Driving a Bargain: Negotiation Skill and Price Dispersion*

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Abstract

We show that individual negotiation skills affect equilibrium prices in societally important contracting. We develop a novel measure of managers' bargaining ability from private vehicle transactions and link it to proprietary data on negotiated hospital prices. Higher-skilled managers negotiate better prices, suggesting negotiation skill is a portable asset. Management turnovers and shocks to insurer bargaining positions support this interpretation. We estimate a model to quantify the role of individual skill and find heterogeneity in negotiation skills explains 37% of the price dispersion attributed to differences in hospitals' bargaining power. Overall, human capital is an important determinant of market-wide price dispersion.

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1 Introduction

Bargaining, or negotiating the terms of trade, is central to many economic transactions and can contribute to significant price dispersion, even for homogeneous goods. While controlled experiments document heterogeneity in individuals' bargaining skills, the empirical evidence often examines bargaining outcomes through the lens of firm or market conditions. We propose a novel micro foundation for price dispersion rooted in the role of individuals in contracting outcomes. We hypothesize that price dispersion for identical goods arises not only from market structure, information frictions, and organizational factors, but also from the portable skillsets of individuals.

Evidence on the role of individuals' skill in negotiating contracts remains elusive. Such an analysis would require measuring an agent's intrinsic bargaining skill out of sample, matching this agent with multiple counterparties in repeated transactions, and observing the resulting effects on contract outcomes for identical products. Our paper makes a step towards such an experiment by focusing on a setting that allows us to connect individual managers' negotiation skills to contract outcomes.

We develop a novel proxy of a manager's negotiation skill and study its role in price negotiations between hospitals and health insurers, a bargaining process that establishes transaction prices for the more than half of Americans with private health insurance. Due to the nature of bilateral negotiations, prices for identical services vary dramatically within and between hospitals (e.g., Finkelstein et al., 2016; Cooper et al., 2019; Craig et al., 2021). While prior literature attributes much of this variation to differences in observable firm or market characteristics, a large portion remains unexplained. Researchers (e.g., Grennan, 2014) have largely attributed this residual variation to unobserved bargaining power—often interpreted as differences in bargaining ability. Such findings highlight the need to open the black box of bargaining power by measuring an agent's negotiation acumen, understanding its origins, and quantifying its contribution to observed price dispersion.

To isolate an individual's intrinsic negotiation skill (*NS*)—distinct from hospital resources or market power—we study the prices paid in significant personal transactions that entitle the individual to all gains: purchasing a car. Bargaining plays an important role in vehicle purchases (Busse and Silva-Risso, 2010) and contributes to the pervasive dispersion of prices for identical vehicles (Chandra et al., 2017). Using individual-level administrative data from the Texas Department of Motor Vehicles (DMV), we calculate whether an individual negotiates a lower price than others purchasing the same vehicle (make-model-year-trim plus other vehicle attributes) in the same month and after controlling for the dealership, travel distance, and market characteristics.

Our proxy for negotiation skill reveals several validating patterns. First, a person's ability to obtain a lower purchase price is persistent over time and across vehicles. Second, *NS* is positively correlated with a manager's self-reported negotiation skill, and this link is distinct from other skillsets. For example, *NS* is uncorrelated with proxies for a manager's innate intelligence (such as the average college SAT score), as well as self-reported general management and leadership skills. Finally, we validate our measure out-of-sample. For managers with available real estate transactions, we find that *NS* correlates with better returns in housing transactions. This out-of-sample evidence suggests that *NS* captures a portable skill that can be transferred across settings.

Next, we study the determinants of negotiation skill and find an important role of familial and personal characteristics. Family fixed effects explain 26 percent of the variation in *NS*, capturing such factors as a manager's endowed socioeconomic status, cultural norms, and formative experiences. This is consistent with the role of familial factors in shaping managerial behaviors (Duchin et al., 2021). An analysis of personal factors reveals a significant gender effect. Female managers pay 1.5 percent higher prices for the same vehicles, consistent with the women's lower propensity to bargain (Kray, 2001; Andersen et al., 2018).

We focus on bilateral bargaining between hospitals and private health insurers that establishes transaction prices for standard medical procedures. To evaluate bargaining outcomes and account for variation in the service mix, we collect insurance claims data from private insurers which provide procedure-level information on the hospital's service prices (Liu, 2022). The data report total allowed amounts, including insurer payments and detailed patient cost sharing such as copayments, coinsurance, and deductibles, and include rich information on procedures, diagnoses, and patient demographics. This granularity allows us to construct average negotiated prices per unit of service and to compare payments across insurers for observably identical procedures at the same hospital. Then, we identify hospital executives in the vehicle purchase data and connect their negotiating skill to the outcomes of hospital-insurer price negotiations.

Our main finding is that hospital managers with higher *NS* achieve significantly better negotiation outcomes for their organizations. For example, a one standard deviation increase in a manager's *NS* is associated with an 10.1% increase in the negotiated reimbursement rate between the hospital system and insurance companies. This magnitude is economically meaningful, highlighting the pivotal role of managerial bargaining ability in shaping hospital prices. The relationship remains robust when the analysis is restricted to prices for identical medical imaging procedures under the same patient diagnosis in the same year, suggesting that the effect is not driven by case mix or service quality.

