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

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Abstract

I use proprietary health insurance claims data covering over 60% of privately insured individuals in the United States to study the impact of private equity (PE) hospital buyouts on hospital–insurer price negotiations, health spending, and patient welfare. I apply a novel structural approach that exploits state-level regulation changes as PE entry shocks. I find that PE buyouts lead to an 11% increase in total healthcare spending for the privately insured in affected markets, driven mostly by higher bargained prices at PE-backed hospitals and price spillovers to local rivals. PE investors' superior bargaining skills account for 43% of the price and spending increases, while financial engineering and bankruptcy threats contribute 40%, changes in patient demand contribute 10%, and reduced focus on social objectives contributes 8%. Operational efficiency gains reduce spending, but only by 1%. A counterfactual ban on PE hospital buyouts would increase patient surplus by an amount equivalent to 10.7% of health expenses. If antitrust regulators who conduct merger reviews ignore PE-backed acquirers' unique features, they risk greatly underestimating the impact of hospital mergers.

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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 (Panel A of Figure 1). Healthcare costs are projected to grow at an average rate of 5.5% per year in the next decade, primarily driven by the surge in healthcare prices. At the same time, private equity (PE) investors have shown a keen interest in the healthcare sector, with a 10-fold increase in deal values over the last decade (Panel B of Figure 1). Active PE involvement has the potential to greatly change this sector, which previously was dominated by public and not-for-profit players. But we still know very little about how PE works and through what mechanisms PE actually affects real outcomes. Proponents of PE argue that it can improve operational efficiency, lowering health costs. In contrast, opponents claim that PE investors are tough negotiators who care only about profits and load up hospitals with debt, hence PE deals push up health expenses and make 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] For all these reasons, it is important to understand the effects of PE on healthcare pricing and patient welfare.

I use new, detailed insurance claims data to study the hospital sector, which constitutes the largest component of healthcare spending ($1.2 trillion dollars in 2019). This setting is important as hospitals play a central role in meeting population health needs and are vital for general social welfare. Importantly, prices for services and products in the sector are generally negotiated between hospitals and private insurers. Pricing via bilateral bargaining is quite common in business-to-business settings beyond the hospital sector. So, it is important in itself to examine how PE buyouts affect the largely understudied bilateral price bargaining between hospitals and insurers. It also provides a lens for understanding how PE investors create and redistribute value among relevant stakeholders by affecting prices. In addition, attempting to achieve better bargaining leverage by merging with a competitor will often cause hospitals to appear on antitrust regulators' radar. But regulators seldom pay attention to the involvement of PE in mergers. This setting provides an opportunity to examine the role of PE-backed acquirers in mergers and sheds light on antitrust regulations. Focusing on this hospital setting, I address the following questions: How do PE buyouts of hospitals affect price bargaining and total health spending? What are the specific channels by which PE investors create and redistribute value among stakeholders? What are the implications for patient welfare and antitrust regulations?

Despite its importance, empirical research on how PE 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 PE buyouts. Typically, the outcomes of hospital–insurer

[1] For example, Congress has recently passed legislation to curb the "surprise medical billing" crisis, in which PE-backed physician staffing firms predominate (Appelbaum and Batt, 2020).

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 for each medical procedure provided 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 investigate PE's impacts on hospital pricing.

I begin by presenting descriptive evidence that PE investment 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 69% within a hospital–insurer pair after PE interventions compared to a matched control sample. 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 PE investors mainly affect prices, not quantities.

PE intervention also imposes heterogeneous spillovers on the negotiated prices of rivals in the local market. After a PE investor acquires any hospital in a region, local non-PE-backed rivals that share common insurers with the PE-backed 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-backed 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 extends 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 changes. On the demand side, I model patients' hospital choices as dependent on a rich set of patient and hospital characteristics, including patients' health conditions, age, gender, and travel distance to the hospital; hospitals' size and availability of specialty services; and other factors.

I also 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.

PE investors can affect bargained prices through five channels in the model. First, 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-backed hospitals make the outside option of insurers worse since they will have to face a more concentrated hospital sector and higher service prices charged in the local market. 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 close and unique relation between financial characteristics of PE buyouts and price bargaining outcomes. It is also consistent with the descriptive evidence that PE-target hospitals with higher leverage have higher prices, whereas leverage is not significantly related to prices among non-PE-backed facilities.

Second, PE firms, as veteran negotiators in financial markets, could potentially bring in new negotiating strategies and expertise that improve hospitals' bargaining power. The model is flexible enough to separate bargaining power (the inherent ability of negotiators to secure a fixed share from the bargain) from the general concept of bargaining position (the outside option of negotiators if the bargain fails). This decomposition allows me to examine how PE buyouts affect hospitals' bargaining power.

Third, the model recognizes that PE intervention affects hospitals' operational efficiency. As shown in the descriptive evidence, a hospital's adjusted average costs per patient discharge indeed decrease after PE investments. In the model, operational efficiency is reflected by the marginal costs of hospitals and thus is factored into price negotiations.

Fourth, the model also incorporates a non-pecuniary motive of hospitals. After PE buyouts, hospitals are more profit-driven and have less focus on their social objectives. Providing medical services becomes less appealing for them unless it is lucrative enough, which presses insurers to offer a higher price. Supporting this mechanism, I show in the descriptive evidence that price increases are more pronounced among hospitals that were not-for-profit prior to buyouts.

Last, the model allows PE investors to alter service quality and hence change patients' demand for the hospital. This demand shift has implications for bargaining outcomes because the redistribution of patient flows in the local region affects both insurers' and hospitals' outside options.

The model also captures spillover effects of price bargaining in the local market. If a PE-backed hospital increases its negotiated price with an insurer in equilibrium, then reallocating patients from local rivals to the PE-backed hospital becomes more costly. Thus, when negotiating with these rivals, the value of the insurer's outside option would diminish if the bargaining breaks down. As a result, the negotiated prices between the insurer and local rivals are predicted to rise as well. Note that only insurers that have contracts with PE-backed hospitals experience disruptive changes in outside options. Stronger spillover effects are expected among hospitals in these insurers' networks, consistent with the heterogeneity described earlier.

The main identification challenges in estimating the model are that PE investors endogenously select target hospitals, and PE-backed 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. The content of CPOM is generally shaped by state laws, court rulings, and medical board opinions, and has evolved over time in different states. 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.

Estimates of demand parameters reveal preferences of patients and their expected utility for each hospital. The granularity of insurance claims data enables observation of a patient's choice set in the local market. Estimates from the multinomial logit choice model reveal that enrollees respond to PE intervention. Typical patients prefer visiting PE-owned hospitals, particularly for female enrollees, yet more senior patients and those with more severe diseases are more likely to go to a non-PE-backed hospital. Consistent with previous literature, I find that enrollees prefer hospitals nearby, hospitals they have visited before, and hospitals that provide specific services accommodating their needs.

Estimates of supply parameters (the bargaining model) come from moment conditions based on orthogonality restrictions on negotiated prices, marginal costs, and leverage choices. I find that PE significantly increases hospitals' bargaining power, consistent with PE sponsors providing superior negotiating expertise. On average, PE-backed hospitals can extract 50% more of the surplus generated by a hospital–insurer relationship than non-PE-backed hospitals. I also find that a higher level of financial leverage renders a more credible bankruptcy threat, improving PE-backed hospitals' bargaining positions. In addition, parameter estimates imply not-for-profit hospitals enjoy non-pecuniary benefits, equivalent to $102 of pecuniary rewards for every unit of service provided to local communities. These non-pecuniary benefits vanish among PE-backed hospitals because they focus less on social objectives. The estimates also show that PE improves hospitals' operational efficiency by reducing marginal costs by 8% on average.

I use the estimated model as a laboratory to conduct a series of counterfactual analyses. First, I consider a counterfactual PE ban in the hospital sector and its implications for negotiated prices and spending, spillover effects, channel decomposition, and patient surplus. Similar policies were recently considered in several state legislatures.[2] The results show that banning PE-based hospital takeovers would lead to an 11% reduction of health spending in affected regions, with savings mainly coming from a decrease of negotiated prices. The quantity-weighted average prices would drop by almost 11%, while the quantities of provided services would barely change in the counterfactual. The savings also exhibit heterogeneity across regions. A local market having a higher percentage of PE-backed hospitals would save more in the counterfactual.

Looking at the spillover effects in the PE-ban counterfactual, the results show that PE-backed hospitals would contribute 86% of the total savings if PE ownership were banned. Another 14% would be contributed by local rivals that share common insurers with the PE-backed hospital, while the remaining hospitals (local rivals that do not share insurers with the PE-backed one) would contribute almost nothing to the total savings. These results are largely consistent with the reduced-form results regarding heterogeneity in spillover effects. More specifically, I find that banning 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. Both groups experience only a modest change in service quantities in the counterfactual: PE-backed hospitals see a 5.5% increase in service provisions while local rivals that share insurers experience a 3.1% reduction.

Next, I use the model to quantify the relative contribution of various channels to the total savings. I do so by adding one channel at a time into the counterfactual and computing total spending changes in each scenario. 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 investors 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% because banning PE would eliminate a small gain in operational efficiency.

[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.

Finally, I quantify how patient surplus would be affected in the PE-ban counterfactual. Under the assumption that the savings on medical expenses would benefit patients through reductions in insurance premiums, the model implies that banning PE would bring patient-surplus gains equivalent to 10.7% of the documented health expenses in PE-target 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 banned.

In the second counterfactual, I use the model to evaluate policy implications for merger reviews. Specifically, I consider 100 hypothetical mergers in 2013 wherein a PE-backed hospital system is randomly assigned to acquire one rival system locally. 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). Note that the No-PE model is essentially the same model used by regulators to evaluate proposed mergers and only takes into account the market concentration effect induced by mergers. I compare the two models' predictions regarding total spending, quantity-weighted average prices, and patient surplus before and after mergers.

The results imply that regulators risk greatly underestimating the impacts of proposed mergers if they disregard PE acquirers' unique features. Not surprisingly, both the full and the plain models predict an increase in total spending and quantity-weighted prices in those regions after hypothetical mergers. The magnitudes are positively correlated with the change in the Herfindahl-Hirschman index (HHI) of the hospital sector after mergers. However, the models produce very different magnitudes: Percentage changes in total spending and quantity-weighted prices after mergers predicted by the No-PE model can be 10 points lower than the PE model. The prediction gap between both models still remains when we examine the changes in patient surplus after mergers. The underestimation mainly comes from merging hospitals, among which the prediction gap in quantity-weighted average prices, for example, could be as high as 25%. For non-merging rival hospitals, the underestimation is much less severe. These results highlight the importance of taking PE acquirers' traits into account when reviewing proposed mergers.

Contribution to the Literature

This work contributes to the empirical literature on the effects of PE buyouts.[3] A number of papers have examined the effects of PE buyouts on firm productivity and growth (e.g., Kaplan, 1989, Lichtenberg and Siegel, 1990, Boucly et al., 2011, and Cohn et al., 2014), 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., 2020), restaurant quality (e.g., Bernstein and Sheen, 2016), student outcomes (e.g., Eaton et al., 2020), and product prices (e.g.,

[3]Kaplan and Strömberg (2009) provide a nice survey on the economics of leverage buyout and PE. More recently, Gulliver and Jiang (2020) give a comprehensive review on studies of PE's impacts on target firms' productivity, revenue per employee, return on assets, and innovation.

Fracassi et al., 2021). This paper adds to this literature by exploring how PE creates and redistributes value among relevant stakeholders in a business-to-business price-bargaining setting. Prominently, it uses a novel structural approach to decompose PE's real effects into operational versus financial channels, and to quantify its implications for hospital pricing, patient welfare, and antitrust regulations. It is the first to introduce the insurance claims "big" data from the DRG Real World Data product and a novel identification strategy by exploiting state-level regulation changes to address the endogenous selection concern of PE investments.

More closely related is a strand of literature in health economics studying the impact of PE investment (e.g., Stevenson and Grabowski, 2008, Pradhan et al., 2014, Huang and Bowblis, 2019, Gondi and Song, 2019, and Gandhi et al., 2020). In recent work, Gupta et al. (2021) study whether PE buyouts affect the mortality outcomes of patients in nursing homes. My paper differs in several important ways. First, the research question is different. This paper studies how PE ownership impacts price negotiations, healthcare spending, patient outcomes, and patient welfare in the market of private insurance, while previous work extensively discusses how buyouts affect patient outcomes. Second, the data and the setting are different. Here, I study the hospital sector and use novel insurance claims data with individual-level diagnosis and pricing information of the privately insured. In contrast, previous work exclusively[4] studies nursing homes, a much smaller sector where Medicare prices are largely regulated, making price negotiation irrelevant.[5] Third, besides the price implications, which are new to the literature, this paper finds distinct conclusions regarding patient outcomes. After PE buyouts, hospital service quality and patient outcomes do not change, and sometimes even improve. This highlights new incentives of PE firms face when they have to negotiate prices with private insurers.

More broadly, this paper contributes to the literature on firm ownership by unveiling how changes in ownership type from not-for-profit to PE-owned affect firms' pricing strategies and consumer welfare. Early discussions include Hansmann (1980) and Lichtenberg et al. (1987). The hospital sector is a perfect setting to study related questions given its diverse ownership types.[6] The seminal work of 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. More recently, Capps et al. (2020) use detailed California data and find no evidence indicating that not-for-profit hospitals are more likely to provide charity care compared to for-profit ones. Different from these papers, I focus on PE ownership transitions and their implications on price negotiations and patient welfare.

[4]One exception is Gondi and Song (2019), in which authors describe the aggregate trend of PE investments in healthcare delivery from 2010 to 2017 and descriptively discuss the potential consequences of increased PE ownership on the healthcare system.

[5]The hospital sector has been the primary driver of the surge in healthcare costs. Hospital services account for the largest share of total health spending. For example, 34% of total health spending is on the hospital sector relative to 4.6% on nursing homes, as of 2019.

[6]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. (2020), and Aghamolla et al. (2021).

It also contributes to the industrial organization literature on hospital transaction prices and hospital competition. Unlike most of the literature focusing on variation in Medicare hospital prices (e.g., Finkelstein et al., 2016),[7] this paper is the first, to my knowledge, to use a national multiyear dataset of transaction prices from the DRG Real World Data in the finance or economics literature. The newly introduced data contribute to the discussion of hospital prices for the privately insured and shed light on how price variations arise from PE buyouts. Regarding hospital competition,[8] this paper extends the models of bargaining and competition between hospitals and insurers from Gowrisankaran et al. (2015) and Ho and Lee (2017). Unlike their papers, I examine a different research question and uncover new channels, in particular the financing side of PE buyouts, that impact hospital price bargaining. Through my second counterfactual experiment, I discuss new policy implications in antitrust regulations.

