Section 3.4. The specification includes $\text{PE}_j \in \{0,1\}$, an indicator if hospital j is backed by PE firms as well as its interaction terms with patient observables. The goal is to provide a flexible enough choice model to incorporate possible heterogeneity of patients in responding to the quality changes after PE buyouts.

Finally, hospital fixed effects, η_j, are added to control for unobserved time-invariant characteristics of hospitals. e_{ij} is an idiosyncratic error with i.i.d. type 1 extreme value distribution that is known by the patients at the time of choosing providers. Patients may visit a hospital in their network, $j \in N_m$, within an HRR. The outside option is modeled as choice 0, which corresponds to patients not going at all, and the delivered utility is normalized as $u_{i0d} = e_{i0}$.

Define $\delta_{ijmd} = u_{ijmd} - e_{ij}$ as the observed expected utility. The logit model implies that the choice probability for patient i with disease d as a function of patient and hospital characteristics is

$$s_{ijmd}(N_m) = \frac{\exp(\delta_{ijmd})}{\sum_{k\in\{0,N_{m(i)}\}}\exp(\delta_{ikmd})}.$$

Then, the expected utility for a patient of disease d in need of outpatient services is

$$CS_{imd}(N_m) = \ln\left(\sum_{k\in\{0,N_{m(i)}\}}\exp(\delta_{ikmd})\right).$$

4.1.2 Insurance Company and Hospital Bargaining

In the local market, insurer m will negotiate a price with hospital system s with hospitals $J_s \subseteq N_m$, wherein N_m denotes the set of hospitals in m's network. Correspondingly, hospital system s will bargain over a price with every insurer $m' \in M_s$, wherein M_s denotes the set of insurers that include hospital system s in their networks. In the baseline model, N_m and M_s are taken as given and matched with the network structure observed in the data.[12]

The bargaining process occurs between hospital system s and insurer m over a benchmark price p_{ms}. One new feature of the bargaining process is emphasized in this paper: the structure of the local market impacts the bargaining positions of hospitals and insurers. Specifically, if any hospital s in N_m declares bankruptcy, the local market of hospitals is changed (and becomes less competitive), and the rest of the hospitals within $N_m - J_s$ will restart negotiations with insurer m. Otherwise, the bargaining process follows the

So, it should be less of a concern that the changing composition of procedures after buyouts would affect the welfare implications.

[12]Previous studies, including Gowrisankaran et al. (2015), Lewis and Pflum (2015), and Brown (2019), assume that the contracted networks of hospitals for insurers are fixed. In Section 6, I extend the baseline model to incorporate the network-formation process following Ghili (2022) and Prager and Tilipman (2020).

standard protocol of the Nash-in-Nash bargaining model used in the applied literature (e.g., Grennan, 2013, Ho and Lee, 2017, and Collard-Wexler et al., 2019). This new feature resulting from hospital bankruptcy introduces an extra consequence to insurers: Letting a hospital fail may bring additional costs. It lowers its disagreement point during the bargaining process. I illustrate the idea by a simple motivating model in the Online Appendix.

Given N_m and M_s, the payoff functions to insurers and hospitals are derived as follows. Notice that the normalized quantity of patients from insurer m to hospital system s is represented by

$$q_{ms}(N_m) = \sum_{j \in J_s} \sum_{i=1}^{I} 1\{m(i) = m\} w_d s_{ijmd}(N_m).$$

It is assumed that insurers maximize a weighted difference of their enrollees' expected utility and costs of paying for health care. Denote the sum of enrollees' expected utility as $W_m(N_m) = \sum_{i=1}^{I} 1\{m(i) = m\} CS_{imd}(N_m)$. Then, the objective function of insurer m can be represented by

$$V_m(N_m, \mathbf{p}_m) = \alpha W_m(N_m) - \sum_{J_s \subseteq N_m} p_{ms} q_{ms}(N_m),$$

wherein α is the insurer's weight on enrollees' expected utility and measures how much insurers care about enrollees' welfare relative to the costs.

If hospital system s declares bankruptcy, the set of intended-to-negotiate hospitals becomes $N_m - J_s$, and they will be renegotiating with insurer m. Rather than sticking to the price $\mathbf{p}_{-s}$, let the renegotiated prices be $\mathbf{p}'_{-s}$ and the payoffs to insurer m become $V_m(N_m - J_s, \mathbf{p}'_{-s})$. This is different from the payoffs in which hospital s stays alive while not reaching an agreement with insurer m. In the alternative case, the payoffs to m are $V_m(N_m \backslash J_s, \mathbf{p}_{-s})$ following the Nash-in-Nash bargaining protocol.

Next, I turn to depicting the behavior of hospitals. In a similar fashion to the service-weight pricing scheme, let mc_{ms} denote the marginal cost of hospital $j \in J_s$ for treating a patient from insurer m with disease weight $w_d = 1$. Then, the treatment costs for an illness with relative weights w_d is $w_d \mathrm{mc}_{ms}$.

Therefore, the profit that hospital system s expects to earn from insurer m is

$$\pi_s(\mathbf{p}_m, N_m, \mathrm{PE}_s) = q_{ms}(N_m) \times (p_{ms} - \mathrm{mc}_{ms}).$$

The total expected profits of hospital system s are $\sum_{m \in M_s} \pi_s(\mathbf{p}_m, N_m, \mathrm{PE}_s)$, wherein M_s is the set of insurers that include hospital system s in their networks. To incorporate the non-pecuniary motive of hospitals, it is assumed that hospitals care about the weighted quantity of patients they serve (e.g., Gaynor and Vogt, 2003 and Lakdawalla and Philipson, 2006) besides its profits. I denote it by τ_{NP}, measuring the non-pecuniary benefits of a not-for-profit hospital for every unit of service it provides. So, the total benefits of hospital s from being included in insurer m's network are

$$\begin{aligned} \varpi_s(\mathbf{p}_m, N_m, \mathrm{PE}_s) &= \pi_s(\mathbf{p}_m, N_m, \mathrm{PE}_s) + \mathrm{NP}_s \cdot (1 - \mathrm{PE}_s) \cdot \tau_{\mathrm{NP}} q_{ms}(N_m) \\ &= q_{ms}(N_m) \cdot [p_{ms} - \mathrm{mc}_{ms} + \mathrm{NP}_s \cdot (1 - \mathrm{PE}_s) \cdot \tau_{\mathrm{NP}}], \end{aligned} \tag{3}$$

wherein NP_s is an indicator of whether hospital s has not-for-profit status and PE_s is an indicator of whether hospital s is owned by PE investors. Notice $\mathrm{NP}_s \cdot (1 - \mathrm{PE}_s)$ captures the impact of PE buyouts on the non-pecuniary motive of hospitals: τ_{NP} would vanish after PE investment.

To incorporate the idea that PE investors can potentially change the operational efficiency of target hospitals, mc_{ms} is assumed to be a function of PE_s, which will be specified later in the estimation step. Summing across all contracted insurers, the objective function of hospital system s (without taking into account the possibility of going bankrupt) is

$$\Pi_s(M_s, \{\mathbf{p}_m\}_{m\in M_s}, \{N_m\}_{m\in M_s}, \text{PE}_s) = \sum_{m\in M_s} \varpi_s(\mathbf{p}_m, N_m, \text{PE}_s). \tag{4}$$

Debt and Threat of Bankruptcy

PE buyouts typically involve massive debt for target hospitals. Given PE's choice of debt level D_s for hospital system s, I assume the interest payments and due debt repayments are a function of the debt level, denoted by $C(D_s)$. PE firms will declare bankruptcy of invested hospitals when their net "income" fails to meet the debt burden, that is, $C(D_s) > \widetilde{\Pi_s}(\cdot)$, wherein $\widetilde{\Pi_s}(\cdot)$ is a function of $\Pi_s(\cdot)$ described in Equation (4). By parameterizing $C(D_s) = \tilde{\theta} D_s$, with $\tilde{\theta}$ reflecting the magnitude of hospitals' debt burden, the bankruptcy rule is

$$\underbrace{\tilde{\theta} D_s}_{\text{Debt Burden}} > \underbrace{\widetilde{\Pi_s}(\cdot)}_{\text{Net Revenue}}. \tag{5}$$

To characterize the disagreement points for both parties, the bankruptcy scenario as well as its probability has to be considered. Two assumptions are made in order: (1) PE-owned hospitals are able to credibly threaten bankruptcy by following the above bankruptcy rule, while other hospitals cannot. It is argued that PE investors are profit-driven with hard budget constraints while other hospitals tend to face soft budget constraints (Kornai et al., 2003 and Kornai, 2009) because of government subsidies and donations, which can potentially help them overcome most financial difficulties. In addition, PE investors have the reputation of closing facilities due to financial considerations,[13] which makes the bankruptcy threat more credible. Most importantly, this assumption is consistent with the empirical results in Section 3.4 that financial leverage of non-PE-owned hospitals does not affect service pricing. This assumption can be relaxed in the model. But it would complicate the computation tremendously without bringing further insights. (2) The second assumption is about the specification of $\widetilde{\Pi_s}(\cdot)$. If hospital system s successfully reaches agreements with all insurers in M_s, we have $\widetilde{\Pi_s}(\cdot) = \Pi_s(M_s, \cdot)$. Otherwise, say the negotiation between hospital system s and insurer m, $m \in M_s$, was halted; then, $\widetilde{\Pi_s}(M_s \backslash m) = \Pi_s(M_s \backslash m, \cdot) - v_{st}$, wherein v_{st} is a random variable to capture the unexpected losses to hospital s due to failed negotiation. To sum up, $\widetilde{\Pi_s}(\cdot)$ is characterized as

$$\widetilde{\Pi_s}(\cdot) = \begin{cases} \Pi_s(M_s, \cdot) & \text{if negotiation is successful with all } m \in M_s \\ \Pi_s(M_s \backslash m, \cdot) - v_{st} & \text{if negotiation between } s \text{ and } m \text{ fails.} \end{cases}.$$

Scaling Equation (5) by hospitals' total assets, the bankruptcy rule can be rewritten as

$$\tilde{\theta} l_s > \widetilde{g_s}(\cdot) = \begin{cases} h_s(M_s) & \text{if negotiation is successful with all } m \in M_s \\ h_s(M_s \backslash m) - \tilde{v}_{st} & \text{if negotiation between } s \text{ and } m \text{ fails} \end{cases},$$

in which $l_s = \frac{D_s}{\text{TA}_s}$ is hospital s's leverage, $\widetilde{g_s}(\cdot) = \frac{\widetilde{\Pi_s}(\cdot)}{\text{TA}_s}$ is the return on assets (ROA), $h_s(\cdot)$ is equal to $\frac{\Pi_s(\cdot,\cdot)}{\text{TA}_s}$, and $\tilde{v}_{st} = \frac{v_{st}}{\text{TA}_s}$ is assumed to be i.i.d. distributed and to follow a logistic distribution with the location

[13] Critics have accused buyout firms of preferring to close invested hospitals rather than keep them running. Stories prevail on media. For instance, the *Wall Street Journal* reports that PE investors threatened to shut down the Easton Hospital in Pennsylvania in the midst of the COVID-19 outbreak, alluding to the reputation of PE closing up unprofitable hospitals.

parameter $\tilde{\mu}$ and the scale parameter $\tilde{s} > 0$.

One direct implication is that in equilibrium, PE-owned hospitals will not choose an extreme level of D_s such that $\tilde{\theta} D_s > \Pi_s(M_s, \cdot)$ because it is not rational for PE firms to let hospitals go bankrupt directly on the equilibrium path. This implicitly imposes a constraint on the choice of D_s in the first stage. Therefore, the bankruptcy risk emerges in the model only if disagreements between the hospitals and the insurer occur, which reflects the idea emphasized in the illustrative model of the Online Appendix: bankruptcy risk arises because of potential losses of income when hospitals do not reach an agreement with insurers, which makes it harder for them to meet their debt obligations.

For PE-owned hospital s, the expected bankruptcy probability is calculated by taking the expectation of $\mathbf{1}\{\widetilde{\Pi_s}(\cdot) < C(D_s)\}$, denoted by $\rho(l_s, \cdot) = \mathbf{E}\left(\mathbf{1}\{\widetilde{\Pi_s}(\cdot) < C(D_s)\}\right)$.

Bargaining Stage

Consider that hospital s is backed by PE investors. The payoffs of hospital s and insurer m under agreement and disagreement scenarios are specified as follows. With successful negotiations, the expected payoffs to s and m are

$$\Omega_s^A(M_s, \mathbf{p}_s) = \underbrace{\widetilde{\Pi_s}(M_s) - C(D_s)}_{\text{Payoffs of } s \text{ after debt}}$$

$$\Omega_m^A(N_m, \mathbf{p}_m) = V_m(N_m, \mathbf{p}_m),$$

and with negotiations broken down, the expected payoffs become

$$\Omega_s^{NA}(M_s \backslash m, \mathbf{p}_{s-ms}) = \underbrace{\mathbf{E}\left(\left[1 - \mathbf{1}\{\widetilde{\Pi_s}(M_s \backslash m) < C(D_s)\}\right] \times \left[\widetilde{\Pi_s}(M_s \backslash m) - C(D_s)\right]\right)}_{\text{Expected payoffs of } s \text{ if not bankrupt}}$$

$$\Omega_m^{NA}(N_m \backslash J_s, \mathbf{p}_{m-s}) = \underbrace{[1 - \rho(l_s, M_s \backslash m)] \times V_m(N_m \setminus J_s, \mathbf{p}_{m-s})}_{\text{Expected payoffs of } m \text{ if } s \text{ survives while excluded}} + \underbrace{\rho(l_s, M_s \backslash m) \times V_m(N_m - J_s, \mathbf{p}'_{m-s})}_{\text{Expected payoffs of } m \text{ if } s \text{ goes bankrupt}},$$

in which $\rho(l_s, M_s \backslash m) = \frac{1}{1 + \exp(\rho h_s(M_s \backslash m) - \theta l_s - \mu)}$ represents the expected bankruptcy probability if hospital system s is excluded by insurer m, wherein $\rho = \frac{1}{\tilde{s}} > 0$, $\theta = \frac{\tilde{\theta}}{\tilde{s}}$, and $\mu = \frac{\tilde{\mu}}{\tilde{s}}$. The payoffs to hospital equity-holders are zero after bankruptcy as hospital assets are seized by debtholders.

Note that the outside option for insurer m consists of two parts: The first corresponds to the scenario wherein hospital s survives when bargaining breaks down. Since the market structure does not change, other hospitals will not renegotiate the contract immediately. The second part embodies the scenario in which hospital s is closed down. As a result, other hospitals start to renegotiate with insurer m, changing the payoffs of m when facing a less competitive hospital sector. The price renegotiation resembles the bargaining protocol in Stole and Zwiebel (1996). However, I emphasize a distinct mechanism: Insurers have to take into account the adverse impact of a more concentrated hospital market if a local hospital fails. Therefore, insurers have the incentive to "subsidize" hospitals to keep them alive and competing with each other.[14]

[14] Practitioners are found to use this strategy quite often. In the article "The Death of Hahnemann Hospital" (June 7, 2021, issue of the *New Yorker*), the management team of Hahnemann explicitly describes: "...The insurance companies had an incentive to compromise. If Hahnemann closed, the privately insured patients treated there would go to other city hospitals, where the cost of their care would rise. You go into Blue Cross and you say, we need some help, and it's in your best interest to help us...Give us ten

For the applied purpose of this paper, the dynamic feature is abstracted away and the implication of market structure changes is reflected in the hybrid bargaining protocol.[15]

Therefore, the Nash bargaining problem is characterized by the exponential product of net values:

$$NB^{m,s}(p_{ms} \mid \mathbf{p}_{m-s}, \mathrm{PE}_s) = \left(\Omega_s^A - \Omega_s^{NA}\right)^{B_{sm}} \times \left(\Omega_m^A - \Omega_m^{NA}\right)^{1-B_{sm}},$$

in which $B_{sm} = b_0 + \mathbf{b} \times \mathbf{Y_s^b} + \mathrm{PE}_s \cdot g_b$ is the bargaining power of hospital s facing insurer m. In the specification of B_{sm}, b_0 is a constant term representing the base bargaining power of a typical hospital system. $\mathbf{Y_s^b}$ is a vector of hospital characteristics, including whether s is a multisystem hospital, its teaching status and for-profit status, whether it is a rural hospital, log of the number of hospital beds, physician arrangement, shares of patient days in local markets, and number of insurers in the local market. PE_s equals one if the hospital is backed by PE firms, and g_b measures the change of hospitals' bargaining power after PE intervention.

The above Nash bargaining problem can be further simplified as

$$\begin{aligned} &NB^{m,s}(p_{ms} \mid \mathbf{p}_{m-s}, \mathrm{PE}_s) \\ &\quad = \left(\varpi_s(\mathbf{p}_m, N_m, \mathrm{PE}_s) - \underbrace{\mathbf{E}\left(\mathbf{1}\{\widetilde{\Pi}_s(M_s \backslash m) < C(D_s)\} \times \left[C(D_s) - \widetilde{\Pi}_s(M_s \backslash m)\right]\right)}_{\text{Denoted by } \Delta\varpi_s}\right)^{B_{sm}} \\ &\quad \times \left(V_m(N_m, \mathbf{p}_m) - V_m(N_m \setminus J_s, \mathbf{p}_{m-s}) + \underbrace{\rho(l_s, M_s \backslash m) \times \left[\sum_{k \in N_m \backslash J_s} q_{mk}(N_m \backslash J_s) \cdot (p'_{mk} - p_{mk})\right]}_{\text{Denoted by } \Delta V_m}\right)^{1-B_{sm}} . \end{aligned} \tag{6}$$

In contrast, for non-PE-owned hospitals, the bargaining problem boils down to

$$NB^{m,s}(p_{mj} \mid \mathbf{p}_{m-s}, \mathrm{PE}_s) = (\varpi_j(\mathbf{p}_m, N_m, \mathrm{PE}_s))^{B_{sm}} \times (V_m(N_m, \mathbf{p}_m) - V_m(N_m \setminus J_s, \mathbf{p}_{m-s}))^{1-B_{sm}}, \tag{7}$$

which is a special case of Equation (6) when $\rho(l_s, M_s \backslash m) = 0$. Note that this goes back to a typical bargaining problem discussed in the literature (e.g., Gowrisankaran et al., 2015 and Ho and Lee, 2017).

million dollars more per year—versus losing fifty million per year..."

[15] Consistent with the prediction of this mechanism, I find that if a PE-owned hospital accommodates a larger share of patient flow from an insurer, this hospital is able to negotiate a higher price with the insurer, as shown in Table OA.11 in the Online Appendix.

First-Order Condition of the Bargaining Problem with PE-owned Hospitals

The Nash bargaining solution is a negotiated price p^*_{ms} that maximizes Equation (6), and it should satisfy the first-order condition (FOC) as follows:

$$
\begin{aligned}
p^*_{ms} = (1-B_{sm})\cdot & \left(\underbrace{\mathrm{mc}_{ms}(\mathrm{PE}_s)}_{\text{Operational Efficiency}} - \underbrace{\mathrm{NP}_s\cdot(1-\mathrm{PE}_s)\cdot\tau_{\mathrm{NP}}}_{\text{Non-pecuniary Objective}} \right) + \\
& \frac{B_{sm}}{q_{ms}(N_m)} \left(\underbrace{\alpha\left(W_m(N_m)-W_m(N_m\backslash J_s)\right)}_{\text{Willingness to Pay (WTP)}} + \underbrace{\sum_{k\in N_m\backslash J_s} p_{mk}\left(q_{mk}(N_m\backslash J_s)-q_{mk}(N_m)\right)}_{\text{Insurer Cost Change due to Exclusion}} \right) + \\
& \mathrm{PE}_s \times \frac{1}{q_{ms}(N_m)} \left(\underbrace{B_{sm}\Delta V_m + (1-B_{sm})\cdot\Delta\varpi_s}_{\text{Financial Engineering}} \right), \qquad (8)
\end{aligned}
$$

wherein ΔV_m is described in Equation (6) and $\Delta\varpi_s = \frac{1}{\rho}\mathrm{TA}_s \ln\left(1+\exp\left(\theta l_s + \mu - \rho h_s(M_s\backslash m)\right)\right)$. Detailed derivation of the FOC is presented in the Online Appendix. To see how various channels of PE buyouts affect negotiated prices, several predictions are discussed based on Equation (8). All these predictions echo the empirical evidence in Section 3.4.

Bargaining power: Under general conditions, the FOC predicts that a hospital's prices increase with its bargaining power. If PE is able to bring in new bargaining skills and expertise to the hospital, reflected by an increase in B_{sm}, higher negotiated prices would emerge in equilibrium.

Bankruptcy threats and financial engineering: The FOC predicts that bankruptcy threats potentially boost negotiated prices of PE-owned hospitals in both extensive and intensive margins. Compared to non-PE-owned hospitals, the ability to credibly threaten bankruptcy grants the PE-owned hospital a better bargaining position. Moreover, among PE-owned hospitals, the FOC predicts that higher leverage would result in an increase in negotiated prices, as shown in the Online Appendix.

Change of demand: The FOC gives ambiguous predictions regarding how changes of consumer demand would affect negotiated prices. On the one hand, PE alters the attractiveness of hospitals relative to others. This directly changes the distribution of patient quantities q_{mk}. On the other hand, hospital quality improvement or deterioration affects the WTP of patients, which leads to changes of negotiated prices.

Non-pecuniary objectives: If PE-owned hospitals care less about their social objectives, transition to PE ownership would lead to a decline of non-pecuniary motives for previously not-for-profit hospitals. Equation (8) predicts an increase in negotiated prices.

Operational efficiency: Suppose PE improves operational efficiency of target hospitals. The FOC predicts that, quite intuitively, a decrease in mc_s would lead to a decrease in hospitals' negotiated prices with insurers.

Spillover effects: The spillover effects are also captured by the FOC. The intuition is that as PE buyouts induce higher negotiated prices at PE-target hospitals, the insurer's cost of excluding any other hospitals in the network also changes, which directly impacts the bargaining outcomes of these local rivals.

4.1.3 PE Investment

I model the decision of PE investment as a binary choice. Denote it by $\mathrm{PE}_s \in \{0,1\}$, in which $\mathrm{PE}_s = 1$ means that PE firms decide to invest in hospital system s. Specifically, PE firms weigh investment costs against potential gains. After agreeing to invest, an optimal debt level is chosen. The cost of debt financing at the buyout stage has to be factored in by PE. I model the debt financing cost for PE firms as $C_d(l_s)$ and assume it is increasing in the leverage level of the portfolio company.

Given leverage level l_s, the potential gains for PE investors are derived from its intervention, calculated as

$$\triangle\Pi_s(l_s^*) = \max_{l_s} \mathrm{TA}_s \times \left(\underbrace{\frac{\Pi_s(M_s, \{\mathbf{p}_m^*\}, \{N_m\} \,|\, \mathrm{PE}_s = 1) - \Pi_s(M_s, \{\mathbf{p}_m\}, \{N_m\} \,|\, \mathrm{PE}_s = 0)}{\mathrm{TA}_s}}_{\text{ROA of PE Deal}} - C_d(l_s) \right),$$

wherein p_{ms}^* with $m \in M_s$ is a function of l_s. Therefore, the optimal level l_s^* satisfies $\partial \triangle\Pi_s(l_s^*)/\partial l_s = 0$, which implies that

$$\underbrace{\sum_{m \in M_s} \left[B_{sm} \frac{\partial \Delta V_m}{\partial l_s} + (1 - B_{sm}) \frac{\partial \Delta \varpi_s}{\partial l_s} \right] / \mathrm{TA}_s}_{\text{Marginal Benefits of Debt Leverage}} = \underbrace{C_d'(l_s^*)}_{\text{Marginal Costs of Debt Leverage}}. \tag{9}$$

However, as a (nonprofessional) corporate investor in medicine, various regulatory requirements are imposed across states, which would lead to variations in entry costs. I assume the entry costs of investing in hospital s in state w in year t to be EC_{swt}. Therefore, the entry/investment decision of PE firms is that $\mathrm{PE}_s = 1$ if and only if

$$\triangle\Pi_s(l_s^*) \geq \mathrm{EC}_{swt}.$$

4.2 Estimation

4.2.1 Estimation and Identification of Patient Demand

The patient demand model is estimated by maximum likelihood using the RWD patient-visit data. The independence of irrelevant alternatives (IIA) property of demand implied by the multinomial logit structure raises a potential concern. To alleviate this, patient choice is parameterized by including rich data at the patient–hospital level to capture the heterogeneity, such as travel time and its interaction terms between diagnosis and hospital facilities. The model also includes hospital fixed effects and interactions of those with disease weights to capture the unobserved quality of hospitals in treating different diseases.

Identification of the demand parameters in Equation (2) follows the standard arguments for the multinomial logit model (e.g., Train, 2009). The identification comes from the cross-sectional and longitudinal variations in observed hospital choices when characteristics of hospitals, patients, or the choice set vary. For example, the coefficient of travel time between a patient's residence to a hospital's location is identified by the variation of choices of a given hospital among patients who live close relative to patients who live further away in the same year within the same HRR area.

4.2.2 Estimation and Identification of Bargaining and PE Investment Model

In this section, I describe the estimation strategy for parameters of the supply side of the model. I exploit the generalized method of moments (GMM) with the TikTak-Melder-Mead algorithm to search for the global optimization solution.[16]

I parameterize marginal costs and use the FOC in Equation (8) to obtain the first two sets of moment conditions. The marginal cost of an outpatient visit is assumed to vary across providers and years. In addition, it is potentially different before and after PE buyouts as PE might change a hospital's operational efficiency. Specifically, I parameterize it in an additively separable form multiplying potential operational efficiency gain or loss due to PE buyouts:

$$\mathrm{mc}_{ms} = (1+\mathrm{PE}_s \cdot g_c)\exp\left(\eta_0+\eta_t+\eta_r+\eta\times\mathbf{Y}_{\mathbf{s}}^{\mathrm{mc}}\right)+\varepsilon_{ms},$$

wherein η_t and η_r are year and census region fixed effects, η_0 is a constant term, $\mathbf{Y}_{\mathbf{s}}^{\mathrm{mc}}$ is a vector of hospital characteristics including average Medicare outpatient costs per user and average HCC risk score at the HRR where hospital s is located, teaching status, for-profit status, rural status, log of the number of hospital beds, Medicare patient ratio, and Medicaid patient ratio. PE_s is an indicator of whether hospital s is backed by PE, g_c measures the proportional change of operational efficiency after PE buyouts, and ε_{ms} is the component of cost that is not observable to econometricians.