Of course, the matching between a manager and hospital is far from random. We address managerial selection in several ways. First, our baseline estimates include both hospital and insurer fixed effects so the identification stems from within hospital changes in manager bargaining ability. (As *NS* is measured using the manager's earliest vehicle purchase, the changes in *NS* are due to new managers rather than new transactions.) The insurer fixed effects control for changes on the payer side that might be correlated with management turnover.

We also present two additional tests to distinguish managers' characteristics from their hospitals'. First, following Acemoglu et al. (2026), we exploit a subset of managerial departures due to natural causes (death, illness, or age-based retirement). These departures induce hospital-manager separations unrelated to hospital fundamentals, a result we confirm in the data. We show that changes in negotiation skill resulting from these separations have a material impact on future negotiated prices. Second, we explore changes in the local insurance market while holding the manager-hospital match fixed. The expectation is that a more consolidated insurance market will strengthen the bargaining position of insurers relative to hospitals (Dafny, 2010; Trish and Herring, 2015).[1] We find that bargaining outcomes vary for hospitals located in MSAs that experience substantial increases in insurance market concentration. The hospitals led by high *NS* managers see no change in negotiated prices, while the hospitals led by low *NS* managers experience a significant decline in negotiated prices following the insurer consolidation.

While our reduced-form analysis indicates that managerial negotiation skill is a significant determinant of hospital pricing, it cannot speak to the mechanisms through which this skill maps into bargaining power, nor quantify its relative contribution to price dispersion in equilibrium. Importantly, negotiated prices are the outcome of complex bilateral negotiations shaped by both bargaining power and bargaining

[1]This basic assumption is also supported by Ho and Lee (2017) in their more nuanced structural analysis.

position, and the latter is largely driven by patient demand, market structure, and network formation. To address these challenges, we resort to a structural approach to recover latent hospital bargaining power (weights) and explicitly link them to manager-specific *NS* while controlling for hospital-insurer network, market structure, and hospital characteristics. Relative to a reduced-form "horse race" that ranks correlates of price levels, the structural approach enables counterfactual analysis—quantifying, for instance, how much of observed price dispersion is attributable to heterogeneity in *NS*. This distinction underscores the importance of modeling the economic environment in which the negotiation unfolds.

We build on the frameworks in Gowrisankaran et al. (2015) and Ho and Lee (2017) and estimate a model incorporating patient demand for outpatient services and bilateral hospital-insurer price negotiations, leveraging the unique datasets we assemble. We recover bargaining power parameters for each hospital (system) and link them to managers' personal negotiation skills. Our analysis reveals a significant positive correlation between managers' *NS* and hospital bargaining power, even when controlling for other common determinants of bargaining power such as market share and multi-facility status. A horse-race test highlights *NS* as one of the most important determinants: a one standard deviation increase in *NS* raises hospital bargaining power by approximately 0.08, representing a 19% increase relative to the sample mean of 0.42.

In a counterfactual exercise, we eliminate differences in hospital managers' *NS* and recompute equilibrium prices negotiated between hospitals and insurers. The results indicate that, on average, the heterogeneity in managers' negotiation skills accounts for over 37% of the price dispersion explained by variation in hospitals' bargaining weights. This finding suggests that the heterogeneity in managers' skills explains a substantial portion of the observed price dispersion in the data.

The first contribution of this article is to develop a novel, scalable proxy of an agent's bargaining skill which can be applied to a variety of negotiation settings. This less explored component of human capital represents a portable asset between personal and professional contexts. Our second contribution is to highlight the role of individual agents in business contracting of high societal importance. The literature in economics and industrial organization on contracting outcomes has focused mostly on the implications of the contracting space, market structure, and firm-level drivers of negotiation outcomes. In the setting of hospital-insurer price bargaining, the literature has discussed the role of firm conditions (Lewis and Pflum, 2015), market structures (Capps et al., 2003; Gaynor and Vogt, 2003; Grennan, 2013; Gowrisankaran et al., 2015; Ho and Lee, 2017; Dafny et al., 2019; Barrette et al., 2022; Dubois et al., 2022), ownership changes (Liu, 2022; Arnold et al., 2024), as well as information and search costs (Sorensen, 2000; Brown, 2019; Grennan and Swanson, 2020). Yet, after accounting for these drivers, researchers find a significant share of unexplained variation in contract outcomes and attribute it to differences in bargaining weights. For instance, Grennan (2013) documents large cross-hospital variation in procurement prices and attributes it to differential bargaining ability.

Our paper complements this prior work in multiple ways. First, in contrast to a focus on the firm or industry, we provide evidence on the role of individual agents in contract negotiations. Second, while most prior work refers to bargaining skill as an unobservable attribute, we develop a quantifiable, out-of-sample measure of this skill. Further, by linking our measure to bargaining ability parameters, we are able to contribute to the structural literature's understanding of what those parameters capture.

Our paper also extends the growing literature on the management of public sector organizations, particularly in the healthcare industry. Numerous papers use the setting to study fundamental questions in corporate governance (Eldenburg et al., 2004; Brickley et al., 2010; Lewellen et al., 2024). For example, Liu (2022) finds that strong principals (private equity firms) extract large improvements in hospital performance while Lewellen (2025) examines how boards perceive female hospital CEOs. Closer to our work, Bloom et al. (2020) and Munoz and Otero (2025) document the impact of hospital managers on hospital productivity and patient mortality. This research underscores the importance of studying hospital management to advance our understanding of healthcare outcomes. We complement this work by providing micro-evidence on the role of managers in business-to-business contracting and thereby contribute to aggregate price dispersion.