Finally, my analysis relates to the empirical literature on bargaining. Besides those papers on the healthcare sector mentioned above,[9] there is a strand of literature discussing bargaining problems in the financial market. Matsa (2010) provides evidence that firms use debt financing as a strategic tool to improve their bargaining position with organized labor. Robles-Garcia (2020) analyzes the welfare implications of regulating brokers' services and compensation when brokers and lenders bargain over commission rates. Dou et al. (2020) study sources of inefficiency in the bankruptcy process in which senior and junior creditors bargain with two-sided incomplete information. Brown et al. (2009) investigate if leveraged buyouts strengthen the bargaining positions of portfolio companies when facing their suppliers. Unlike these papers, I study a different question, namely, how PE buyouts affect portfolio companies' bargaining power and position in a business-to-business setting.

2 Institutional Details and Data

2.1 Institutional Details

Hospitals are major providers of medical, diagnostic, and treatment services in the United States. In 2019, these facilities accounted for over one-third of total health spending (Panel A of Figure 2), and accommodated over 145.6 million patient visits in emergency rooms. According to the most recent American Hospital Association (AHA) annual survey, there are over 6,000 hospitals in the United States; among them, about 3,000 hospitals are not-for-profit, 1,200 are investor-owned for-profit, and the rest are government-owned (federal, state, or local government). Typically, hospitals provide both inpatient and

[7] One prominent exception is Cooper et al. (2019). They quantify price variations within hospitals by using insurance claims data from the Health Care Cost Institute (HCCI) that cover the privately insured nationwide from 2007 to 2011. Lopez et al. (2020) provide a literature review on the differences of hospital transaction prices for private insurers and Medicare.

[8] In survey papers, Gaynor and Town (2011) and Gaynor et al. (2015) introduce the general framework to study the impact of competition on price and quality.

[9] Other empirical papers studying hospital price bargaining include Grennan (2013), Lewis and Pflum (2015), Ho and Lee (2019), Dafny et al. (2019), and Barrette et al. (2021). A survey by Grennan and Swanson (2021) discusses the most recent developments in the literature.

outpatient services: inpatient includes any services for patients who are formally admitted to a hospital by doctor's order, while outpatient includes emergency department services, observation services, outpatient surgery, lab tests, or any other services when doctors do not admit a patient.

Hospital spending is mainly determined by patient volume and payment rates per service or diagnosis, most of which are paid by insurers. Besides public health insurance programs like Medicare and Medicaid, commercial insurers are major payers and cover over 50% of the total population.[10] For public health insurance, the reimbursement rates are set unilaterally by the government (e.g., the Centers for Medicare & Medicaid Services [CMS]) and identically applied to providers across the nation, except for adjustments to account for local price and wage variations and other cost factors. Regarding commercial insurance, insurers must periodically negotiate local-market hospital contracts on service prices, which could be tremendously different from the charged prices in hospitals' chargemaster (listing prices on their menus). Such negotiations are commonly bilateral bargaining and could take months to reach an agreement. The finalized contract will not specify negotiated prices for each item as millions of prices would have to be listed. In most cases, a benchmark price is negotiated and used to multiply the service weights provided to calculate the final prices, which is similar to the reimbursement rules in Medicare's Hospital Inpatient/Outpatient Prospective Payment System. Given these features, hospitals in a local market compete with each other by deciding which private insurers' networks to join and negotiating prices bilaterally, unlike the standard Bertrand price competition. Patient demand for hospital service is very inelastic because patients pay little out-of-pocket costs.

Though reimbursement rates diverge between public and private insurance, hospitals are able to sustain their profitability by negotiating much higher private payment rates. Previous research has shown that hospitals have quite stable profit margins, which have risen to their highest levels in the past decade thanks to the expansion of health insurance coverage after the Affordable Care Act. A 2016 AHA report reveals that the profit margin of the hospital industry was estimated to be 7.8%, outperforming many other sub-industries in the healthcare sector, including health insurers, pharmacies, and pharmacy benefit managers. Both the huge cash flow and stable profitability of the industry greatly intrigue PE investors. The last decade has witnessed tremendous PE money and deals in the hospital arena. Panel B of Figure 2 exhibits the number of PE deals and the number of hospitals that were involved in buyouts between 2006 and 2019.

On the one hand, PE can bring many turnarounds to the table. As deep-pocket investors, PE firms are able to provide capital for necessary investments such as IT system upgrades. As professional investors, PE can add value by improving operational efficiency and recruiting the very best management for hospitals.

[10] More statistics are shown at the Kaiser Family Foundation website https://www.kff.org/other/state-indicator/total-population/. Specifically, Medicare and Medicaid cover 14.2% and 19.8% of the total U.S. population, respectively. Among privately insured individuals, 89.3% are covered by employer-based private insurance, which is typically purchased by employers for their employees and financed through employer or joint employer–employee contributions. The rest are covered by non-group insurance, which is purchased directly from an insurance company either as policy holder or as dependent.

When dealing with hospitals' suppliers and customers, they can also provide useful skills and experience to negotiate better terms. As veteran financial advisers, they can advise hospitals to adopt a better financial structure and more flexible financial tools. On the other hand, many argue that PE leads to adverse consequences. PE demands a higher rate of return than other traditional financing sources and such a high-profit-driven motive conflicts with hospitals' missions. High debt loads resulting from financial engineering potentially press hospitals to take more aggressive cost-cutting measures and staff reductions, hence compromising their service quality. PE has a structured investment timeline, and such a short horizon renders it impossible to focus on long-term success.

2.2 Data

The main data used in the paper are from the proprietary database DRG Real World Data Product (RWD Product). The RWD product was developed by Decision Resources Group,[11] a global information and technology services company that provides proprietary data and solutions to the healthcare industry. A more detailed discussion about the data is provided in the Online Appendix. The raw RWD data contain over 26 billion claims, track more than 300 million longitudinal patient lives in the United States, and cover over 98% of U.S. healthcare plans (private insurance, Medicare, and Medicaid, but not uninsured patients). The database includes claim rejection rates, adjusticated payments, and out-of-pocket costs for detailed cost analysis. The database is built on the DRG Repository that sources claims from various originators, including hospitals, physician offices, pharmacies, long-term care facilities, and nursing facilities.

One contribution of this paper is that it is the first, to my knowledge, to introduce and use DRG RWD data in healthcare finance and economics. The prominent alternative insurance claims data include the IBM MarketScan and Health Care Cost Institute (HCCI) databases, which have been used in several previous papers. Both are closed-network sources in the sense that MarketScan's claims are sourced primarily from commercial and/or employee-sponsored health plans and HCCI's claims come from three insurance companies in the United States: Aetna, Humana, and UnitedHealth.[12] In contrast to those closed-network sources, the DRG RWD Product contains open-network claims sourced from billing software used by healthcare service providers and pharmacies. So, it has an overall larger capture of patients with claims data and is more representative across multiple payer categories compared to closed-network sources. Another advantage is its ability to track patients even after they change payers, which is usually infeasible in closed-network databases. Most importantly, DRG RWD claims can be updated daily, granting access to the most up-to-date medical claim information, while others, such as the HCCI database, can only access claims data with a delay.

The RWD Product includes a unique provider identifier (the National Plan and Provider Enumeration

[11] The company was acquired by Clarivate Analytics from Piramal Enterprises Limited in May 2020.

[12] 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.

System Identifiers [NPI]), a unique patient identifier, a unique payer/insurer 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 payments, 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 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. For a given set of provided health services, final payments are generally broken down by institutional payments that paid for facility services, and professional payments that go to physicians. Institutional and professional payments are processed separately. As the first filter, this paper restricts analysis to insurance claims with institutional payments in the database. The second filter limits the sample to the outpatient setting, though previous work mainly focuses on the inpatient one.[13] I do this for two primary reasons. First, in the sample, PE-backed hospitals have better coverage of outpatient visits, which provides more power to detect the impact of PE intervention. Second, to construct the relative service-mix weights and benchmark prices in the inpatient setting requires the use of diagnosis-related group (DRG) codes, which are not reliably reported in the RWD product. Reconstructing DRG classifications from the data without proprietary software would introduce additional noise into the analysis. The detailed method for identifying outpatient claims in the sample is provided in the Online Appendix. The last filter restricts the sample exclusively to claims sourced from private insurers, which means that Medicaid, Medicare, and Medicare Advantage claims are excluded from the analysis. In the end, I obtain a sample of over 600 million commercial insurance claims in outpatient settings.

In the main analysis, I group claim lines to each patient visit and calculate the payment and medical information up to the patient-visit level. 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 or negative service-mix weights are excluded as well. Lastly, I require that a hospital has at least 10 patient visits a year in the sample. Applying all

[13] Some exceptions, for example, include Liebman (2016) and Prager and Tilipman (2020).

these filters leads to a final sample of 72,663,354 patient visits between 2013 and 2019.

The data on PE deals are from four proprietary sources: PitchBook, Preqin, Capital IQ, and SDC Platinum. I synthesize them to construct a comprehensive database on PE investments in hospitals. The primary source is a list of deals from PitchBook. Specifically, I restrict the industry to healthcare services with "Clinics/Outpatient Services" and "Hospitals/Inpatient Services" and select all PE deals that are already completed. I focus on deals that took place between 1994 and 2019 and that invested in companies located in the United States. In the end, I obtain a sample of 2,324 companies involved in 2,827 deals initiated by 1,339 investors. As a complement, I also download all PE deals in Preqin and restrict those deals to the healthcare sector in the United States within the same time frame. In addition, I restrict deal types to buyouts, public to private, merger, add-on investment, and growth capital. In a similar fashion, I download PE investment from the Capital IQ and SDC Platinum databases to supplement PitchBook and Preqin for a few missing deals.

For characteristics of hospitals, I tap the AHA annual survey sample from 2005 to 2019. It provides detailed information on operational, staffing, technology, finances, and IT characteristics. There are many categories of hospitals in the sample. A typical example is a general acute care hospital, but in my analysis, I also include specialty hospitals for rehabilitation, mental healthcare, transplants, and long-term care. To match AHA survey data to RWD claims, I follow Cooper et al. (2019) and use the NPI codes in both datasets to link them using the detailed procedure provided in the Online Appendix.

I also use the Healthcare Cost Report Information System (HCRIS) to complement the AHA survey data. HCRIS contains information from cost reports submitted annually to CMS by all Medicare-certified hospitals. It supplements the AHA data with detailed financial and cost information. To evaluate the quality information of hospitals, I leverage the quality scores from various CMS-managed quality programs: outpatient imaging efficiency scores, 30-day mortality rates, 30-day readmission rates, patient safety indicators, and surveyed patients' satisfaction scores. Other supplemental data used in the paper include annual ambulatory payment classifications (APC) code files and annual relative value unit (RVU) 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.

2.3 Summary Statistics

For the sample of PE hospital buyouts from 2006 to 2019, Table 1 reports key features and statistics of the deals. It records a total of 243 deals. Panel A classifies them into six categories based on deal types. Over half are add-on deals: transactions where an existing PE-backed hospital system acquired other facilities; these deals involve 4.9 hospitals on average. The second-largest group is private-to-private buyouts, including transactions where PE investors directly bought out a private hospital system. Compared to other deal types, private-to-private buyouts typically have large transaction sizes, with 13.7 hospitals per deal on average. The third group is PE growth deals, which occur when hospitals invite PE money and use the financing to upgrade technologies or expand facilities. A total of 32 transactions belong to this group. A typical deal involves around 4.4 hospitals, the smallest transaction size across all categories. The remaining deals are 18 secondary buyouts, 6 public-to-private buyouts, and 5 management buyouts. Secondary buyouts are transactions where a PE bought hospital systems from another PE firm. In public-to-private buyouts, PE firms target hospital systems that are publicly traded companies. Note that the public-to-private buyouts entail the largest transaction size with 26 hospitals per deal on average.

A total of 838 hospital facilities were ever involved in these PE deals.[14] Panel B of Table 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 two-thirds of them were for-profit: there are 466 facilities previously owned by for-profit corporations, 101 facilities owned by for-profit partnerships, and a handful of facilities owned by individuals. On the other hand, about one-third of hospitals were not-for-profit prior to PE investments, including 125 community-owned or other not-for-profit facilities, 105 church-owned facilities, and 34 facilities owned by local government. 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.

To explore how PE-target hospitals are geographically spread, Figure 3 demonstrates their location distribution across hospital referral regions (HRRs), which is a geographic concept commonly used to delineate distinct local markets of hospital services in the United States.[15] Panels A and B exhibit the number and the relative ratio of hospitals ever invested in by PE in each HRR. As observed, PE-target hospitals are widely spread across the United States. However, they tend to be more concentrated in the south and west, particularly in states like Texas, Florida, and Tennessee. In the Online Appendix, I provide figures of the geographic distribution of PE-backed hospitals at the county level.

For the insurance-claim sample of my main analysis, Table 2 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 2 shows variables at the patient-visit level. The mean age of patients is 46 and

[14] Note that a hospital might experience multiple PE deals across the sample period. For example, some hospitals would be double counted in Panel A of Table 1 if they experienced a secondary buyout—the first-time buyout and the secondary buyout. Therefore, the net count of hospitals reported in Panel B is smaller than that in Panel A.

[15] Hospital referral regions (HRRs) are developed by the Dartmouth Atlas. It divides the United States into 306 distinct HRRs. Each represents regional healthcare markets for tertiary medical care that generally requires the services of a major referral center. An HRR is determined at the zip code level using an algorithm reflecting commuting patterns and is required to have at least one city where both major cardiovascular surgical procedures and neurosurgery are performed. Many previous studies, including Cutler and Sheiner (1999), Chandra and Staiger (2007), and Ericson and Starc (2015), use HRRs to define boundaries of local hospital markets and argue that it is preferable to conduct analyses at this level.

about 62% of them are female. The gender and age differences are insignificant between the "Never Treated" and "Ever Treated" groups. 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*.[16] Also, patients exhibit some degree of inertia, as they prefer hospitals that they have visited before. 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.[17] The relative service-mix weights are roughly one-third higher in the "Ever Treated" group, either because patients of more severe diseases prefer to visit them, or those hospitals overutilize resources to treat patients. These two explanations will be distinguished later in Section 3.2. In terms of hospital prices, the mean listing price on hospitals' chargemaster for a typical visit is around $2,675 (dollars in 2019 adjusted by GDP deflators). In contrast, the average negotiated payment per visit is only $814, of which insurers cover about 82%. The remaining balance has to be paid by patients themselves, although there is wide variation in this number as the median patient pays zero out-of-pocket costs. The total paid amounts do not exhibit significant differences between the "Never Treated" and "Ever Treated" groups, which by no means implies that negotiated prices are unchanged after PE intervention. A closer scrutiny should look into price variations within the hospital–insurer pair.

Panel B of Table 2 reports variables at the hospital-year level. It shows that PE-backed hospitals tend to have less personnel, though the number of hospital beds is similar to other hospitals. They are less likely to have teaching status and tend to be located in rural areas. They accommodate fewer outpatient visits and Medicaid patients, but more Medicare patients.