Notice that the current specification of marginal costs does not include insurer fixed effects, implying that there are no systematic factors making the marginal cost of treating patients vary across insurers for a given hospital. It corresponds to the second specification proposed in Gowrisankaran et al. (2015). There are two reasons why this assumption is appropriate for the current setting. First, hospitals are generally believed not to discriminate against patients based on their insurance carriers (among private insurers) when choosing treatment and medical resources for them. Second, for non-treatment costs in the outpatient setting, such as administrative costs, hospitals face similar burdens regardless of patients' insurance carriers. Plugging the parameterized marginal cost into the FOC given by Equation (8), the error term now becomes

$$\begin{aligned}\varepsilon_{ms} = &-(1+\mathrm{PE}_s\cdot g_c)\cdot\exp\left(\eta_0+\eta_t+\eta_r+\eta\times\mathbf{Y}_{\mathbf{s}}^{\mathrm{mc}}\right)+\mathrm{NP}_s\cdot(1-\mathrm{PE}_s)\cdot\tau_{\mathrm{NP}}+\frac{p_{ms}}{1-B_{sm}}-\\ &\frac{B_{sm}}{(1-B_{sm})\cdot q_{ms}(N_m)}\left(\alpha\left[W_m(N_m)-W_m(N_m\backslash J_s)\right]+\sum_{k\in N_m\backslash J_s}p_{mk}\left[q_{mk}(N_m\backslash J_s)-q_{mk}(N_m)\right]\right)-\\ &\mathrm{PE}_s\times\frac{1}{q_{ms}(N_m)}\left(\frac{B_{sm}}{1-B_{sm}}\Delta V_m+\Delta\varpi_s\right).\end{aligned}\tag{10}$$

ΔV_m and $\Delta\varpi_s$ are represented in Equation (6). Equation (10) forms the basis for the price moment conditions used in the estimation. In the Online Appendix, I describe how to derive the equilibrium benchmark prices from claims data in detail.

The second set of moment conditions uses cost information filed by hospitals. I adopt a strategy akin to Crawford and Yurukoglu (2012), Byrne (2015), and Hackmann (2019) to construct an additional "cost" moment using the average cost data from HCRIS. It is assumed that the average marginal cost $\bar{\mathrm{mc}}_s$ in the outpatient setting of hospital system s is linear to the cost per adjusted discharge in a year, AC_s, computed in

[16] Arnoud et al. (2019) describe the TikTak algorithm and present its applications. In their paper, they benchmark seven global optimization algorithms by comparing their performance on multidimensional test functions as well as a method of simulated moments estimation of a panel model of earnings dynamics. The authors conclude that the TikTak method overall outperforms other algorithms. More details can be found in the Online Appendix.

Section 3. It is expressed as $\bar{\text{mc}}_s = \lambda_1 \cdot \text{AC}_s + \lambda_2$.[17] The underlying argument is that any factor that impacts operational efficiency is hospital-wide and affects the marginal costs in both outpatient and inpatient services proportionally. Previous work in medical research (e.g., Alexander et al., 1996 and Spang et al., 2001) commonly use AC_s to measure hospital operational efficiency. More closely, Ho and Lee (2017) use an average cost measure as the approximation for the marginal cost of inpatient care. This is a restrictive parameterization; however, it does capture the marginal cost changes due to PE intervention. By taking the mean of mc_{ms} across insurers during a year, the hospital-wide average marginal cost is $\bar{\text{mc}}_s = \sum_{m\in M} \frac{q_{ms}}{\sum_{m\in M} q_{ms}} \text{mc}_{ms}$. By first-order differencing $\bar{\text{mc}}_s$ and AC_s across years, the following equation holds:

$$\triangle \bar{\text{mc}}_s = \lambda_1 \triangle \text{AC}_s \Longrightarrow \triangle \left(\sum_{m\in M} \frac{q_{ms}}{\sum_{m\in M} q_{ms}} \text{mc}_{ms} \right) / \triangle \left(\text{AC}_s\right) = \lambda_1,$$

which generates the cost moment condition as follows:

$$\triangle \bar{\varepsilon}_s = \triangle \frac{\triangle \{(1 + \text{PE}_s \cdot g_c) \exp\left(\eta_0 + \eta_t + \eta_r + \eta \times \mathbf{Y}_\mathbf{s}^{\text{mc}}\right)\}}{\triangle \left(\text{AC}_s\right)}. \tag{11}$$

The last set of moment conditions comes from the optimal leverage choice. I parameterize the marginal cost of raising debts as $C_d'(l_s) = \mu_1 + \mu_2 l_s + \xi_s$, which is a linear function of hospitals' leverage. ξ_s is the component of debt costs not observable to econometricians. Plugging $C_d'(l_s)$ into Equation (9) yields

$$\xi_s = \sum_{m\in M_s} \left[B_{sm} \frac{\partial \Delta V_m}{\partial l_s} + (1 - B_{sm}) \frac{\partial \Delta \varpi_s}{\partial l_s} \right] / \text{TA}_s - \mu_1 - \mu_2 l_s^*, \tag{12}$$

wherein expressions of $\frac{\partial \Delta V_m}{\partial l_s}$ and $\frac{\partial \Delta \varpi_s}{\partial l_s}$ are provided in the Online Appendix.

Parameters in the supply side of the model, namely τ_{NP}, the non-pecuniary motive for not-for-profit hospitals; (b_0, b), the bargaining-power coefficients; $(\eta_0, \eta_t, \eta_r, \eta)$, the marginal-cost coefficients; (ρ, θ, μ), the debt burden and bankruptcy probability parameters; (μ_1, μ_2), the ex ante debt-raising costs; and (g_b, g_c), the changes in the bargaining power and marginal costs after transition to PE ownership, are estimated by the following moment conditions:

$$\mathbf{E} \left(\begin{array}{c|c} \varepsilon_{ms} & \\ \triangle \bar{\varepsilon}_s & Z_{ms} \\ \xi_s & \end{array} \right) = 0,$$

wherein Z_{ms} is a vector of exogenous variables.

Identification

To identify the supply side of the model, the identifying assumption is that exogenous variables and instrumental variables are orthogonal to unobserved shocks to hospitals' marginal costs and debt raising costs. Utilizing price moment condition (10), the bargaining-power parameters (b_0, b) are informed by variations of the relative importance of an insurer's patient-redistribution costs if hospitals are excluded on respective negotiated prices within the insurer. For example, suppose we observe very different negotiated outcomes between a particular insurer and two hospitals, both of which impose similar patient-reallocation costs for the insurer if either hospital is excluded. Such price variations can translate into hospitals' differential

[17] This assumption can be relaxed by allowing hospital-specific coefficients, λ_1^j and λ_2^j, which yields the same moment conditions as shown afterwards.

bargaining power. The parameter on bargaining power changes due to PE buyouts (g_b) is identified by variations of bargaining power changes before and after PE investment for the same hospital.

Given estimates of the bargaining-power parameters, the insurer's weight on enrollee surplus (α) is identified by variations of the relative importance of enrollees' expected utility on negotiated prices within an insurer. One implicit assumption is that α is identical across insurers, akin to Gowrisankaran et al. (2015). Though the model is flexible enough to accommodate the case with α varying across insurers (e.g., α_m being insurer-specific as in Prager and Tilipman, 2020), this enormously increases the dimension of parameters to be estimated, making computation extremely challenging. Lastly, the debt burden and bankruptcy probability parameters (ρ, θ, μ) are identified by price variations across PE-owned hospitals that have different levels of debt leverage and revenues from various insurers.

Unlike Gowrisankaran et al. (2015), marginal-cost parameters $(\eta_0, \eta_t, \eta_r, \eta)$ are not solely identified from price variations across hospitals in the price moment conditions. Introducing cost moment condition (11) also helps to pin down cost parameters. Under certain circumstances, price moment conditions alone cannot distinguish the parameter on the change of marginal costs after PE intervention (g_c) from the non-pecuniary motive parameter (τ_{NP}). For example, if all ownership transition events from not-for-profit to for-profit in the sample coincide with PE buyouts, PE would impact negotiated prices by changing the marginal costs and the not-for-profit status simultaneously, making g_c and τ_{NP} indistinguishable. Therefore, it is important to introduce the cost moment conditions to uniquely identify g_c by comparing the average costs of target hospitals before and after PE intervention. τ_{NP} can then be disentangled by the price differences between the for-profit and the not-for-profit hospitals.

Leverage moment condition (12) is helpful to identify the ex ante debt-raising cost parameters (μ_1, μ_2). Given the expected patient quantities from demand estimation and observed prices, μ_1 and μ_2 are essentially identified by variations of expected revenues and chosen leverage among PE-owned hospitals.

Instrumental Variables

In this subsection, I describe a set of instrumental variables used in the estimation. The source of endogeneity is that the model assumes bargaining participants know mc_{ms} and $C'_d(l_s)$ as well as their error terms ε_{ms} and ξ_s. This assumption implies that the price p_{ms}, the leverage choice l_s, and the PE investment choice $\text{PE}_s \in \{0,1\}$ are potentially correlated with the error terms and hence are endogenous.

To identify the effect of prices, I follow the previous literature by including three instruments: enrollees' expected utility for the hospital system, the expected utility per enrollee for each insurer, and the predicted hospital quantity.

For PE investment decisions, I construct a novel instrumental variable by exploiting the exogenous changes of state regulations—the corporate practice of medicine (CPOM) doctrine. If a state prohibits the doctrine, only licensed professionals, such as physicians and dentists, may own or control the provision of health care. It essentially bans unlicensed entities (e.g., PE firms) from engaging in the professional practice of medicine. However, imposing the CPOM prohibition does not mean that corporate or other nonprofessional entities are completely barred from operating in the healthcare sector. There is some leeway for PE firms to circumvent the regulation by, for example, forming management services organizations (MSOs) with target hospitals, rather than directly owning them. Nevertheless, more stringent prohibition of

CPOM can hugely increase deal costs since PE must cautiously structure the deal and face potential risks in the future. More discussions about CPOM are provided in the Online Appendix.

I construct a CPOM regulation index to measure the regulation's strictness across states based on three aspects: (1) state statutes and regulations prohibiting/allowing CPOM; (2) legal precedent/case law prohibiting or allowing CPOM; and (3) attorney general opinions or state medical board opinions prohibiting or allowing CPOM. The index construction starts from a summary by Michal et al. (2006) of the CPOM statuses across 50 states in 2006. I introduce the detailed procedure to construct the CPOM regulation index as well as the descriptions of relevant legal events in the Online Appendix.

Though not a formal validation of the first stage, Table 4 provides a heuristic first-stage regression by examining the correlation between PE investment decisions and the CPOM regulation index. Standard errors are clustered at the hospital level. As expected, we see a strong, positive relation between *PE* and the CPOM regulation index, indicating that PE firms are more likely to target hospitals in states with more lenient CPOM regulations. The Kleibergen-Paap Wald F statistic is 10.4 in column 3, strongly rejecting weak instruments at the 0.1% significance level. Results are robust when (1) clustering standard errors at the state by year level, (2) controlling for Medicaid expansion of states after ACA, (3) dropping hospitals in Texas or Tennessee, and (4) dropping observations in the year of 2012, as shown in the Online Appendix.

Table 4: Examine the First Stage of CPOM Regulation Index

This table examines the first-stage correlation between PE investment decisions and the CPOM regulation index. The sample includes U.S. hospitals in the AHA's Annual Survey data between 2006 and 2019. The dependent variable is an indicator of whether a hospital is under PE ownership in a year. The independent variable, *CPOM Regulation Index*, measures how lenient states are about the corporate practice of medicine regulations. The detailed procedure of the index construction is provided in the Online Appendix. The 1st stage *F-stat* is the *Kleibergen-Paap Wald F statistic*, whose p-value is indicated in parentheses. Standard errors are clustered at the hospital level. *t*-statistics are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent variable:		
	PE Indicator		
	(1)	(2)	(3)
CPOM Regulation Index	0.026***	0.011***	0.010***
	(8.514)	(3.488)	(3.220)
F-stat	72.489	12.164	10.368
	(0.000)	(0.001)	(0.001)
Hospital Controls	N	N	Y
Year FE	N	Y	Y
Hospital FE	Y	Y	Y
Adj. R^2	0.635	0.642	0.646
Observations	83,684	83,684	83,673

To alleviate concerns about the exclusion restriction, I take several steps: (1) Compare hospitals' observables. I test whether there are significant differences in observables between hospitals facing more and less stringent CPOM regulation. A hospital is in more (less) stringent CPOM regulation if the CPOM index of the state where the hospital is located in a given year is within the bottom (top) 20% of all indices across the state's history. Table OA.16 in the Online Appendix exhibits no significant differences between the two sets of hospitals across a list of observables such as hospital size, ratio of Medicare patients, total outpatient visits, total inpatient days, etc. Only the share of for-profit hospitals is significantly higher when in more lenient states, consistent with the first-stage results that PE is more likely to target and convert hospitals facing less stringent CPOM regulation. (2) Conduct a placebo test. It is expected that the CPOM only affects PE's acquisition of hospitals. It should not impact mergers and acquisitions between hospitals. In the placebo test, I regress an indicator if the hospital involved in any M&As without PE backing on the CPOM regulation index. Table OA.17 reports the results, and indeed the CPOM regulation does not significantly affect the M&A decisions of non-PE-owned hospitals.

The annual ICE BofA U.S. high yield index option-adjusted spread is another instrumental variable used in the estimation and is helpful in identifying the effect of leverage. It is a valid IV since the market prices of credit risk presumably do not correlate with ε_{ms} and ξ_s but do correlate with the leverage choices of PE-owned hospitals (e.g., Axelson et al., 2013). Estimates are robust by using an alternative measure—credit spread between high-yield U.S. corporate bonds and the U.S. LIBOR.

In addition, the instrument set includes all fixed effects and other exogenous time-varying variables appearing in the marginal-cost and bargaining-power specifications.

4.3 Results

4.3.1 Demand Estimates

I estimate the patient demand separately for each HRR, so Table 5 summarizes the estimates by reporting the visit-number-weighted coefficients and standard errors of all HRRs. The first set of coefficients reports PE-ownership impacts on utility. The positively significant estimate of the PE dummy indicates that, on average, patients respond positively to the PE ownership of hospitals and quality changes after PE intervention, though different groups respond differently: females are more willing to visit PE-owned hospitals, while senior patients and patients with more severe diseases (reported by the PE $\times$ Weight interaction) are less likely. This result echoes the reduced-form evidence that some hospital quality measures improve after PE buyouts while others are unchanged and consumer satisfaction scores deteriorate. Hence, patients respond heterogeneously to the operational adjustments, and their expected utility towards PE-owned hospitals changes.

Consistent with prior literature, the coefficient of travel time is negative and statistically significant, indicating that patients prefer nearby hospitals. The willingness to travel is increasing in the size of hospitals, teaching status, severity weights of diseases, and patient age, and decreasing if patients are female. The coefficient of past use of the hospital is significantly positive, implying that patients are inertial and more likely to stick to the hospital they have visited before. In addition, patients in need of specific services are more likely to choose hospitals that are able to accommodate their needs. For instance, patients with a psychological or cancer diagnosis are more likely to visit a hospital providing psychological and oncological services, respectively.

Table 5: Estimation of Multinomial Logit Model of Patient Choice

This table shows the estimates for the multinomial logit hospital choice model. Since the patient choice is estimated separately for each HRR, the table reports the visit-number-weighted coefficients and standard errors. Standard errors are in parentheses.

VARIABLE	Coeff.	Std. Error
PE Intervention		
PE Indicator	1.4527	(0.1349)
PE×Female	0.0276	(0.0601)
PE×Age/100	−0.1200	(0.1510)
PE×Weight	−0.0423	(0.0177)
Travel Time to Hospital		
Travel Time	−0.1057	(0.0021)
Travel Time Squared	3.7466×10^{-4}	(0.2066×10^{-4})
Travel Time Interactions		
×Beds/100	0.0011	(0.0003)
×Age/100	0.0064	(0.0007)
×For-profit	0.0021	(0.0886)
×Teaching	0.0162	(0.0010)
×Wgt/1000	0.0906	(0.0474)
×Female	−0.0008	(0.0003)
Past Use of this Hospital		
Visit Before	0.4770	(0.0292)
Hospital Characteristics		
Hospital Dummy	Yes	
Hospital Dummy×Weight	Yes	
Teaching×Weight	−0.0190	(0.0071)
Diagnoses×Hospital Services (largest coeffs)		
Pregnancy: Obstetrics Services	1.0878	(0.0646)
Mental: Psych. Services	0.7375	(0.0823)
Cancer: Oncology Services	0.4790	(0.0327)

4.3.2 Supply Estimates

Table 6 reports the coefficients and standard errors of parameters related to hospitals' bargaining power and marginal costs as well as impacts of PE intervention. Panel A exhibits estimates of the bargaining-power parameters. The mean and standard deviation of hospitals' bargaining weights in the sample are 0.374 and 0.269. Several hospital characteristics are associated with larger bargaining power. The estimates imply that multi-hospital systems, for-profit hospitals, teaching hospitals, and hospitals affiliated with any type of physician organization have, on average, higher bargaining power, corresponding to an increase of 0.29, 0.18, 0.28, and 0.11, respectively. Other features turn out to affect bargaining power negatively. Hospitals in rural areas have smaller bargaining power. Hospitals with larger bed numbers have smaller bargaining power. At first glance, it seems counterintuitive that larger hospitals have smaller bargaining power. But, as argued in Lewis and Pflum (2015), this does not mean that larger hospitals are unable to exercise market power via their better bargaining positions. I also find that the local market structure matters: Hospitals with larger market shares measured by inpatient days in the local market would enjoy larger bargaining power, while hospitals in markets with more insurers tend to have less bargaining power.

Table 6: Estimation of Bargaining Model Parameters

This table presents estimates for the bargaining model. Panel A shows the estimates related to hospitals' bargaining weights. Panel B shows the estimates related to hospitals' marginal costs. Panel C collects the estimates related to PE's impacts and other parameters in the model. Standard errors are in parentheses.

Panel A: Bargaining Weight Parameter

VARIABLE	Coeff.	Std. Error
Multi-hospital System	0.2908	(0.0028)
For-profit	0.1750	(0.0001)
Teaching Status	0.2775	(0.0002)
Physician Arrangement	0.1143	(0.0001)
Rural Hospital	−0.0938	(0.0005)
ln(#Hospital Beds)	−0.0852	(0.0001)
Market Share of Inpatient Days	1.4793	(0.0012)
# Insurer in HRR	−0.0172	(0.0000)
Constant	0.6421	(0.0028)

Panel B: Marginal Costs Parameter

For-profit	−0.0616	(0.0405)
Teaching Status	0.6333	(0.0278)
Rural Area	−0.3092	(0.0315)
ln(#Hospital Beds)	−0.2204	(0.0138)
Medicare Patient Ratio	0.1176	(0.1520)
Medicaid Patient Ratio	1.8653	(0.1825)
HCC Score	−0.6175	(0.0833)
HRR Medicare Avg. OP. Cost/1000	0.0426	(0.0306)
Census Region FEs	Yes	
Year FEs	Yes	

Panel C: Impacts of PE and Other Parameters

Insurer Preference		
Insurer Weight (α)	1,236.8354	(2.0389)
Social Objectives		
Non-pecuniary Motive (τ_{NP})	101.9772	(2.0051)
Bankruptcy Threat		
Debt Burden (θ)	0.0050	(0.0000)
Location of Logistic Dist. (μ)	−2.1088	(0.0025)
Scale of Logistic Dist. (ρ)	70.4975	(0.1767)
Ex-ante Debt Raising Costs		
Linear Debt Costs (μ_1)	0.6792	(14.1961)
Quadratic Debt Costs (μ_2)	1.0190	(53.3584)
Impacts of PE Intervention		
Marginal Cost Change (g_c)	−0.0835	(0.0205)
Bargaining Power Change (g_b)	0.1878	(0.0002)

Panel B demonstrates estimates for the marginal-costs specification. The estimated parameters imply that the marginal costs of for-profit hospitals are 6% lower on average; for teaching hospitals, they are 63% higher; and for rural hospitals, they are 31% lower. The results also suggest economies of scale for hospitals: A 1% increase in the number of hospital beds is associated with a 0.2% decrease in marginal costs. In addition, the estimates indicate that hospitals accepting a larger portion of Medicare and Medicaid patients have higher marginal costs. They increase by about 0.1% if the Medicare patient ratio increases by 1%, though the estimate is insignificant. The marginal costs would rise by 1.9% if the Medicaid patient ratio increases by 1%. This is consistent with previous evidence that Medicaid reimbursements are usually lower than those of Medicare, and much lower than private payers. When a hospital accepts a higher portion of Medicaid patients, subsidizing effects from private payers to Medicaid would be reflected in higher marginal costs in the model. Lastly, the result intuitively suggests a positive correlation between the marginal costs of hospitals and the Medicare average outpatient costs of the HRR (average costs in the local market) where these hospitals are located.

Panel C highlights estimates of PE's impacts on price bargaining and other parameters in the model. The estimate for insurers' preference, α, is approximately 1,237. The magnitude is comparable to that in Prager and Tilipman (2020). One possible interpretation is that private insurers treat one unit of consumers' utils as equivalent to \$1,237 in their objective function. The second coefficient is the non-pecuniary motive for not-for-profit hospitals, estimated to be approximately 102 and significantly different from zero. This indicates that not-for-profit hospitals place strictly positive values on social objectives. Providing one unit of medical service brings an equivalent of \$102 in benefits besides profits. This supports prior discussions that not-for-profit hospitals have different objectives than for-profit ones (Lakdawalla and Philipson, 2006). The third set of coefficients includes the impacts of bankruptcy threats on price bargaining. The estimate of debt burden θ is significantly positive at 0.1% level, consistent with the descriptive evidence in Section 3 that higher leverage of PE-owned hospitals imposes greater impacts on price negotiations. The negative estimate of μ and relatively large estimate of ρ, two parameters governing the distribution of bankruptcy shocks, indicate that typical bankruptcy risks to PE-owned hospitals are low (while increasing in debt leverage) but with large variances. The fourth set of estimates concerns the ex ante debt-raising costs for PE firms. Though statistically insignificant, it suggests that PE-owned hospitals face convex debt-raising costs: the marginal cost of debt is increasing in the amount of debt taken up by a PE-backed hospital. The last set of estimates examine PE's impacts on hospitals' operational efficiency and bargaining power. After PE buyouts, hospitals' operational efficiency improves—marginal costs decrease by approximately 8%. At the same time, hospitals' bargaining power increases by 0.19. The magnitude is economically significant in contrast to the average bargaining weights in the sample (equal to 0.374).

4.3.3 Model Fit

To evaluate the model fit, I conduct two exercises of comparing model predictions with those observed in the data. First, I compare the predicted distribution of hospital–insurer negotiated prices to the distribution of negotiated prices in the data. Figure OA.7 of the Online Appendix displays kernel density plots of the natural logarithm of predicted and observed negotiated price distributions, pooled across all hospital–insurer pairs and years in the sample. Panel A of Figure OA.7 demonstrates the price distribution of the full sample, while Panels B and C assess fit of price distributions separately for hospitals ever bought out by PE firms and hospitals never acquired by PE firms. The vertical lines in each plot represent the arithmetic mean of the respective distributions. For the full sample, the overall fit is pretty good. For the subsample of PE-backed hospitals, the model-predicted price distribution has a left-biased spike and a fat right tail compared to the realized one. But the distribution matches the first and second moments well. For the subsample of non-PE-backed hospitals, the whole price distribution matches well.

Second, I compare the predicted distributions of HRRs' outpatient spending to distributions of outpatient spending observed in the data. The total spending in an HRR is determined by the negotiated prices and the weight-adjusted patient quantities in a year. Panel A of Figure OA.8 in the Online Appendix displays the spending distribution for the full sample, while Panels B and C exhibit spending distributions of subsamples of HRRs that ever had PE-backed hospitals and those that never had. The spending distributions fit well in the full sample and the two subsamples, which indicates that the structural model not only captures price variations nicely, but also matches the hospital choices of patients well.

In another exercise, I derive the local sensitivity measures following Andrews et al. (2017) to assess the asymptotic bias in the estimated parameters implied by violations of the exclusion restrictions. Figure OA.9 in the Online Appendix presents the results for two selective parameters, g_c and g_b, which measure the impacts of PE buyouts on hospitals' marginal costs and bargaining power. The figure shows that the asymptotic bias in both parameters is very sensitive to the CPOM regulation index, credit spreads, and expected utility per enrollee. It makes a lot of sense that the CPOM regulation index and credit spreads are vital to identify g_c and g_b, since these variables closely relate to PE investment decisions. It also suggests that the demand-side instruments, such as the expected utility per enrollee, matter for the validity of the estimates. This is consistent with the practice in prior literature of using demand-side instruments as the main variation sources to identify cost and bargaining parameters.

5 Counterfactual Analysis

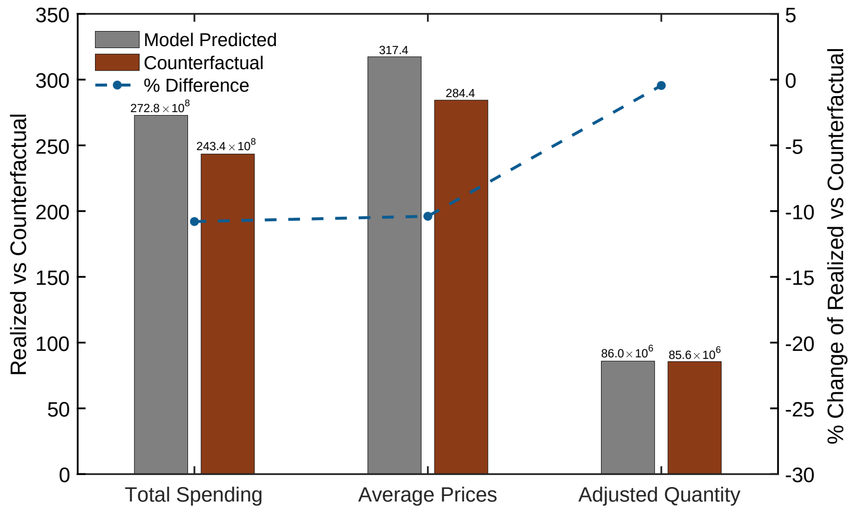
By using the baseline estimates from Section 4, I perform a series of counterfactual analyses. The first considers a scenario in which PE ownership in the United States were restricted by regulators. This counterfactual by no means implies that restricting PE in the hospital sector is the optimal policy regulators should consider, but it provides a lens through which I could quantify the impacts of PE ownership on negotiated prices and patient surplus. It also enables me to assess the spillover effects and decompose the relative contribution of various channels. In the second counterfactual, I demonstrate the importance of taking into account the PE ownership of acquirers when reviewing proposed mergers. I compare predictions with regard to post-merger outcomes of a plain model, which ignores the PE ownership, and my model.

5.1 Restrict PE Ownership

Whether to restrict PE ownership in the healthcare sector has been at the forefront of current policy discussions. For example, in June 2022 U.S. antitrust enforcers took the first strike against the JAB Consumer

Partners, a PE firm actively acquiring healthcare businesses.[18] So, it is important to understand the impacts of PE ownership in the sector.