More broadly, our paper extends the governance literature on managerial skill. Managers vary in skill and style in ways that materially impact corporate outcomes (Bertrand and Schoar, 2003; Schoar and Zuo, 2016; Nguyen, 2026). Adams et al. (2018) find that non-cognitive skills are the strongest predictor of future CEOs. Weidmann et al. (2026) documents the importance of economic decision making for manager performance and Kaplan et al. (2012) shows that employers consider a manager's execution skill to be one of the most valuable traits. While a manager's ability to extract surplus in business transactions seems integral to effective execution, measuring such skill - particularly for a large number of executives - is challenging. This paper introduces a novel and scalable proxy for individual bargaining skill.

Lastly, our measure of negotiation skill is grounded in the theory of behavioral consistency. This theory, dating back at least to Allport (1937), and developed in Epstein (1979) and Funder and Colvin (1991), postulates that agents behave similarly between personal and professional settings. Consistent with this hypothesis, managers' off-the-job behaviors predict their on-the-job actions in multiple contexts, including debt management (Cronqvist et al., 2012), tax avoidance (Chyz, 2013), fraud (Davidson et al., 2015), risk taking (Brown et al., 2018), misconduct (Griffin et al., 2019), and gender policies (Duchin et al., 2021). Our measure of negotiation skill based on the observed division of surplus in personal vehicle purchases predicts negotiated prices in corporate contracting.

2 Data

This paper leverages a number of unique datasets to unpack the role of bargaining ability in determining negotiated price outcomes. In this section, we introduce our proprietary data on private insurance claims, which capture the prices negotiated between hospitals and insurers. This granular dataset allows us to observe significant price dispersion at the procedure level for each hospital-insurer pair. To complement this data, we incorporate widely used hospital financial and governance information, including details about hospital managers. Then, we describe the administrative data on vehicle purchases used to calculate negotiation skill (*NS*). Within this framework, we identify individual hospital managers and connect their bargaining abilities to the outcomes of corporate contracting.

2.1 Negotiated Hospital Prices

For detailed evidence of price dispersion in corporate contracts, we start with proprietary insurance claims sourced from the Clarivate Real-World Data (RWD) Product, previously known as Decision Resources Group Real-World Data. The dataset draws from multiple payer sources and a variety of insurance plans and captures claims submitted through the billing software of the healthcare providers, such as hospitals, clinics, and long-term care facilities. The data include unique identifiers for the patient, provider, and payer, the dates of service and payment, and a detailed categorization of the patient's diagnosis (International Classification of Disease) and the medical procedure (Healthcare Common Procedure Coding System). The dataset also provides additional details on the patient's age, gender, insurance company and specific plan, and place of residence (three-digit zip code).

A key advantage of the RWD data is the ability to identify insurance payers. This data feature allows us to study how negotiation outcomes vary within the same hospital-insurer pairs but across different negotiating agents after management turnovers. It also allows us to study the variation in negotiation outcomes across hospitals, but within the same negotiating counterparty, namely the insurance company.

We obtain data on the Texas hospital outpatient claims for the hospitals in our sample from commercial payers between 2013 and 2021. Our focus on Texas is motivated by the availability of detailed vehicle purchase data in this jurisdiction. To identify commercial outpatient claims, we follow the algorithm in Liu (2022). We exclude duplicate claims and claims denied, pended, or suspended by payers. To avoid including Medicare Advantage claims, we limit our sample to claims for patients between 18 and 64 years old at the time of medical service. In our main analysis, we exclude any patient visits with missing claim numbers, payer ID, patient ID, age, gender, 3-digit ZIP code, service data, or service-mix weight. Our final sample includes 20,078,935 patient visits (claim encounters) with detailed medical claims between 2013 and 2021. Of these claims, 6,788,490 outpatient visits are matched with remittance claims that contain non-missing and positive payment information.

To compute the negotiated prices for medical services, we use RWD's data on the service charges paid by the insurance payer and the patient, which also list deductibles, coinsurance, and copayments. We aggregate the total paid amounts for specific services in a patient visit to construct a hospital-insurer price index (*Hospital Price Index*), which reflects the dollar amount per unit of outpatient service, adjusted for the service-mix weight (*APC weight*).[2] The additional details on the index construction appear in Section OA-1.1 of the Online Appendix. As summarized in Panel A of Table 1, the mean hospital price index in our sample is $241.5, with a median of $226.1. The distribution exhibits substantial variation, with a standard deviation of 150.2.

It is important to recognize that hospitals and insurers do not negotiate the individual prices of the

[2] APC (Ambulatory Payment Classification) weights for outpatient reimbursements are from the Centers for Medicare and Medicaid Services and reflect the costliness of service

full menu of possible hospital services and procedures. Generally, negotiations focus on benchmark pricing (Dorn, 2024). Two common approaches are to negotiate a percent adjustment or case rate. For the percent adjustment, the insurer negotiates a percent discount off of the hospital's chargemaster or list price or a percent premium relative to Medicare pricing. With case rates, the negotiation focuses on a base rate per unit of service and then services are priced based on service-mix weights (costliness of service, e.g., APC weights).

In addition to the hospital-insurer price index, we focus on X-ray exams for robustness. X-rays are a routine and standardized high-volume service. Narrowing the scope to these procedures allows us to minimize variation in service quality. The medical imaging procedure regression sample includes the top 10 most common X-ray procedures occurring in our sample.[3] While X-rays are considered one of the least differentiated services, Figure 1 reveals the wide dispersion in the price charged by different hospitals to the same insurer in the same year. For example, the negotiated prices for a shoulder X-ray range from under $100 to $350. This figure also shows that the price dispersion across Texas hospitals is comparable in magnitude to the price dispersion documented in the broader national samples (Cooper et al., 2019, Liu, 2022).