Panels C and D of Table 2 summarize variables at the local region level. Median household income is higher in counties where PE-target hospitals are located. Their residents have a slightly lower coverage ratio of private insurance, but slightly higher ratio of Medicaid. At the HRR level, PE tends to target those more competitive regions with more hospitals and lower HHIs in hospital beds and inpatient days. One conjectured reason is that PE firms would like to reduce pre-merger scrutiny from antitrust regulators by picking targets in more competitive markets (e.g., Wollmann, 2020).

[16] I rely on the Stata command "georoute" developed by Weber and Péclat (2020) to retrieve travel distance and travel time between two geographical coordinates. The coordinates of a patient's zip code prefix centroid are calculated by the AgGIS Pro software.

[17] 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).

3 Descriptive Evidence

3.1 Empirical Specification

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

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

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.[18] 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 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.[19] Standard errors are clustered at the hospital level.

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 Strömberg (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.

The coefficient of interest, α_1, essentially captures the difference of negotiated service prices between PE- and non-PE-backed 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

[18] 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.

[19] Note that it is important to include $Hospital \times Insurer$ FEs in the specification given the nature of price setting in this sector, i.e., through bilateral bargaining between each pair of hospitals and insurers in a local market. As argued in Craig et al. (2021), $Hospital$ FEs alone cannot distinguish whether the price changes are due to renegotiation between hospitals and insurers, or from provider switching on the insurer's end.

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 3. Panel A of Table 3 uses the log of total paid amounts as the dependent variable. The coefficient on PE is positive and statistically significant at the 5% level, and its magnitude is quite stable across varying inclusions of controls and fixed effects. It suggests that after PE buyouts, negotiated prices between a hospital and an insurer increase by 32%. To split the payment increase between insurers and patients, Panels B and C of Table 3 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. The last panel explores whether PE-backed hospitals change the utilization of medical resources for patient treatment. 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.

In addition to the full-sample OLS regressions, I run another model in which I match the PE-target hospitals to a subset of non-PE-backed ones that are similar along observable dimensions. Specifically, I match each PE-backed hospital to three control hospitals using the optimal Mahalanobis matching, wherein the "distance" between hospitals is defined using 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 as the target one, be in the same census division, and have the same service code. The results of the matched-sample estimates are reported in Table 4. Similar to the full-sample OLS regressions, negotiated prices between hospitals and insurers increase by about 69% after PE buyouts. This increase is mostly shouldered by insurers rather than patients, while the relative service-mix weights of patient visits do not change significantly after PE intervention. The increased magnitude of price estimates in the matched sample deserves comment: though OLS and matched-sample estimates are unable to fully resolve the endogenous selection concern of PE investments, the matched sample provides more precise estimates of the treatment effect as it creates a balanced panel and eliminates potential influence of confounding factors.

To explore the dynamics of these effects, I conduct an event study based on the matched sample.[20]

[20] 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., Ivanov et al., 2020 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.

I implement it at the quarterly frequency in order to better visualize how PE buyouts affect prices and whether the pre-trend assumption is violated. Specifically, I look into a time window of four years before and after PE investments and bin distant relative periods (Abraham and Sun, 2020). 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 4. 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 4 witness a spike in the total paid amounts and insurer paid amounts. The effects are significantly positive and persistent for the following quarters. Such pattern is not observed for the patient paid amounts[21] or the relative service-mix weights of each visit as shown in the top-right and bottom-right panels. Overall, the figure implies that when a hospital is bought out by PE, there is a prompt, persistent rise in the negotiated prices between PE-backed hospitals and insurers, and such price increases are mostly borne by insurers. There is no indication that PE-backed hospitals increase utilization of medical resources or quantities of services to boost revenues.

One potential concern of pooling all outpatient visits 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 with respect to clinical quality among millions of available health services items (Chernew et al., 2021). I follow Brown (2019) to pool X-ray and MRI scan procedures together and regress negotiated prices of one procedure (rather than prices aggregated to patient visit level) on the PE-ownership indicator. Results are demonstrated in Table 5. The first column contains OLS estimates by only including hospital–insurer pair fixed effects. Consistent with Panel A of Table 3, it implies that after PE investments, prices of imaging procedures increase by approximately 10%, significant at 5% level. Other columns vary the inclusions of controls and other fixed effects and deliver very similar estimates. For example, the last column indicates that prices will increase about 11% at 1% significance level. Furthermore, I 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 5. Each cross represents the point estimate for a specific imaging procedure and the capped spikes denote the 95% confidence intervals. For most imaging procedures, the figure supports the conclusion that after PE investments, negotiated prices between hospitals and insurers increase significantly.

[21] 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.3 of the Online Appendix.

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 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.[22] 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 6.

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 detail in Section 3.5.

3.4 Potential Channels

The hospital sector has experienced phenomenal consolidation in recent decades. Some might attribute the increase in negotiated prices after PE buyouts to the market consolidation effect as a result of M&As. 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 7 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 Panel A of Table 3, indicating that the impacts of PE are unique. I explore several novel channels that might explain the observed price increases after PE intervention.

[22] Note that this is equivalent to a "diff" specification by comparing negotiated prices before and after a "shock" occurs. The results are robust to a standard diff-in-diff model by including hospitals in regions that never had PE-backed hospitals as a control group.

Financial Engineering

One of the most prominent features involved in PE buyouts is the heavy use of debt (so-called financial engineering). Investors typically inject large amounts of debt and jack up the target firm's leverage (e.g., Kaplan and Strömberg, 2009). Higher leverage dictates higher probability of bankruptcy, and as discussed in previous literature (e.g., Brown et al., 2009 and Matsa, 2010), could enhance the firm's bargaining position. Panel A of Table OA.2 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.[23] Column 4 shows that after PE buyouts, the leverage of a hospital increases by 10% on average, statistically significant at the 1% level. 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-backed hospital, in Panel B of Table OA.2 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-backed 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-backed hospitals does not affect price negotiations. This supports the idea that the financial engineering channel is unique to PE-backed 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 prominent feature of PE firms is that they are profit-centered due to their fiduciary duty to investors (e.g., Shleifer and Summers, 1988 and Lerner et al., 2011). This contrasts with the ownership type of most not-for-profit hospitals in the sector. 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-backed 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-backed hospital was previously for-profit. Note that the Previously For-profit dummy itself is

[23] Both long-term liabilities and total assets are book values. The total long-term liabilities are the sum of debt with a maturity longer than 12 months, including mortgages payable (line 46 in the HCRIS database), notes payable (line 47), unsecured loans (line 48), and other long-term liabilities (line 49); and the total assets are equal to the sum of total current assets (line 11), total fixed assets (line 30), and total other assets (line 35). I focus on this definition for two reasons: (1) leveraged buyouts usually take debt with relatively longer maturities; and (2) in HCRIS data, short-term liabilities include items such as accounts payable due suppliers, or salaries and wages payable due employees, which might contaminate the analysis. To avoid the pitfall of excluding relevant short-term debt, as a robustness test I introduce a variant of the leverage measure, defined as total long-term liabilities plus notes and loans payable (line 40), and then divided by total assets. All results are robust under the new definition.

absorbed by hospital fixed effects. 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.4 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 3.

Operational Efficiency

Previous literature documents that PE improves operational efficiency of its portfolio companies, commonly translating into lower marginal costs (e.g., Davis et al., 2014, Bernstein and Sheen, 2016, and Bircan et al., 2020). Theoretically, lower marginal costs are associated with lower prices, which can be another channel affecting negotiated prices of PE-backed hospitals. 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). Specifically, it captures the average operational cost of a hospital to take care of a patient, defined as

$$\mathrm{AC}_{it} = \frac{\mathrm{TC}_{it}}{D_{it} \times (1 + \frac{R^O_{it}}{R^I_{it}})},$$

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^O_{it} is the outpatient charges, and R^I_{it} is the inpatient charges.[24]

I depict the average cost dynamics before and after PE investment in Figure OA.4 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. For example, 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. So 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,

[24] Essentially, AC_{it} measures the average cost for an effective inpatient discharge by converting outpatient activities into the equivalent number of inpatient ones. Given that our main analysis focuses on the outpatient prices, the underlying assumption here is that PE buyouts have an overall effect on hospitals' operational efficiency for both outpatient and inpatient settings, which allows us to infer the operational efficiency change of a hospital for an outpatient visit.

outpatient imaging efficiency, and consumer assessment scores. Results are exhibited in Figure OA.5 in the Online Appendix. Each cross denotes the point estimate for one specific quality measure and the capped spikes denote its 95% confidence interval. In contrast to Gupta et al. (2021), quality implications after PE buyouts are mixed: In general, 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.

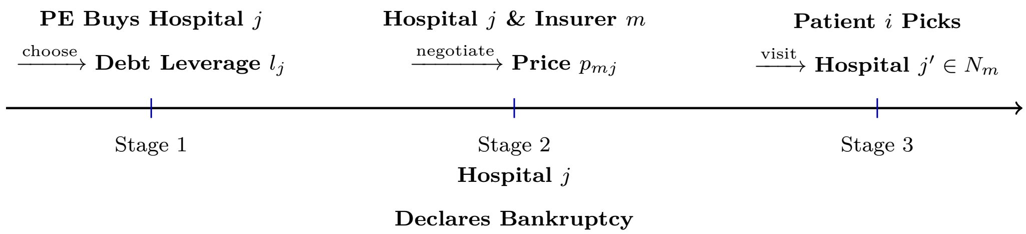
3.5 Challenges of the Reduced-form Approach

Though the reduced-form regression is a transparent way to examine the impacts of PE, there are a couple of challenges to that approach 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 (Berg et al., 2020). 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 and importance of various channels on price bargaining outcomes, though it does provide evidence on the directional effects. In addition, some potential channels are difficult to find proxies for and to isolate using the reduced-form techniques. For example, PE firms are believed to be professional investors in financial markets and have rich experience in business negotiations. It is possible that after PE investment, hospitals learn better negotiation skills and increase their bargaining power. But finding a proxy for negotiation skills in reduced form is difficult. 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. It provides guidance to empiricists so that one can estimate parameters linked, either directly or indirectly, to the underlying theory of PE investment and hospital price determination. 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 Capps et al. (2003), 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.



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.[25] 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

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

This specification encompasses different models used in the literature (e.g., Town and Vistnes, 2001, Capps et al., 2003, Gowrisankaran et al., 2015, Shepard, 2016, 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

[25] 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.

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[26] and relative service-mix weights interacted with hospital dummies. Following Shepard (2016), the indirect utility specification also includes the past outpatient status, PastPatient_{ij}, to capture relationships between patients and a hospital's physicians, which is observed to be a key source of heterogeneity in hospital choice. Note that, following previous literature (e.g., Capps et al., 2003 and 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 going to an out-of-network hospital or 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

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

[26] 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.6 in the Online Appendix. So, it should be less of a concern that the changing composition of procedures after buyouts would affect the welfare implications.

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.[27]

The bargaining process occurs between hospital system s and insurer m over a benchmark price p_{ms}. Before discussing the details of bargaining protocol, I cover one new feature emphasized in this paper: the structure of the local market impacts the bargaining positions of hospitals and insurers. Specifically, if any hospital system 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 standard protocol of the Nash-in-Nash bargaining model widely used in the applied literature (e.g., Horn and Wolinsky, 1988, Crawford and Yurukoglu, 2012, Grennan, 2013, Gowrisankaran et al., 2015, Ho and Lee, 2017, and Collard-Wexler et al., 2019). This new feature resulting from hospital bankruptcy introduces an extra consequence to insurance companies: 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

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

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 $W_m(N_m) = \sum_{i=1}^{I} \mathbf{1}\{m(i) = m\} CS_{imd}(N_m)$. 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 $V_m(N_m - J_s, \mathbf{p}'_{-s})$. Notice this is different from the

[27] Previous studies, including Gowrisankaran et al., 2015, Lewis and Pflum (2015), Ho and Lee, 2017, Brown (2019), and Raval et al. (2020), 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 (2016) and Prager and Tilipman (2020).

payoffs in which hospital system s stays alive while not reaching an agreement with insurer m. In this 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 $w_d \text{mc}_{ms}$.

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

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

And the total expected profits of hospital system s are $\sum_{m \in M_s} \pi_s(\mathbf{p}_m, N_m, \text{PE}_s)$, 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

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

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 $\text{NP}_s \cdot (1 - \text{PE}_s)$ captures the impact of PE buyouts on the non-pecuniary motive of hospitals: τ_{NP} would vanish after PE investment. This is because PE firms have to turn hospitals into for-profit entities if they would like to distribute profits. 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

Leveraged buyouts typically involve massive financial engineering that would lead to a large debt burden 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 in the bargaining game, the bankruptcy scenario as well as its probability has to be considered. Two assumptions are made in order: (1) PE-backed 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, private grants, and donations, which can potentially help them overcome most financial difficulties. Often, local governments tend to bail out distressed non-PE-backed hospitals to prevent a loss of access to medical services in local communities. In addition, PE investors have the reputation of closing facilities due to financial considerations,[28] 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-backed hospitals does not affect service pricing. (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 parameter $\tilde{\mu}$ and the scale parameter $\tilde{s} > 0$.[29]

One direct implication is that in equilibrium, PE-backed hospitals will not choose an extreme level

[28] 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.

[29] The logistic distribution can be rationalized by adding error terms to both sides of Equation (5) and assuming those terms follow i.i.d. type I extreme value distribution, which is a typical assumption in the discrete choice literature.

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-backed hospital s, the expected bankruptcy probability is calculated by taking the expectation of $\mathbf{1}\{\widetilde{\Pi}_s(\cdot) < C(D_s)\}$, denoted by $\rho(l_s, \cdot) = \mathbf{E}\left(\mathbf{1}\{\widetilde{\Pi}_s(\cdot) < C(D_s)\}\right)$. For example, on the equilibrium path where hospital s successfully reaches agreements with all the insurers in M_s, the previous discussion implies that the expected bankruptcy probability satisfies $\rho(l_s, M_s) = 0$.

Bargaining Stage

Consider the case where 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 $\rho(l_s, M_s \backslash m) = \frac{1}{1+\exp(\varrho h_s(M_s \backslash m) - \theta l_s - \mu)}$ represents the expected bankruptcy probability if hospital system s is excluded by insurer m, wherein $\varrho = \frac{1}{\tilde{s}} > 0$, $\theta = \frac{\tilde{\theta}}{\tilde{s}}$, and $\mu = \frac{\tilde{\mu}}{\tilde{s}}$. The payoffs to hospital equityholders are zero after bankruptcy. 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 going bankrupt leads to a more concentrated hospital sector. 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 wherein negotiations are non-binding and contingent on the network of hospitals never reaching disagreement (Stole and Zwiebel, 1996). However, I emphasize a distinct mechanism: In a repeated setting, 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.[30] This intuition shares a similar spirit with the idea of Raskovich (2003) in which pivotal buyers tend to have worse bargaining positions since they have to cover a larger portion of fixed costs incurred by the seller. But 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.[31]

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

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

[30] Practitioners are found to use this strategy quite frequently. For example, 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 million dollars more per year—versus losing fifty million per year...".