Figure 3: 1st Counterfactual: Aggregate Changes



This figure presents outcomes of a sample of 339 HRR-years in the counterfactual of restricting PE ownership between 2013 and 2018. Total spending is the sum of the outpatient payments captured by the sample. Average prices are the quantity-weighted negotiated prices between hospitals and insurers. Adjusted quantity is the sum of the relative service-mix weights of all patient visits. Spending and prices are adjusted to dollars in 2019 by GDP deflators. The gray bars represent the model-predicted outcomes in the realized scenario. The orange bars represent the counterfactual outcomes if PE ownership was restricted. The dashed line represents the percentage differences in outcomes between the realized and the counterfactual scenarios.

To this end, I examine an extreme scenario in which PE investments were prohibited. Specifically, I look into a sample of hospitals in 339 HRR-years that ever had PE-owned hospitals between 2013 and 2018.[19] For each HRR-year, I simulate negotiated prices between hospitals and insurers for the realized case and the case with a PE restriction. All prices are adjusted by GDP deflators to dollars in 2019. Figure 3 summarizes the aggregate outcomes.[20] The gray bars represent variables in the realized case while the red bars denote the PE-restricted case. The total realized outpatient spending in the sample is about \$27 billion. Restricting PE ownership leads to a reduction of approximately \$3 billion in spending, which accounts for 11% of the total realized spending. The saving largely comes from decreases in negotiated prices: The quantity-weighted average price drops from \$317 to \$284 if restricting PE ownership, almost the same percentage reduction as that of the total spending. In contrast, the weight-adjusted quantities of patients barely change.

It is important to note that the weight-adjusted quantities of patients change in the counterfactual because patients are allowed to choose an outside option in the logit model. So, aggregate shift in patient quantities does not capture the reallocation of patients across providers, which would impact patients' expected utility

[18] More discussions can be found in the *Wall Street Journal* article (June 14th, 2022) titled "Antitrust Authorities Take Aim at Private-Equity Healthcare Deals" (`https://www.wsj.com/articles/antitrust-authorities-take-aim-at-private-equity-healthcare-deals-11655243804`).

[19] Hospitals from a subset of 40 HRR regions are dropped due to missing key variables (e.g., debt levels for PE-owned hospitals). A few other HRR areas are discarded because the model fails to converge for them in the simulation. So, the final sample in the counterfactual analysis only includes hospitals in those 339 HRR-years.

[20] To explore the heterogeneity, Figure OA.11 of the Online Appendix demonstrates how the savings of hospital expenses in the counterfactual correlates with the degree of presence of PE-backed hospitals in the local market.

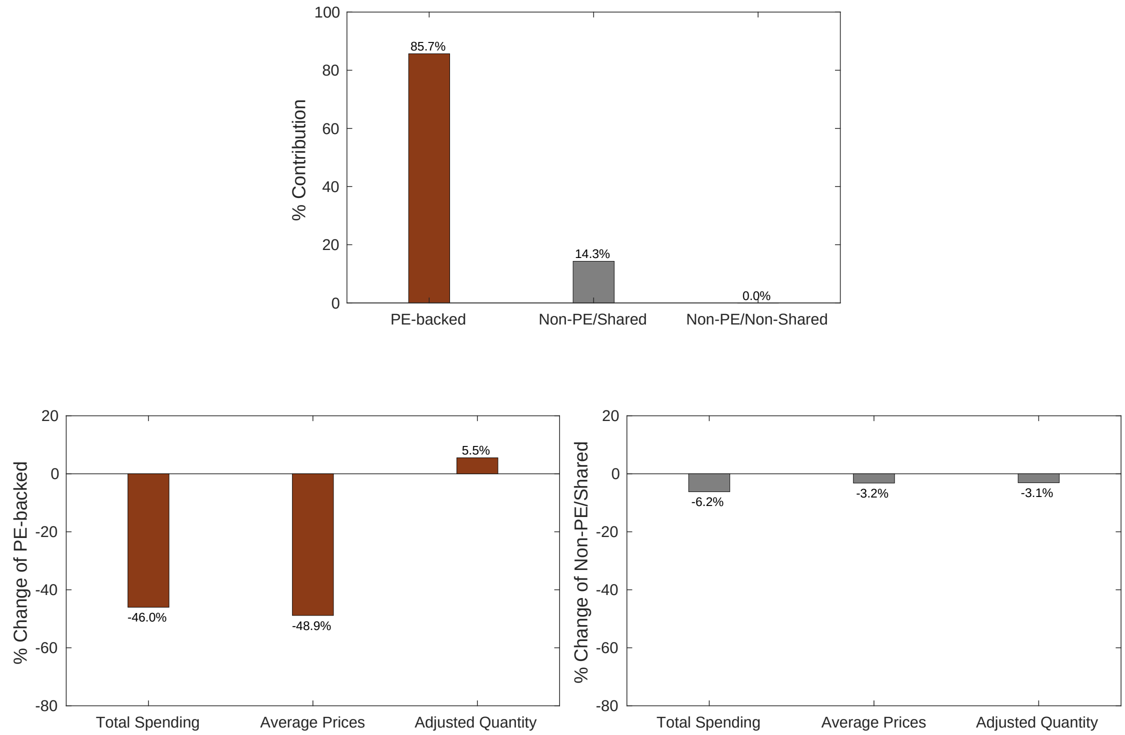
and outside options of hospitals/insurers in price bargaining. I will discuss the implications of this when decomposing the relative contribution of various channels and evaluating patient welfare.

Next, I investigate the spillover effects and quantify how they vary across rival hospitals. I categorize hospitals into three groups, echoing the results in Section 3.3: (1) PE-backed hospitals (*PE-backed*), which would be directly impacted by PE intervention; (2) non-PE-backed hospitals sharing insurers with the PE-backed one in the local market (*Non-PE/Shared*), which could potentially be affected through changes in insurers' outside options; and (3) remaining hospitals (*Non-PE/Non-Shared*).

Figure 4 reports how these groups respond in the *counterfactual scenario*.[21] Not surprisingly, the *PE-backed* contributes the most among all groups, with about 86% of total saved expenses. Noticeably, hospitals in the *Non-PE/Shared* group also contribute a non-negligible share, reaching 14% of the total savings. This captures the spillover effects of PE intervention: non-PE-backed hospitals respond to the shock, though they are not directly targeted. In contrast, hospitals in the *Non-PE/Non-Shared* group are barely affected, as their contribution is almost negligible. Furthermore, I dissect those changes within the first two groups that have positive contribution to the total savings. Hospitals in the *PE-backed* group undergo dramatic changes, described in the bottom-left panel of Figure 4. Their total healthcare spending gets cut by 46%, most of it coming from a 49% decrease in quantity-weighted average prices. Nevertheless, they experience an uptick in weight-adjusted patient quantities by 5.5% in the counterfactual. In the *Non-PE/Shared* group, hospitals experience modest changes in the counterfactual. The bottom-right panel of Figure 4 shows that their own total spending decreases by 6.2%, along with a 3.2% reduction in quantity-weighted average prices and a 3.1% decrease in weight-adjusted patient quantities. The price decrease of *Non-PE/Shared* hospitals reflects the spillover effects in the price bargaining. By removing PE ownership, the treatment effects on negotiated prices between PE-backed hospitals and insurers are wiped out. This in turn changes the outside options of local rivals with which these insurers are simultaneously negotiating, resulting in a new level of price for the *Non-PE/Shared* group in equilibrium.

[21] Figure OA.10 of the Online Appendix reports levels of total health spending, quantity-weighted average prices, and weight-adjusted patient quantities for each group in the *realized scenario*.

Figure 4: 1st Counterfactual: Quantify Spillover Effects

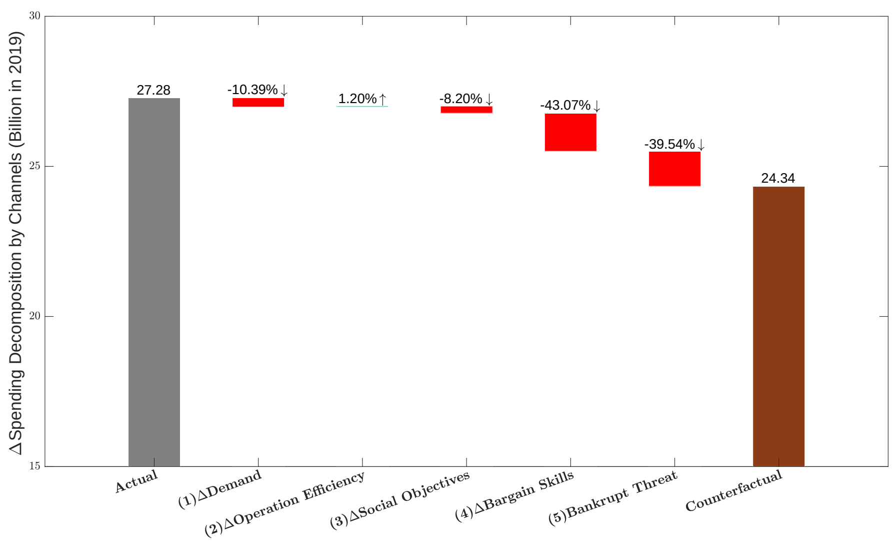


This figure quantifies the spillover effects of PE intervention in local markets. The top panel presents the relative contribution to the total savings in the counterfactual across different groups, including *PE-backed*, *Non-PE/Shared*, and *Non-PE/Non-Shared*. The bottom-left panel presents the percentage changes in the total spending, quantity-weighted prices, and total relative service-mix weights of hospitals within the *PE-backed* group in the counterfactual. The bottom-right panel presents the percentage changes within the *Non-PE/Shared* group in the counterfactual. Remaining details are the same as Figure 3.

Besides quantifying the aggregate effect in the counterfactual, the structural model allows me to decompose it to measure the relative contribution of various channels. Figure 5 reports the results. Recall that the model highlights five key channels of how PE buyouts affect price bargaining: First, as veteran investors, PE firms have superior experience in business negotiations. They are able to hand down this expertise to portfolio hospitals and strengthen their bargaining skills. To mute this channel in the counterfactual, I set $g_b = 0$. Second, by ratcheting up hospitals' debt loads in buyouts via financial engineering, credible bankruptcy threats give hospitals an edge in price negotiations. To evaluate the contribution of this channel, I make both ΔV_m and $\Delta\varpi_s$ equal to zero in the counterfactual. Third, PE intervention can lead to changes in service quality and consumer satisfaction, resulting in a reshuffling of patient demands in the local market. The relative contribution of this channel is reflected in the counterfactual by removing the PE dummy and its interaction terms in the multinomial logit model and then recomputing patients' demand. Fourth, PE would change portfolio hospitals' focus on social objectives, shifting hospitals' willingness to reach agreements in price bargaining. I mute this channel by setting $\tau_{\text{NP}} = 0$ in the counterfactual. Lastly, PE can improve operational efficiency of target hospitals and lower their marginal costs. This channel is muted by letting $g_c = 0$ in the counterfactual.

Figure 5 exhibits the decomposition results. The first and the last bars are copied from Figure 3, corresponding to the total spending in the realized and the counterfactual scenarios. The waterfall bars in between represent the relative contribution of the above five channels. Prominently, PE investors' superior bargaining skills and bankruptcy threats are two major channels affecting bargaining outcomes. The change in bargaining skills explains about 43% of the price and spending decreases in the counterfactual, and the bankruptcy threats contribute around 40%. The other two channels, changes in patient demand and social objectives, contribute around 10% and 8%. The only channel that leads to an increase in spending in the counterfactual is the change of operational efficiency, which increases spending by only 1%. It suggests that PE investors indeed improve the operational efficiency of hospitals, though only a tiny portion of cost reductions is factored into negotiated prices.

Figure 5: 1st Counterfactual: Decomposition by Channels



This figure presents the relative contribution of various channels to the total savings in the counterfactual. The first gray bar denotes the model-predicted spending for the realized scenario, and the last orange bar denotes the counterfactual spending if PE ownership were to be restricted, which replicates results in Figure 3. The waterfall charts in between denote the relative contribution of five key channels highlighted in the model. Numbers on top of each bar denote their respective contribution percentages.

So far, I have explored the implications of PE ownership on hospital prices and spending. To push the model to the limit, Table 7 reports how patient surplus is affected in the counterfactual. I calculate the change of patient surplus on a dollar basis in the following way:

$$\Delta Surplus = \Delta Spending + \Delta Quality.$$

Two assumptions are in order. First, I assume that changes in hospital spending will be passed through to consumers in the form of insurance premium reductions. Due to lack of data, the model does not include the stage of insurers setting insurance premiums. But it is a reasonable assumption that a reduction of medical spending would translate to a decrease in premiums since insurers normally negotiate with hospitals over a fixed payment for inclusion on their networks (Ho and Lee, 2017). Moreover, markups in health insurance are regulated by the Medical Loss Ratio provision in the ACA (Cicala et al., 2019). Insurers' profit margins are capped at 15% or 20%, thus insurance premiums typically go hand-in-hand with incurred medical expenses.

Second, a mild assumption is imposed on the price-to-utility sensitivity. Recall that in the step of estimating patient demand, I exclude the out-of-pocket costs from the indirect utility to simplify the main analysis. In order to obtain the price sensitivity estimate, I add them back here and re-estimate the multinomial logit model of patient choice. I then leverage the sensitivity estimate to convert the change in patients' expected utility into dollar terms in the counterfactual.

Results are collected in the first row of Table 7. Changes in patients' expected utility are mainly due to the change in hospitals' service quality. The results indicate the counterfactual restriction on PE ownership worsens service quality on average, leading to an equivalent reduction of \$22 million in patients' expected utility. This implies that PE buyouts on average improve hospital services, though the impact is fairly modest compared to the \$2.95 billion savings from hospital price changes. Summing both terms, the aggregate patient surplus in the counterfactual increases by \$2.92 billion, which accounts for about 10.7% of the total spending documented in these affected regions.

Table 7: Implications for Patient Surplus in Counterfactual

This table shows how restricting PE ownership affects patient surplus in the counterfactual. The first row represents patient surplus changes in dollar terms due to the alteration of service quality. The second row represents patient-surplus changes resulting from hospital expense savings. The third row represents the aggregate changes of patient surplus by adding the previous two rows. The last row computes the ratio of the aggregate patient-surplus changes in dollar terms to the total hospital spending documented in the sample. All dollar terms are adjusted to dollars in 2019 by GDP deflators.

Counterfactual: Restricting PE Ownership	
ΔQuality (\$billion)	−0.022
ΔSpending (\$billion)	2.945
Summing up...	
= ΔSurplus (\$billion)	2.923
Equivalent to...	
% Total Spending	10.71%

Discussion

Note that this counterfactual examines a specific scenario in which other sources of capital would have always filled the hole if PE would have not invested in these targeted hospitals. This is consistent with the majority of previous studies that examine the impacts of PE ownership. However, it leaves out an important alternative scenario in which hospitals are forced to shut down if without the backing of PE investors. It might potentially affect the quantification of consumer surplus since patients might lose access to medical services after hospital closures. I find this is a less relevant concern by examining hospitals' financial conditions before PE intervention. Table OA.18 of the Online Appendix compares financial indicators of PE-target hospitals to those non-PE-target local rivals one year prior to buyouts. It suggests the PE-target hospitals tend to be financially robust before buyouts. For example, they share similar debt leverage and interest coverage rates to those non-PE-target ones before buyouts. But they tend to have a significantly higher operating markup, though receiving fewer government subsidies and donations. Therefore, this group of hospitals is likely to survive even in the absence of PE investors' backing.

Relatedly, the counterfactual considered in the paper also leaves out the impact of hospital closures due to PE's financial engineering. I argue the impact is potentially limited and, if anything, it should have a minimal effect on the estimate of consumer surplus. Specifically, I examine a sample of rural hospitals, which is more vulnerable to changes in financial conditions, and see if PE ownership leads to more hospital closures.[22] Consistent with the financial engineering channel, I find the average annual closure rate of PE-backed rural hospitals is about 0.4%, which is more than twice as large as that of non-PE-backed counterparts, 0.18%. But on the absolute level, hospital closures after PE buyouts are still rare events that occur with a frequency of less than 1% per year. This is consistent with the model implication that on the equilibrium path no hospital is closed down. It also indicates that the hospital closures after PE intervention have a negligible effect on the estimate of consumer surplus.

One caveat is that the counterfactual exercise only focuses on a subgroup of patients—privately insured patients—in estimating the impact of PE on consumer surplus. It misses out the potential effects on Medicare and Medicaid patients. Based on the estimates, PE buyouts of hospitals could potentially have a positive externality on Medicare/Medicaid patients. Why? While the Medicare/Medicaid reimbursements are highly regulated and prices are not easily changed, PE buyouts can benefit Medicare/Medicaid patients by improving the average service quality. However, as documented in Table 7, the surplus gain from the quality externality is expected to be modest, dwarfed by the hospital price changes facing the privately insured patients.

Overall, the counterfactual results suggest that PE ownership increases total social surplus by improving hospitals' operational efficiency and the average medical service quality. Given a larger surplus pie, PE investors grab a greater share through their superior bargaining skills and bankruptcy threats from the financial engineering, which might potentially compromise consumer surplus. In light of this trade-off, it is hence an interesting extension to explore what the optimal regulations look like in future work.

5.2 Evaluate Mergers and Acquisitions

Given the features of PE buyouts, how should regulators who oversee mergers respond? In this counterfactual, I underscore the importance of considering PE acquirers' unique traits when reviewing proposed mergers. Otherwise, regulators might potentially underestimate the impacts of mergers on local markets.

Specifically, I conduct merger reviews by using two different sets of tools: One is the typical model used by regulators (e.g., the FTC) to evaluate mergers in the hospital sector (hereafter the *No-PE model*), which mainly focuses on the market consolidation effects arising from mergers. The other is the full-fledged model considered in this paper (hereafter the *PE model*).

To replicate the No-PE model, I re-estimate the patient choice by dropping all PE-related variables. Then, based on the new demand estimates, I re-estimate the bargaining model by removing all PE-related features (e.g., bankruptcy threats) and moment conditions containing PE-related instrumental variables. The estimation results are tabulated in the Online Appendix. Compared to the PE model, most estimates of bargaining weight coefficients are quite stable. For the marginal-cost estimates, the coefficients of for-profit and teaching status become smaller, while the estimates for rural area, Medicare and Medicaid patient ratios, HCC scores, and the average outpatient costs in the local market are larger than those in the PE model. In

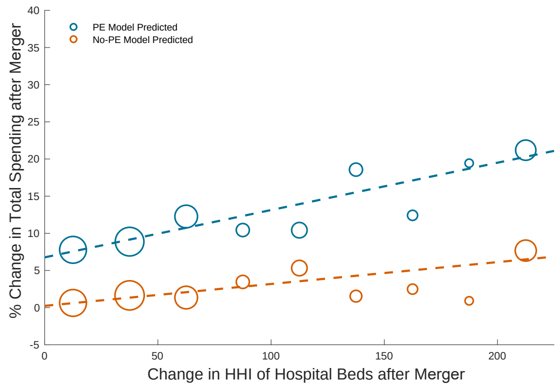
[22] Rural hospital closures data come from UNC Rural Health Research Program (https://www.shepscenter.unc.edu/programs-projects/rural-health/rural-hospital-closures/). It covers closure events of rural facilities since 2005.

addition, the No-PE model delivers a larger estimate for the non-pecuniary motive of not-for-profit hospitals and a smaller estimate for insurer's preference on enrollee surplus.

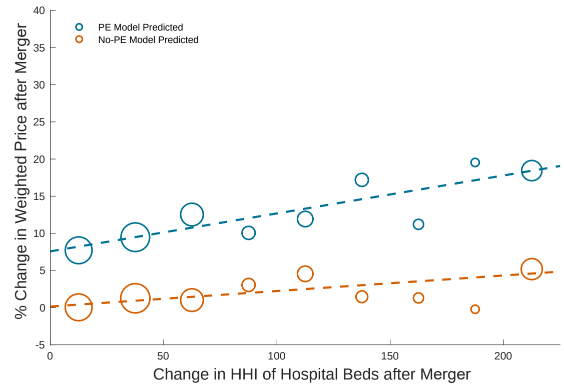
To investigate the discrepancy of predictions between the PE model and the No-PE model, I construct a sample of hypothetical merger cases in 2013 and randomly choose 100 cases to evaluate using both models. Each merger includes a hypothetical acquirer, which must be a PE-owned hospital system, and a target, which is a non-PE-owned hospital system in the same HRR. The hypothetical mergers include, for example, the Steward Health Care System backed by the Cerberus Capital Management in the Boston Hospital Referral Area (HRR code 227) acquiring the Anna Jaques Hospital in the same region. For each hypothetical merger, it is assumed that the resulting number of hospital beds, inpatient day shares in the local market, and total assets are equal to the combined values of the acquirer and the target. It is also assumed that the merging hospital's financial leverage stays the same as that of the PE-owned acquirer prior to mergers, and the network of insurers in the local market does not change after mergers. In the counterfactual, I simulate predictions of hospital–insurer negotiated prices and total spending in the local market before and after each hypothetical merger, and compute their percentage changes. I also look at predictions on patient-surplus changes from both models.

Figure 6 displays the results. Panel A demonstrates how the total spending in an HRR changes after a merger. The x-axis denotes the change in the HHI of hospital beds in an HRR, and the y-axis denotes the percentage change in the total spending of an HRR. I bin together the hypothetical mergers for every 25-unit increase of HHI and compute the average percentage changes within each bin. The size of a circle represents the number of merger cases contained in an interval. The blue circles are predictions from the PE model, while the orange circles represent predictions from the No-PE model. Dashed lines in the figure are linear fits of data. As a sanity check, both models predict that changes in the total spending positively relate to changes in the HHI after mergers, which is in line with the theoretical predictions on market competition. However, there is a prominent gap of predictions between the PE model and the No-PE model, reaching as high as 10% in some circumstances. This shows that regulators could systematically underestimate the impacts of mergers on total spending if they follow the typical tool used for merger reviews. Panel B of Figure 6 delivers a similar message. Instead of the total spending, Panel B examines how the quantity-weighted average prices change after mergers. The pattern resembles the one observed in Panel A. But again, there is a persistent gap of predicted negotiated price changes between the PE and No-PE models. In Panel C, I examine model predictions about the changes in patient surplus. Following a similar strategy as in Section 5.1, I translate the surplus changes into dollar amounts and compute the change as a percentage of the HRR's total spending. For mergers inducing only an uptick in the HHI (<50), the PE model and No-PE model provide indistinguishable predictions about patient-surplus changes. But for mergers prompting larger disruptions in the market (increases in the HHI>50), the No-PE model clearly underestimates the impacts of mergers on patient surplus compared to the PE model.

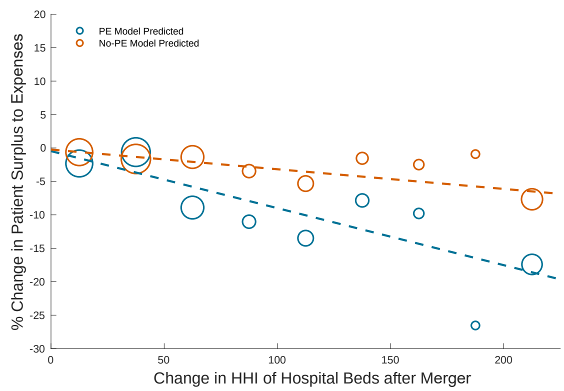
Figure 6: 2nd Counterfactual: Changes after Mergers



(a) %Spending Changes after Mergers



(b) %Price Changes after Mergers

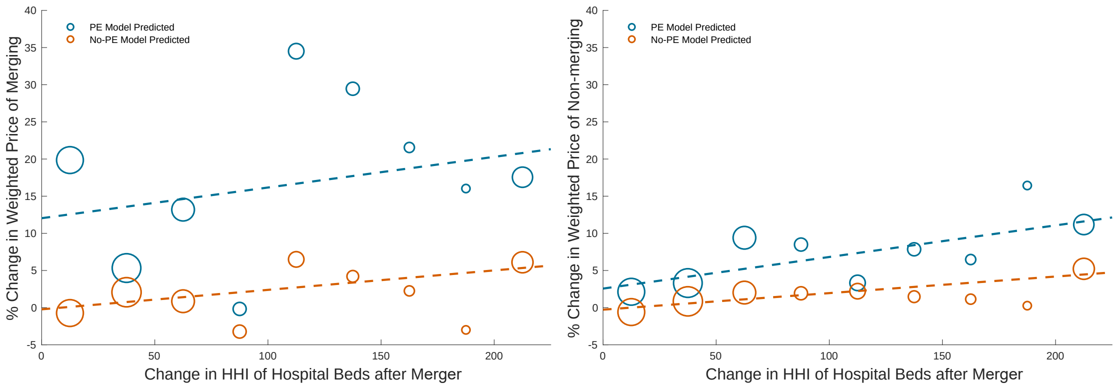


(c) %Surplus Changes after Mergers

This figure presents predictions about changes in the total spending and prices in a sample of 100 hypothetical mergers using the *PE model* and the *No-PE model*. The unit of observation is an HRR. In Panel A, the y-axis denotes the percentage change of the total spending in an HRR after mergers. In Panel B, the y-axis denotes the percentage change of the quantity-weighted prices in an HRR after mergers. In Panel C, the y-axis denotes the changes in patient surplus (in dollar terms) after mergers as a percentage of the total spending in the HRR. Each circle corresponds to the mean percentage change in a bin. Circle size represents the number of observations within each bin. The blue circles represent predictions from the *PE model* and the orange circles represent predictions from the *No-PE model*. The dashed line denotes the best-fit line.

To explore the prediction gaps in different groups, Figure 7 looks into the price predictions for merging hospitals and non-merging rival hospitals after each hypothetical merger. Panel A exhibits percentage changes in the quantity-weighted average prices of the merging hospitals (acquirers plus targets), while Panel B exhibits that of the non-merging rival hospitals (other rival hospitals), evaluated by both models. The prediction gap of negotiated prices is asymmetric for these two groups. For the merging hospitals, as shown in Panel A, the prediction gap could reach as high as 25%. In contrast, Panel B implies that the No-PE model only underestimates the price changes to a modest level, 3% on average, among the non-merging rival hospitals. This, to some extent, underscores that the gaps in predictions largely come from the underestimation of merging parties in mergers.