2.2 Hospitals: Governance and Fundamentals

We expand this rich dataset with detailed information on hospital operations as well as their governance by combining two sources: (1) the American Hospital Association (AHA) Annual Survey and (2) the Healthcare Cost Report Information System (HCRIS). The AHA dataset contains detailed information on a hospital's location, scope of services, system affiliation, and management personnel. These data also include information on internal staffing and operations, such as hospital admissions, surgeries, workforce composition, and capacity utilization. In the AHA dataset, we identify the highest ranking manager with a direct responsibility for the hospital or hospital system. Since the top manager's title varies across hospitals (e.g., President, CEO, or Chief Administrator), we refer to them as hospital managers.

[3]This includes X-ray chest for two views (CPT code 71020), X-ray exam of foot (CPT code 73630), X-ray exam of lower spine (CPT code 72100), X-ray exam of shoulder (CPT code 73030), X-ray chest for a single view (CPT code 71010), X-ray exam of hand (CPT code 73130), X-ray exam of ankle (CPT code 73610), X-ray exam of knee (CPT code 73562), X-ray exam of neck spine (CPT code 72040), X-ray exam of wrist (CPT code 73110).

Both industry and academic surveys recognize the role of CEOs or top managers in hospital-insurer negotiations (Devers et al., 2003; Tocknell, 2012; Emerson, 2025) and specific examples can be found in general interest and trade publications. In an interview with *Becker's Hospital Review*, Duke University Health System CEO Craig Albanese specifically discussed his negotiations with UnitedHealthcare (Ashley, 2024). Similarly, the *Texas Observer* chronicled how Iraan General Hospital's interim CEO Keith Butler navigated negotiations with Blue Cross Blue Shield. 'Blue Cross Blue Shield of Texas... sent Butler a letter asking to renegotiate its contract with the hospital. Attached was a new contract. All Butler had to do was sign. 'I pulled it up and started looking at the contract,' Butler told the Observer. 'It was terrible. It would have hurt this hospital a lot.' ... Butler sent the company a counteroffer.' Another industry article noted, 'Whether it's working to improve reimbursement rates or decrease prior authorizations, hospital and health system CEOs must get insurers to play ball' (Asser, 2025).

These contract negotiations are a key determinant of a hospital's financial performance—a priority for both for-profit and non-profit hospitals. More than 90% of non-profit hospital boards report that financial performance is on the agenda at every board meeting, far exceeding the 63% which report consistently discussing quality performance (Jha and Epstein, 2010). Further, both for-profit and non-profit hospital managers receive incentive compensation packages linked to financial performance (Brickley and Van Horn, 2002; Lewellen et al., 2024).

The AHA sample covers 1,754 hospital managers for 718 hospital facilities and 92 multi-facility systems in Texas between 2013 and 2021. HCRIS provides additional information on hospitals' financials, including their balance sheets and income statements (Adelino et al., 2022; Dafny et al., 2019; Aghamolla et al., 2024). As described below, we merge these data with information from Lexis Nexis Public Records and DMV data to obtain our final sample. Table 1 Panel A provides summary statistics for these hospital facilities. It demonstrates hospital characteristics across dimensions such as hospital type, operations, and patient type and prices. In our sample, there is an even representation of for-profit and non-profit hospital but only 3% are teaching oriented and 15% are rural. Almost two thirds are a member of a hospital system. There is a large right skew in hospital size metrics such as number of beds, total personnel, and total registered nurses. Figure 2 plots hospitals' locations and reveals significant heterogeneity in their concentration across local markets. While the majority of hospitals are located in metropolitan areas, a significant minority serve rural communities, suggesting significant variation in local competition. This pattern is also evident in Figure 3, which presents ridgeline density plots of the *Hospital Price Index* by market concentration.[4] Hospitals in more competitive markets (Q1) exhibit not only lower mean prices than those in less competitive markets (Q4), but also a thinner upper tail: the density of prices above $400 is visibly greater in less competitive markets (Q3 and Q4).

2.3 Characteristics of Hospital Managers

We hand-match the initial sample of 1,754 hospital managers to the Lexis Nexis Public Records (LNPR) database, using each manager's full name and work location. LNPR aggregates information on over half a billion U.S. individuals (live and deceased), who are traced via a unique ID linked to one's social security number (with the last four digits redacted) and employment records. Examples of records available in LNPR include real estate deeds and tax assessments, mortgage records, voter registrations, utility and phone connections, professional licenses, close relatives, and criminal filings. Prior studies have used LNPR to obtain personal information on CEOs (Cronqvist et al., 2012; Decaire and Sosyura, 2024), portfolio managers (Chuprinin and Sosyura, 2018; Pool et al., 2018), securitization agents (Cheng et al., 2014), and financial journalists (Ahern and Sosyura, 2015). We manually validate the accuracy of each match by ensuring that the employment records in LNPR match the hospital manager's professional position and work history. Employment records in LNPR usually include an individual's job title in the organization, and this feature minimizes the possibility of a spurious match. After imposing these criteria, we are able to establish unambiguous LNPR matches for 92% of our hospital managers.