[31] Consistent with the prediction of this mechanism, I find that if a PE-backed 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.5 in the Online Appendix.

In contrast, for non-PE-backed hospitals, as they are unable to credibly threaten bankruptcy, the bargaining problem boils down to

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

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, Lewis and Pflum, 2015, and Ho and Lee, 2017).

First-Order Condition of the Bargaining Problem with PE-backed 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:

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

wherein ΔV_m is described in Equation (6) and $\Delta \varpi_s = \frac{1}{\varrho} \mathrm{TA}_s \ln \left(1 + \exp \left(\theta l_s + \mu - \varrho h_s(M_s \backslash m)\right)\right)$. 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).

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-backed hospitals in both extensive and intensive margins. Compared to non-PE-backed hospitals, the ability to credibly threaten bankruptcy grants the PE-backed hospital a better bargaining position. Moreover, among PE-backed 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 after PE intervention affects the WTP of patients, which leads to changes of negotiated prices.

Non-pecuniary objectives: If PE-backed hospitals care less about their social objectives and more about their fiduciary duties, 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 $\text{PE}_s \in \{0, 1\}$, in which $\text{PE}_s = 1$ 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. It is different from the debt burden modeled in the bargaining stage. Potential risks of using larger amounts of debt include higher costs resulting from debt overhang (Hennessy and Livdan, 2009 and Hege and Hennessy, 2010), larger risk of financial distress (Myers, 2001), and more severe agency conflict between general and limited partners (Axelson et al., 2009). I model the average cost of debt 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

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

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

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

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

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

In reality, the potential gains are split between the PE firm and the original hospital owners under a fixed sharing rule. I follow SØrensen (2007) to assume that PE expects to receive a fraction, λ, of the total gains. This assumption rules out transfers. Since PE's investment decision does not quite depend on the constant λ, I abstract the sharing rule away by assuming $\lambda = 1$ for simplicity.

4.2 Estimation

4.2.1 Estimation and Identification of Patient Demand

The patient demand model is estimated by maximum likelihood using the patient-visit data aggregated from the RWD Product. Identification of the demand parameters in Equation (2) follows the standard arguments for the multinomial logit model (e.g., Train, 2009).

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. 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.[32]

I parameterize marginal costs and use the FOC in Equation (8) to obtain the first two sets of moment

[32] 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.

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:

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

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. In addition, PE_s is an indicator of whether hospital s is backed by PE, g_{c} measures the proportional change of operational efficiency for hospitals 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, which implies 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), which enables me to identify the variation of bargaining power across hospital–insurer pairs. 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

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

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. Specifically, it is assumed that the average marginal cost $\bar{\text{mc}}_s$ in the outpatient setting of hospital system s is linear to the cost per adjusted discharge in a year, AC_s, computed in Section 3. It is expressed as $\bar{\text{mc}}_s = \lambda_1 \cdot \text{AC}_s + \lambda_2$.[33] 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:

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

The last set of moment conditions comes from the optimal leverage choice. I parameterize the costs of debt raising 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, and it introduces another source of endogeneity to the model. 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; $(b_0, \boldsymbol{b})$, the bargaining-power coefficients; $(\eta_0, \eta_t, \eta_r, \boldsymbol{\eta})$, 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 to the bargaining power and marginal costs after PE buyouts, are estimated by the following moment conditions:

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

wherein $\boldsymbol{Z}_{ms}$ is a vector of exogenous variables.

[33] 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.

Identification

Parameter identification relies on the variation of data and the way it affects constructed moments. The identifying assumption underlying this research design 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 $(b_0, \boldsymbol{b})$ 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 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. Furthermore, the simplifying assumption of constant α seems to be innocuous given that I exclusively focus on the commercial health insurance market, wherein payers share quite similar behaviors. Lastly, the debt burden and bankruptcy probability parameters (ϱ, θ, μ) are identified by price variations across PE-backed hospitals that have different levels of debt leverage and revenues from various insurers.

Unlike Gowrisankaran et al. (2015), marginal-cost parameters $(\eta_0, \eta_t, \eta_r, \boldsymbol{\eta})$ 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-backed 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 $\mathrm{PE}_s \in \{0, 1\}$ 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. I follow a common assumption in the industrial organization literature that marginal-cost shifters do not affect preferences directly.

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. The regulation has been adopted in one form or another by many state legislatures and refined by state courts, state professional licensing boards, and other health regulatory agencies. 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, it is worth noting that imposing the CPOM prohibition does not mean that corporate or other nonprofessional entities are completely barred from operating in the healthcare sector. Certain types of entities are exempt from the CPOM prohibition in a few states. There is also 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.

In a similar vein as Rice and Strahan (2010), Cain et al. (2017), and Karpoff and Wittry (2018), 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.

As the first step, three panels of indicators are created: State statute indicator in 2006 equals (negative) one if the statute of a state explicitly prohibits (allows) CPOM, and zero otherwise. Legal precedent indicator in 2006 equals (negative) one if any previous state supreme court rulings were against (in favor of) CPOM, and zero otherwise. Board opinion indicator in 2006 equals (negative) one if opinions from the attorney general or medical board of a state are against (in favor of) CPOM, and zero otherwise. For years after 2006, I track changes of these indicators by manually searching state statutes, legislation files, court cases, administrative materials, and other secondary materials in the Lexis Advance Research

Database. If any record was to relax (strengthen) the CPOM prohibition in a state of year t, a new value will be assigned as the previous value minus (plus) one. 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. Detailed descriptions of relevant legal events are provided in the Online Appendix.

In the second step, I run a regression of PE-ownership dummies for hospitals on the indicators collected in the first step, after controlling hospital fixed effects, year fixed effects, and time-varying characteristics of hospitals. Results are exhibited in Table OA.7 of the Online Appendix. 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 6 exhibits time series of the CPOM regulation indices for a subset of 16 states from 2006 to 2019.

Though not a formal validation of the first stage, Table 8 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) two-way clustering standard errors by state and year, and (2) controlling for Medicaid expansion of states after ACA, as shown in the Online Appendix.

To alleviate concerns about the exclusion restriction, I take several steps: (1) Compare hospitals' observables. Specifically, I explore whether significant differences in observables occur between hospitals facing more and less stringent CPOM 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. Table OA.9 in the Online Appendix describes the results. I find no significant differences between the two sets of hospitals across a list of observables such as hospital size, ratio of Medicare patients, ratio of Medicaid 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.10 reports the results, and indeed the CPOM regulation does not significantly affect the M&A decisions of non-PE-backed 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-backed hospitals (e.g., Axelson et al., 2013 and Davis et al. 2019). 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 9 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 positive and statistically 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-backed 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-backed 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.

4.3.2 Supply Estimates

Table 10 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, which are largely consistent with previous studies (e.g., Lewis and Pflum, 2015). The model assumes that bargaining weights are determined linearly by hospitals' characteristics. To have a better sense, 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, in their bargaining weights at a significance level of 0.1%. 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 impacts hospitals' bargaining power. The estimates suggest that 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.

Panel B demonstrates estimates for the marginal-costs specification, which is assumed to be determined exponentially by hospitals' characteristics. 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. Providers typically lose money by treating Medicaid patients. 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, average costs in the local market are incorporated into the marginal-cost specification. The result intuitively suggests a positive correlation between the marginal costs of hospitals and the Medicare average outpatient costs of the HRR 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 (e.g., 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-backed 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-backed 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-backed 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 directly examine PE's impacts on hospitals' operational efficiency and bargaining power. I find that 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.

4.4 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 7 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 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. Recall that individual hospital fixed effects are not included in estimating the bargaining model due to the sizable computation burden. The predicted negotiated prices are purely driven by hospital, insurer, and local market characteristics; patients' demand; PE ownership; and year and region time-invariant factors. Given the relative inflexibility of the model with respect to price variations across hospitals, the overall fit is pretty good. For the subsample of PE-backed hospitals, the model-predicted price distribution does not perfectly align with the realized one. The model-predicted distribution has a left-biased spike and a fat right tail. 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 8 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.

As an additional 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.7 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 delivers some valuable insights on the estimation. It 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, really 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 investments in the United States were banned by regulators. Through the lens of the experiment, I quantify the impacts of PE ownership on negotiated prices, total spending, 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 is typically used by Federal Trade Commission (FTC) and Department of Justice (DOJ), and my model.

5.1 Ban PE Investments

Whether to ban PE investments in the healthcare sector has been at the forefront of current policy discussions. For example, Congress has recently passed legislation to curb the "surprise medical billing" crisis, in which PE-backed physician staffing firms predominate (Appelbaum and Batt, 2020). So, it is important to understand the impacts of PE buyouts in the sector.

To this end, I examine a counterfactual scenario in which PE investments were prohibited. Specifically, I look into a sample of hospitals in 339 HRR-years that ever had PE-backed hospitals between 2013 and 2018.[34] For each HRR-year, I simulate negotiated prices between hospitals and insurers for the realized case and the case with a PE ban. All prices are adjusted by GDP deflators to dollars in 2019. As an interim step of the simulation, I re-estimate patients' choices of hospitals for the counterfactual ban

[34] Hospitals from a subset of 40 HRR regions are dropped due to missing key variables (e.g., debt levels for PE-backed 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.

scenario. Figure 9 summarizes the aggregate outcomes. The gray bars represent variables in the realized case while the red bars denote the PE-banned case. The total realized outpatient spending in the sample is about $27 billion. Banning 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 is about $284 in the counterfactual ban and $317 in the realized case, almost the same percentage reduction as that of the total spending. In contrast, the weight-adjusted quantities of patients barely change from the realized case to the counterfactual scenario.

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 directly impact patients' expected utility 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.

To explore the heterogeneity, Figure 10 demonstrates how the savings of hospital expenses in the counterfactual correlates with the degree of presence of PE-backed hospitals in the local market. The x-axis of Panel A is the ratio of PE-backed hospitals in an HRR during a year, and the y-axis is the percentage change of spending when banning PE ownership in the HRR. Observations are grouped for every 5% interval in the x-axis. The circle size represents the number of observations within each bin. The red dashed line is a linear fit of data, which exhibits a noticeable downward trend, indicating that hospital expense savings would grow with the number of PE-backed hospitals in a region if PE ownership were banned in the counterfactual. Panel B depicts an alternative specification with the x-axis being the ratio of PE-backed hospital beds in an HRR of a year. The conclusion of more PE presence leading to more savings under the counterfactual is robust.

Next, I investigate the spillover effects and quantify how they vary across rival hospitals. To do so, I categorize hospitals into three groups: (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 11 reports levels of total health spending, quantity-weighted average prices, and weight-adjusted patient quantities for each group in the realized scenario. The top panel focuses on the *PE-backed* group. The realized spending is about $5.5 billion, accounting for about 20% of total spending documented in the sample. The quantity-weighted average price is $588, and the weight-adjusted patient quantity is about 9.3 million. In contrast, the *Non-PE/Shared* group, depicted in the bottom-left panel, has slightly higher total spending with $6.8 billion, though its quantity-weighted average price is only $234, less than half of the price in the *PE-backed* group. The total quantity of patients accommodated by *Non-PE/Shared* hospitals is much larger, about 29 million after adjusting for the relative service-mix weights. The bottom-right panel presents the realized amounts for the last group. It shows that hospitals in this group treated the majority of patients in the sample, with total spending amounting to \$15 billion and total quantity of patients being about 48 million. Their quantity-weighted average prices lie in between that of the *PE-backed* and the *Non-PE/Shared* group at \$315.

Figure 12 reports how these groups respond to the counterfactual ban. The top panel documents the relative contribution of different groups to the total savings after banning PE ownership. 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 12. 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 ban. In the *Non-PE/Shared* group, hospitals experience modest changes in the counterfactual. The bottom-right panel of Figure 12 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. Noticeably, 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.

Besides quantifying the aggregate effect in the counterfactual ban, the structural model allows me to decompose it to measure the relative contribution of various channels. Figure 13 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, PE has a reputation for closing down financially distressed facilities. 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 $\tau_{\mathrm{NP}} = 0$ 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. In Figure 13, the first and the last bars are copied from Figure 9, 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 with relatively small magnitude. Thus, lower efficiency increases the total spending in the counterfactual if PE ownership were to be banned.

So far, I have explored the implications of PE ownership on hospital prices and spending. To push the model to the limit, Table 11 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 for insurers will be passed 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 insurers' interests are largely aligned with patients' and a reduction of medical spending would translate to a decrease in premiums. 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% (20% in the individual and small group market segments), 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 11. Changes in patients' expected utility are mainly due to the change in hospitals' service quality. The results indicate the counterfactual ban worsens service quality on average, leading to an equivalent reduction of \$22 million in patients' expected utility. This implies that PE buyouts in general 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, accounting for 10.7% of the total spending documented in these regions.

It is worth noting that this counterfactual examines a specific scenario in which other sources of capital would have always filled the hole from PE not investing in those targeted hospitals. This is consistent with the majority of previous studies that examine the impacts of PE. However, it leaves out an important alternative scenario in which hospitals have to shut down without the backing of PE investors. This would be an interesting extension to explore in future work.

5.2 Evaluate Mergers and Acquisitions

It was not until recently that antitrust enforcers put a spotlight on the consolidation activities of PE firms. For example, FTC chairwoman Lina Khan has recently said she would investigate whether the private equity investment model encourages unfair business practices.[35] Given these trends, in this counterfactual, I underscore the importance of considering PE acquirers' unique traits when regulators reviewing proposed mergers. Otherwise, regulators could 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 based on 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 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-backed hospital system, and a target, which is a non-PE-backed 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

[35] More discussions are provided in the *Wall Street Journal* article (September 30th, 2021) titled "Antitrust Regulators Fix Their Sights on Private Equity" (https://www.wsj.com/articles/antitrust-regulators-fix-their-sights-on-private-equity-11632999600).

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-backed 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 14 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 of spending within each bin. The size of a circle in the scatter plot 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 14 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 terms 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 structure (increases in the HHI>50), the No-PE model clearly underestimates the impacts of mergers on patient surplus compared to the PE model.

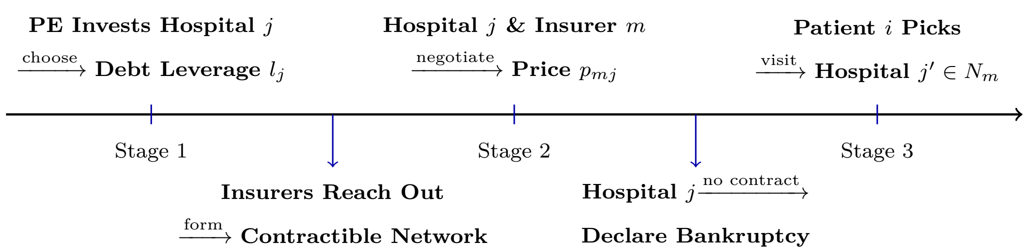
To explore the prediction gaps in different groups, Figure 15 looks into the price predictions for merging hospitals and non-merging rival hospitals after each hypothetical merger. Panel A exhibits percentage changes in the quantity-weighted average prices of the merging hospitals (acquirers plus targets), 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.