Figure 7: 2nd Counterfactual: Price Changes in Subgroups after Mergers



(a) %Price Changes of Merging Hospitals **(b)** %Price Changes of Rival Hospitals

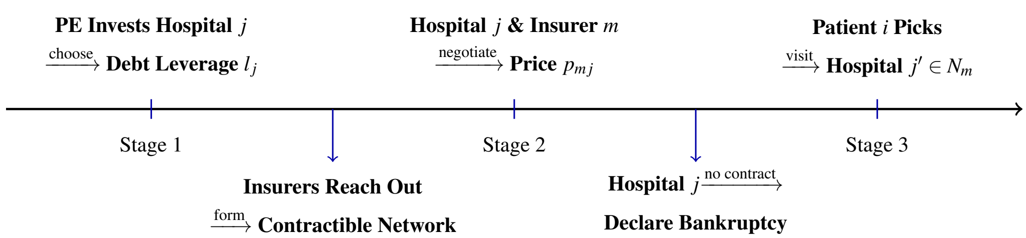
This figure presents predictions about the price changes across subgroups in a sample of 100 hypothetical mergers using the *PE model* and the *No-PE model*. Panel A reports the percentage change of the quantity-weighted prices of merging hospitals (acquirers and targets) in an HRR after mergers (relative to the quantity-weighted prices of acquirers before mergers). Panel B reports the percentage change of the quantity-weighted prices of non-merging rival hospitals after mergers. Remaining details are the same as in Figure 6.

This counterfactual exercise emphasizes the impacts of mergers resulting from the unique traits of PE acquirers, instead of the anti-competitive behaviors caused by typical market consolidations. Therefore, antitrust laws might not have much bite from the regulatory perspective. But for a regulator whose objective is to protect consumer welfare, the exercise conveys a clear message: mergers involving PE ownership might systematically exhibit distinct attributes. Regulators could possibly risk underestimating their impacts on healthcare prices and patient surplus if they treat them as typical mergers.

6 Discussion and Robustness

6.1 Network Formation

In the baseline model, the networks between insurers and hospitals, namely, N_m and M_s, are assumed to be fixed exogenously. Here, I show that the main estimates are robust to extending the model with an endogenous network-formation stage between hospitals and insurers. The new model timeline is exhibited below.



In the added stage, any pair of hospitals and insurers must decide whether to form a contractible link when they formally negotiate prices. It is assumed that each insurer reaches out to a subset of hospitals with which it would like to form negotiation links (and hence maximize its expected payoffs). The locked-in bilateral relation results in a contractible network for insurer m, which is a subset of hospitals in the local market, denoted by N_m, and a contractible network for hospital system s, which is a subset of insurers in the local market, denoted by M_s. As a result, insurer m will negotiate prices with every hospital system s with $J_s \subseteq N_m$, and hospital system s will negotiate prices with every single insurer $m' \in M_s$.[23]

This leads to an optimization step for insurers and introduces a set of additional inequality moments from the network-determination decisions. In particular, a subset of necessary conditions are implied by the observed equilibrium network structure: adding hospitals from outside or dropping hospitals within N_m would generate lower expected payoffs to the insurer than what it earned in equilibrium. I construct these moments following previous literature (e.g., Crawford and Yurukoglu, 2012, Pakes et al., 2015, and Prager and Tilipman, 2020). More details about the estimation process are provided in the Online Appendix, and the new estimates are tabulated in Table OA.20 of the Online Appendix. Using the new estimates produces \$2.74 billion savings in the first counterfactual of restricting PE ownership, comparable to the main estimates in the paper (\$2.95 billion).

6.2 New Entry

Though the structural model incorporates the closure threats of hospitals, it does not explicitly consider entry of new hospitals. Here, I briefly discuss implications of new entry and argue that the structural model is flexible enough to tackle the issue. First, recall that in the model, the price bargaining process is analyzed separately for each local market given a set of hospitals. Any new hospital that enters the market and generates insurance claims that are captured by the database will be included in the set of hospitals and considered in the price bargaining process. So, the entry of new hospitals should not impact the estimation outcomes.

Second, I argue that new entry should have a very moderate—if any—impact on local markets, due to the role of Certificate of Need (CON) regulations across states. CON regulations, adopted by 35 states so far, require healthcare providers to obtain state approval before opening up a new facility or expanding existing facilities, which greatly increases entry costs and deters new entry (e.g., Cutler et al., 2010 and Ho, 2020). Therefore, it is relatively rare to observe entry of new hospitals in the data, and they would have very limited impact on the estimates.

7 Conclusion

PE investment in healthcare has ballooned over the past decade. Though it has drawn considerable policy interest among regulators, there is a lack of systematic studies on how the ownership change impacts healthcare markets, regulations, and patient welfare. This paper addresses these questions by introducing novel insurance claims data, structurally estimating a model, and quantifying PE ownership's equilibrium

[23] One innocuous timing assumption, which simplifies the pairwise network-stability analysis later on, is that hospitals and insurers simultaneously implement network formation and price bargaining in the model.

impacts. The paper finds that PE buyouts lead to an 11% increase in bargained prices between PE-owned hospitals and insurers. Local rivals respond by also negotiating higher prices, though responses exhibit strong heterogeneity. The counterfactual simulations imply that under the assumption that private insurers pass through all changes in medical spending to patients by adjusting insurance premiums, restricting PE ownership would bring gains in patient surplus, mainly by reducing hospital prices while not through changing the quantity or quality of service. It also shows that regulators potentially underestimate the impact of proposed mergers if they ignore PE acquirers' unique features.

The paper highlights several mechanisms via which PE firms bargain prices with private insurers. These mechanisms are closely related to the unique features of PE ownership. They can be applied beyond the healthcare sector studied in this paper. Therefore, it might be helpful if policymakers are aware of them when evaluating PE investments involving any business-to-business bargaining settings.

This paper concentrates on the implications of PE hospital buyouts on hospital–insurer price negotiations and medical service quality, conditioning on the assumption that patients are already assigned to insurance plans. Extending the framework and data to accommodate insurer competition is an interesting area for future work (Ho and Lee, 2017). In addition, it seems important to consider the response of physicians after PE buyouts. Physician arrangements with hospitals are varied and complicated. Besides hospital prices, private insurers also need to negotiate physician fees separately (Cooper et al., 2020). Though beyond the current scope of the analysis, it would be interesting to explore how physician arrangements with hospitals and the structure of physician pay respond to the ownership change.

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For Online Publication

Online Appendix for "Bargaining with Private Equity: Implications for Hospital Prices and Patient Welfare"

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This appendix provides supplementary materials for "Bargaining with Private Equity: Implications for Hospital Prices and Patient Welfare." Section A introduces the main datasets used in the paper. Section B outlines the procedure used to construct the main regression sample. Section C introduces the procedure used to compute the service-mix weights in the main analysis. Section D provides details on how to derive the benchmark prices for a hospital–insurer pair. Section E discusses an illustrative model based on Lee and Fong (2013). Section F provides details on solving the bargaining model in the main text. Section G discusses an extended model with an endogenous network-formation stage and how to estimate it. Section H provides details on the corporate practice of medicine (CPOM) prohibition. Section I introduces the numerical methods used to estimate the model and simulate the counterfactuals. Section J contains additional figures and tables mentioned in the main text.

A Description of Data

This section introduces the main datasets used in the paper.

Decision Resources Group Real World Data (DRG RWD) Product: My insurance claims data are from the Real World Data Product of Decision Resources Group. The raw data cover over 300 million longitudinal US patients with multiple-payer and multiple plan starting from 2011. The claims are sourced from billing software used by health service providers including hospitals, physician offices, pharmacies, long-term care facilities, etc. More details about the data can be found at https://decisionresourcesgroup.com/solutions/real-world-data/.

The open-network RWD Product has a broad capture of patients with different payer types: It covers over 310 million patients from commercial payers, which is the focus of the analysis. Besides, it covers about 70 million patients from Medicare and 79 million patients from Medicaid. The RWD Product contains seven main tables—claim header, diagnosis, institutional, professional, patient, payer, and provider tables. As the paper focuses on hospital service prices, it mainly leverages the price information in the institutional tables.

There are several advantages of using the RWD Product for my study purpose. Compared to the closed-network claims dataset such as MarketScan, the RWD Product is of greater size in terms of claims number and are more representative across multiple payer categories. Moreover, the hospital IDs are not provided in the MarketScan database, which makes it difficult to match the MarketScan data with external datasets on hospital characteristics and PE investment records, and almost impossible to analyze the price variations before and after PE intervention for the same facility.

Another prominent database is the Health Care Cost Institute (HCCI) data used by Cooper et al. (2019). The HCCI data include commercial claims sourced from three major health insurance companies: Aetna, Humana, and UnitedHealthcare.[1] While the HCCI data have a large coverage across the country, some limitations make it hard to fulfill the type of analysis conducted in this paper. For example, the HCCI data only cover these three large insurance companies and under-represent the market for smaller commercial payers. Additionally, it does not provide identifiers to distinguish claims among these three payers, which are indispensable to identify the price variations within a hospital-payer pair before and after PE buyouts. While with the RWD Product, I have a more representative sample across different types of commercial payers and overcome the obstacle as a unique identifier number is linked to each payer in the data. Besides above advantages, the RWD Product provides more granular diagnosis information via the International Classification of Disease (ICD) codes in the claims and is able to track patients even as patients change payers.

PitchBook Financial Database: The PitchBook platform is a leading market intelligence on private market deals, including private equity, venture capital, and M&A transactions. More information can be found at https://pitchbook.com/. I complied a list of PE transactions in the healthcare sector following several steps: (1) Select the "Deal Criteria" and restrict "Deal Date" between 1994 and 2019 and the "Deal Status" to be completed; (2) In "Deal Types", select Private Equity with "All Buyout Types" and "Other Private Equity Types"; (3) In "Industry", restrict it to be "5.2.1. Healthcare-Healthcare Services-Clinics/Outpatient Services" and "5.2.4. Hospitals/Inpatient Services"; (4) Lastly, restrict the location of targeted firms to be "United States". It results in a sample containing 2,324 companies, 2,827 deals, 1,339 investors, and 477 exits (as of 2019/11/15). In order to determine the exit time of PE deals, I conduct extensive web searches on each hospital and infer the ultimate outcomes of these transactions based on news reports. For those deals I am still unable to determine the exit time for, I assume the holding period of PE investors to be ten years, which is consistent with the evidence documented by Stromberg (2008) that the median firm stays in leveraged buyout (LBO) ownership for more than nine years in a sample of worldwide LBO transactions from 1970 to 2007.

Preqin Financial Database: Preqin is the alternative assets industry's leading source of data and intelligence. More information can be found at https://www.preqin.com/. I downloaded relevant tables regarding private

[1] HCCI suspended their data services in 2019 when UnitedHealth terminated their agreement of claim data sharing. HCCI's dataset "2.0" is currently under construction with Blue Health Intelligence as a new raw data provider.

equity deals from the Preqin on the Wharton Research Data Service (WRDS). After restricting the industry to health care and deal types to buyouts, public to private, merger, add-on investment, and growth capital, I complement it with the PE deal sample from PitchBook.

S&P Capital IQ Database: Capital IQ is another commonly-used platform for PE research. More information can be found at https://www.spglobal.com/marketintelligence. I use it to complement PitchBook and Preqin. Specifically, I apply the screening criteria as follows: I require the industry to be healthcare services, healthcare facilities, or managed health care in the US. I also require the deal type to be going-private transaction, leveraged buyout, management buyout, platform, or secondary LBO.

SDC Platinum Database: The SDC Platinum is a platform providing information on new equity issues, M&A, syndicated loans, and private equity for the global financial market. More information can be found at https://www.refinitiv.com/en/products/sdc-platinum-financial-securities. I downloaded the SDC M&A sample from WRDS and used it for two purposes: the first one is to complement the PE deals sample by focusing on a subsample of leveraged buyout deals among the SDC M&A transactions in the healthcare sector. The second one is to supplement the sample of hospital M&As from Levin Associates' M&A database, which is introduced below.

Irving Levin Associates' Health Care Services Acquisition Reports: The Levin Associates is a leading publisher of business intelligence in the healthcare M&A markets. More information can be found at https://www.levinassociates.com/. I downloaded the data from WRDS and used it to identify hospital M&A deals in the US between 2006 and 2019.

American Hospital Association (AHA) Annual Survey Data: The AHA annual survey data provide detailed demographic, operational, staffing, employment model, insurance and utilization characteristics of over 6,000 hospitals across the US. More information can be found at https://www.ahadata.com/aha-annual-survey-database. I downloaded the AHA annual survey data between 1994 and 2019 and matched them to the DRG RWD data.

Healthcare Cost Report Information System (HCRIS) Data: The HCRIS data are maintained by the Centers for Medicare and Medicaid Services (CMS). Every year, Medicare-certified hospitals are required to submit an annual cost report to CMS. The cost reports contain hospital characteristics, utilization data, cost and charges (in total and for Medicare only), and financial statements. More information can be found at https://www.cms.gov/Research-Statistics-Data-and-Systems/Downloadable-Public-Use-Files/Cost-Reports. I construct a sample of hospital HCRIS data from 1996 to 2019, and leverage it to construct hospitals' average-cost measures and financial leverage.

CMS Hospital Quality Data: Annual hospital quality data are from the Hospital Outpatient Quality Reporting Program and the Hospital Inpatient Quality Reporting Program implemented by CMS. More information can be found at https://qualitynet.cms.gov/. I use five sets of widely-used measures in outpatient and inpatient settings to proxy for hospitals' service quality, including hospital mortality rates, hospital readmission rates, patient safety indicators, imaging efficiency measures, and hospital consumer assessment scores.

CMS Outpatient Service Weight Data: To construct the relative service-mix weights, I exploit the data from Addendum B file of CMS's hospital outpatient prospective payment system. This payment system is used by CMS to reimburse for hospital outpatient services, and it develops an Ambulatory Payment Classification (APC) by grouping procedures (or procedure codes) that are supposed to be "similar clinically and with regard to resource consumption." More information can be found at https://www.cms.gov/Medicare/Medicare-Fee-for-Service-Payment/HospitalOutpatientPPS. Each APC code has a numeric weight to represent the service weight of procedures. The Medicare reimbursement rate is equal to the relative service-mix weights multiplied by an adjusted base price. I strictly follow the APC grouping method and calculate the relative service-mix weights for each patient visit in the RWD sample. Detailed construction procedures are depicted in Section C.

CMS Physician Fee Schedule (PFS) Relative Values Files: The PFS is an reimbursement system developed by CMS for the Medicare physician fees. Similar to the APC codes, the PFS has relative value units (RVU) to represent the service weights associated with every physician procedure. More information can be found at https://www.cms.gov/apps/physician-fee-schedule/overview.aspx. Following a similar strategy by

Frost et al. (2018), I use the RVU files to compute the relative service-mix weights for insurance claims that are unable to map to an appropriate APC code.

CMS Medicare Geographic Variation Data: The CMS provides Medicare geographic variations data on demographic, average and total spending, total utilization, and quality indicators at the HRR level. More information can be found at https://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/Medicare-Geographic-Variation/index. I include the annual average-outpatient costs and average HCC scores in the structural model's marginal-cost specification.

Dartmouth Atlas Data: I use the crosswalk file from the 3-digit zip codes to the HRR region codes provided by Dartmouth Atlas. More information can be found at https://atlasdata.dartmouth.edu/.

Clinical Classifications Software (CCS) Data: The CCS for ICD-9 and ICD-10 codes is a diagnosis and procedure categorization scheme developed by the Healthcare Cost and Utilization Project (HCUP). The main purpose is to group and collapse ICD codes into a smaller number of clinically meaningful categories. More information can be found at https://www.hcup-us.ahrq.gov/toolssoftware/ccs/ccs.jsp. I use the CCS data to group patients' diagnosis according to their main ICD-9 or ICD-10 codes.

Lexis Advance Research Database: The Lexis is a database for legal research with a collection of case law, statutes and regulations. More information can be found at https://www.lexisnexis.com/en-us/products/lexis.page. I use the Lexis database to search for legislative events regarding the corporate practice of medicine (CPOM).

B Sample Construction

B.1 Matching National Plan and Provider Enumeration System Identifiers to AHA Annual Survey Data

This section introduces the procedure to match the National Plan and Provider Enumeration System Identifiers (NPI) with the hospital identifier in the AHA annual survey database. The NPI is a unique identification number for covered healthcare providers. They must use the NPIs in the administrative and financial transactions adopted under Health Insurance Portability and Accountability Act (HIPAA). The NPI is a 10-position, intelligence-free numeric identifier. Single hospitals can be assigned multiple NPIs because different wings of hospitals or different units can have their NPIs independently. To address this issue, I adopt a similar approach as Cooper et al. (2019) to consolidate providers' multiple NPIs into a single AHA ID following steps specified below:

1. Check all NPIs in the 2005-2019 AHA annual survey database to make sure that they are valid. Remove invalid NPIs, e.g., misrecorded NPIs which have less than 10 digits, or misreported ones which do not exist in the CMS NPI Registry system.

2. Split the AHA annual survey sample into three subsamples based the number of recorded NPIs associated with one AHA ID: one subsample of providers with missing NPI, one subsample of providers with a single NPI per AHA ID, and the remaining providers associated with multiple NPIs per AHA ID.

3. For the subsample with multiple NPIs, I manually look up them in the NPI Registry and compare information of provider names, address, and other information via Google Search, to make sure all NPIs are accurate.

4. For the subsample with missing NPIs, I first exploit the crosswalk table from Medicare Certification Number (CCN) to NPI on the NBER website[2] and match each observation based on CCN if there is any. For those matched observations, I repeat Step 3 to ensure their accuracy[3]. For those unmatched observations, I look up

[2] See more details in https://data.nber.org/data/npi-medicare-crosswalk.html

[3] In the crosswalk table, some NPIs are for individual rather than for organizational facilities. Some NPIs are incorrectly linked to other organizations that might be under the same system with the focal providers.

hospitals in the NPI Registry by name, zip code, street address, and other information from Google searches and find NPIs associated with each AHA ID.

5. I compile all variations of AHA ID/hospital name/address/city/state/zip code/NPI[4] in the AHA annual survey sample after combining three subsamples, retaining the row for the latest year.

6. Extract all organizational rows from the CMS NPI Registry where the primary taxonomy code is for Hospitals (287300000X, 281P00000X, 281PC2000X, 282N00000X, 282NC2000X, 282NC0060X, 282NR1301X, 282NW0100X, 282E00000X, 286500000X, 2865C1500X, 2865M2000X, 2865X1600X, 283Q00000X, 283X00000X, 283X00000X, 283XC2000X, 282J00000X, 284300000X), hospital unit (273100000X, 275N00000X, 273R00000X, 273Y00000X, 276400000X), or Ambulatory Health Care Facilities---Critical Access Hospital (261QC0050X).

7. Match the AHA compiled file in Step 5 with the hospital NPI file based on NPI numbers.

8. After standardizing organization names, other organization names, practice addresses, business addresses in AHA annual survey and NPI files[5], match remaining rows in the hospital NPI file and consolidate those unmatched NPIs to AHA IDs in the matched compiled file according to the following criteria:

    (a) Organization name, practice address , city, state, zip code
    (b) Other organization name, practice address, city, state, zip code
    (c) Practice address, city, state, zip code, similar organization name
    (d) Practice address, city, state, zip code, similar other organization name
    (e) Organization name, similar practice address, city, state, zip code
    (f) Other organization name, similar practice address, city, state, zip code
    (g) Similar organization name, similar practice address, city, state, zip code
    (h) Similar other organization name, similar practice address, state, zip code
    (i) Practice address, city, state, zip code, different name (validated name changes via web search)
    (j) Medicare number, city, state, zip code

9. When a match is found, use the AHA ID as the unique identifier for a NPI number. To validate the matching quality and to include those missed-out observations in the matching process, sort the sample based on organization name, 5-digit zip code, and practice address. Manually go through the file to correct mis-matches and add those missed-out observations.

10. As an additional step of manual check, sort the sample based on 5-digit zip code, organization name, and AHA ID. Then add those missed-out observations within each zip code area.[6]

B.2 Identify Outpatient Claims

In this subsection, I introduce the method to identify outpatient claims in the sample. In the DRG RWD data, an inpatient flag is provided. However, I found the flag is not a complete and accurate indicator. I identify other inpatient claims via following steps:

[4]Note that the US zip codes start from 501 as the first 3-digit prefix. I manually correct mis-recorded zip codes based on web search.

[5]I exploit the customized version of Stata command *stn_compname* and *stn_address* to standardize hospital names and addresses. More details can be found in Wasi and Flaaen (2015).

[6]The manual check in Step 9 is to look up those missed-out matches, for example, observations that are a department of a hospital, or stored with various conventions of hospital/city/address names. The purpose of the manual check in Step 10 is to find those missed-out matches, for example, due to abbreviated names (e.g., CHOP vs. The Children's hospital of Philadelphia), or inconsistency of zip codes recorded between the AHA annual survey database and the NPI file. Both steps cost hundreds of RA hours.

1. A claim is identified as inpatient if the associated DRG (MS-DRG) codes are not null.
2. Following White and Whaley (2019), a claim is identified as inpatient if the type-of-bill codes are equal to 111 or 117.
3. Following Frost et al. (2018), a claim is identified as inpatient if (1) they contain valid revenue codes; and (2) the place-of-service codes are equal to 21, 51, 56, or 61, or a room and board revenue codes are between 100 and 219.
4. Based on the Status Indicator (SI) of the HCPCS codes, a claim is identified as inpatient if the SI code is equal to C.

I then obtain the outpatient sample by excluding all identified inpatient claims.

C Construct Service-Mix Weights

I follow a similar strategy by Frost et al. (2018) to assign a relative service-mix weight for the outpatient visits in the sample. The main reference for relative service-mix weights comes from the Ambulatory Payment Classification (APC) system, which is a key component of the Hospital Outpatient Prospective Payment System (OPPS) developed by CMS.

As the first step, I map each claim line to a APC code based on the CPT/HCPCS code associated with the claim. Since certain procedures are deemed as supportive, dependent, or adjunctive to a primary service, they are not paying separately according to the APC payment rules (and hence not assigning independent weights). Two major types of packaging methods are provided in the APC reimbursement rules: (un)conditional packaging APCs and comprehensive APCs. Unconditional packaged services carry the Status Indicator (SI) of N and conditional packaged ones are associated with the SI's of Q1, Q2, Q3, or Q4. Comprehensive APCs carry the SI's of J1 or J2, in which a single payment will be paid for the primary procedure while all other services reported within the claim will be packaged with few exceptions. I follow the detailed reimbursement rules in OPPS[7] and assign zero weights to all (un)conditional packaged and comprehensively packaged claim lines. All APC weights were updated to the 2020Q2 version of the CMS addendum D.

For claims that were not matched to an appropriate APC code, in the second step I fill the relative service-mix weights by using the relative value units (RVUs) for facility procedure codes. RVUs are the key component of the Physician Fee Schedule (PFS) payment mechanism devised by CMS, which is an independent payment system from OPPS[8]. However, the weights of RVUs share a similar spirit of APCs to measure the resource intensity required to complete one line of service. I map those unmatched claim lines to RVUs based on the CPT/HCPCS codes and assign a weight according to the facility practice expense RVU. All RVU weights are updated to the 2020Q2 version of the CMS RVU file. To adjust RVU weights as they were treated equally with APC weights, I follow Frost et al. (2018) to convert it based on the difference between calendar year 2020 RVU conversion factor and calendar year 2020 APC conversion factor, which is equal to 0.447.

In the last step, I impute the missing weights for claim lines which were not assigned weights after above two steps, which accounts for less than 7% of total outpatient claim lines. Some of them occurred due to the missing or misdocummented CPT/HCPCS codes. I take a simplified approach by assigning the average weights of outpatient claim lines that have already weights assigned through previous process in a given year. The underlying

[7] More reference can be found in the following documents provided by CMS: (1) "Medicare Claims Processing Manual-Chapter 4 Part B Hospital" https://www.cms.gov/Regulations-and-Guidance/Guidance/Manuals/Downloads/clm104c04.pdf; (2) "Medicare CY 2019 Outpatient Prospective Payment System (OPPS) Final Rule Claims Accounting" https://www.cms.gov/Medicare/Medicare-Fee-for-Service-Payment/HospitalOutpatientPPS/Downloads/CMS-1695-FC-2019-OPPS-FR-Claims-Accounting.pdf

[8] The manual of RVUs as well as the data can be downloaded from the following link https://www.cms.gov/Medicare/Medicare-Fee-for-Service-Payment/PhysicianFeeSched/PFS-Relative-Value-Files

assumption is that the unmatched sample is comparable to the matched one in terms of the level of resources used to treat patients.

D Derive Benchmark Prices

In this section, I describe how to derive the benchmark negotiated prices between hosptials and insurers. I follow a similar approach of Gowrisankaran et al. (2015), Shepard (2016), Ho and Lee (2017), Tilipman (2022), and others by recognizing the fact that hospitals and insurers do not negotiate over a full menu of prices for different items, but rather negotiate over a benchmark price and multiply it by the relative service-mix weights to obtain a payment for each diagnosis and procedure.

Given the sample of hospital outpatient claims, I adjust the total paid amounts $Y_{ijm(i)dt}$ for patient i with diagnosis d on insurance plan from insurer m seeking care from hospital j in year t to dollars in 2019 by GDP deflators. Then I estimate the benchmark price by running the following model:

$$\frac{Y_{ijm(i)dt}}{w_d} = \gamma_{jmt} + \beta X_{it} + \varepsilon_{ijm(i)dt},$$

wherein w_d is the relative service-mix weights for disease d, γ_{jmt} are fixed effects for every hospital–insurer–year combination, and X_{it} is a vector of patient characteristics, including patients' age and gender. $\varepsilon_{ijm(i)dt}$ is the stochastic error term.

To derive the benchmark prices, I first recover the vector of hospital–insurer–year fixed effects $\hat{\gamma}_{jmt}$. I then evaluate the fitted value of patient characteristics at the sample means, i.e., $\hat{\beta}\bar{X}$ for each year. Combining both items give us the benchmark price between hospital j and insurer m in year t:

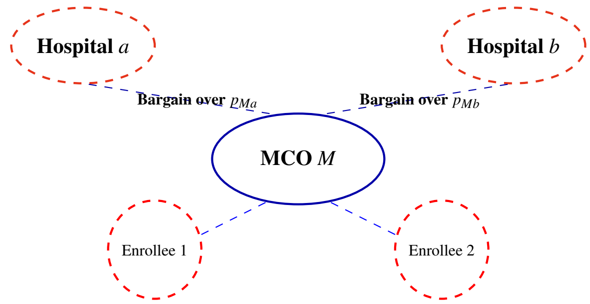
$$p_{mj} = \hat{\gamma}_{jmt} + \hat{\beta}\bar{X}.$$

E An Illustrative Model

The model features a repeated setting based on Lee and Fong (2013). Suppose in a local market, there is one insurance company (MCO) M and two hospitals a and b. In addition, two enrollees of M are living in the neighborhood and their utility of visiting either hospital is identical and denoted by v. The cost of treating one patient is the same across hospitals, denoted by c. It's assumed that $v > c$ so that treating a patient is always welfare-improving. Hospitals and MCO are discounting future payoffs with a factor $\beta \in (0,1)$. Noticeably, heterogeneity among hospitals and patients are abstracted away in this simplifying model, so we can focus on the mechanism of how bankruptcy threats affect service pricing.