Table 1 Panel B presents summary statistics for hospital managers included in the final analysis sample, which comprises both facility-level and system-level managers/CEOs.[5] The majority of hospital managers are male (70%), and the average manager is 60 years old in 2023. Race/ethnicity is missing for approximately 29% of managers. Among the non-missing sample, 86.8% of the managers are White and

[4] Market concentration is measured using a bed-based Herfindahl-Hirschman Index (HHI) at the HRR-year level. Q1 represents the lowest HHI quartile (least concentrated markets), while Q4 represents the highest HHI quartile (most concentrated markets)

[5] In constructing the final analysis sample, we match all managers to the Texas DMV records. If certain local Texas facilities belong to non-Texas systems or are acquired by out-of-state owners whose system-level managers do not reside in Texas, those system-level managers are excluded from the sample while their corresponding facility-level managers located in Texas remain included.

9.1% are Hispanic, making Hispanics the next most common category. This composition resembles the broader population demographics for white-collar jobs in Texas, where Hispanics represent the largest minority group. About half of managers are Texas natives, as inferred from the state of issuance of their social security number. This sample feature is consistent with nationwide evidence that executives often work in their home state (Yonker, 2017). The rest of the managers come from all of the remaining 49 U.S. states, the District of Columbia, and two U.S. territories.

Hospital managers are financially comfortable, but they are far less wealthy than executives at large publicly traded firms. While our data does not include compensation, Saini et al. (2022) and Lewellen (2025) document that the median hospital manager earns approximately $600,000. Our data on managers' real estate assets indicate that the median manager lives in a home purchased for approximately $700,000. For comparison, over the last decade, the median Fortune 500 CEO earned more than $10 million per year. Consistent with national patterns on managers' political affiliations, the majority (58%) of hospital managers are registered as Republicans, 23% are Democrats, 2% are independent, and 17% do not declare a consistent party affiliation. In terms of advanced degree held, while this information is missing for approximately 43% of managers, MBAs are the most common credential among those observed (31.7%), followed by MDs (4.0%), PhDs (3.1%), and JDs (2.2%). In summary, the typical hospital manager is a 60-year-old white male with a Republican leaning. Most managers make comfortable incomes but are not high net worth individuals.

2.4 Vehicle Purchase Data

We obtain administrative data on motor vehicle transactions in Texas from 2014 to 2023 from the Texas Department of Motor Vehicles (DMV).[6] Recent work has used the Texas DMV data to study the impact of fiscal stimulus on consumer spending (Hoekstra et al., 2017) and the pass-through effects of trade policy on consumer credit (Hankins et al., 2026). Our panel includes over 50 million transactions of new and used vehicles. For each observation, the dataset includes the date of the transaction and the sale price, the name and address of the buyer and seller, the dealer's license number (if the seller is a car dealer), and vehicle characteristics. The vehicle characteristics include its make, model, and trim (e.g.,

[6]Note that some months in 2014 and 2015 are missing from the raw data, specifically January to August 2014 and June to October 2015. Overall, our raw vehicle transaction sample covers 107 unique year-months.

Toyota Camry XLE, respectively), year of manufacturing, odometer reading, and vehicle identification number (VIN). This 17-digit VIN, unique for each vehicle worldwide, contains additional information on the engine size and type, body style and series, model year, and the country of its manufacturing plant. We extract these vehicle characteristics by using the VIN decoder service from the National Highway Traffic Safety Administration (NHTSA). To compare negotiation outcomes with the same counterparties, we restrict our sample to transactions in which the seller is a car dealer with a valid dealer license number and the buyer is a retail customer. After imposing this filter, we are left with about 24 million vehicle transaction records.

2.5 Buyer Demographic Data

We augment our data on motor vehicles purchases with demographic information on their owners using a proprietary consumer database from Data Axle. This data provider specializes in direct marketing and customer research and maintains a nationwide panel of over 180 million U.S. consumers. Consumers are linked to their households, and their addresses are traced over time via the United States Postal Service's change-of-address data. Our version of the dataset includes an annual nationwide consumer panel from 2006 to 2022. The dataset contains the names of each family member in a household and their demographic and financial attributes, such as age, gender, ethnicity[7], marital status, mailing address, number of children, and income and wealth brackets. We merge our vehicle purchase data with the Data Axle panel by using a customer's name and residential address from Texas DMV. This procedure serves as another check to identify vehicle transactions that occur only between dealerships and retail customers.

Using the dealer's license number, we retrieve additional details about dealerships, including their business name, license type, parent company, and most importantly, their business address, from Texas DMV's online directory of Independent Motor Vehicle Dealers. We calculate the distance (in kilometers) between buyers' addresses and sellers' locations using the ArcGIS API. After matching with Data Axle, we are left with about 12.3 million vehicle transactions. To avoid attrition of hospital managers' vehicle transaction records in the process of matching with Data Axle, we supplement the demographic

[7] We follow the US Census Bureau and categorize race and ethnicity into the following diversity groups: Hispanic; White alone, non-Hispanic; Black or African American alone, non-Hispanic; American Indian and Alaska Native alone, non-Hispanic; Asian alone, non-Hispanic; Native Hawaiian and Other Pacific Islander alone, non-Hispanic; Some Other Race alone, non-Hispanic; Multiracial, non-Hispanic, and Unknown.

information of hospital managers using Lexis Nexis Public Records.