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, traditional antitrust laws might not have much bite from a regulatory perspective. However, for a benevolent regulator whose objective is to protect consumer welfare, the exercise conveys a clear message: Mergers involving PE firms systematically exhibit distinct attributes. Regulators could possibly risk underestimating these mergers' 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 estimating an extended model by adding an endogenous network-formation stage between hospitals and insurers. The new model timeline is exhibited below.



Specifically, 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 $m' \in M_s$.[36]

[36] 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.

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.12 of the Online Appendix. Using the new estimates produces \$2.74 billion savings in the first counterfactual of banning PE ownership, comparable to the main estimates in the paper (\$2.95 billion).

6.2 New Entry

Though the structural model incorporates potential hospital closures through PE's bankruptcy threats, 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 the impacts of PE buyouts on healthcare markets, regulations, and patient welfare. This paper addresses these questions by introducing novel insurance claims data, structurally estimating a new model, and quantifying PE investors' equilibrium impacts. The paper finds that PE buyouts lead to an 11% increase in bargained prices between PE-backed hospitals and insurers, meaning that insurers pay hospitals more for the same services after a PE buyout. Local rivals respond by also negotiating higher prices, though responses exhibit strong heterogeneity. The counterfactual simulations imply that banning PE ownership would bring gains in patient surplus, mainly by reducing hospital prices rather than 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.

Several prior studies show that PE buyouts negatively impact patient welfare mainly through changes in health service quality. Their findings can be reconciled with mine by noting that they study nursing homes, for which the major payer is Medicare. The Centers for Medicare & Medicaid Services (CMS) sets fixed reimbursement rates in Medicare. As a result, PE firms must take aggressive cost-cutting measures to increase revenues, which could negatively affect service quality. When it comes to the hospital sector—the focus of this paper—prices are widely negotiated between hospitals and private insurers. Downgrading service quality might be an unwise strategy for PE firms, because negotiated prices are responsive to service quality. So, as documented in this paper, PE firms make other changes to directly impact the price bargaining outcomes. These mechanisms are closely related to the unique features of PE. However, they can be applied beyond the healthcare sector studied in this paper. Policymakers should therefore be aware of them when evaluating PE investments involving any business-to-business bargaining settings.

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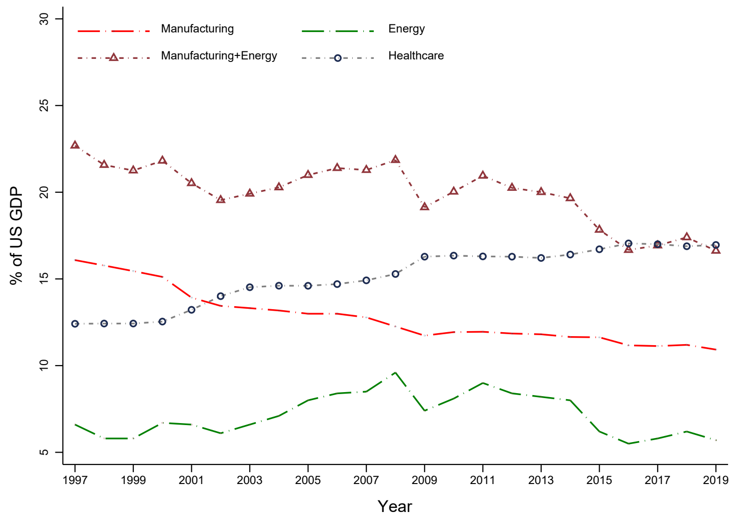
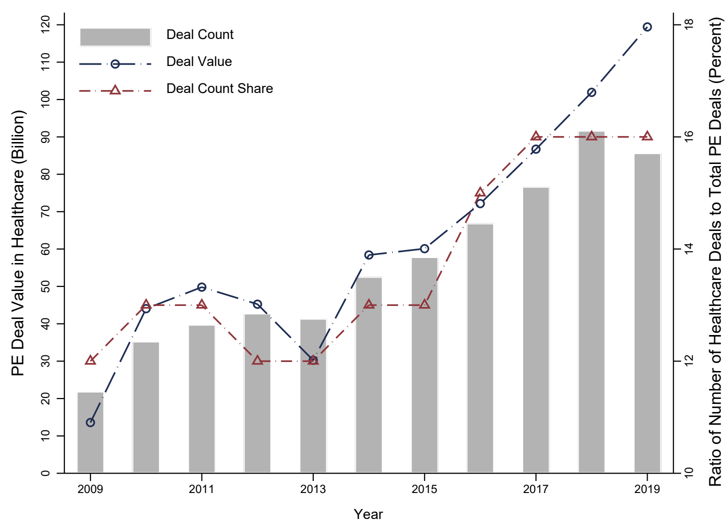
I. Appendix

I.A Figures

Figure 1: Total Health Expenditure Trend and PE Investment in Healthcare



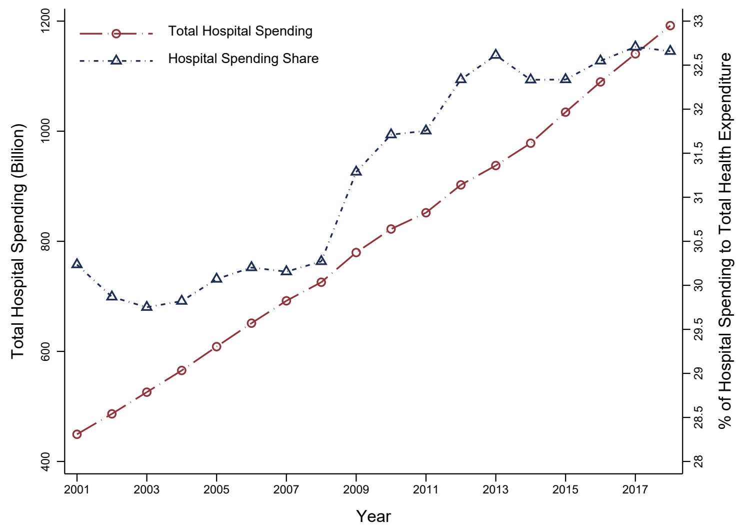
(a) Health Expenditure versus Other Sectors



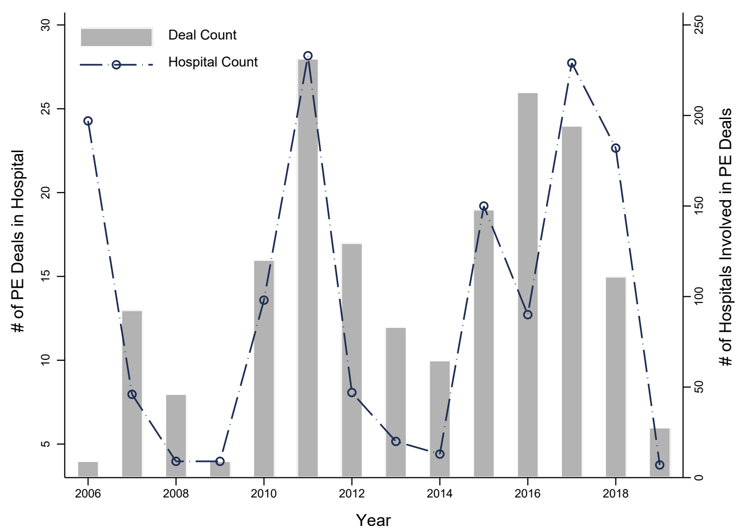
(b) PE Investments in Healthcare

This figure shows the aggregate trends in health spending and PE investments in the healthcare sector. Panel A plots the U.S. health expenditures as well as manufacturing sector and energy expenditures as a percentage of U.S. gross domestic product (GDP) from 1997 to 2019. The data on health-related expenditures within GDP is from the National Health Expenditure Accounts (NHEA). More details about the estimates of healthcare spending are provided here https://www.bea.gov/system/files/papers/BEA-WP2020-8.pdf. Panel B plots the PE healthcare deal values and deal counts as well as the ratio of healthcare deals to total PE deal counts in the United States from 2009 to 2019.

Figure 2: Hospital Spending and PE Investment



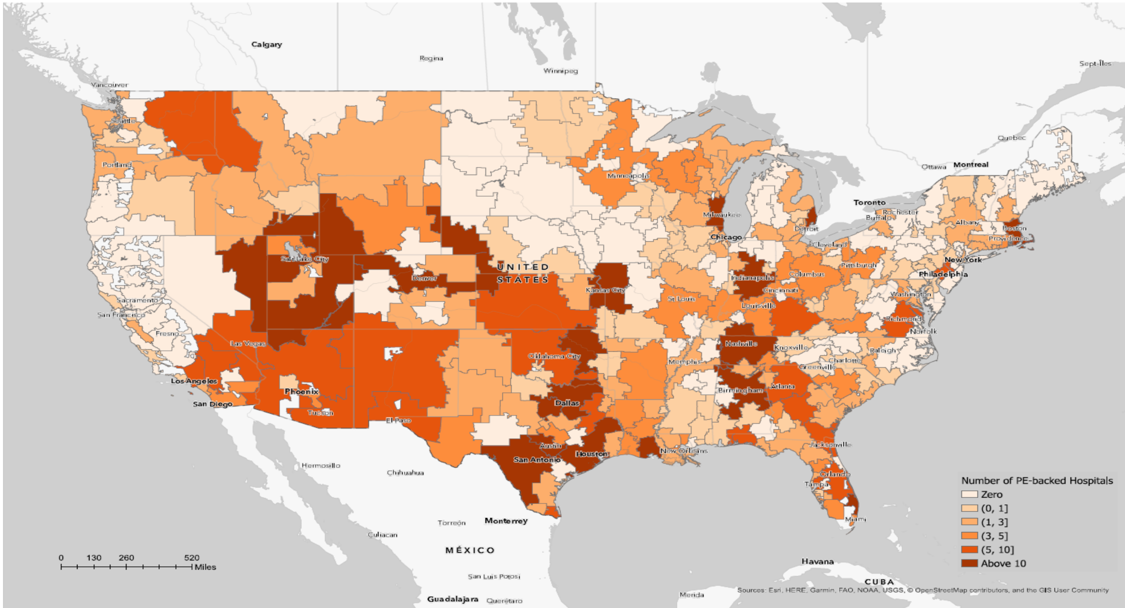
(a) Hospital Spending per Year



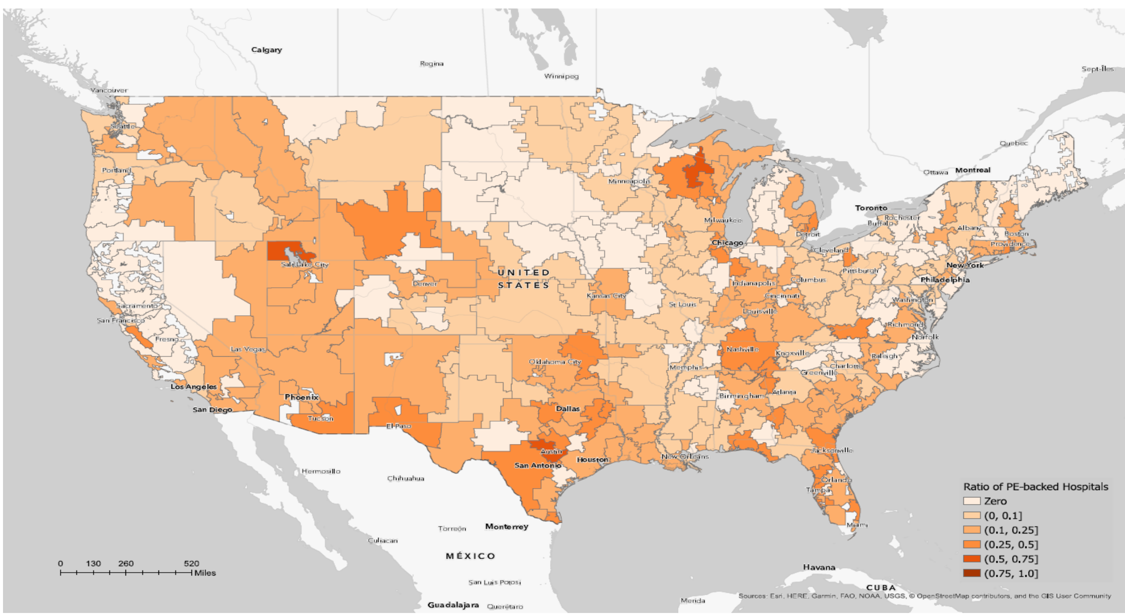
(b) PE Hospital Buyouts within Sample

This figure shows the aggregate hospital spending and PE investments in the hospital sector in the United States. Panel A plots the total hospital spending and the ratio of hospital spending to total health expenses in the United States from 2001 to 2018. Panel B plots the number of PE deals in the hospital sector and the number of hospital facilities involved in these deals in the United States from 2006 to 2019.

Figure 3: Geographic Distribution of PE-backed Hospitals



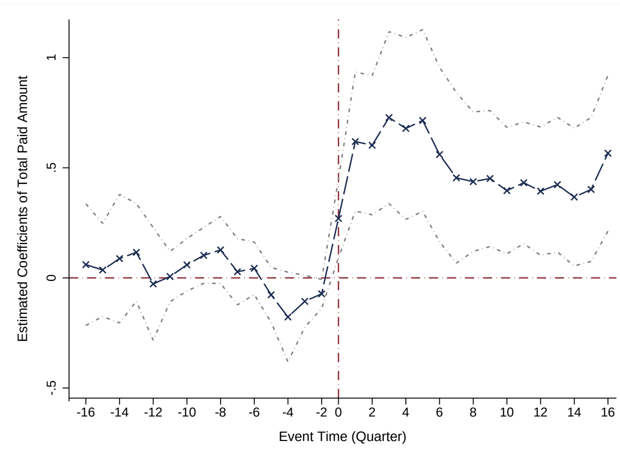
(a) Number of PE-backed Hospitals



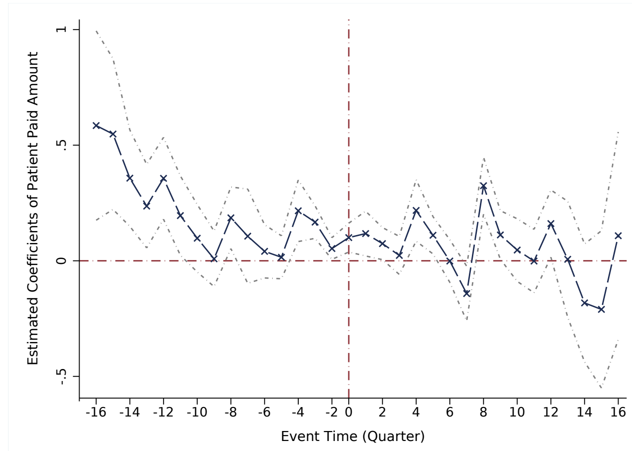
(b) Ratio of PE-backed Hospitals

This figure shows the geographic distribution of PE-backed 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.