No Bankruptcy Threat

Consider a case in which both hospitals are negotiating with MCO M and none of them can threaten to close the facility. Every period, M will negotiate a price p_{Mi} with hospital i where $i \in \{a,b\}$. As patients are indifferent between hospitals, it's assumed each enrollee will visit one hospital if a and b are included in the network of M. The setup is depicted in the following figure.



Within each period, hospitals and MCO will bargain over a benchmark price. The bargaining process follows the protocol of Nash-in-Nash bargaining models and prices are determined simultaneously (Horn and Wolinsky, 1988, Gowrisankaran et al., 2015, and Collard-Wexler et al., 2019). The only difference is when specifying their payoffs, each party has to take into account their continuation values for future periods. For example, in period t, the bargaining game between hospital i and MCO M can be formulated as follows:

$$NB(p_{Mi}) = (p_{Mi} - c + V_i - V_i)^{\frac{1}{2}} \left((2v - p_{Mi} - p_{Mj} + V_M) - (2v - 2p_{Mj} + V_M)\right)^{\frac{1}{2}}, \tag{OA.1}$$

wherein V_i is the continuation value for hospital i, and V_M represents the continuation value for MCO M. It is assumed that hospitals are having an equal bargaining power, $1/2$, when facing the MCO. Compared to Lee and Fong (2013), my simplifying model abstracts away any intertemporal uncertainty and network formation costs. Therefore, the continuation values for hospitals and MCO at the current period stay the same no matter whether they reach an agreement or not. Given the symmetry of these two hospitals, in equilibrium it must have $p = p_{Mi} = p_{Mj}$ for $i, j \in \{a, b\}$. Solving the bargaining game, it yields

$$p = c.$$

This outcome is not surprising given the homogeneity assumption of hospitals. There are no differences or added values that any hospital can provide to the network relative to the rival. Both hospitals are essentially competing with each other under the standard Bertrand-Nash price-setting game. Therefore, competition leads to an equilibrium in which negotiated prices are equal to the marginal cost of hospitals.

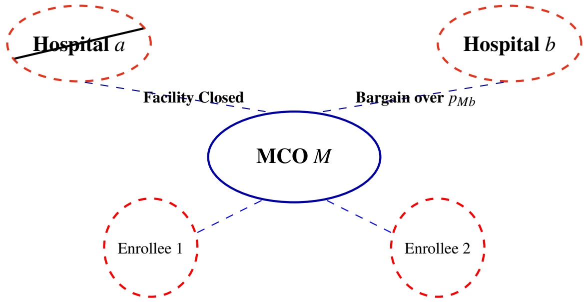
Credible Threat of Bankruptcy

Let us turn to another case in which hospitals threaten to close the facility if they are excluded from the network. After closure, hospitals will lose their future profits and have a zero continuation value. Let the current benchmark prices in equilibrium be $p' = p'_{Mi} = p'_{Mj}$. The new bargaining game in period t is represented by

$$NB(p'_{Mi}) = \left(p' - c + V'_i\right)^{\frac{1}{2}} \left(\left(2v - 2p' + V'_M\right) - \left(2v - 2p' + V''_M\right)\right)^{\frac{1}{2}}, \tag{OA.2}$$

in which V'_i is the new continuation value for hospital i if the bankruptcy threat is committed, V'_M is the continuation value for MCO M. Moreover, V''_M indicates the continuation value of M when i is closed.

On the equilibrium path, we must have $V'_i = \frac{\beta(p'-c)}{1-\beta}$ and $V'_M = \frac{\beta(2v-2p')}{1-\beta}$. On the off-equilibrium path, hospital i is closed and hospital j becomes the only surviving hospital negotiating with M in the future, as exhibited below:



On the off-equilibrium path, hospital j becomes the only facility in the local market and starts to negotiate a new price with M. Denote the new negotiated price by p''. So, the new bargaining game under the off-equilibrium path becomes

$$NB(p'') = \left(2p'' - 2c + V_j'' - 0\right)^{\frac{1}{2}} \left(2v - 2p'' + V_M'' - 0\right)^{\frac{1}{2}}, \tag{OA.3}$$

wherein V_j'' is the continuation value for hospital j if it is the only facility in the local market. For both parties, the outside option is zero when disagreement occurs. Again, it's known that $V_j'' = \frac{\beta(2p''-2c)}{1-\beta}$ and $V_M'' = \frac{\beta(2v-2p'')}{1-\beta}$. Plugging these terms back to Equation (OA.3), it generates

$$p'' = \frac{v+c}{2} > p \qquad \text{and} \qquad V_M'' = \frac{\beta(v-c)}{1-\beta}.$$

By inserting the expression of V_M'' back into Equation (OA.2), the equilibrium negotiated prices satisfy

$$p'' > p' = \frac{\beta v + (1+\beta)c}{1+2\beta} > p = c.$$

To validate the equilibrium strategy (to include both hospitals in the network) is optimal for MCO M, it can be seen that $V_M' > V_M''$. Similarly, for hospital i, $i \in \{a,b\}$, the committed bankruptcy strategy is optimal because $V_i' > 0 = V_i$.

To close the discussion, it is worth highlighting the key insight from this illustrative model: MCOs are willing to "subsidize" hospitals and pay a higher price in order to keep them competing with each other. This would benefit MCOs in the long run since a more competitive hospital sector will grant them a better bargaining position in future (re)negotiations.

F Details on Solving the Bargaining Problem

F.1 Derivation of the First Order Condition

In this section, I describe the derivation of the first order condition (FOC) for the bargaining problem depicted in Equation (6).

Note that the bankruptcy probability of PE-owned hospital j with leverage level l_s can be characterized as

$$\begin{aligned}
\rho(l_s, M_s \backslash m) &= \mathbf{Pr}(\theta l_s > h_s(M_s \backslash m) - v'_{st}) \\
&= \mathbf{Pr}(v'_{st} > h_s(M_s \backslash m) - \tilde{\theta} l_s) \\
&= 1 - \frac{\exp(\frac{h_s(M_s \backslash m) - \tilde{\theta} l_s - \tilde{\mu}}{\tilde{s}})}{1 + \exp(\frac{h_s(M_s \backslash m) - \tilde{\theta} l_s - \tilde{\mu}}{\tilde{s}})} \\
&= \frac{1}{1 + \exp(\frac{h_s(M_s \backslash m) - \tilde{\theta} l_s - \tilde{\mu}}{\tilde{s}})} = \frac{1}{1 + \exp(\rho h_s(M_s \backslash m) - \theta l_s - \mu)},
\end{aligned}$$

in which the third equality comes from the assumption that v'_{st} follows i.i.d. logistic distribution, and $\rho = \frac{1}{\tilde{s}} > 0$, $\theta = \frac{\tilde{\theta}}{\tilde{s}}$, and $\mu = \frac{\tilde{\mu}}{\tilde{s}}$.

In addition, I derive an explicit expression for the expected payoffs of PE-owned hospital s:

$$\begin{aligned}
\mathbf{E}\left(\mathbf{1}\{\widetilde{\Pi_s}(M_s \backslash m) < C(D_s)\} \times \left[C(D_s) - \widetilde{\Pi_s}(M_s \backslash m)\right]\right) &= \mathrm{TA}_s \mathbf{E}\left(\mathbf{1}\{v'_{st} > h_s(M_s \backslash m) - \tilde{\theta} l_s\} \cdot \left[\tilde{\theta} l_s - h_s(M_s \backslash m) + v'_{st}\right]\right) \\
&= \mathrm{TA}_s \int_{h_s(M_s \backslash m) - \tilde{\theta} l_s}^{+\infty} \left[\tilde{\theta} l_s - h_s(M_s \backslash m) + x\right] \frac{\exp(\frac{x - \tilde{\mu}}{\tilde{s}})}{\tilde{s}\left(1 + \exp(\frac{x - \tilde{\mu}}{\tilde{s}})\right)^2} dx,
\end{aligned}$$

in which

$$\mathrm{TA}_s \int_{h_s(M_s \backslash m) - \tilde{\theta} l_s}^{+\infty} \left[\tilde{\theta} l_s - h_s(M_s \backslash m)\right] \frac{\exp(\frac{x - \tilde{\mu}}{\tilde{s}})}{\tilde{s}\left(1 + \exp(\frac{x - \tilde{\mu}}{\tilde{s}})\right)^2} dx = \mathrm{TA}_s \left[\tilde{\theta} l_s - h_s(M_s \backslash m)\right] \rho(l_s, M_s \backslash m),$$

and

$$\begin{aligned}
\mathrm{TA}_s \int_{h_s(M_s \backslash m) - \tilde{\theta} l_s}^{+\infty} x \frac{\exp(\frac{x - \tilde{\mu}}{\tilde{s}})}{\tilde{s}\left(1 + \exp(\frac{x - \tilde{\mu}}{\tilde{s}})\right)^2} dx &= \mathrm{TA}_s \left[\frac{-x}{1 + \exp(\frac{x - \tilde{\mu}}{\tilde{s}})} - \tilde{s} \ln\left(1 + \exp(-\frac{x - \tilde{\mu}}{\tilde{s}})\right)\right] \Bigg|_{h_s(M_s \backslash m) - \tilde{\theta} l_s}^{+\infty} \\
&= \mathrm{TA}_s \left[h_s(M_s \backslash m) - \tilde{\theta} l_s\right] \rho(l_s, M_s \backslash m) + \tilde{s} \mathrm{TA}_s \ln\left(1 + \exp\left(-\frac{h_s(M_s \backslash m) - \tilde{\theta} l_s - \tilde{\mu}}{\tilde{s}}\right)\right).
\end{aligned}$$

Summing both terms yields that

$$\begin{aligned}
\Delta \varpi_s &= \mathbf{E}\left(\mathbf{1}\{\widetilde{\Pi_s}(M_s \backslash m) < C(D_s)\} \times \left[C(D_s) - \widetilde{\Pi_s}(M_s \backslash m)\right]\right) \\
&= \tilde{s} \mathrm{TA}_s \ln\left(1 + \exp\left(-\frac{h_s(M_s \backslash m) - \tilde{\theta} l_s - \tilde{\mu}}{\tilde{s}}\right)\right) \\
&= \frac{1}{\rho} \mathrm{TA}_s \ln\left(1 + \exp\left(\theta l_s + \mu - \rho h_s(M_s \backslash m)\right)\right).
\end{aligned}$$

Plugging above term into $NB^{m,s}$ in Equation (6) and taking the derivative with respect to p_{ms} generates

$$\begin{aligned}
&B_{sm}\left(V_m(N_m, \mathbf{p}_m) - V_m(N_m \setminus J_s, \mathbf{p}_{m-s}) + \mathbf{1}\{PE_s = 1\} \cdot \Delta V_m\right) \frac{\partial \varpi_s}{\partial p_{ms}} + \\
&\qquad (1 - B_{sm}) \left(\varpi_s(\cdot) - 1\{PE_s = 1\} \cdot \frac{1}{\rho} \mathrm{TA}_s \ln\left(1 + \exp\left(\theta l_s + \mu - \rho h_s(M_s \backslash m)\right)\right)\right) \frac{\partial V_m}{\partial p_{ms}} = 0,
\end{aligned}$$

wherein $\partial \varpi_s / \partial p_{ms} = q_{ms}$ and $\partial V_m / \partial p_{ms} = -q_{ms}$. Rearranging terms replicates the FOC in Equation (8).

F.2 Discussion of the FOC for a Single-hospital System

In this subsection, I discuss how PE-owned hospitals' financial leverage affects their negotiated prices with insurers. Taking derivative of the right-hand-side (RHS) of Equation (8) with respect to l_s:

$$\frac{\partial \text{RHS}}{\partial l_s} = \frac{1}{q_{ms}(N_m)} \left(B_{sm} \frac{\partial \Delta V_m}{\partial l_s} + (1 - B_{sm}) \cdot \frac{\partial \Delta \varpi_s}{\partial l_s} \right),$$

in which

$$\begin{aligned} \frac{\partial \Delta V_m}{\partial l_s} &= \frac{\partial \rho(l_s, M_s \backslash m)}{\partial l_s} \left[V_m(N_m \setminus s, \mathbf{p}_{m,-s}) - V_m(N_m - s, \mathbf{p}'_{m,-s}) \right] \\ &= \frac{\theta \exp(\rho h_s(M_s \backslash m) - \theta l_s - \mu)}{(1 + \exp(\rho h_s(M_s \backslash m) - \theta l_s - \mu))^2} \left[V_m(N_m \setminus s, \mathbf{p}_{m,-s}) - V_m(N_m - s, \mathbf{p}'_{m,-s}) \right] \geq 0, \end{aligned}$$

wherein the last inequality comes from the fact that $\theta > 0$ and $[V_m(N_m \setminus j, \cdot) - V_m(N_m - j, \cdot)] \geq 0$ since insurer m is believed to have lower V if the hospital sector becomes more concentrated. Similarly, for $\partial \Delta \varpi_s / \partial l_s$ it has

$$\frac{\partial \Delta \varpi_s}{\partial l_s} = \frac{\theta}{\rho} \text{TA}_s \frac{\exp(\theta l_s + \mu - \rho h_s(M_s \backslash m))}{1 + \exp(\theta l_s + \mu - \rho h_s(M_s \backslash m))} > 0.$$

Therefore, it indicates that $\frac{\partial \text{RHS}}{\partial l_s} \geq 0$ for the FOC. This implies that PE-owned hospitals' negotiated prices are increasing in their chosen leverage in equilibrium.

G Extended Model with Network Formation

In this section, I discuss an extended model with an endogenous network-formation stage and how to estimate it. In the model, any pair of hospitals and insurers in a local market have to decide whether to form a contractible link when they formally negotiates prices. Each insurer reaches out to a subset of hospitals it would like to form negotiation links. The locked-in bilateral relation results in a contractible network for insurer m, denoted by N_m, and a contractible network for hospital system s, denoted by M_s. As a result, insurer m would negotiate a benchmark price with every hospital system s with $J_s \subseteq N_m$, and hospital system s would negotiate a benchmark price with every single insurer $m' \in M_s$.

This leads to an additional optimization step for insurers to endogenously form a contractible network of hospitals, and introduces a set of new inequality moments. The observed network structure in equilibrium implies a subset of necessary conditions: Adding hospitals from outside or dropping hospitals within N_m would generate lower expected payoffs to the insurer than what it earned in equilibrium. Specifically, assume the difference in expected payoffs to insurer m from choosing the equilibrium network N_m and an alternative network N'_m given its information set I_m to be

$$\Delta \Omega^A_m(N_m, N'_m) = \Omega^A_m(N_m, \mathbf{p}_m; N_{-m}, \mathbf{p}_{-m}) - \Omega^A_m(N'_m, \mathbf{p}'_m; N_{-m}, \mathbf{p}_{-m}) + \upsilon_{N_m, N'_m},$$

in which υ_m is conditional mean zero resulting from either measurement or specification errors. Note that the Nash assumption is imposed as insurer m takes the equilibrium network and price bargaining outcomes of other agents as given.[9] Therefore, the inequality moment conditions become

$$\mathbf{E}\left(\Delta \Omega^A_m(N_m, N'_m)\right) = \mathbf{E}\left(\Omega^A_m(N_m, \mathbf{p}_m; N_{-m}, \mathbf{p}_{-m}) - \Omega^A_m(N'_m, \mathbf{p}'_m; N_{-m}, \mathbf{p}_{-m})\right) \geq 0.$$

In terms of choosing N'_m, I permute the observed network by adding or dropping one hospital each time, which is akin to the idea embedded in the network pairwise stability conditions (e.g., Ghili, 2022). There are only certain parameters satisfying that adding or dropping hospitals is less profitable than keeping the observed ones. In the estimation, I punish candidate parameter estimates if they imply that altering observed hospital network is profitable deviation for insurers, i.e.,

[9] It is assumed that if insurer m claims an alternative hospital network, it has to start over and negotiate new prices under the alternative contractible network between m and all hospitals in N'_m while holding the network structure and price bargaining outcomes of other agents fixed.

$$\mathbf{E}\left(\underbrace{\min\left\{0, \Omega_m^A(N_m, \mathbf{p}_m; N_{-m}, \mathbf{p}_{-m}) - \Omega_m^A(N_m', \mathbf{p}_m'; N_{-m}, \mathbf{p}_{-m})\right\}}_{\text{Denoted by } \varphi_{ms}} \Big| Z_{ms}\right) = 0. \tag{OA.4}$$

So, this forms an extra moment condition

$$\mathbf{E}\left(\varphi_{ms} | Z_{ms}\right) = 0.$$

Inequality moments conditions are not only helpful in endogenizing network formation decisions and better matching data, but also beneficial for identifying the insurer's weight on enrollee surplus (α) following a similar argument in Prager and Tilipman (2020). The basic idea is to leverage variations of network inclusion/exclusion decisions of insurers to identify α. For instance, if insurers are observed to include hospitals which are charging high prices and hence the costs of including them are pretty large, it implies that insurers put a high weight on enrollees' expected utility and maps into a high value of α. Estimation results are collected in Table OA.20.

H Corporate Practice of Medicine

The corporate practice of medicine (CPOM) prohibition is a pretty old body of law dated back to early 20th century. Its main goal is to ensure that physicians and doctors are able to exercise professional medical judgment solely based on the health condition and medical needs of patients without interference of fiduciary duty or other pressures from corporations and laypeople. Many states have enacted laws to keep non-physicians or corporate entities out of the practice of medicine. To this day, the CPOM is shaped by varied sources of state legislation, case laws and other guidance from the governing body of government such as state attorneys general and state medical board, and its contents still keeps evolving.

Taking a similar approach to Rice and Strahan (2010), Cain et al. (2017), and Karpoff and Wittry (2018), I construct the CPOM regulation index to measure the regulation strictness across states and years based on three aspects: (1) whether there are state statutes and regulations prohibiting/allowing CPOM; (2) whether there are legal precedents/case law prohibiting/allowing CPOM; (3) whether there are attorney general opinions or medical board of state opinions prohibiting/allowing CPOM.

As the first step, I construct a 3×1 score vector for each state in every year based on *legislature score, case law score,* and *opinion score*. A state will score (minus) one in legislature if it has explicit statutes and regulations prohibiting (allowing) CPOM. If there is no clear standing regarding CPOM, zero will be assigned to the state. Similarly, the state will score (minus) one in case law if it has any legal precedents prohibiting (allowing) CPOM, otherwise a zero score will be assigned. Finally, it will score (minus) one in opinion if the state has any attorney general opinion or medical board opinion prohibiting (allowing) CPOM, otherwise a zero score will be assigned. As a starting point, I construct the initial score vector for 50 states in 2006 based on a summary from Michal et al. (2006). For years after 2006, I track the state-level regulation changes on CPOM prohibition by analyzing key events from the Lexis Advance Research Database and focusing on state-level statues and legislation files, court cases, administrative materials, and other secondary materials. If any relevant events appear for a state in a given year, the score vector would be updated accordingly by adding (deducting) one if the legal event aims to tighten (loosen) the CPOM prohibition. CPOM regulation changes after 2006 across different states is summarized in Table OA.13. For example, Texas expanded the exemptions from the CPOM prohibition by passing a legislative bill (S.B. 894) in 2011, so I change the state statute indicator of Texas from one to zero after 2011.

After constructing a panel of score vectors for 50 states, as the second step, I run a regression of hospitals' PE ownership status on the constructed score vector collected in the first step, after controlling hospitals' time-varying characteristics as well as hospital and year fixed effects. The regression results are demonstrated in Table OA.14. It is observed that all three elements in the score vector have negative coefficients, though the impact of state statutes is more pronounced than the case law and attorney or medical board opinions. It implies that more stringent CPOM regulation within a state will lead to fewer PE investments, and the state statute seems to be a major obstacle for

PE investors. I construct the CPOM regulation index by multiplying the score vector with the respective regression coefficients in Table OA.14. The CPOM regulation index is then calculated as the sum of predicted values of the three indicators for state s in year t multiplied by one hundred. A lower score implies stronger CPOM prohibition. Figure OA.6 exhibits time series of the CPOM regulation indices for a subset of 16 states from 2006 to 2019.

I Numerical Methods

In this section, I discuss the computational algorithm to estimate the model. I provide details about the computation of hypothesized prices if any PE-owned hospital goes bankrupt, steps of implementing GMM, and the optimization algorithm used to search for global solution.

I.1 Expected Negotiated Prices when PE-owned Hospitals Going Bankrupt

In constructing moment conditions and conducting counterfactual analyses, a key step is to compute the expected negotiated prices, p'_{mk}, between insurer m and other hospitals $k \neq s$ when an off-equilibrium scenario occurs in which PE-owned hospital s goes bankrupt in the local market, as depicted in Equation (6).

Computing these prices is recursive. For example, in a local market with two PE-owned hospitals, $N = \{1,2\}$, to calculate the hypothetical prices between other hospitals and insurer m when hospital 1 is missing, it resorts to solving an equation system consisting of Equation (8). But recall that in order to obtain p'_{m2}, namely the hypothetical price between hospital 2 and insurer m when hospital 1 is missing, it has to go deeper along the event tree and analyze a scenario where hospital 2 also goes bankrupt. To sum up, a recursive method to compute the hypothetical prices starts with the scenario at the bottom of the event tree—all PE-owned hospitals are dropped. Then recursively, hypothetical prices are calculated for scenarios of adding one PE-owned hospital back, then two PE-owned hospitals back, and so on, until the moment when all hospitals except the PE-owned hospital s are added back. These prices correspond to the expected negotiated prices, p'_{mk}, that I am looking for. Detailed steps are as follows:

Step 1. Compute $p^{(0)}_{mk}$ of Dropping all PE-owned Hospitals

- Denote $\hat{N}_m$ as the set of hospitals in the observed equilibrium network to negotiate prices with insurer m in a HRR during year t. Among them, identify a subset of PE-owned hospitals, $N^{PE}_m \subseteq \hat{N}_m$, and let $n^{PE} = \left|N^{PE}_m\right|$ be the number of PE-owned hospitals.

- Update choice probabilities and expected utility of insurer m's enrollees in year t, given the choice set $N^{(0)}_m = \hat{N}_m / N^{PE}_m$.

- Compute $p^{(0)}_{mk}$ for $k \in N^{(0)}_m$ by implementing the following matrix inversion: $\mathbf{p}^{(\mathbf{0})}_{\mathbf{m}} = (\mathbf{X_0})^{-1} \cdot \mathbf{Y_0}$, which is derived from the FOC in Equation (8). Specifically, each row of vectors $\mathbf{p}^{(\mathbf{0})}_{\mathbf{m}}$ and $\mathbf{Y_0}$ and square matrix $\mathbf{X_0}$ corresponds to a particular hospital $k \in N^{(0)}_m$. kth entry of $\mathbf{p}^{(\mathbf{0})}_{\mathbf{m}}$ is the hypothetical negotiated price between hospital k and insurer m, $p^{(0)}_{mk}$. kth entry of $\mathbf{Y_0}$ is:

$$(1 - B_{km}) \cdot (\mathrm{mc}_{mk}(\mathrm{PE}_k) - (\mathbf{1}\{\mathrm{NP}_k = 1\}(1 - \mathbf{1}\{\mathrm{PE}_k = 1\}) \cdot \tau_{\mathrm{NP}})) + \alpha \frac{B_{km}}{q^{(0)}_{mk}} \left(W_m(N^{(0)}_m) - W_m(N^{(0)}_m / k) \right),$$

  wherein $q^{(0)}_{mk} = q_{mk}\left(N^{(0)}_m\right)$ is the expected quantity of patients. kth row and lth column of $\mathbf{X_0}$, denoted by$\mathbf{X_0}(k,l)$, is $-\frac{B_{km}}{q^{(0)}_{mk}}\left(q_{ml}(N^{(0)}_m / k) - q^{(0)}_{ml}\right)$ if $k \neq l$; and $\mathbf{X_0}(k,l) = 1$ otherwise.

- Set the iteration number $i = 1$.

Step 2. Compute $p^{(i)}_{mk}$ of Adding Back i PE-owned Hospitals

- For $0 < i < n^{PE}$, all combinations of i PE-owned hospitals out of the collection n^{PE} should be considered. For a particular subset of hospitals, for example, $N_m^{PE(i)} \subseteq N_m^{PE}$ and $i = \left| N_m^{PE(i)} \right|$, I add them back to the choice set in step 1. Denote the new set of hospitals by$N_m^{(i)} = \left\{ \hat{N}_m / N_m^{PE} \right\} \cup N_m^{PE(i)}$.

- Update choice probabilities and expected utility of insurer m's enrollees in year t, conditional on the updated choice set, $N_m^{(i)}$.

- For PE-owned hospital $k \in N_m^{PE(i)}$, update its expected revenue losses, $h_k(M_k \backslash m)$, and bankruptcy probability, $\rho^{(i)}(l_k, M_k \backslash m)$, if k doesn't reach an agreement with m given its leverage l_k, while holding the equilibrium prices between hospitals and insurers other than m fixed. Note that if the network in equilibrium is under consideration, $\rho^{(i)}(l_k, M_k \backslash m) = \rho(l_k, M_k \backslash m)$, i.e., identical to the expected bankruptcy probability in equilibrium.