In our final step, we exclude transactions by dealers that hold only wholesale licenses (i.e., transactions between dealers) and dealers that use only non-negotiable prices, including *AutoNation*, *Carmax*, *Carvana*, *Drive Time*, and *EchoPark*.[8] This restriction removes approximately 0.6 million observations from the sample. We further exclude transactions missing the sale price, key vehicle characteristics required for constructing *NS* (e.g., Vin number, dealer ID, and transaction date), or customer demographics information used in the *NS* construction (e.g., age, marital status, and number of children). This filter eliminates an additional 2.8 million observations. After applying these restrictions, our final dataset consists of approximately 9 million vehicle transactions and includes 1,279 hospital managers.

3 A Measure of Negotiation Skill (*NS*)

3.1 Constructing the NS Measure

We use the vast DMV vehicle purchase data to construct an individual-specific measure of negotiation skill based on the actual vehicle purchase price relative to other individuals purchasing the same vehicle (e.g., same make-model-trim-year with the same body type, restraint system, transmission type, and engine code) controlling for the month, dealer, and buyer's residential county fixed effects. We also control for the number of competing dealers, travel distance, and the purchaser's demographic information.

We adopt the following empirical specification to construct the negotiation skill measure:

$$\begin{aligned}\ln(Sale\ Price_{ijdt}) = &\alpha_1 Veh\ Char_{jt} + \alpha_2 Demographics_{it} + \alpha_3 Mkt\ Comp_{dt} + \alpha_4 Travel\ Distance_{id} + \\ &VIN\ Num\ FE + YearMonth\ FE + Dealer\ FE + FIPS\ FE + \varepsilon_{ijdt}\end{aligned} \tag{1}$$

where $Sale\ Price_{ijdt}$ is the sale price of a transaction initiated by buyer i from dealer d for vehicle j at time t. $Veh\ Char_{jt}$ represents odometer reading group at the time of transaction.[9] $Demographics_{it}$ is a

[8] Tesla, a vehicle manufacturer that does not permit price negotiations, does not sell directly to customers in Texas. Accordingly, we exclude Tesla from the analysis, as well as any purchases made outside of Texas or used-vehicle transactions that are nonetheless recorded by the Texas DMV.

[9] We group odometer reading into 22 groups, including new cars with 0-200 miles, used cars with 200-5,000 miles, 5,000-10,000 miles, and increased miles ranges with 5,000 miles gap until 100,000 miles. We then group 100,000 miles and above a single group. Exempt reporting group is the last group.

list of demographic variables of buyer i at time t, including their age group, marital status, and number of children.[10] $Mkt\ Comp_{dt}$ is the number of nearby dealers (50 miles radius) who sell vehicles with the same make and same model (year) as the transacted one, capturing market competition level between dealers (or outside option of buyers).[11] $Travel\ Distance_{id}$ is the travel distance between buyer i's residency and dealer d's location. *VIN Num FE* is constructed using the 1st through 8th digits and the 10th digit of a vehicle's VIN. According to NHTSA, the first three digits of the VIN identify the manufacturer, the manufacturer's country of origin, and the vehicle type. Digits 4 through 8 encode information on the make, model, series, body type, engine type, restraint system, and related characteristics, while the 10th digit identifies the model year. By combining these digits, *VIN Num FE* ensures that we compare sale prices across vehicles with the same make, model, (model year), and trim, as well as identical body type, engine configuration, restraint system, and other key vehicle attributes. This construction allows for an apples-to-apples comparison of transaction prices. *YearMonth FE* is the transaction year-month fixed effects. *Dealer FE* and *FIPS FE* are dealer and buyer county-fips code fixed effects. ε_{ijdt} is the residual term.

Our individual negotiation skill (*NS*) measure is defined as the negative ε_{ijdt}. In essence, this captures whether an individual paid more or less (in percentage) than others for the same make-model-trim-year vehicle controlling for the dealership, month, and other observables. If a manager has multiple transactions, we use the earliest transaction as the manager's *NS* measure in our hospital-price analysis. That is, there is no time variation in an individual's *NS* score. In Section 4.1, we confirm that our results are robust to alternative measures as well as the inclusion of demographic controls in the construction of the *NS* measure.

3.2 Validating the *NS* Measure

To validate our *NS* measure, we begin by relating it to observable manager characteristics and credentials. Table 2 reports a set of univariate validation regressions. We group these characteristics into three categories. The first category captures personal characteristics, the second captures advanced de-

[10] Papers such as Chandra et al. (2017) and D'haultfoeuille et al. (2018) highlight the role of demographic characteristics on vehicle bargaining outcomes.

[11] See Murry and Zhou (2019) and Yavorsky et al. (2021) for evidence on the role of dealer competition and travel distance in vehicle price negotiations.

grees, including MBA, JD, PhD, and MD indicators, and the third captures self-reported or endorsed professional skills from LinkedIn. We manually collect the education and skills measures from LinkedIn and, where missing, supplement with press releases and corporate management biographies. Professional skills reflect managers' self-reported or endorsed skills, including keywords such as negotiation, management, leadership, and research.

Examining personal characteristics, we first find that female managers exhibit slightly worse negotiation outcomes, with *NS* about 1.5% lower on average, consistent with a large literature documenting systematic differences in bargaining outcomes by gender (Kray, 2001; Andersen et al., 2018). Column 2 shows *NS* is uncorrelated with *Non-White*. We also examine two proxies for cognitive skill: the average SAT score of the manager's undergraduate institution (College Board, 2013) and an indicator for whether the manager attended an Ivy League institution. Both are insignificant. The absence of any correlation between these IQ proxies and negotiation skill is consistent with Kaplan et al. (2012).