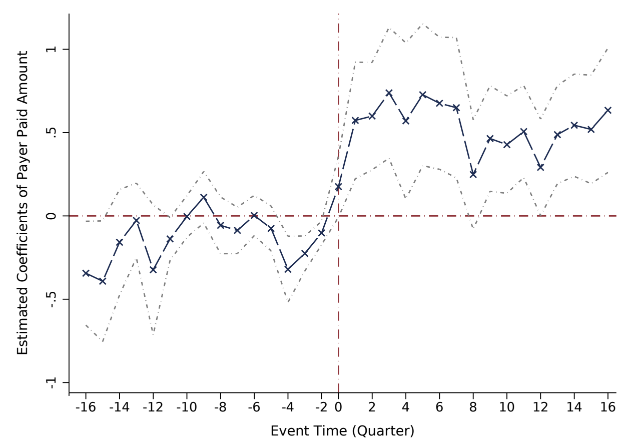
Figure 4: Dynamic Effects of PE Intervention



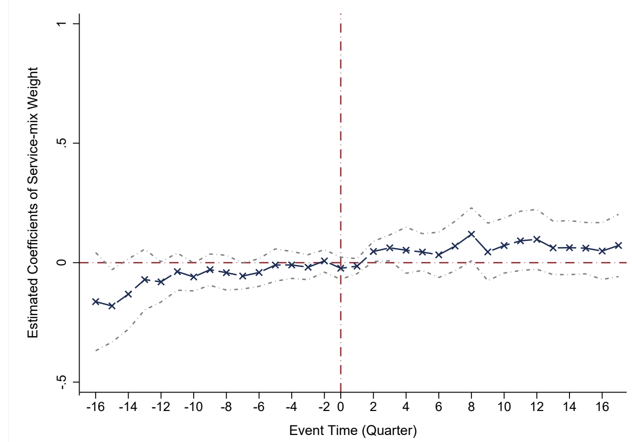
(a) Log of Total Paid Amounts



(b) Log of Patient Paid Amounts



(c) Log of Payer Paid Amounts



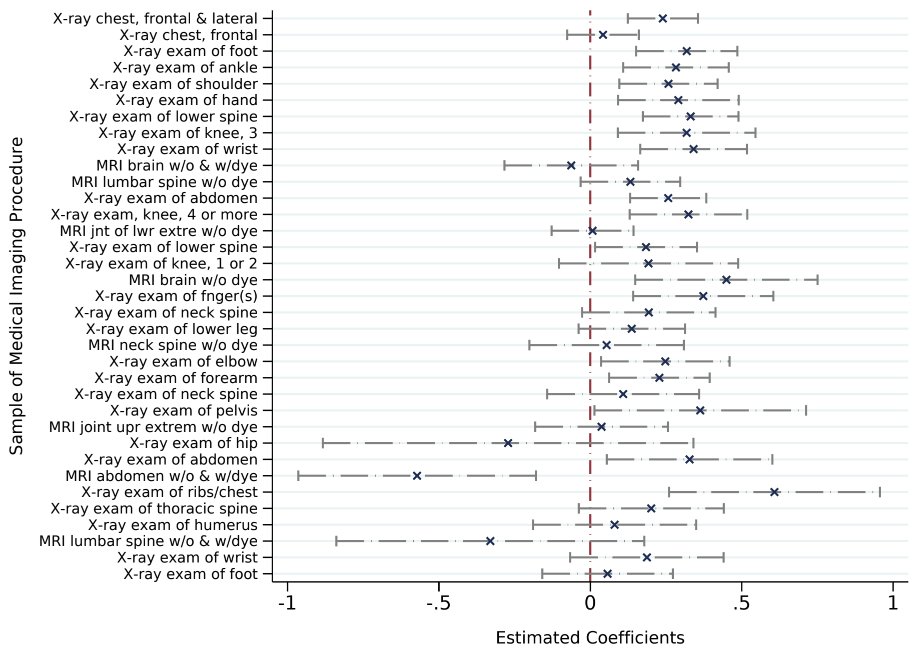
(d) Log of Service-mix Weights

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

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

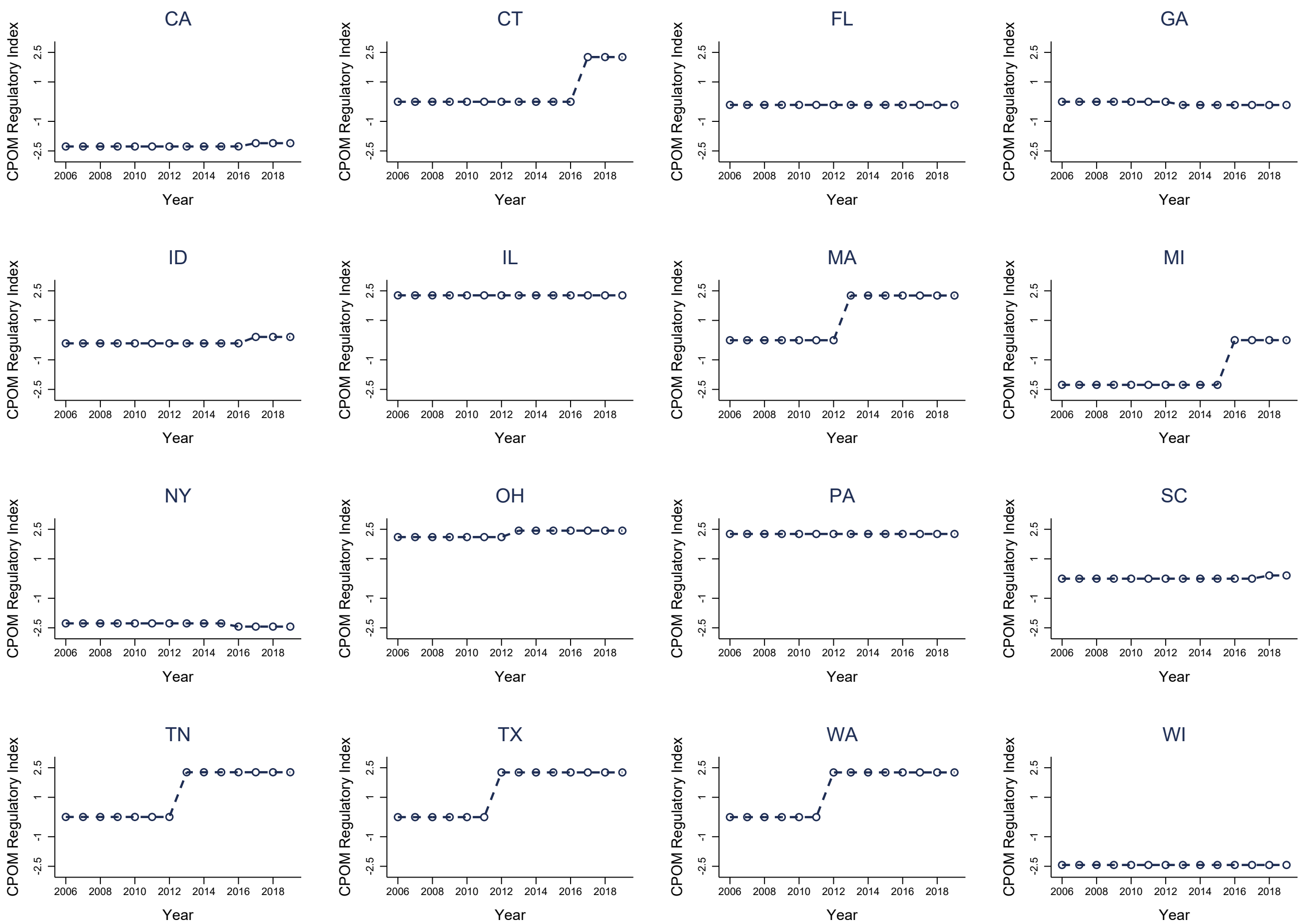
wherein t_0 denotes the first quarter when $\text{PE}_j = 1$ for hospital j. The coefficient with $\tau = -1$ is excluded as a benchmark category. Any quarters beyond 16 (-16) are binned into the 16th (-16th) quarter. Panel A exhibits the coefficient dynamics using the natural logarithm of the total paid amounts as the dependent variable. Panel B uses the natural logarithm of the patient paid amounts, and Panel C uses the natural logarithm of the payer paid amounts. Panel D uses the natural logarithm of the relative service-mix weights as the dependent variable. All standard errors are clustered at the hospital level. Gray dotted lines represent 95% confidence intervals.

Figure 5: Regression Coefficients for Medical Imaging Procedures



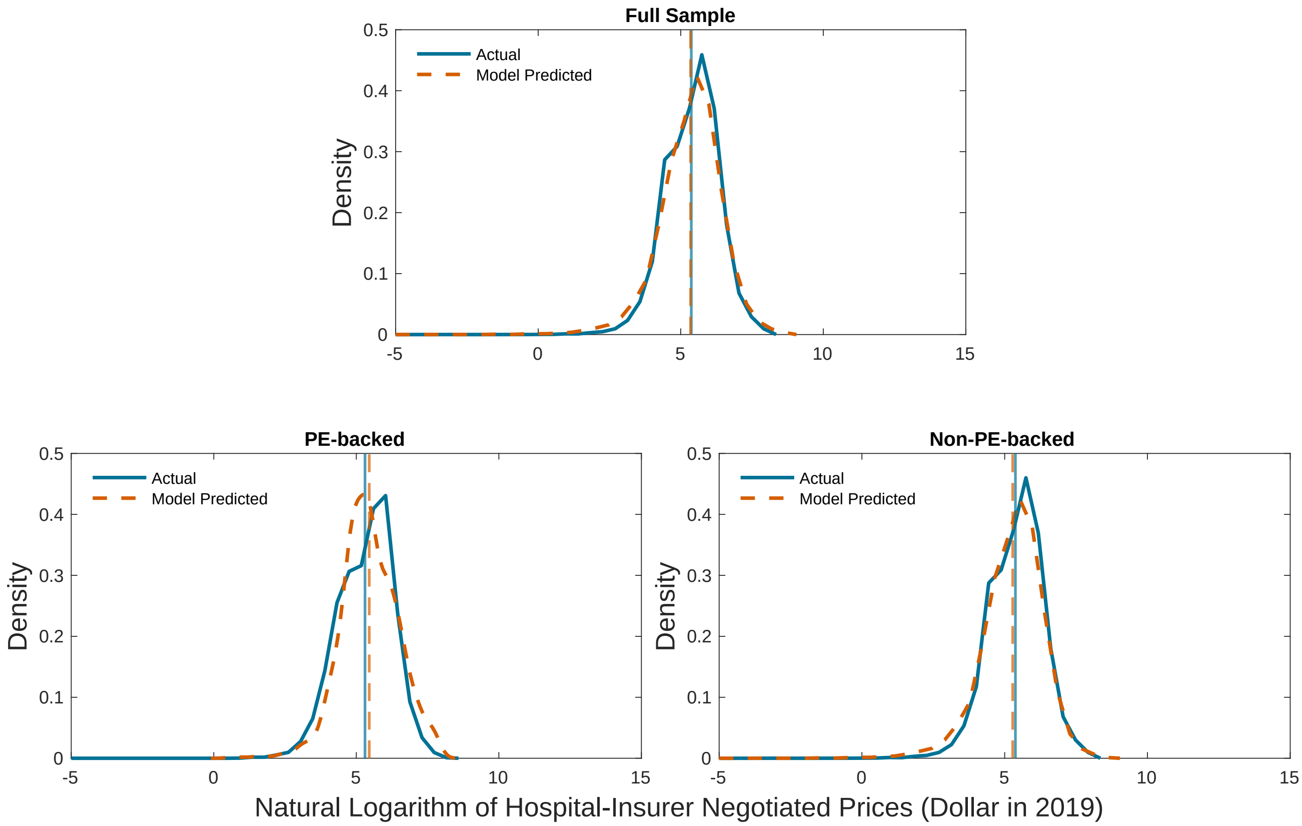
This figure exhibits the estimated coefficients of the PE dummy in Regression (1) for the subsamples of the top 35 medical imaging procedures. The y-axis denotes the names of medical imaging procedures. All standard errors are clustered at the hospital level. Capped spikes represent 95% confidence intervals.

Figure 6: Constructed CPOM Regulation Index across States



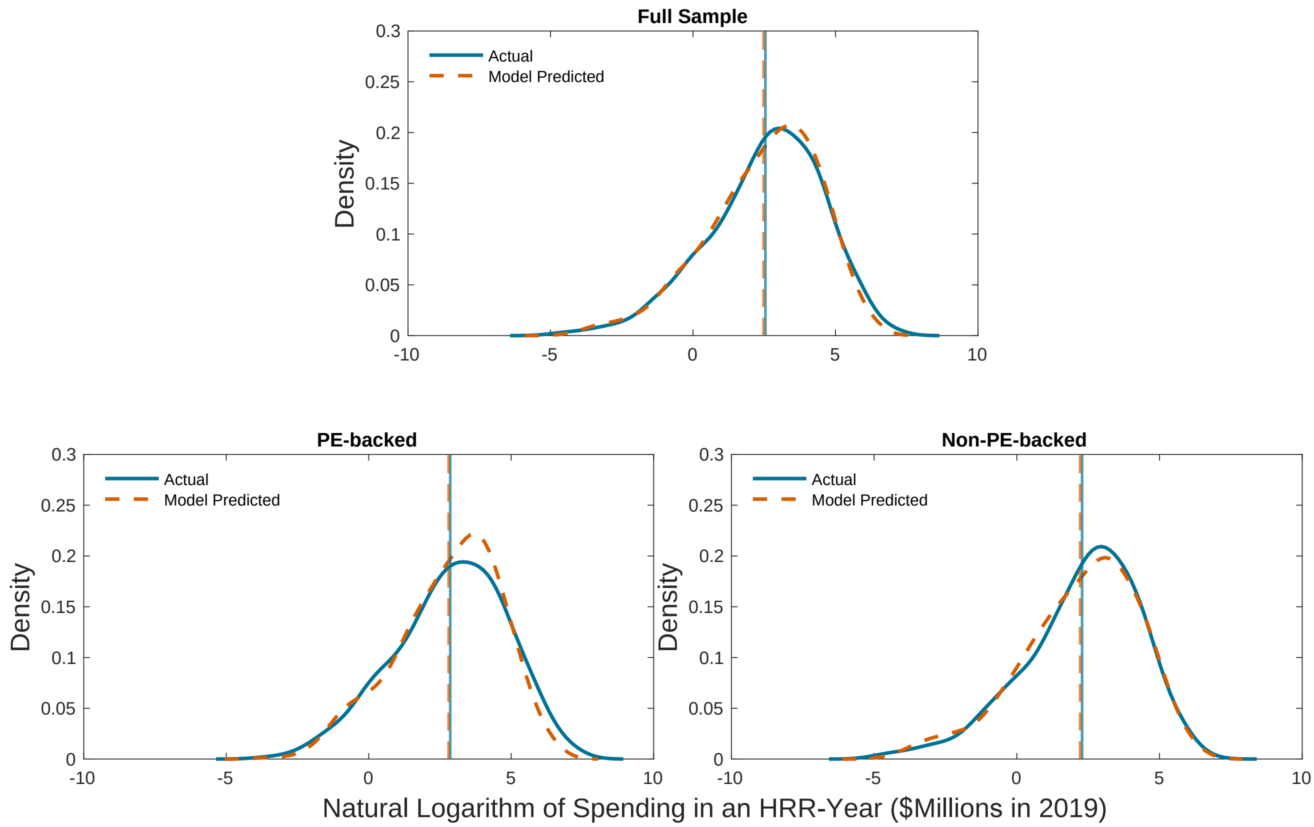
This figure shows the time series of the constructed CPOM regulation indices for 16 states between 2006 and 2019. The detailed construction procedure of the CPOM regulation index is collected in the Online Appendix.