- Compute $p_{mk}^{(i)}$ for $k \in N_m^{(i)}$ by implementing the following matrix inversion: $\mathbf{p_m^{(i)}} = (\mathbf{X_i})^{-1} \cdot \mathbf{Y_i}$. Similarly, each row of vectors $\mathbf{p_m^{(i)}}$ and $\mathbf{Y_i}$ and square matrix $\mathbf{X_i}$ corresponds to a particular hospital $k \in N_m^{(i)}$. kth entry of $\mathbf{p_m^{(i)}}$ is the hypothetical negotiated price between hospital k and insurer m, $p_{mk}^{(i)}$. When hospital k is a non-PE-owned hospital, kth entry of $\mathbf{Y_i}$ is:

$$(1 - B_{km}) \cdot (\text{mc}_{mk}(\text{PE}_k) - (\mathbf{1}\{\text{NP}_k = 1\}(1 - \mathbf{1}\{\text{PE}_k = 1\}) \cdot \tau_{\text{NP}})) + \alpha \frac{B_{km}}{q_{mk}^{(i)}} \left(W_m(N_m^{(i)}) - W_m(N_m^{(i)}/k) \right),$$

wherein $q_{mk}^{(i)} = q_{mk}\left(N_m^{(i)}\right)$ is the expected quantity of patients given the updated choice set. When hospital k is a PE-owned hospital, kth entry of $\mathbf{Y_i}$ is:

$$\begin{aligned}(1 - B_{km}) \cdot (\text{mc}_{mk}(\text{PE}_k) - (\mathbf{1}\{\text{NP}_k = 1\}(1 - \mathbf{1}\{\text{PE}_k = 1\}) \cdot \tau_{\text{NP}})) + \alpha \frac{B_{km}}{q_{mk}^{(i)}} \left(W_m(N_m^{(i)}) - W_m(N_m^{(i)}/k) \right) \\ + \frac{B_{km}}{q_{mk}^{(i)}} \rho^{(i)}(l_k, M_k \backslash m) \left[\sum_{k' \in N_m^{(i)}/k} q_{mk'}(N_m^{(i)}/k) p_{mk'}^{(i-1)} \right] + \frac{1 - B_{km}}{q_{mk}^{(i)}} \text{TA}_k \ln\left(1 + \exp(\theta l_k - h_k^{(i)}(M_k \backslash m))\right),\end{aligned}$$

wherein $p_{mk'}^{(i-1)}$ comes from the $i-1$th iteration in which all possible combinations of $i-1$ PE-owned hospitals have been gone through. When hospital k is non-PE-owned, kth row and lth column of $\mathbf{X_i}$, namely$\mathbf{X_i}(k,l)$, is $-\frac{B_{km}}{q_{mk}^{(i)}} \left(q_{ml}(N_m^{(i)}/k) - q_{ml}^{(i)} \right)$ if $k \neq l$; and $\mathbf{X_i}(k,l) = 1$ otherwise. When hospital k is PE-owned, $\mathbf{X_i}(k,l)$ becomes

$$-\frac{B_{km}}{q_{mk}^{(i)}} \left(q_{ml}(N_m^{(i)}/k) - q_{ml}^{(i)} \right) + \frac{B_{km}}{q_{mk}^{(i)}} \rho^{(i)}(l_k, M_k \backslash m) q_{ml}(N_m^{(i)}/k)$$

if $k \neq l$; and $\mathbf{X_i}(k,l) = 1$ otherwise.

- Stop the iteration until $i = n^{PE} - 1$; The resulting prices are the hypothetical negotiated prices $\{p'_{mk}\}_{k \in \{\text{PE-backed Hospitals}\}}$.

I.2 Generalized Method of Moments

The moment vector is constructed as $\mathbf{g}(w_i; \text{Param}) = \begin{pmatrix} \varepsilon_{ms} \\ \xi_s \\ \zeta_s \end{pmatrix} \otimes Z_{ms}$ where $\otimes$ denotes the Kronecker product. The objective function of GMM is formulated as

$$J(\text{Param}) = \left[N^{-1} \sum_{i=1}^{N} \mathbf{g}(w_i; \text{Param}) \right]' \Xi \left[N^{-1} \sum_{i=1}^{N} \mathbf{g}(w_i; \text{Param}) \right],$$

wherein $\varXi$ is the optimal weighting matrix.[10] I implement a two-step procedure and obtain the optimal weighting matrix in the first step. Specifically, I estimate parameters using $\varXi \equiv I$ where I is the identity matrix in the first step. This will produce a consistent though not efficient estimate Param_{1st}.

For the optimal weighting matrix, it is the inverse of the variance matrix of $\mathbf{g}(w_i;\text{Param})$. I plug Param_{1st} into $\mathbf{g}(\cdot)$ and leverage the influence function technique to calculate its variance matrix. An influence function is a function of the sample data in which its mean has the identical asymptotic distribution as the estimator. Therefore, the asymptotic covariance of two estimators can be computed as the covariance of their influence functions. More discussions can be found in Newey and McFadden (1994), Erickson and Whited (2002), and Bazdresch et al. (2018). After obtaining the estimate for the optimal weighting matrix $\hat{\varXi}$, I insert it into the objective function and search the optimal solution in the second step.

I.3 Optimization Algorithm

The goal is to find a global solution for the GMM objective function $J(\text{Param})$. I exploit a slightly-modified version of the TikTak global optimization algorithm introduced by Guvenen (2012). In Arnoud et al. (2019), authors compare various global algorithms and conclude that the TikTak outperforms others on both the math test functions and the economic application. Detailed steps are described below:

Step 1. Parallel Local Optimization

- Determine bounds for each parameter. For a subset of parameters, their bounds are clear enough based on the model specification and previous estimates in literature. For rest of them, I provide large enough bounds to let data speak.
- Produce a sequence of Halton's quasi-random points of length N, denoted by $H_N = (h_1, h_2, \cdots, h_N)$.
- Using these N Halton's points as initial guesses, utilize the Nelder-Mead method to search for the local minimizer by parallel computation. Let the vector of function values be $(J(h_1^*), J(h_2^*), \cdots, J(h_N^*))$ where $(h_1^*, h_2^*, \cdots, h_N^*)$ is a sequence of local minimums corresponding to each initial guess. Rank the local minimized function values in descending order and pick the top 1% of local minimums, denoted by $H^* = \left(h_{l1}^*, h_{l2}^*, \cdots, h_{ln}^*\right)$.[11]

Step 2. Global Optimization

- Set the global iteration number $i = 1$. Store h_{l1}^* as well as its function value $J(h_{l1}^*)$ in the "`GlobalData.txt`" file.
- For iteration number $i > 1$, read the function value and corresponding parameter vector of the smallest recorded local minimum in the "`GlobalData.txt`" file. Let the lowest function value found so far as of iteration $i-1$ be J_{i-1}^{cand} and the associated parameter vector be h_{i-1}^{cand}.
- Generate a new initial guess h_i^{guess} as the convex combination of the ith element of $H^*$and the parameter candidate h_{i-1}^{cand}: $h_i^{guess} = (1-\theta_i)h_{li}^* + \theta_i h_{i-1}^{cand}$ where the weight parameter θ_i satisfies that $0 \leq \theta_i < 1$ and increases with i.
- In iteration i, use h_i^{guess} as an initial guess and the Nelder-Mead method to search for the local minimum. Store the outcome in the ith column of "`GlobalData.txt`."

[10] Notice it might be the case that different moment condition comprises of incongruent number of observations N. So I compute the optimal weighting matrix using the influence function technique.

[11] I modify the original TikTak algorithm in this step by searching for local minimums with each Halton's point as the initial guess, while the original algorithm in Arnoud et al. (2019) directly evaluates objective function values on these Halton's points and chooses a subset of lowest points. The purpose of newly-added local minimization step is to ensure we are searching the most promising areas in the parameter space.

- Update $i = i + 1$ and repeat the above steps until going through all elements in H^*.
- Return the point with the lowest function value in "`GlobalData.txt`" as the global minimum.

Step 3. Polishing Final Results

- The final step is a "polishing phase." It uses the global minimum found in Step 2 as an initial guess, and utilizes the local search algorithm with a more stringent stopping rule and a larger function-iteration number.

I.4 Simulation in Counterfactuals

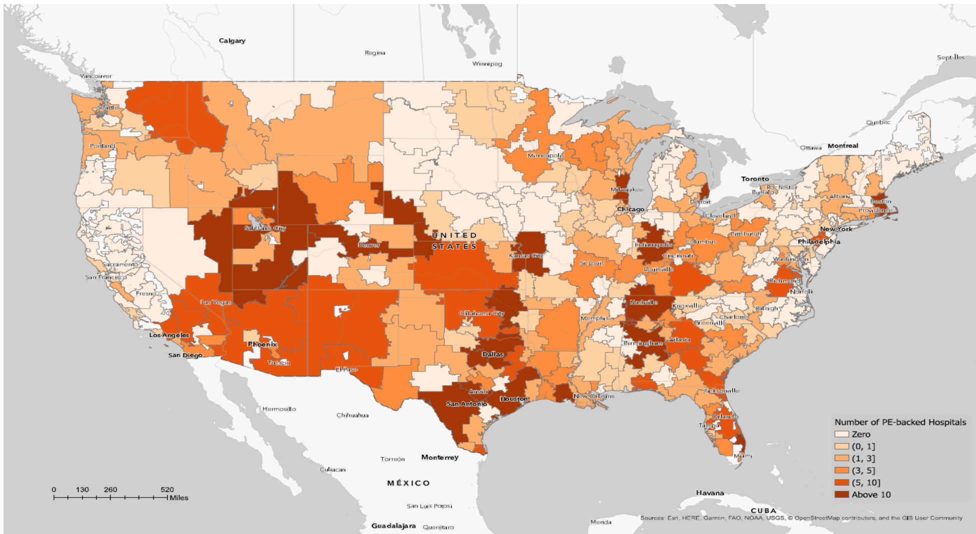
In the first and second counterfactual exercises, I simulate the equilibrium negotiated prices when a subset of hospitals are (not) PE-owned. Here I detail the simulation procedure for the first counterfactual.

- Make leverage level l and network links N_{ms} the same as what is observed in the data.
- Given the model estimates, for iteration number $i \geq 1$, use the first-order condition for price bargaining to simulate negotiated prices p_{ms}^k with following steps:
  - For iteration number $i \geq 1$, use FOC condition (8) to update $p_{ms}^{k(i)}$, where $p_{ms}^{k(1)}$ is the price vector observed in the sample.
  - The iteration stops when $|\max_{m,s}\{p_{ms}^{k(i+1)} - p_{ms}^{k(i)}\}| \leq \varepsilon$, where ε is a preset tolerance level equal to 0.01. The converged price $p_{ms}^{k(i+1)}$ is defined as p_{ms}^k.

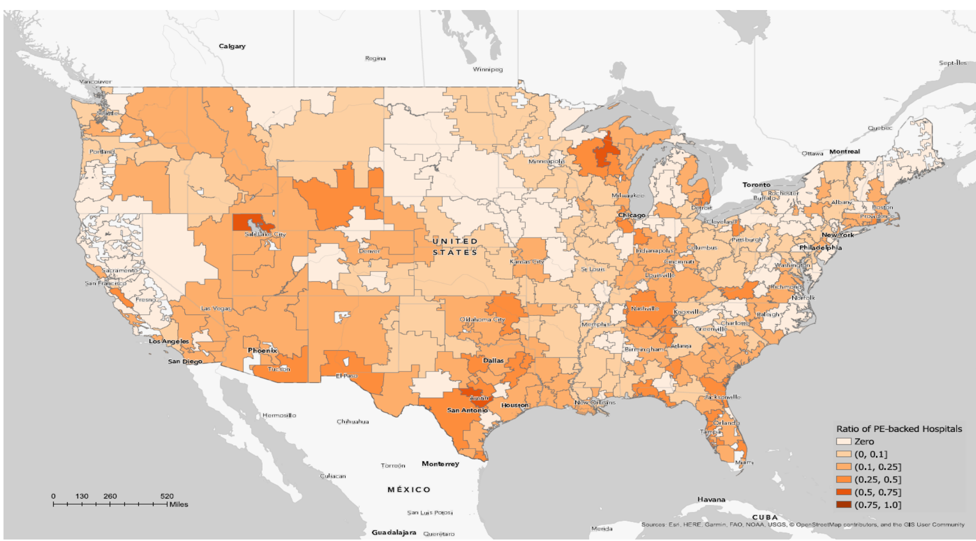
J Additional Figures and Tables

J.1 Figures

Figure OA.1: Geographic Distribution of PE-owned Hospitals



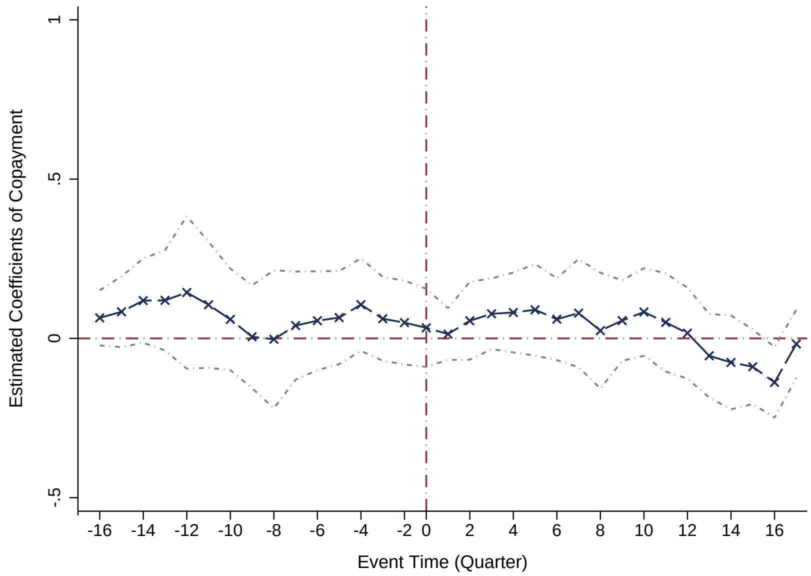
(a) Number of PE-owned Hospitals



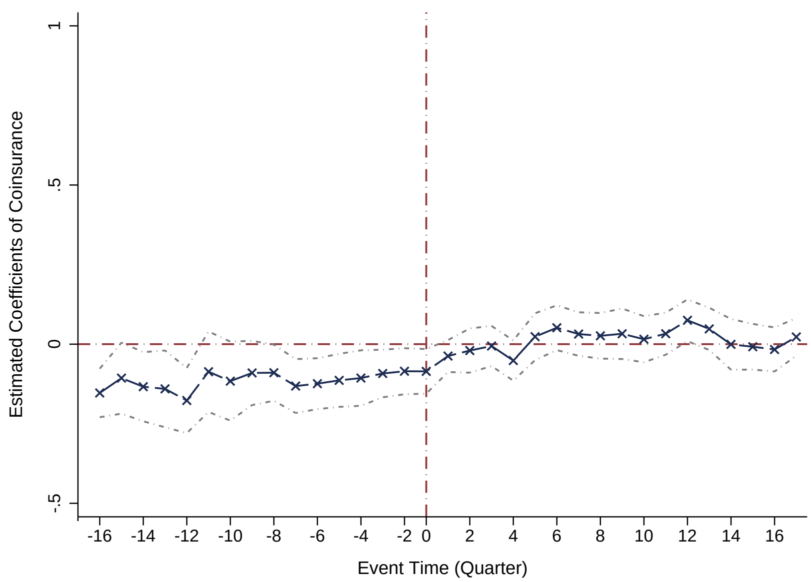
(b) Ratio of PE-owned Hospitals

This figure shows the geographic distribution of PE-owned hospitals at the hospital referral region (HRR) level between 2006 and 2019. Panel A counts the number of hospitals that were ever involved in any PE buyouts in each HRR. Panel B exhibits the ratio of the number of PE-target hospitals to the total number of hospitals in each HRR.

Figure OA.2: Dynamic Effects of PE Intervention on Patient Payments



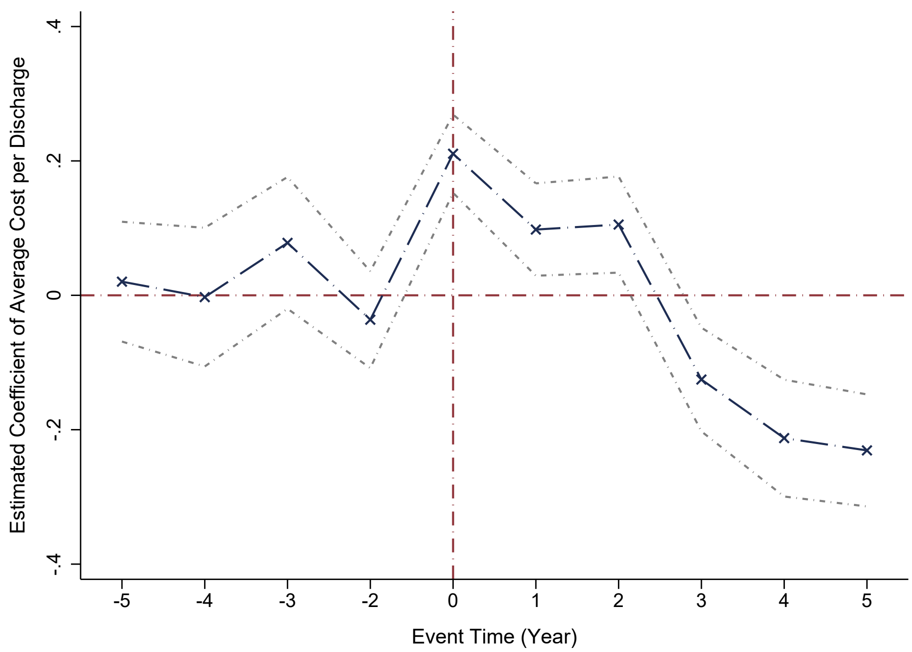
(a) Dynamic Estimates of Log of Copay



(b) Dynamic Estimates of Log of Coinsurance

This figure replicates the event studies in Figure 1, except I use the natural logarithm of one plus patients' copayment amounts as the dependent variable in Panel A, and the natural logarithm of one plus patients' coinsurance amounts as the dependent variable in Panel B. All other details are the same as in Figure 1.

Figure OA.3: Dynamic Estimates of Average Cost per Adjusted Discharge

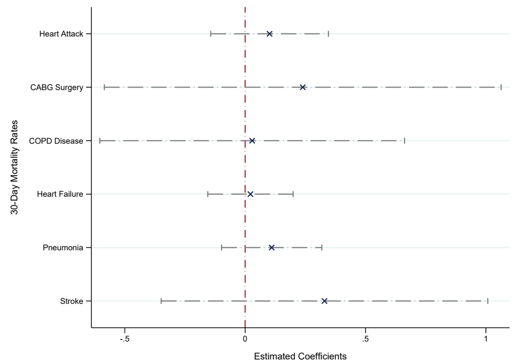


This figure presents the dynamic treatment effects of PE buyouts on average costs per adjusted discharge. The unit of observation is the hospital-year. It plots the OLS coefficients α_τ from the following regression:

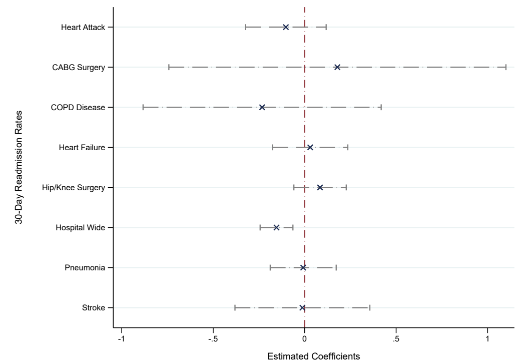
$$Y_{jt} = \sum_{\tau=-5,\tau\neq-1}^{5} \alpha_\tau \mathrm{PE}_{j,\{t-t_0=\tau\}} + \mathrm{Controls} + \mathrm{FEs} + \varepsilon_{jt},$$

wherein Y_{jt} is the cost per adjusted discharge for hospital j in year t. t_0 denotes the first year when $\mathrm{PE}_j = 1$ for hospital j. The coefficient with $\tau = -1$ is excluded as a benchmark category. Any years beyond 5 (-5) are binned into the 5th (-5th) year. All standard errors are clustered at the hospital level. Gray dotted lines represent 95% confidence intervals.

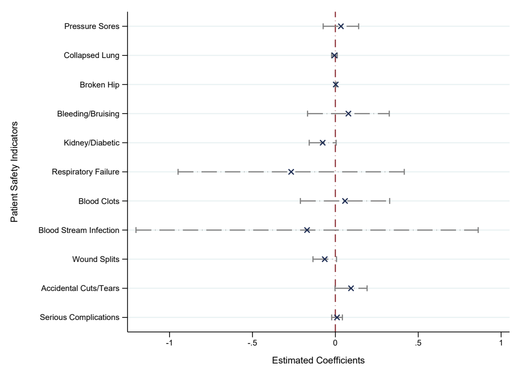
Figure OA.4: Estimates for Hospital Quality and Patient Satisfaction



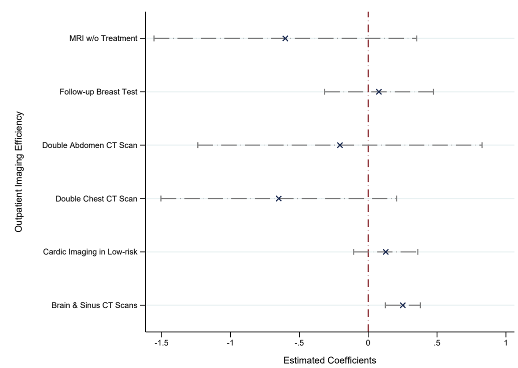
(a) 30-day Mortality Rates



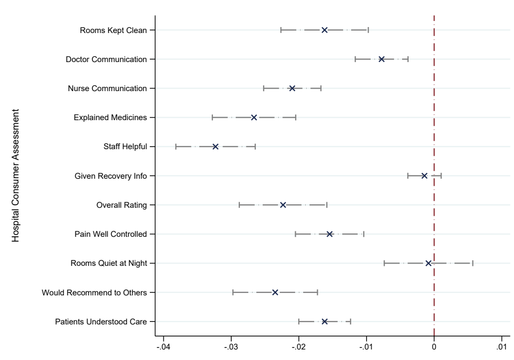
(b) 30-day Readmission Rates



(c) Patient Safety Indicators



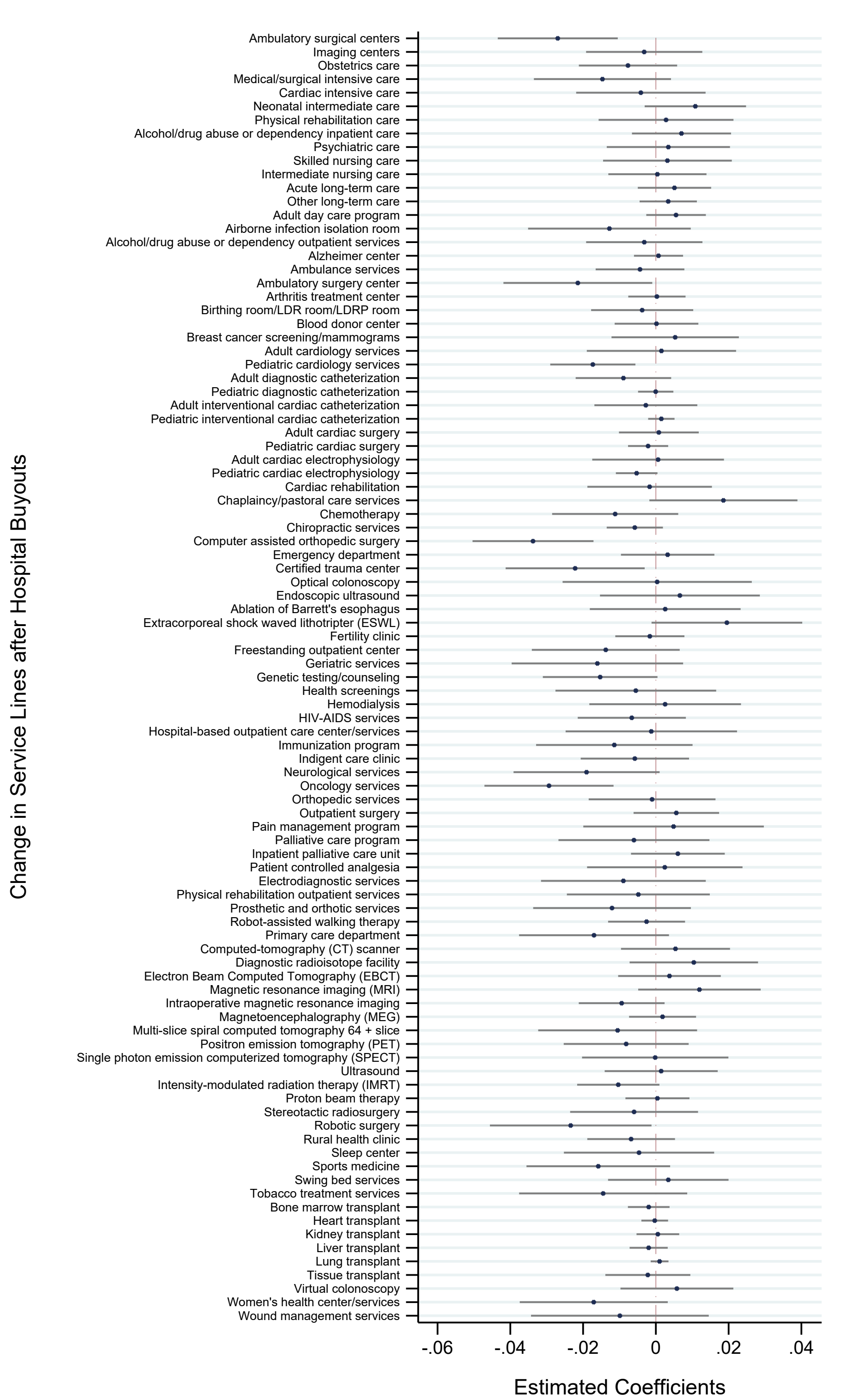
(d) Outpatient Imaging Efficiency



(e) Hospital Consumer Assessment

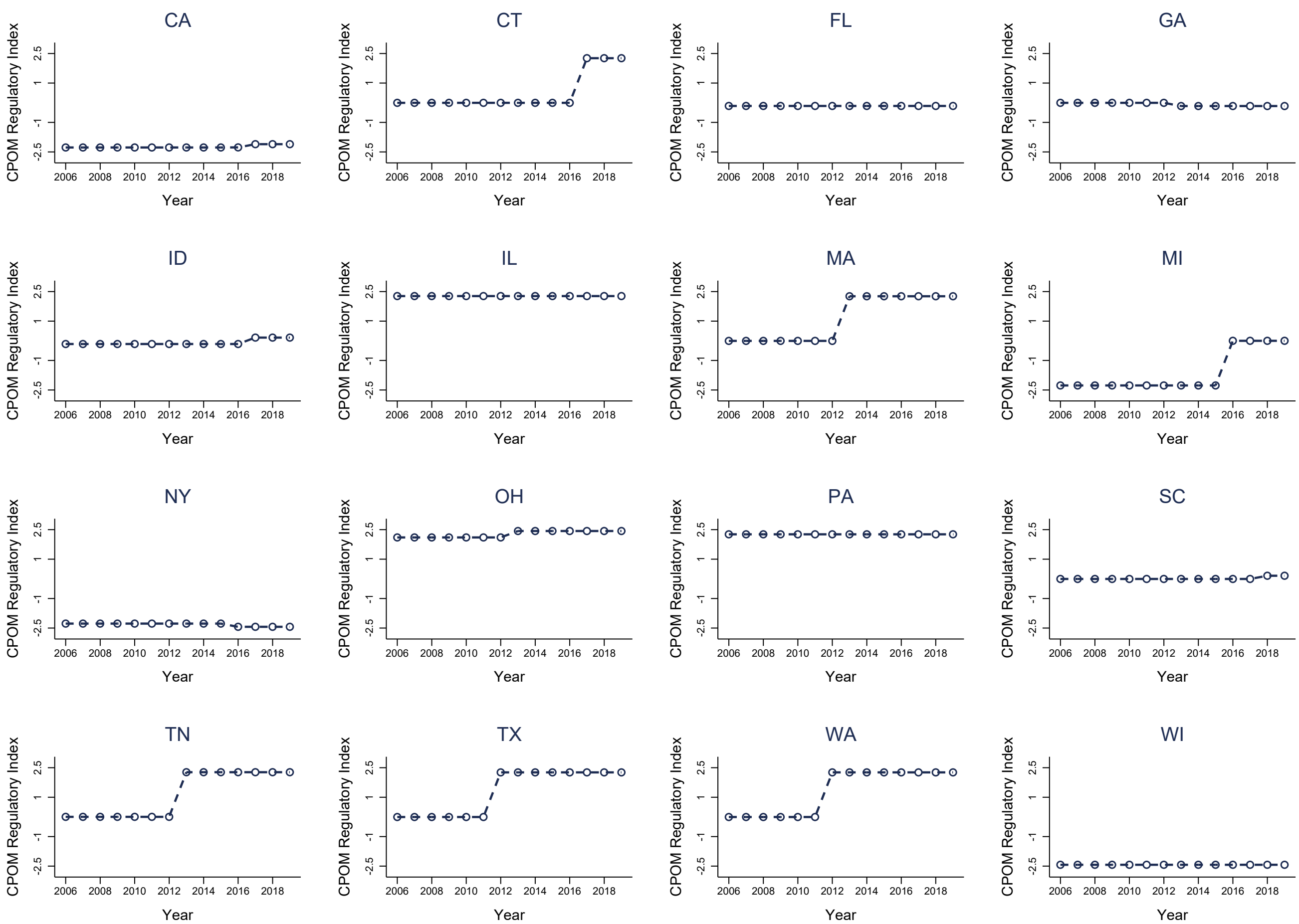
This figure exhibits the impacts of PE buyouts on hospital service quality. Panels A to E use five different sets of quality measures, including 30-day mortality rates, 30-day readmission rates, patient safety indicators, outpatient imaging efficiency, and hospital consumer assessment scores. The y-axis denotes the names of service quality measures. All standard errors are clustered at the hospital level. Capped spikes represent 95% confidence intervals.