Advanced degrees, our second category, also display limited systematic correlation with *NS*. MBA, PhD, and MD indicators are not meaningfully related to negotiation outcomes. The one exception is a positive association for JD holders, which is economically intuitive. Legal training is directly relevant to contract structure, bargaining mechanics, and the strategic use of institutional details that often matter in negotiated agreements.

The third category captures professional skills, which reflect managers' self-reported or endorsed skills from LinkedIn across areas such as negotiation, management, leadership, and research. Here the patterns are more targeted. Managers tagged with negotiation-related skills exhibit higher *NS*, while broader descriptors such as management, leadership, and research show little relationship. This split is useful for interpretation: negotiation-specific experience aligns with our outcome-based skill measure, whereas generic professional labels do not. Collectively, Table 2 highlights that our *NS* measure derived from the universe of Texas vehicle purchase price negotiations is not related to proxies for intelligence or general professional degrees and skills. Rather, it varies systematically with gender, legal training, and is largely consistent with self-perceived skill sets.

We present additional tests to validate our negotiation skill proxy. We confirm that *NS* is individually persistent across multiple vehicle purchases and present evidence that it has origins in familial experience. Further, we validate the measure using managers' real estate transactions and an alternative vehicle-based outcome, the discount of new-vehicle prices relative to list prices.

To start, we perform a variance decomposition analysis to evaluate the importance of individual fixed effects in explaining *NS* for individuals with multiple vehicle transactions during the sample period. Given the existing evidence that negotiation ability is persistent across interactions (Elfenbein, 2013), we expect that individual fixed effects should capture a substantial portion of its variation. Table 3 Panel A Columns (1) and (2) report the R-square for regressions with the full sample while Columns (3) and (4) report the results for the subsample of hospital managers. Columns (1) and (3) include only individual fixed effects, while Columns (2) and (4) incorporate additional controls, including buyers' age group, marital status, and number of children as well as time (year-month) and county fixed effects.

The results show that individual fixed effects alone account for 44% of the variation in *NS* for the full sample. Adding extra controls does not increase the R-square meaningfully (from Column 1 to Column 2). In the manager subsample, individual fixed effects explain 34% of the variation, and the inclusion of additional controls increases the explanatory power to 43% (Column 4). These findings indicate that individual-specific attributes play a crucial role in shaping negotiation skills, with other contextual and demographic variations adding limited incremental explanatory power.

If *NS* is an individual specific attribute, we would also expect it to exhibit persistence over time. Panel B of Table 3 explores this by regressing an individual's current *NS* measure on their initial *NS* measure, derived from their first transaction in the administrative vehicle sales dataset. Columns (1) and (3) include only the initial *NS*, while Columns (2) and (4) additionally control for the time elapsed since the initial transaction (measured in months). For the full sample, the coefficient on initial *NS* is 0.098 in Column (1) and remains nearly unchanged when controlling for time (0.096 in Column 2), both highly statistically significant. For the manager subsample, the persistence of *NS* is weaker but still significant, with coefficients of 0.049 (Column 3) and 0.053 (Column 4). These results confirm that negotiation skill is persistent over time, with the time elapsed since the initial transaction having no significant effect on its persistence.

Given *NS* persists as an individual attribute, a natural question is why some managers differ from others in their negotiation skills. The literature on the determinants of personality underscores the role of familial factors in the formation of interpersonal skills, such as cultural origins, endowed socioeconomic status, and intra-family competition for limited resources. For example, bargaining is significantly more common in some ethnic cultures than others, and research finds large and persistent cross-cultural differences in the negotiation propensity, intensity of bargaining, and comfort with negotiations (e.g., Adair and Brett, 2004; Gunia et al., 2016). Prior work also highlights the role of formative family experiences in shaping negotiation skills, such as the balance of power within the family, endowed resource constraints, and intra-family competition for resources (du Bois-Reymond et al., 1993; Krüger et al., 1994).

To study the influence of cultural origins and formative family experiences, we focus on the parents and siblings of hospital managers. An advantage of this approach is that it allows us to capture the effects of cultural norms, family upbringing, and formative experiences specific to the household where the manager grew up. Prior work shows that family-specific formative experiences have long-lasting effects on the formation of managerial attributes (Duchin et al., 2021). Another advantage is that these familial experiences are mostly outside of a manager's control and represent endowed or exogenously imposed influences in adolescence and early adulthood that long precede the manager's professional tenure.

We manually collect data on the parents and siblings of hospital managers from Lexis Nexis Public Records (LNPR). This database identifies a person's relatives by cross-referencing birth, marriage, and cohabitation records, providing details on relationships (e.g., father, brother), residential addresses, partial social security numbers, and unique personal identifiers (*LexIDs*). To reconstruct the household where the manager grew up, we retrieve comprehensive reports on their parents and siblings, including address histories derived from deed and tax records, utility bills, and voter registration records. Using this information, we match relatives to their vehicle purchase transactions from the Texas DMV and estimate their *NS* measures following the same procedure used for hospital managers.