Figure 7: Model Fit: Negotiated Prices



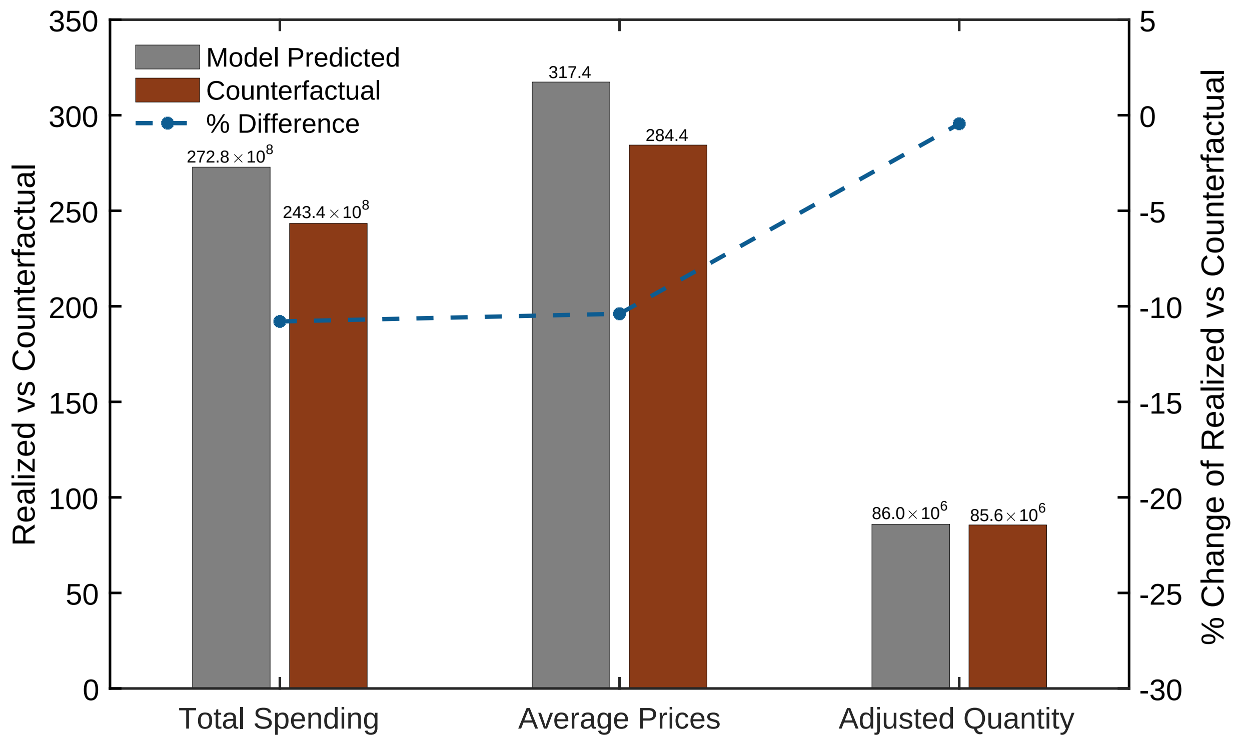
This figure demonstrates the kernel density plots of the predicted and observed distributions of negotiated prices between hospitals and insurers on a log scale for the full sample, the subsample of hospitals ever targeted by PE, and the subsample of non-PE-backed hospitals. All years are pooled, and 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 9 and 10.

Figure 8: Model Fit: HRR Outpatient Spending



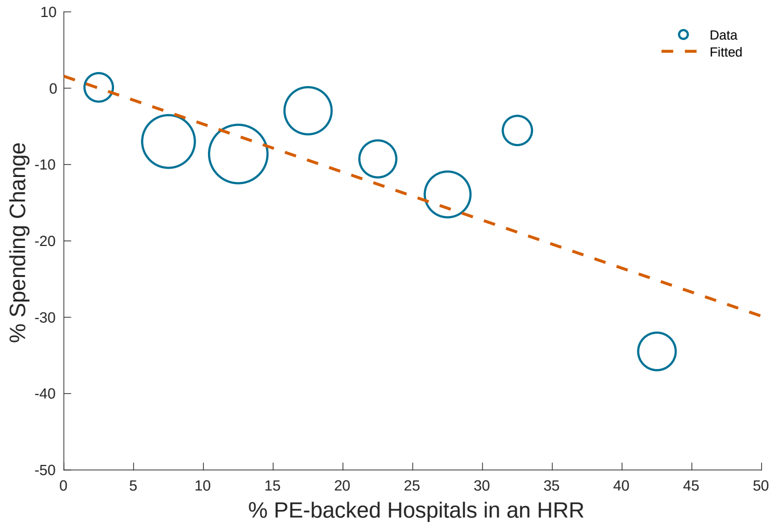
This figure demonstrates the kernel density plots of the predicted and observed distributions of total outpatient spending in local markets ($millions) on a log scale for the full sample, the subsample of HRRs that ever had PE-backed hospitals, and the subsample of HRRs that were never targeted by PE. 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 9 and 10.

Figure 9: 1st Counterfactual: Aggregate Changes

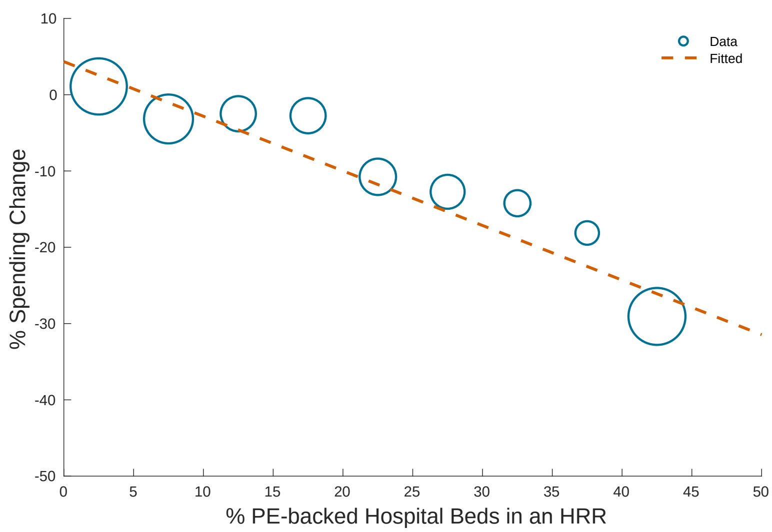


This figure presents outcomes of a sample of 339 HRR-years in the PE-ban counterfactual between 2013 and 2018. Total spending is the sum of the outpatient payments captured by the sample. Average prices are the quantity-weighted negotiated prices between hospitals and insurers. Adjusted quantity is the 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 banned. Both are simulated based on the estimates from Table 10. Numerical values are indicated on top of each bar. The dashed line represents the percentage differences in outcomes between the realized and the counterfactual scenarios.

Figure 10: 1st Counterfactual: Spending Changes across Regions



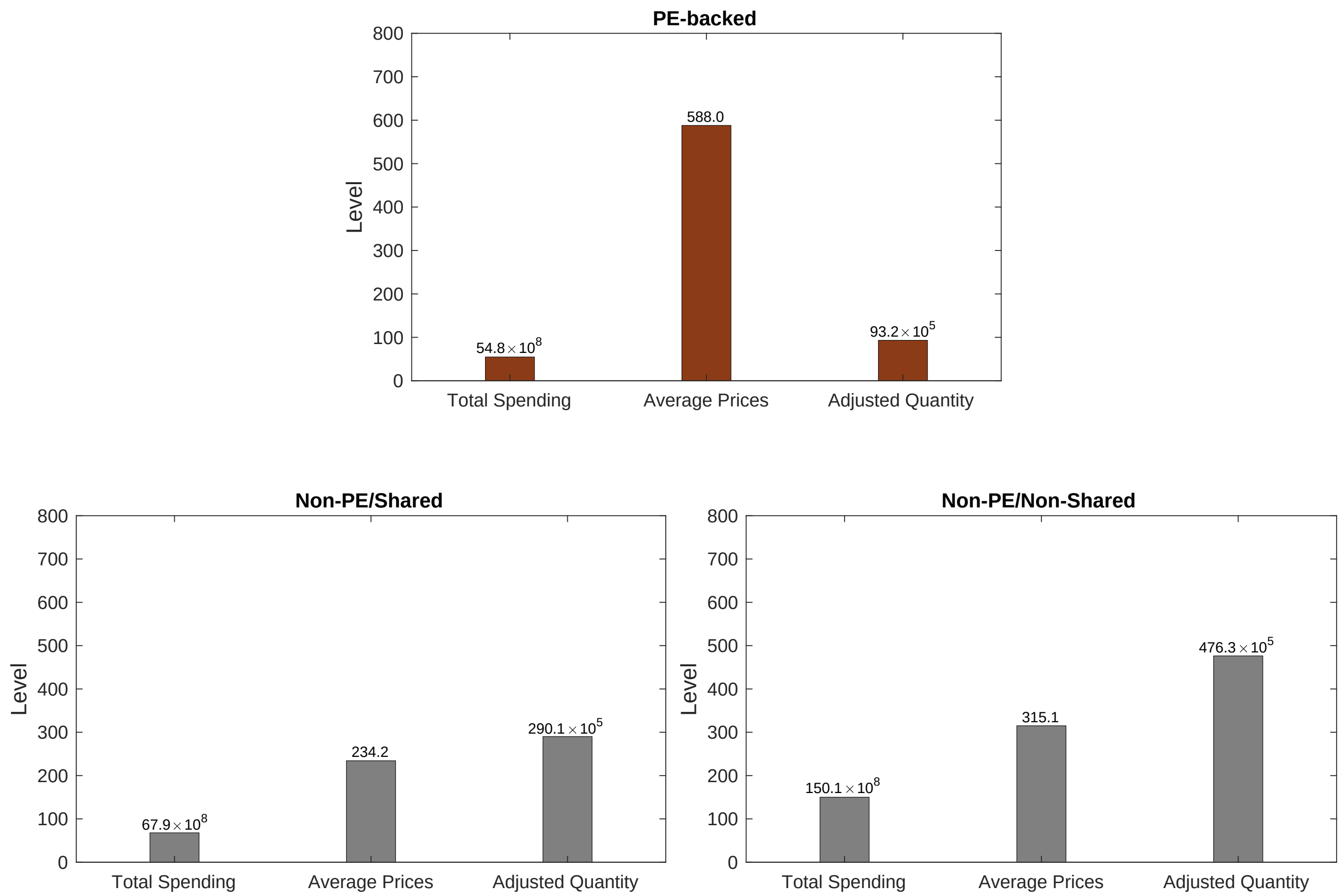
(a) %PE-backed Hospital of HRRs and Spending Change in Counterfactual



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

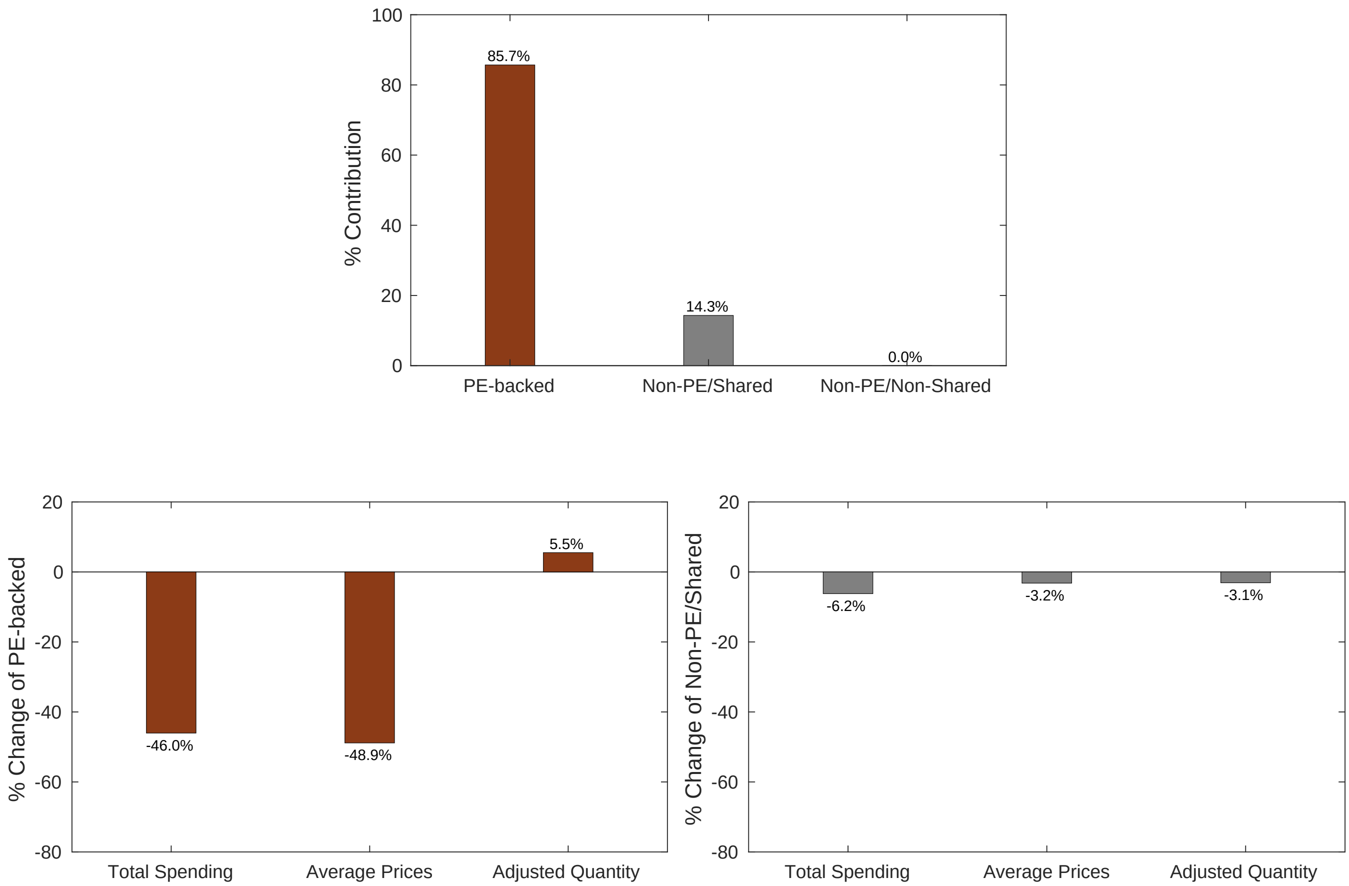
This figure presents how the hospital spending varies across regions with different degrees of PE intervention in the PE-ban counterfactual. The unit of observation is an HRR-year. Observations are grouped for every five-percent interval on the x-axis. In Panel A, the x-axis denotes the percentage of PE-back hospitals in an HRR of a year. In Panel B, the x-axis denotes the percentage of PE-backed 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.