Figure OA.5: Regression Coefficients for Changes in Hospital Service Lines



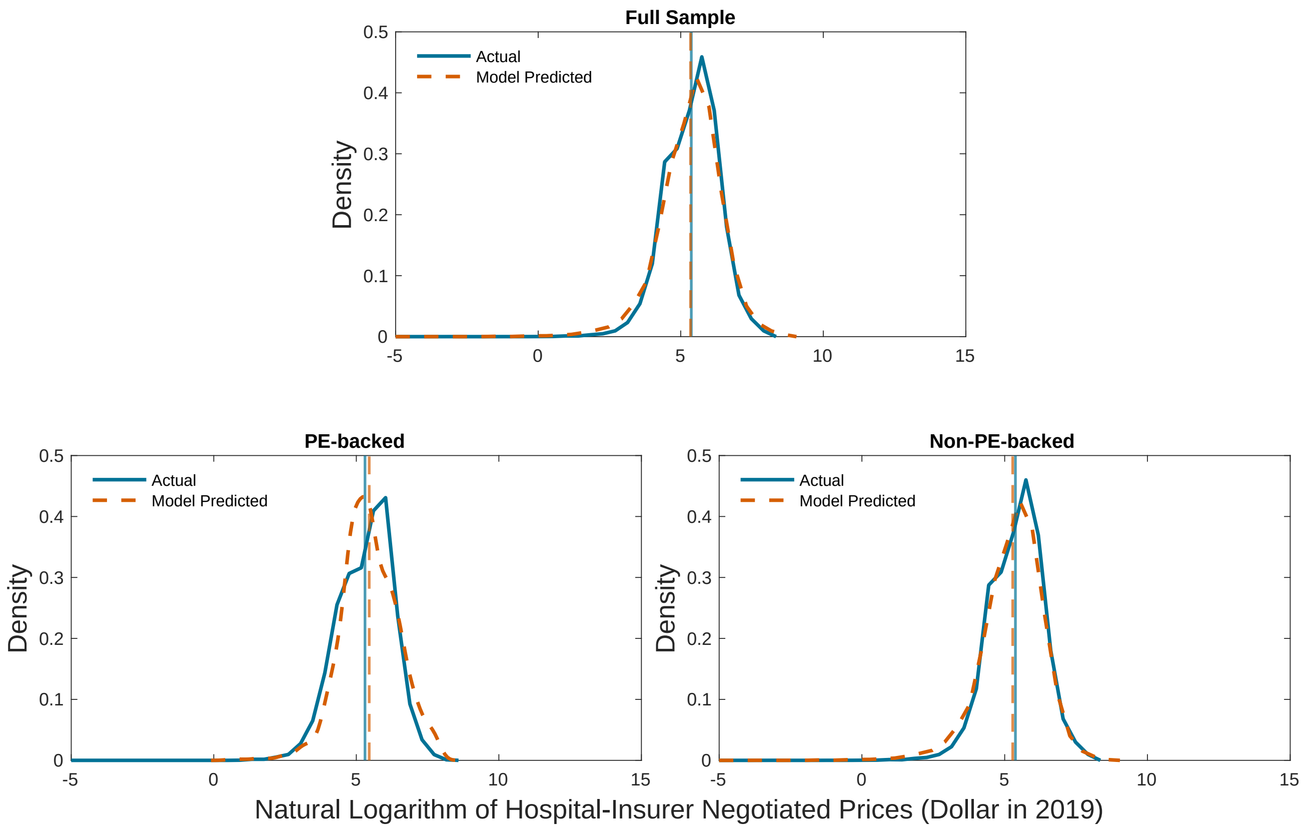
This figure exhibits the estimated coefficients of the PE dummy in Regression (1) for 95 categories of hospital service lines. The y-axis denotes the names of service lines within a hospital. All standard errors are clustered at the hospital level. Gray lines represent 95% confidence intervals.

Figure OA.6: Constructed CPOM Regulation Index across States



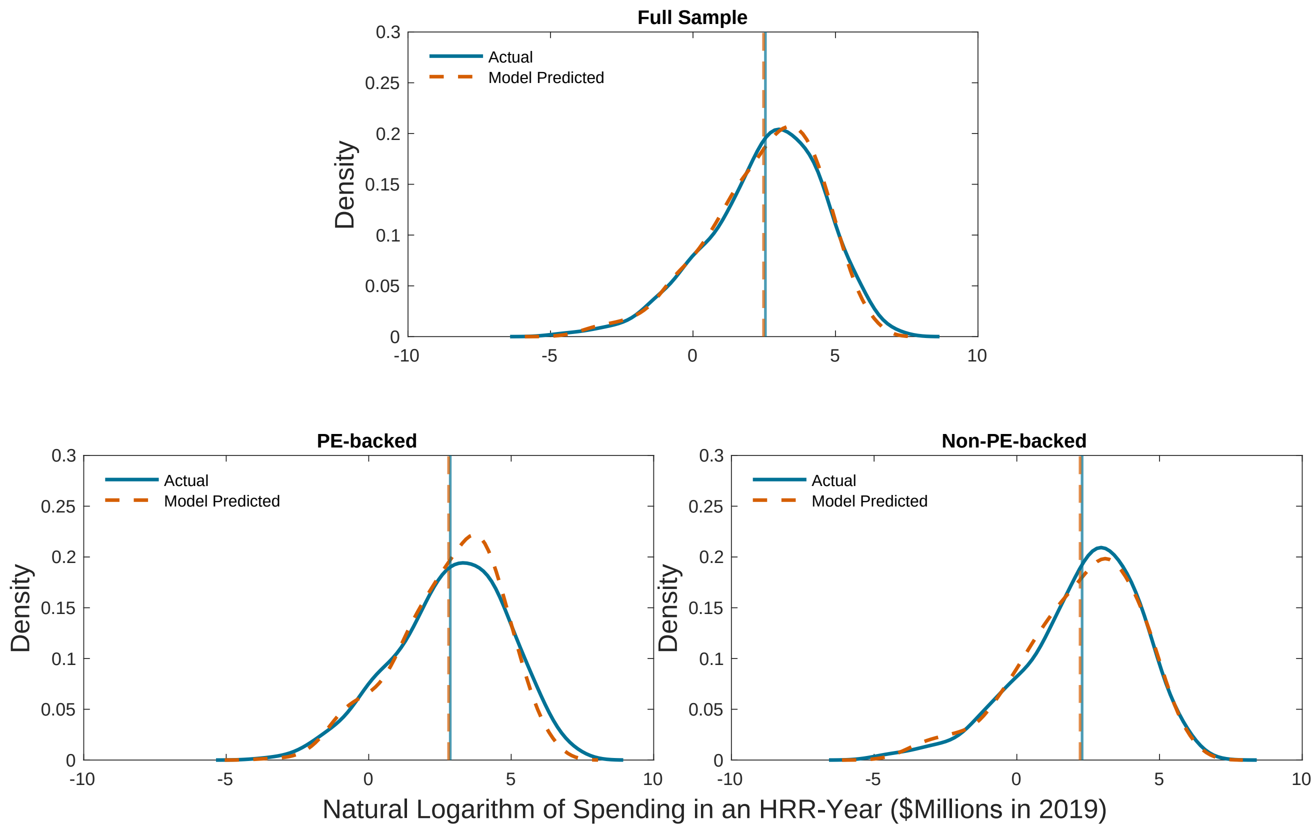
This figure shows the time series of the constructed CPOM regulation indices for 16 states between 2006 and 2019. The detailed construction procedure of the CPOM regulation index is collected in Section H.

Figure OA.7: Model Fit: Negotiated Prices



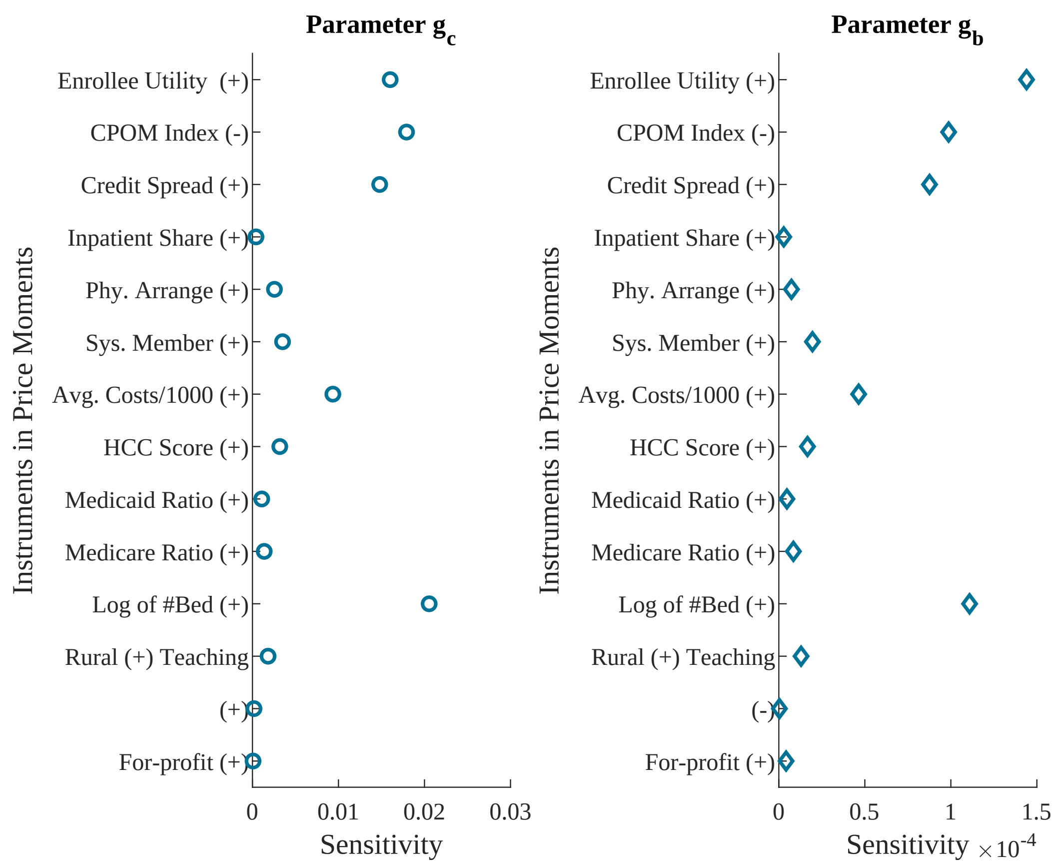
This figure demonstrates the kernel density plots of the predicted and observed distributions of negotiated prices between hospitals and insurers on a log scale for the full sample, the subsample of hospitals ever targeted by PE, and the subsample of non-PE-backed hospitals. All years are pooled, and prices are adjusted to dollars in 2019 by GDP deflators. An observation in the sample is a hospital–insurer–year. Vertical lines denote the mean of the respective distributions. Predicted prices are simulated based on the estimates from Tables 5 and 6.

Figure OA.8: Model Fit: HRR Outpatient Spending



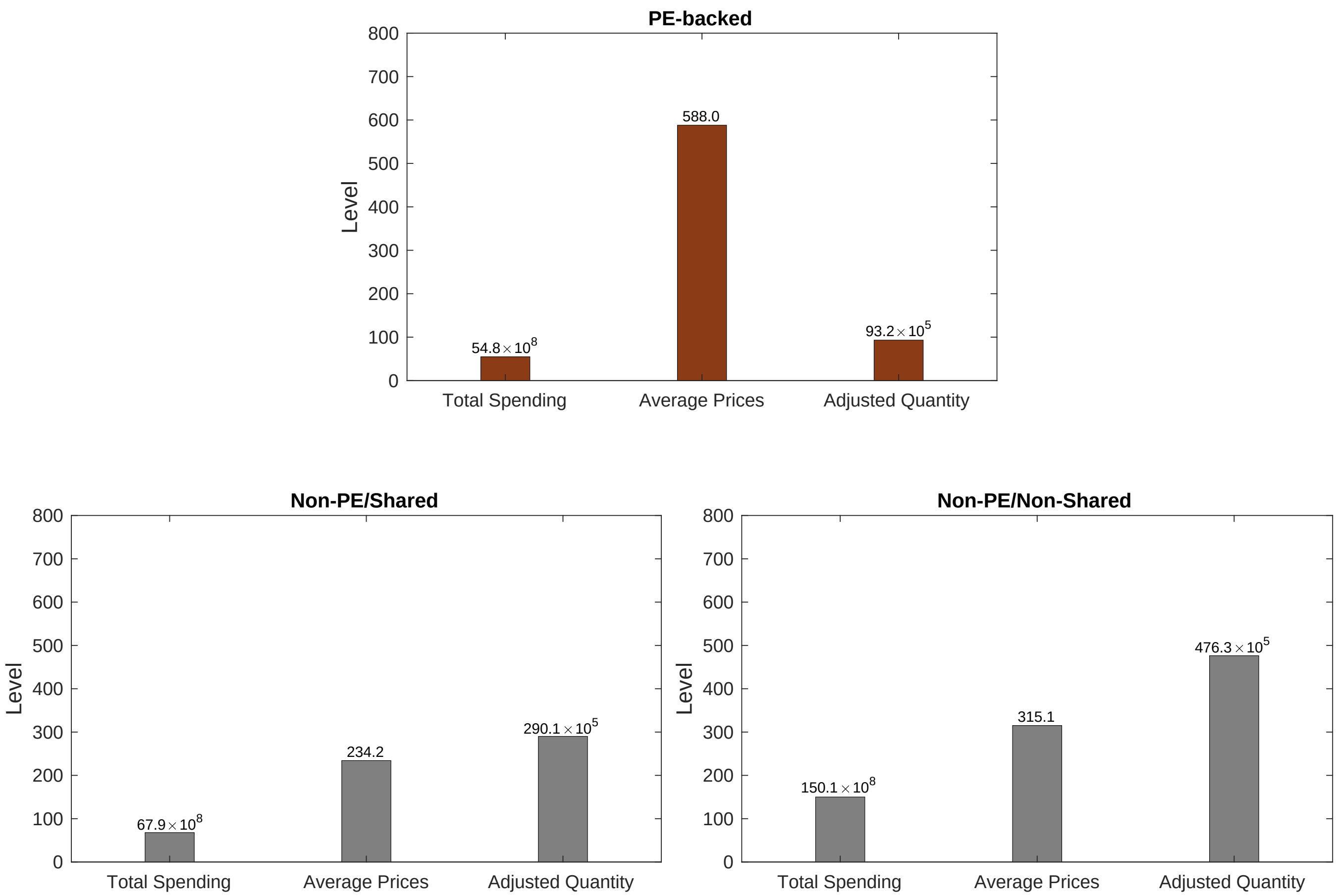
This figure demonstrates the kernel density plots of the predicted and observed distributions of total outpatient spending in local markets ($millions) on a log scale for the full sample, the subsample of HRRs that ever had PE-backed hospitals, and the subsample of HRRs that were never targeted by PE. All years are pooled, and prices are adjusted to dollars in 2019 by GDP deflators. An observation in the sample is an HRR-year. Vertical lines denote the mean of the respective distributions. Predicted spending is simulated based on the estimates from Tables 5 and 6.

Figure OA.9: Sensitivity of g_c and g_b to Local Violations of the Exclusion Restrictions



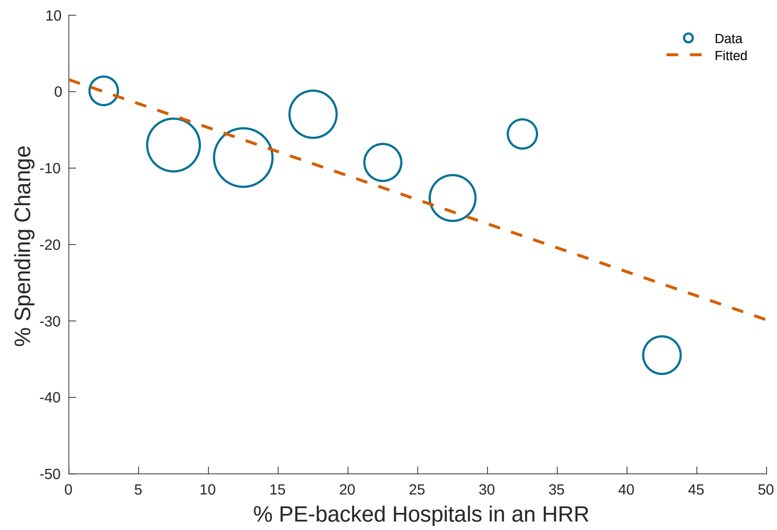
This figure shows the absolute value of the sensitivity measure $\Lambda\Omega_{ZZ}$ following Andrews et al. (2017), where Λ is sensitivity of parameters to estimation moments, and Ω_{ZZ} is variance-covariance matrix of the instruments. The sign of $\Lambda\Omega_{ZZ}$ is shown in parentheses. Instrumental variables (including other exogenous variables), which are a subset of selective instruments used in constructing price moments, are indicated on the y-axis. Panel A shows the sensitivity of parameter g_c, while Panel B shows the sensitivity of parameter g_b.

Figure OA.10: 1st Counterfactual: Model-predicted Amounts across Groups

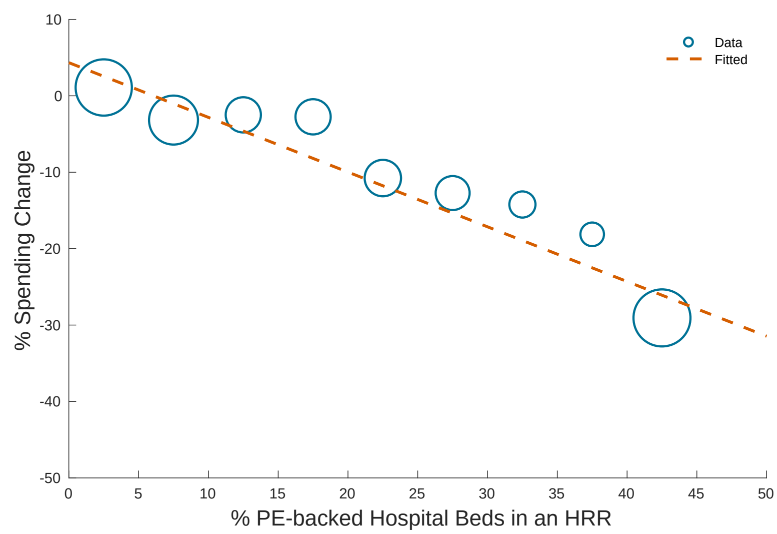


This figure presents the model-predicted outcomes across groups. The top panel exhibits the model-predicted outcomes of the *PE-backed* group, which includes hospitals under PE ownership. The bottom-left panel exhibits the model-predicted outcomes for the *Non-PE/Shared* group, which consists of non-PE-backed hospitals that share common insurers with the PE-backed one in an HRR. The bottom-right panel exhibits the model-predicted outcomes of the *Non-PE/Non-Shared* group, which includes other hospitals that do not belong to the previous two groups. Remaining details are the same as Figure 4.

Figure OA.11: 1st Counterfactual: Spending Changes across Regions



(a) %PE-owned Hospital of HRRs and Spending Change in Counterfactual



(b) %PE-owned Hospital Beds of HRRs and Spending Change in Counterfactual

This figure presents how the hospital spending varies across regions with different degrees of PE intervention in the counterfactual of restricting PE ownership. The unit of observation is an HRR-year. Observations are grouped for every five-percent interval on the x-axis. In Panel A, the x-axis denotes the percentage of PE-back hospitals in an HRR of a year. In Panel B, the x-axis denotes the percentage of PE-owned hospital beds in an HRR of a year. The y-axis denotes the percentage change in hospital spending. Each circle corresponds to the mean percentage change in a bin. Circle size represents the number of observations within each bin. The dashed line denotes the best-fit line.

J.2 Tables

Table OA.1: Summary Statistics of PE Deals

This table reports summary statistics for the sample of PE hospital deals in the United States between 2006 and 2019. The unit of observation is the PE deal in Panel A, and the hospital in Panels B and C. Panel A focuses on the classification of deal types, and Panels B and C focus on the characteristics of PE-target hospitals and their ownership statuses prior to PE intervention.

Panel A: Classification of PE deals

Deal Type	# of Deal	Avg. # of Hospitals
Add-on	149	4.85
Private to Private	33	13.71
PE Growth/Expansion	32	4.42
Secondary Buyout	18	9.06
Public to Private	6	26
Management Buyout	5	9.40
Total	243	6.91

Panel B: Characteristics of PE-target hospitals

	Yes	No
Rural Area	153	685
Teaching School	12	826
Critical Access	66	525

Panel C: Previous ownership Status

Ownership Status	# of Hospitals
Local Government/Hospital Authority	34
Church Operated	105
Other Not-for-profit	125
For-profit (corporation)	466
For-profit (partnership)	101
For-profit (individual)	7

Table OA.2: Summary Statistics

This table reports summary statistics for the sample of outpatient visits aggregated from the DRG insurance claims between 2013 and 2019. The unit of observation is the patient visit in Panel A, the hospital in Panel B, the county in Panel C, and the HRR at Panel D. Summary statistics are presented for the full sample and the subsamples of "Never Treated" and "Ever Treated." The last column reports the difference between these subsamples. Patient visits are categorized as "Never Treated" if the visiting hospital is non-PE-backed, and "Ever Treated" otherwise. Counties and HRRs are categorized as "Never Treated" if no hospitals in the region were ever owned by PE across the sample period, and "Ever Treated" otherwise. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively, clustering at the hospital level.

	Full Sample			Never Treated	Ever Treated	
Variable	Mean	SD	Median	Mean	Mean	Diff
Panel A: Patient Visit Level						
Female	0.620	0.485	1.000	0.620	0.622	-0.002
Patient Age	45.720	23.589	50.000	45.627	46.582	-0.955
Travel Time (Minutes)	41.677	48.447	31.517	41.932	39.025	2.907
Visit Before	0.472	0.499	0.000	0.478	0.378	0.100***
Service-mix Weight	6.508	49.604	1.435	6.357	9.017	-2.660***
Charge Amount ($)	2,675.287	8,508.866	726.308	2,625.482	3253.815	-628.333***
Total Paid Amount ($)	814.324	77,525.560	193.316	810.419	810.158	0.261
Patient Paid Amount ($)	143.182	77,484.770	0.000	142.408	148.095	-5.687
Payer Paid Amount ($)	671.422	2,440.494	141.614	668.283	662.385	5.898
Panel B: Hospital Level						
Num of Beds	150.103	184.304	82.000	149.929	152.566	-2.637
Total Personnel	841.584	1,423.151	346.000	855.721	642.016	213.705***
Teaching (%)	4.689	21.140	0.000	4.939	1.155	3.784***
Rural Area (%)	34.759	47.621	0.000	36.060	16.399	19.661***
Inpatient Days (k)	36.342	52.029	17.429	36.490	34.261	2.229
Outpatient Visits (k)	116.124	209.429	47.668	118.507	82.482	36.025***
Medicare Ratio (%)	48.676	22.775	51.893	48.417	52.328	-3.911***
Medicaid Ratio (%)	18.438	16.734	15.168	18.589	16.303	2.286***
Panel C: County Level						
Poverty Rate (%)	15.922	6.032	15.100	15.933	15.821	0.111
Median Household Income ($k)	46.487	12.366	44.312	46.016	50.901	-4.885***
Insurance Coverage (%)	88.291	5.647	89.115	89.063	86.252	2.811***
Private Insurance Coverage (%)	68.784	9.461	69.321	70.091	65.339	4.752***
Medicaid Coverage (%)	17.414	6.499	16.767	17.057	18.355	-1.298**
Medicare Coverage (%)	16.147	4.370	15.590	16.187	16.041	0.146
Panel D: HRR Level						
HHI in Hospital Beds	0.183	0.126	0.154	0.212	0.146	0.066***
HHI in Inpatient Days	0.209	0.143	0.171	0.241	0.170	0.071***
Num of Hospitals	19.560	18.314	14.000	14.735	25.671	-10.936***

Table OA.3: Robustness Check—Inverse Hyperbolic Sine Transformation

This table replicates Columns (1) to (3) in Table 1, except I use the inverse hyperbolic sine transformation, that is, $\tilde{y} = \ln(y + \sqrt{y^2+1})$, of total paid amounts, payer paid amounts, and patient paid amounts as the dependent variable. All other details are the same as in Table 1.

Panel A: Transformation of total paid amount

PE	0.344**	0.349**	0.355**	0.365**
	(2.099)	(2.218)	(2.307)	(2.367)
Hospital Controls	N	N	N	Y
Patient Controls	N	N	Y	Y
Diagnosis×Year FE	N	Y	Y	Y
Hospital×Payer FE	Y	Y	Y	Y
Adj. R^2	0.226	0.279	0.301	0.301
Observations	70,861,556	70,861,542	70,861,542	70,861,542

Panel B: Transformation of patient paid amount

PE	0.015	0.021	0.046	0.055*
	(0.368)	(0.545)	(1.516)	(1.815)
Hospital Controls	N	N	N	Y
Patient Controls	N	N	Y	Y
Diagnosis×Year FE	N	Y	Y	Y
Hospital×Payer FE	Y	Y	Y	Y
Adj. R^2	0.293	0.350	0.355	0.355
Observations	70,861,556	70,861,542	70,861,542	70,861,542

Panel C: Transformation of payer paid amount

PE	0.338**	0.332**	0.320**	0.320**
	(2.118)	(2.163)	(2.090)	(2.076)
Hospital Controls	N	N	N	Y
Patient Controls	N	N	Y	Y
Diagnosis×Year FE	N	Y	Y	Y
Hospital×Payer FE	Y	Y	Y	Y
Adj. R^2	0.122	0.162	0.176	0.176
Observations	70,861,556	70,861,542	70,861,542	70,861,542

Table OA.4: Robustness Check—Subsample of General Acute Hospitals

This table replicates Columns (1) to (3) in Table 1, except I restrict to a subsample of insurance claims from general acute-care hospitals. All other details are the same as in Table 1.

Panel A: Logarithm of total paid amount

PE	0.299**	0.304**	0.310**	0.320**
	(2.032)	(2.149)	(2.251)	(2.319)
Hospital Controls	N	N	N	Y
Patient Controls	N	N	Y	Y
Diagnosis×Year FE	N	Y	Y	Y
Hospital×Payer FE	Y	Y	Y	Y
Adj. R^2	0.213	0.274	0.299	0.299
Observations	64,625,150	64,625,136	64,625,136	64,625,136

Panel B: Logarithm of patient paid amount

PE	0.008	0.015	0.037	0.045
	(0.267)	(0.449)	(1.475)	(1.681)
Hospital Controls	N	N	N	Y
Patient Controls	N	N	Y	Y
Diagnosis×Year FE	N	Y	Y	Y
Hospital×Payer FE	Y	Y	Y	Y
Adj. R^2	0.280	0.342	0.347	0.347
Observations	64,616,826	64,616,812	64,616,812	64,616,812

Panel C: Logarithm of payer paid amount

PE	0.294**	0.288**	0.278**	0.279**
	(2.053)	(2.092)	(2.031)	(2.023)
Hospital Controls	N	N	N	Y
Patient Controls	N	N	Y	Y
Diagnosis×Year FE	N	Y	Y	Y
Hospital×Payer FE	Y	Y	Y	Y
Adj. R^2	0.113	0.159	0.175	0.175
Observations	64,624,724	64,624,710	64,624,710	64,624,710

Table OA.5: Robustness Check—Exclude PE Growth/Expansion Deals

This table replicates Columns (1) to (3) in Table 1, except I code PE = 0 for those hospitals involved in PE growth/expansion deals. All other details are the same as in Table 1.

Panel A: Logarithm of total paid amount

PE	0.277*	0.289**	0.295**	0.304**
	(1.916)	(2.101)	(2.204)	(2.260)
Hospital Controls	N	N	N	Y
Patient Controls	N	N	Y	Y
Diagnosis×Year FE	N	Y	Y	Y
Hospital×Payer FE	Y	Y	Y	Y
Adj. R^2	0.227	0.285	0.308	0.308
Observations	70,861,556	70,861,542	70,861,542	70,861,542

Panel B: Logarithm of patient paid amount

PE	-0.016	0.001	0.023	0.031
	(-0.475)	(0.031)	(0.856)	(1.167)
Hospital Controls	N	N	N	Y
Patient Controls	N	N	Y	Y
Diagnosis×Year FE	N	Y	Y	Y
Hospital×Payer FE	Y	Y	Y	Y
Adj. R^2	0.290	0.347	0.352	0.352
Observations	70,852,714	70,852,700	70,852,700	70,852,700

Panel C: Logarithm of payer paid amount

PE	0.276**	0.274**	0.264**	0.265**
	(1.964)	(2.035)	(1.975)	(1.963)
Hospital Controls	N	N	N	Y
Patient Controls	N	N	Y	Y
Diagnosis×Year FE	N	Y	Y	Y
Hospital×Payer FE	Y	Y	Y	Y
Adj. R^2	0.124	0.168	0.183	0.183
Observations	70,861,127	70,861,113	70,861,113	70,861,113

Table OA.6: Impacts of PE Ownership in Matched Sample

This table reports the results of Regression (1) for the matched sample of patient visits between 2013 and 2019. The matched sample is constructed by matching each PE-owned hospital to three control hospitals using the optimal Mahalanobis method. Remaining details are the same as in Table 1.

Panel A: Logarithm of total paid amount

PE	0.649***	0.644***	0.672***	0.689***
	(2.923)	(3.134)	(3.415)	(3.456)
Hospital Controls	N	N	N	Y
Patient Controls	N	N	Y	Y
Diagnosis×Year FE	N	Y	Y	Y
Hospital×Payer FE	Y	Y	Y	Y
Adj. R^2	0.182	0.258	0.288	0.288
Observations	11,140,533	11,140,503	11,140,503	11,140,503

Panel B: Logarithm of patient paid amount

PE	0.045	-0.028	0.003	-0.005
	(0.938)	(-0.545)	(0.075)	(-0.126)
Hospital Controls	N	N	N	Y
Patient Controls	N	N	Y	Y
Diagnosis×Year FE	N	Y	Y	Y
Hospital×Payer FE	Y	Y	Y	Y
Adj. R^2	0.233	0.314	0.322	0.322
Observations	11,139,158	11,139,128	11,139,128	11,139,128

Panel C: Logarithm of payer paid amount

PE	0.671***	0.725***	0.729***	0.746***
	(3.220)	(3.794)	(3.823)	(3.862)
Hospital Controls	N	N	N	Y
Patient Controls	N	N	Y	Y
Diagnosis×Year FE	N	Y	Y	Y
Hospital×Payer FE	Y	Y	Y	Y
Adj. R^2	0.087	0.140	0.156	0.156
Observations	11,140,502	11,140,472	11,140,472	11,140,472

Panel D: Logarithm of relative service-mix weight

PE	0.076*	0.037	0.037	0.049
	(1.784)	(0.897)	(0.999)	(1.352)
Hospital Controls	N	N	N	Y
Patient Controls	N	N	Y	Y
Diagnosis×Year FE	N	Y	Y	Y
Hospital×Payer FE	Y	Y	Y	Y
Adj. R^2	0.182	0.290	0.294	0.294
Observations	11,140,533	11,140,503	11,140,503	11,140,503

Table OA.7: Outcomes on Medical Imaging Procedures

This table reports the results of Regression (1) for the sample of the top 35 medical imaging procedures. All procedures are pooled together in the estimation. The dependent variable is the natural logarithm of the total paid amounts. All columns contain hospital×payer fixed effects. Columns (2) to (5) include year fixed effects. Columns (3) to (5) include imaging procedure fixed effects. Patient controls, including *gender*, *age group*, *insurance type*, and *relative service-mix weights* (except in Panel D), are added in columns (4) and (5). Hospital controls, including *hospital bed numbers*, *teaching status*, *rural status*, *for-profit status*, *ratio of Medicare patients*, and *ratio of Medicaid patients*, are added in column (5). Standard errors are clustered at the hospital level. *t*-statistics are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent variable:				
	Logarithm of total paid amount				
	(1)	(2)	(3)	(4)	(5)
PE	0.099**	0.121***	0.104***	0.098***	0.112***
	(2.225)	(3.003)	(2.689)	(2.617)	(3.031)
Hospital Controls	N	N	N	N	Y
Patient Controls	N	N	N	Y	Y
Procedure FE	N	N	Y	Y	Y
Year FE	N	Y	Y	Y	Y
Hospital×Payer FE	Y	Y	Y	Y	Y
Adj. R^2	0.316	0.317	0.438	0.448	0.449
Observations	15,940,360	15,940,360	15,940,357	15,940,357	15,940,357

Table OA.8: Impact of Financial Leverage on Negotiated Prices

This table shows how hospitals' financial leverage affects negotiated prices. The unit of observation is the hospital×year in Panel A, and the patient visit in Panel B. Dependent variables are indicated in the column titles. Panel A examines how hospitals' financial leverage responds to PE buyouts. PE_{jt} is an indicator of whether hospital j is owned by PE firms in year t. $Leverage_{jt}$ denotes the level of financial leverage for hospital j in year t. $PE \times Leverage_{jt}$ denotes their interaction term. Patient controls include *gender*, *age group*, *insurance type*, and *relative service-mix weights*. Hospital controls include *hospital bed numbers*, *teaching status*, *rural status*, *for-profit status*, *ratio of Medicare patients*, and *ratio of Medicaid patients*. Standard errors are clustered at the hospital level. t-statistics are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Change of hospital leverage

	Dependent variable:			
	LT/TA			
	(1)	(2)	(3)	(4)
PE	0.067	0.082***	0.121**	0.103***
	(0.429)	(3.721)	(2.396)	(2.928)
Hospital Controls	N	N	N	Y
Year FE	N	N	Y	Y
Hospital FE	N	Y	Y	Y
Adj. R^2	-0.000	0.006	0.006	0.006
Observations	66,332	66,281	66,281	66,281

Panel B: Impact of hospital leverage on prices

	Dependent variable:			
	Logarithm of total paid amount			
	(1)	(2)	(3)	(4)
PE×Leverage	0.065**	0.063**	0.059**	0.065**
	(2.196)	(2.403)	(2.261)	(2.560)
PE	0.333**	0.333**	0.340**	0.350**
	(2.160)	(2.242)	(2.357)	(2.418)
Leverage	-0.001	-0.001	-0.001	-0.001
	(-0.088)	(-0.119)	(-0.045)	(-0.061)
Hospital Controls	N	N	N	Y
Patient Controls	N	N	Y	Y
Diagnosis×Year FE	N	Y	Y	Y
Hospital×Payer FE	Y	Y	Y	Y
Adj. R^2	0.232	0.290	0.314	0.314
Observations	64,483,493	64,483,481	64,483,481	64,483,481

Table OA.9: Robustness Check—Alternative Financial Leverage Definition

This table replicates Table OA.9, except an alternative definition of hospitals' financial leverage is used. Remaining details are the same as in Table OA.9.

Panel A: Change of hospital leverage

	Dependent variable:			
	(LT + Notes + Loan Payable)/TA			
	(1)	(2)	(3)	(4)
PE	0.053	0.066***	0.105**	0.089**
	(2.396)	(2.928)	(2.071)	(2.477)
Hospital Controls	N	Y	N	Y
Year FE	N	N	Y	Y
Hospital FE	N	Y	Y	Y
Adj. R^2	-0.000	0.006	0.006	0.006
Observations	66,281	66,281	66,281	66,281

Panel B: Impact of hospital leverage on prices

	Dependent variable:			
	Logarithm of total paid amount			
	(1)	(2)	(3)	(4)
$PE \times Leverage$	0.058**	0.058**	0.055**	0.061**
	(2.023)	(2.305)	(2.186)	(2.483)
PE	0.333**	0.332**	0.340**	0.350**
	(2.157)	(2.239)	(2.354)	(2.414)
Leverage	-0.002	-0.003	-0.002	-0.002
	(-0.119)	(-0.235)	(-0.138)	(-0.167)
Hospital Controls	N	N	N	Y
Patient Controls	N	N	Y	Y
Diagnosis × Year FE	N	Y	Y	Y
Hospital × Payer FE	Y	Y	Y	Y
Adj. R^2	0.232	0.290	0.314	0.314
Observations	64,483,493	64,483,481	64,483,481	64,483,481

Table OA.10: Previously For-profit vs Non-for-profit

This table replicates Column (1) of Table 1, except I include an interaction term *PE* $\times$ Previously For-profit, which is an indicator of whether a hospital is owned by PE firms and was previously for-profit prior to PE buyouts. All other details are the same as in Table 1.

	Dependent variable:			
	Logarithm of total paid amount			
	(1)	(2)	(3)	(4)
PE$\times$*Previously For-profit*	-0.565**	-0.472**	-0.497**	-0.510**
	(-2.445)	(-2.188)	(-2.311)	(-2.345)
PE	0.591**	0.548**	0.566***	0.585***
	(2.576)	(2.470)	(2.634)	(2.700)
Hospital Controls	N	N	N	Y
Patient Controls	N	N	Y	Y
Diagnosis$\times$Year FE	N	Y	Y	Y
Hospital$\times$Payer FE	Y	Y	Y	Y
Adj. R^2	0.227	0.285	0.308	0.308
Observations	70,772,308	70,772,294	70,772,294	70,772,294

Table OA.11: Results Supporting the Bankruptcy Mechanism

This table replicates Column (1) of Table 1, except I include a variable *More Patient Flow in Network* as well as its interaction term with *PE* in Column (1), and a variable *More Service Weight in Network* as well as its interaction term with *PE* in Column (2). *More Patient Flow in Network* is an indicator equal to one for a hospital–insurer–year if the number of patients from the insurer accommodated by the hospital is above the median level among all hospitals within the insurer's network. *More Service Weight in Network* is an indicator equal to one for a hospital–insurer–year if the hospital's total service-mix weights of accomodated patients from the insurer is above the median level among all hospitals within the insurer's network. All other details are the same as in Table 1.

	Dependent variable:	
	Logarithm of total paid amount	
	(1)	(2)
PE×*More Patient Flow in Network*	0.110**	
	(2.553)	
More Patient Flow in Network	0.009	
	(0.613)	
PE×*More Service Weight in Network*		0.116**
		(2.326)
More Service Weight in Network		0.053**
		(2.553)
PE	0.207**	0.201*
	(1.760)	(1.657)
Hospital Controls	Y	Y
Patient Controls	Y	Y
Diagnosis×Year FE	Y	Y
Hospital×Payer FE	Y	Y
Adj. R^2	0.308	0.308
Observations	71,109,577	71,109,577

Table OA.12: Impact of PE on Negotiated Prices by Buyout Type

This table replicates Column (1) of Table 1, except I include indicators for different buyout types, Add-on, Private to Private, Public to Private, Secondary Buyout, Growth/Expansion, and Management Buyout following the deal type definition in Table 1. All other details are the same as in Table 1.

	Total Paid Amount
Add-on	0.093
	(1.407)
Private to Private	0.372**
	(2.248)
Public to Private	0.164***
	(3.038)
Secondary Buyout	0.036
	(0.565)
Growth/Expansion	0.237**
	(2.348)
Management Buyout	0.096
	(0.424)
Patient Controls	Yes
Hospital Controls	Yes
Hospital×Payer FE	Yes
Diagnosis×Year FE	Yes
Adj. R^2	0.306
Observations	71,502,729

Table OA.13: Summary of CPOM Regulation Changes

This table provides a brief summary of the CPOM regulation changes after 2006 across different states.

STATE	TIME	REGULATORY EVENT
Arizona	2008/12	Midtown Medical Group, Inc. v. State Farm Mutual Automobile Insurance
California	2015/12	Epic Medical Management v. Paquette
	2017/01	Amended California Business and Professions Code Section 2401
Connecticut	2016/07	Senate Bill No. 351
Georgia	2012/06	Georgia Composite Medical Board issued opinions
Idaho	2016/03	Idaho Board of Medicine Disavows the CPOM prohibition
Kansas	2018/09	Central Kansas Medical Center v. Hatesohl
Massachusetts	2012/02	The Massachusetts Board of Registration in Medicine revised regulations
Michigan	2015/10	Senate Bill No. 65
Minnesota	2014/03	State Farm Mutual Automobile Insurance v. Mobile Diagnostic Imaging
Nevada	2010/04	Nevada Attorney General Opinion prohibits CPOM
New York	2015/06	Attorney General of New York opined the prohibition of CPOM
North Carolina	2016/03	North Carolina Medical Board adopted a position statement
Ohio	2012/03	State Medical Board of Ohio published a statement
Oregon	2018/01	House Bill No.3439
South Carolina	2017/10	South Carolina State Board of Medical Examiners approved the CPOM
Tennessee	2012/07	Senate Bill No.3263
Texas	2011/09	Senate Bill No.894
	2019/09	House Bill No.1532
Washington	2011/07	House Bill No.1315
West Virginia	2014/11	State of West Virginia Board of Medicine issued a position statement

Table OA.14: CPOM Regulation Index Construction

This table presents the results of the interim step in constructing the CPOM regulation index. The sample includes universal U.S. hospitals in the AHA Annual Survey between 2006 and 2019. The dependent variable is an indicator of whether a hospital is under PE ownership during a year. The independent variables, *Statute*, *Precedent*, and *Opinion*, are the 3×1 score vector for each state in a year created in the first step of constructing the CPOM regulation index. All columns contain hospital fixed effects. Columns (2) and (3) include year fixed effects. Control variables, including *hospital bed numbers*, *teaching status*, *rural status*, *for-profit status*, *ratio of Medicare patients*, and *ratio of Medicaid patients*, are added in the last column. Standard errors are clustered at the hospital level. t-statistics are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent variable:		
	PE Dummy		
	(1)	(2)	(3)
Statute	-0.058***	-0.024***	-0.022***
	(-8.449)	(-3.459)	(-3.202)
Precedent	-0.002	-0.002	-0.001
	(-0.517)	(-0.528)	(-0.424)
Opinion	-0.020***	0.001	-0.000
	(-3.419)	(0.159)	(-0.001)
Beds/100			-0.003
			(-0.617)
Teaching			-0.025*
			(-1.693)
Rural			-0.002
			(-0.261)
For-profit			0.117***
			(7.365)
Medicare%			-0.011
			(-1.407)
Medicaid%			-0.003
			(-0.315)
Year FE	No	Yes	Yes
Hospital FE	Yes	Yes	Yes
Adj. R^2	0.635	0.642	0.646
Observations	83,684	83,684	83,673

Table OA.15: Robustness Check—Examine the 1st Stage of CPOM Regulation Index

This table replicates Table 4, except in column (1) standard errors are clustered at the state by year level; in column (2) I control for, *Medicaid Expansion State*, an indicator of whether a state is a Medicaid-expanding state in a year; in column (3) I drop Texas and Tennessee; and in column (4) I drop the year of 2012. Remaining details are the same as in Table 4.

	Dependent variable:			
	PE Indicator			
	(1)	(2)	(3)	(4)
CPOM Regulation Index	0.010***	0.010***	0.017***	0.010***
	(4.193)	(3.448)	(3.990)	(3.060)
ln(# Hospital Beds)	-0.003	-0.003	-0.002	-0.004
	(-1.017)	(-0.573)	(-0.291)	(-0.626)
Teaching	-0.025***	-0.023	-0.026	-0.025*
	(-4.078)	(-1.604)	(-1.616)	(-1.690)
Rural	-0.002	-0.003	-0.002	-0.003
	(-0.511)	(-0.338)	(-0.224)	(-0.250)
For-profit	0.117***	0.116***	0.117***	0.120***
	(9.122)	(7.358)	(7.240)	(7.433)
Medicare Patient Ratio	-0.011*	-0.011	-0.010	-0.011
	(-1.920)	(-1.476)	(-1.295)	(-1.348)
Medicaid Patient Ratio	-0.003	-0.005	-0.008	-0.006
	(-0.477)	(-0.534)	(-0.864)	(-0.583)
Medicaid Expansion State		0.011**		
		(2.316)		
F-stat	17.58	11.89	15.92	9.37
	(0.000)	(0.001)	(0.000)	(0.002)
Year FE	Yes	Yes	Yes	Yes
Hospital FE	Yes	Yes	Yes	Yes
Adj. R^2	0.646	0.646	0.639	0.626
Observations	83,673	83,673	73,459	77,675

Table OA.16: CPOM Regulation Index and Hospital Characteristics

This table presents differences in hospital characteristics between hospitals facing more stringent CPOM regulation and those facing less stringent regulation. A hospital is classified in facing more (less) stringent CPOM regulation if the CPOM index of the state where the hospital is located in a given year is within the bottom (top) 20% of all indices across the state's history. Columns (1) and (2) report the variable mean for each group. Column (3) reports the difference between the means of two groups. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively, clustered at the hospital level.

CPOM Regulation Index Threshold	Bottom 20%	Top 20%	Diff
#Hospital Beds	144.293	159.441	-15.148
For-profit	0.259	0.381	-0.122**
Medicare Patient Ratio	0.486	0.475	0.011
Medicaid Patient Ratio	0.183	0.160	0.023
Medical Intensive Care	0.603	0.675	-0.072
Total Medicare Days	14,244.050	18,148.810	-3,904.760
Total Medicaid Days	7,515.376	7,301.274	214.102
Total Inpatient Days	34,484.010	38,274.870	-3,790.860
Total Outpatient Visits	110,180.800	120,954.000	-10,773.200
#Medical Residents	19.957	22.532	-2.575

Table OA.17: Placebo Test—Examine the Impact of CPOM on M&A

This table replicates Table 4, except that the dependent variable is an indicator of whether the hospital was involved in any M&As without PE backing in a year. Remaining details are the same as in Table 4.

	Dependent variable:		
	M&A Indicator		
	(1)	(2)	(3)
CPOM Regulation Index	0.092***	0.007	0.007
	(20.883)	(1.483)	(1.507)
ln(#Hospital Beds)			-0.018**
			(-2.084)
Teaching			0.028
			(1.156)
Rural			0.011
			(0.525)
For-profit			0.021
			(0.996)
Medicare Patient Ratio			0.027**
			(2.022)
Medicaid Patient Ratio			0.036
			(2.182)
Year FE	N	Y	Y
Hospital FE	Y	Y	Y
Adj. R^2	0.565	0.640	0.640
Observations	83,684	83,684	83,673

Table OA.18: Examine Hospitals' Financial Health before PE Buyouts

This table reports the mean of hospitals' financial indicators one year prior to PE buyouts and compares the differences in these variables between PE-target hospitals and non-PE-target local rivals. *Financial Leverage* is computed as the total debt level of a hospital divided by its total assets. *Interest Coverage* is the ratio of the total interest payments of a hospital to its total assets. *Operating Markup* is calculated as the gross patient revenues of a hospital less its total operating expenses, then divided by its net patient revenues. *Revenue Ratio* is equal to the total gross revenues of a hospital divided by its total assets. *Government Subsidy Ratio* (in percentage) is the ratio of the total government subsidies received by a hospital divided by its total assets. *Donation Ratio* (in percentage) is the ratio of the total donation received by a hospital divided by its total assets. *Avg. Negotiated Prices* is the hospital-wide average negotiated price per unit of service-mix weight across insurers. Prices are adjusted to dollars in 2019 by GDP deflators. The last column reports the differences in these variables between PE-target hospitals and non-PE-target local rivals. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	PE-target	Non-PE-target	
Variable	Mean	Mean	Diff
Financial Leverage	0.300	0.273	0.027
Interest Coverage	0.014	0.013	0.001
Operating Markup	0.054	0.013	0.041*
Revenue Ratio	0.199	0.229	-0.030*
Government Subsidy Ratio (%)	0.041	0.330	-0.289***
Donation Ratio (%)	0.212	0.480	-0.268***
Avg. Negotiated Prices	268.914	330.864	-61.950***

Table OA.19: Estimates of the No-PE Model

This table presents estimates for the No-PE model in the second counterfactual. Panel A shows the estimates related to hospitals' bargaining weights. Panel B shows the estimates related to hospitals' marginal costs. Panel C collects the estimates for other parameters in the model. Standard errors are in parentheses.

Panel A: Bargaining Weight Parameter

VARIABLE	Coeff.	Std. Error
Multi-hospital System	0.2916	(0.0251)
For-profit	0.1756	(0.0090)
Teaching Status	0.2796	(0.0084)
Physician Arrangement	0.1149	(0.0087)
Rural Hospital	−0.0143	(0.0230)
ln(#Hospital Beds)	−0.0850	(0.0092)
Market Share of Inpatient Days	1.4764	(0.0573)
# Insurer in HRR	−0.0174	(0.0007)
Constant	0.6420	(0.2682)

Panel B: Marginal Costs Parameter

For-profit	−0.3488	(0.0681)
Teaching Status	0.5693	(0.2476)
Rural Area	−0.1064	(1.1083)
ln(#Hospital Beds)	−0.2206	(0.0107)
Medicare Patient Ratio	0.1267	(0.2260)
Medicaid Patient Ratio	2.0988	(0.9195)
HCC Score	−0.5509	(0.0239)
HRR Medicare Avg. OP. Cost/1000	0.0777	(0.0332)
Census Region FEs	Yes	
Year FEs	Yes	

Panel C: Other Parameters

Insurer Preference		
Insurer Weight (α)	1,097.5530	(79.4760)
Social Responsibility		
Non-pecuniary Motive (τ_{NP})	136.2716	(6.8274)

Table OA.20: Estimates of an Extended Model with Network Formation

This table presents estimates for an extended model by adding an endogenous network-formation stage between hospitals and insurers. Panel A shows the estimates related to hospitals' bargaining weights. Panel B shows the estimates related to hospitals' marginal costs. Panel C collects the estimates related to PE's impacts and other parameters in the model. Standard errors are in parentheses.

Panel A: Bargaining Weight Parameter

VARIABLE	Coeff.	Std. Error
Multi-hospital System	0.2710	(0.0884)
For-profit	0.1166	(0.0000)
Teaching Status	0.3775	(0.0001)
Physician Arrangement	0.1134	(0.0001)
Rural Hospital	−0.1166	(0.0000)
ln(#Hospital Beds)	−0.1097	(0.0000)
Market Share of Inpatient Days	1.3171	(0.0002)
# Insurer in HRR	−0.0046	(0.0000)
Constant	0.6160	(0.0884)

Panel B: Marginal Costs Parameter

For-profit	−0.0308	(0.0001)
Teaching Status	0.6214	(0.0003)
Rural Area	−0.3172	(0.0026)
ln(#Hospital Beds)	−0.0826	(0.0001)
Medicare Patient Ratio	0.1127	(0.0046)
Medicaid Patient Ratio	2.0439	(0.5124)
HCC Score	−0.5576	(0.3307)
HRR Medicare Avg. OP. Cost/1000	0.0434	(0.0974)
Census Region FEs	Yes	
Year FEs	Yes	

Panel C: Impacts of PE and Other Parameters

Insurer Preference		
Insurer Weight (α)	935.7861	(0.2891)
Social Responsibility		
Non-pecuniary Motive (τ_{NP})	43.3210	(2.5847)
Bankruptcy Threat		
Debt Burden (θ)	0.0050	(0.0000)
Location of Logistic Dist. (μ)	−2.1239	(0.0002)
Scale of Logistic Dist. (ρ)	70.2298	(0.1072)
Ex-ante Debt Raising Costs		
Linear Debt Costs (μ_1)	0.6646	(0.6163)
Quadratic Debt Costs (μ_2)	0.9600	(2.6168)
Impacts of PE Intervention		
Marginal Cost Change (g_c)	−0.0169	(0.0001)
Bargaining Power Change (g_b)	0.1959	(0.0001)

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