Figure 11: 1st Counterfactual: Model-predicted Amounts across Groups



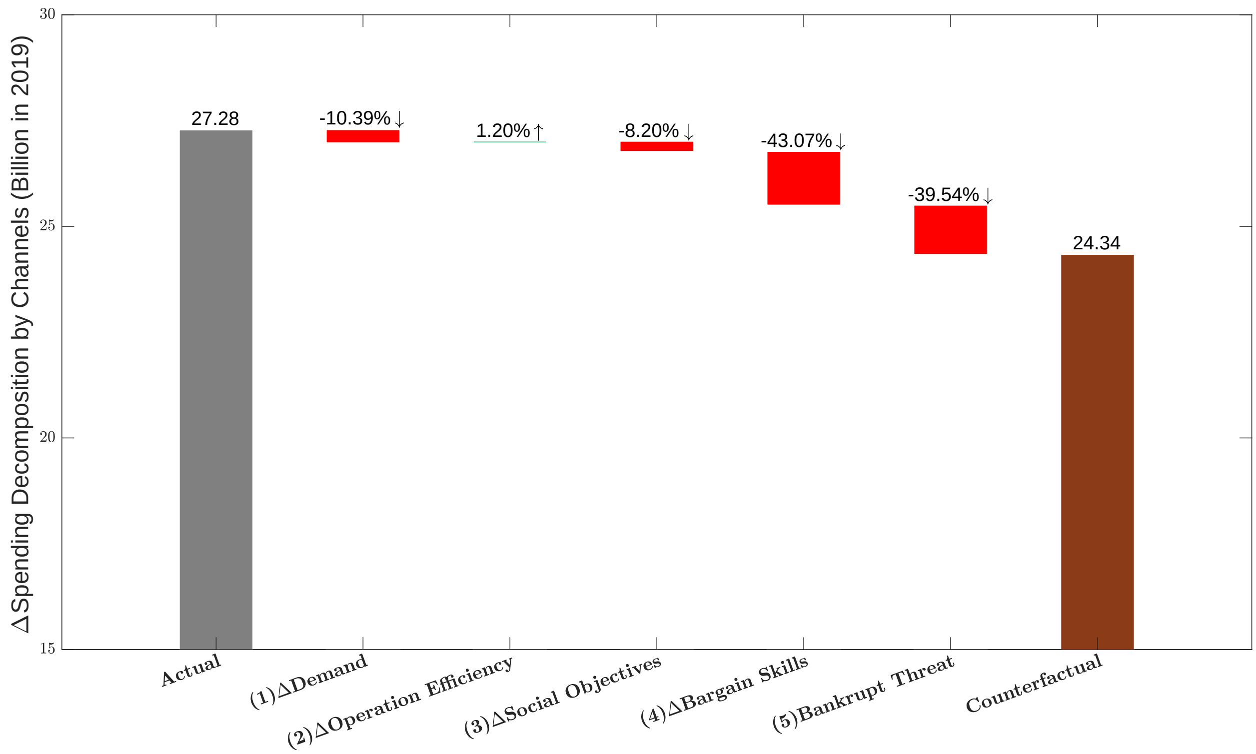
This figure presents the model-predicted outcomes across groups. The top panel exhibits the model-predicted outcomes of the *PE-backed* group, which includes hospitals under PE ownership. The bottom-left panel exhibits the model-predicted outcomes for the *Non-PE/Shared* group, which consists of non-PE-backed 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 9.

Figure 12: 1st Counterfactual: Quantify Spillover Effects



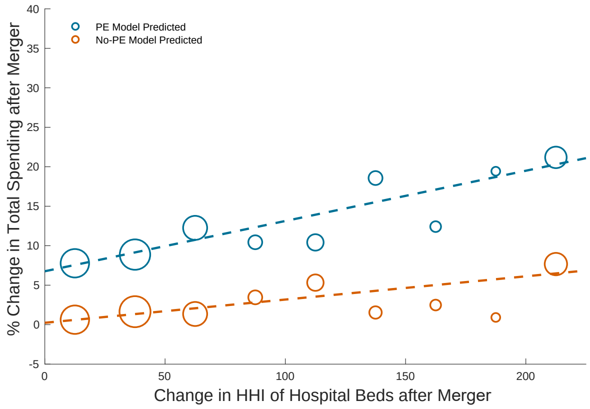
This figure quantifies the spillover effects of PE intervention in local markets. The top panel presents the relative contribution to the total savings in the counterfactual across different groups, including *PE-backed*, *Non-PE/Shared*, and *Non-PE/Non-Shared*. The bottom-left panel presents the percentage 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 in the total spending, quantity-weighted prices, and total relative service-mix weights of hospitals within the *Non-PE/Shared* group in the counterfactual. Remaining details are the same as Figure 11.

Figure 13: 1st Counterfactual: Decomposition by Channels

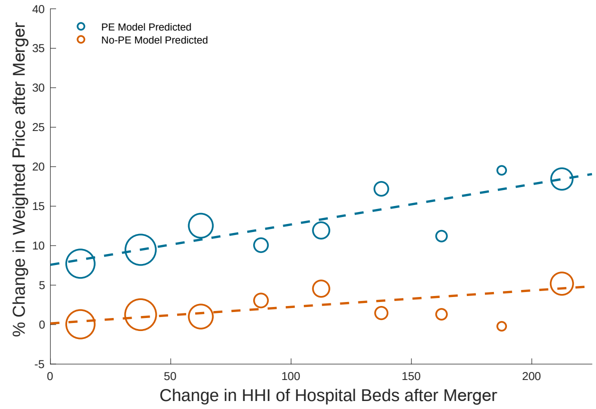


This figure presents the relative contribution of various channels to the total savings in the counterfactual. The first gray bar denotes the model-predicted spending for the realized scenario, and the last orange bar denotes the counterfactual spending if PE ownership were to be banned, which replicates results in Figure 9. The waterfall charts in between denote the relative contribution of five key channels highlighted in the model: (1) changes in patients' demand; (2) changes in the operational efficiency; (3) changes in the focus on social objectives; (4) changes in hospitals' bargaining skills; and (5) bankruptcy threats and financial engineering. Numbers on top of each bar denote their respective contribution percentages. Red (green) bars indicate positive (negative) contribution in the counterfactual.

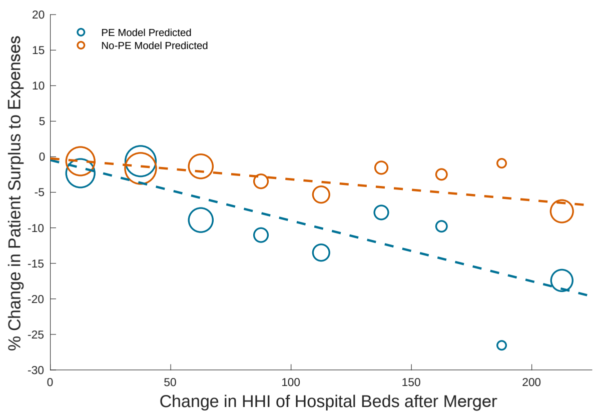
Figure 14: 2nd Counterfactual: Changes after Mergers



(a) %Spending Changes after Mergers



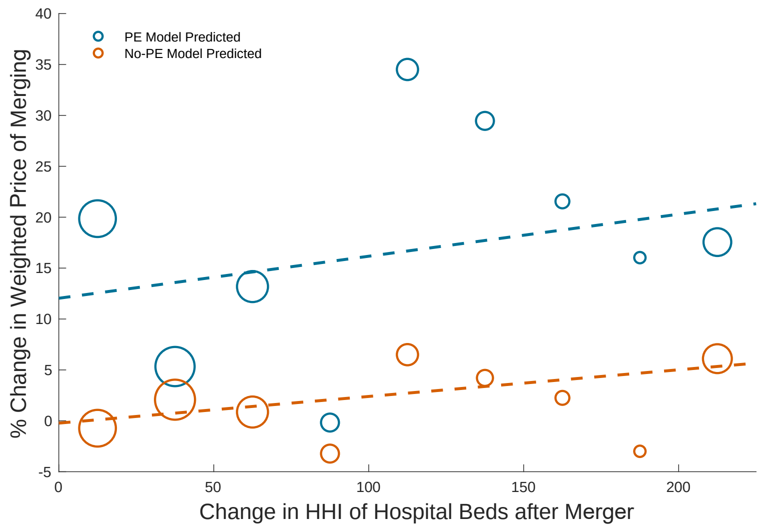
(b) %Price Changes after Mergers



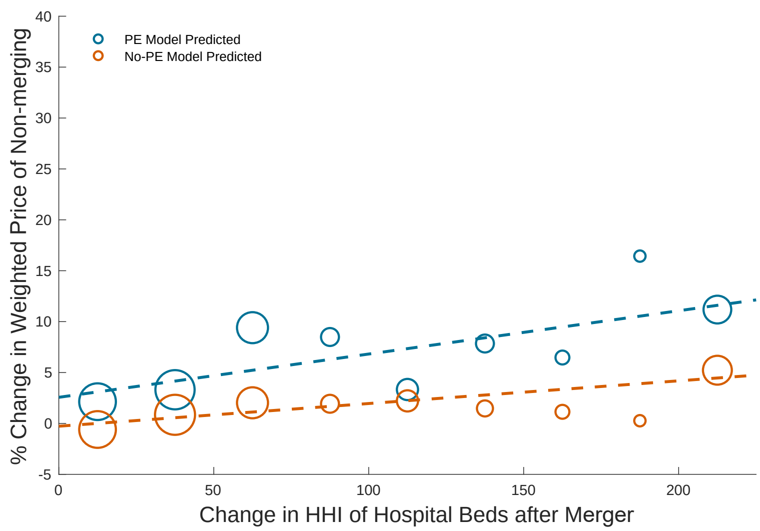
(c) %Surplus Changes after Mergers

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 *PE model* refers to the full-fledged model estimated in Section 4.3. The *No-PE model* refers to a plain model after removing all PE-related features in the *PE model*. The sample of mergers is randomly chosen among hypothetical cases with PE-backed hospital systems acquiring local rivals in 2013. The unit of observation is an HRR. Observations are grouped for every 25-unit interval on the x-axis, which denotes the change in the Herfindahl-Hirschman index (HHI) of hospital beds after mergers. 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. Changes in patient surplus are calculated following the method described in Section 5.1. 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.

Figure 15: 2nd Counterfactual: Price Changes in Subgroups after Mergers



(a) %Price Changes of Merging Hospitals after Mergers



(b) %Price Changes of Non-merging Rival Hospitals after Mergers

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 15.

I.B Tables

Table 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 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 3: Impacts of PE Ownership

This table reports the results of Regression (1) for the full sample of patient visits between 2013 and 2019. Panels A to D 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. Columns (2) to (4) include diagnosis×year fixed effects. Patient controls, including *gender*, *age group*, *insurance type*, and *relative service-mix weights* (except in Panel D), are added in columns (3) and (4). 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 (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.

Panel A: Logarithm of total paid amount

PE	0.300**	0.304**	0.309**	0.319**
	(2.056)	(2.180)	(2.278)	(2.340)
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	0.009	0.016	0.037	0.046*
	(0.267)	(0.449)	(1.375)	(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	0.290	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	0.295**	0.290**	0.279**	0.280**
	(2.083)	(2.132)	(2.065)	(2.053)
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

Panel D: Logarithm of relative service-mix weight

PE	0.013	0.017	0.017	0.019
	(0.440)	(0.635)	(0.695)	(0.720)
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	0.214	0.303	0.305	0.305
Observations	70,861,556	70,861,542	70,861,542	70,861,542

Table 4: 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-backed hospital to three control hospitals using the optimal Mahalanobis method. Remaining details are the same as in Table 3.

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 5: 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 6: 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. All columns contain hospital×payer and diagnosis×year fixed effects. 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.

	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

Table 7: 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, including *gender*, *age group*, *insurance type*, and *relative service-mix weights*, are added in columns (3) and (4). 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 (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 × 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 8: 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. All columns contain hospital fixed effects. Columns (2) to (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. 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)
ln(# Hospital Beds)			-0.003
			(-0.618)
Teaching			-0.025*
			(-1.694)
Rural			-0.002
			(-0.262)
For-profit			0.117***
			(7.364)
Medicare Patient Ratio			-0.011
			(-1.406)
Medicaid Patient Ratio			-0.003
			(-0.317)
F-stat	72.489	12.164	10.368
	(0.000)	(0.001)	(0.001)
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

Table 9: 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. *PE indicator* equals one if hospital j is under PE ownership in year t. Its interactions with patient gender, age, and relative service-mix weights are included. *Travel time* (minutes) is computed between the centroid of a patient's 3-digit zip code prefix and the location of a hospital under normal traffic conditions. The square term of *Travel Time* and its interactions with hospital and patient characteristics are included. *Visit Before* is an indicator of whether a patient has visited a specific hospital before. The Diagnosis×Hospital Services includes ten interactions: *Mental Illness*×*Psychiatric Care*; *Pregnancy*×*Obstetrics Services* and ×*NICU*; *Injury Diagnosis*×*Level 1 Trauma Center*; *Nervous, Circulatory, and Muscle Diagnosis*×*Magnetic Resonance Imaging*; *Cardiac Diagnosis*×*Cath Lab*, ×*Interventional Cardiology*, and ×*Heart Surgery Services*; *Cancer*×*Oncology Services*; *Musculoskeletal Diagnosis*×*Arthritis Services*. 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)

Table 10: 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)

Table 11: Implications for Patient Surplus in Counterfactual

This table shows how banning 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: Banning PE Ownership	
ΔQuality ($billion)	-0.022
ΔSpending ($billion)	2.945
Summing up...	
= ΔSurplus ($billion)	2.923
Equivalent to...	
% Total Spending	10.71%