Table 3 Panel C presents a similar variance decomposition analysis using the sample of individuals with family linkages. This includes the subset of hospital managers for whom *NS* is available for at least one parent or sibling (managers without such records are excluded). Columns (1) and (2) replicate the individual fixed effects analysis from Panel A for this sample, confirming that individual fixed effects account for a substantial portion of the variation in *NS*. Columns (3) and (4) replace individual fixed effects with family fixed effects, revealing that family fixed effects explain 26 to 39 percent of the cross-sectional variation in *NS*. While these estimates are slightly smaller than those of individual fixed effects, they suggest that a large fraction of time-persistent individual heterogeneity in negotiation skill is related to the factors common to the manager's family.

To provide additional validation, we assess how a manager's negotiation skill correlates with two distinct outcomes. The first uses managers' realized annual returns in residential real estate transactions, which involve bargaining in a different setting than motor vehicles.[12] We manually collect hospital managers' real estate transaction histories from LNPR and supplement these records with property details from Zillow. Specifically, we identify all properties for which a manager is listed as a current or previous owner based on county deed records and tax assessment records in LNPR. We then retrieve the property's history on Zillow by searching for its address. This approach allows us to verify each manager's transactions by cross-checking the transaction date listed in Zillow against the transaction date based on deed records in LNPR. For each property, we collect detailed information, including the listing date and price, transaction date and price, and various property features such as the number of bedrooms and bathrooms, square footage of the property and its land lot, year of construction, and property type (e.g., single-family or multi-family).

For each transaction with available purchase and sale prices, we compute a manager's realized annual return. The underlying intuition is that for a given property, managers with higher negotiation skill should achieve greater returns by negotiating a lower purchase price and a higher sale price for the same property. However, one notable data limitation is that Texas, where the majority of these managers reside, is one of 11 states that do not require disclosure of historical property prices in public records, resulting in sparse coverage of prices on Zillow and LNPR. As a result, most of the estimation results are based on managers' real estate transactions outside of Texas, such as vacation homes, investment properties, and previous residences in other states. As such, we only have 96 observations where we observe both

[12] We alert the reader to two caveats with this validation analysis. First, real estate assets are far less standardized than motor vehicles. While we collect data on common property features, many of the price-relevant property characteristics remain unobservable to the econometrician, such as the home condition, renovations, and or remodeling options. Second, while motor vehicle transactions allow us to compare negotiation outcomes with the same counterparty (same dealership), each real estate transaction involves a unique counterparty, adding an additional source of unobserved variation. These limitations introduce noise in measuring negotiation skill in real estate transactions.

the purchase and sale price for a hospital manager's real estate and can calculate an annualized return in the spirit of Goldsmith-Pinkham and Shue (2023). Panel A of Figure 4 plots these observations (y-axis) against the manager's *NS* measure derived from motor vehicle transactions (x-axis), controlling for observable property features (e.g., number of bathrooms and bedrooms, square footage, lot size, and Zillow's current price estimate). The scatterplot reveals a positive relationship, with most observations distributed along an upward-trending line.

We next provide a complementary validation within the automobile market using an alternative measure of negotiation outcomes that benchmarks the transaction price against the vehicle's list price. While the Texas DMV data do not include the list price, we manually collect list prices for hospital managers' new vehicle purchases by searching their individual VINs on VehicleHistory.com.[13] We then calculate the transaction price discount relative to the specific vehicle list price. Panel B of Figure 4 shows a positive relationship between our *NS* measure and this alternative measure of vehicle negotiation skill. These results suggest that a manager's negotiation outcomes are positively correlated across different bargaining settings and measures.

A central assumption in linking negotiation outcomes across settings is that individual skill exhibits behavioral consistency—even when the environments differ markedly. While the context of vehicle purchases, real estate transactions, and hospital-insurer bargaining varies in complexity, stakes, and institutional structure, all require the application of persuasion, strategic reasoning, and responsiveness to incentives. The underlying traits that drive negotiation performance are likely to be stable over time and generalizable across domains. However, we acknowledge that certain context-specific factors may play a more prominent role in one setting than the other. For example, thriftiness and sensitivity to monetary outcomes may lead to better vehicle prices but may not directly map onto success in institutional bargaining. Similarly, social status, experience, and technical knowledge may enhance negotiation outcomes in hospital settings but are less relevant in consumer transactions. Despite these differences, we view negotiation skill as a partially time-invariant attribute shaped by both innate talent and learned behaviors, and our empirical design accommodates the possibility that context-specific factors generate noise rather than systematically biasing the correlation. Ultimately, consistent behavioral tendencies, such as the

[13] Data access limitations do not allow us to replicate the measure for the universe of vehicle sales.

ability to secure favorable prices, are likely to manifest across diverse bargaining environments, even if the specific mechanisms differ.

In sum, the empirical evidence suggests that our proxy of a manager's negotiation skill derived from vehicle purchase history captures a persistent attribute with familial origins. The fact that it also is correlated with the individual's bargaining skill in real estate transactions provides further validation. The subsequent sections will explore whether a manager's negotiation skill contributes to observed price dispersion in the hospital sector.

4 Negotiation Skill and Hospital Prices

In this section, we present preliminary evidence on the relationship between hospital managers' bargaining ability and the prices negotiated with insurers. We examine the average negotiated price for specific hospital-insurer pairs and then look into the prices negotiated for specific medical imagining procedures. The next section will address endogeneity concerns.

4.1 Hospital-Insurer Price Index

Hospital Price Index, described in Section 2.1, aggregates the information from millions of outpatient visits to capture the average dollar amount per unit of service at the hospital-insurer-year level. This approach is similar to Gowrisankaran et al. (2015). We conduct the analysis at both the hospital facility level and the hospital system level. For the system-level sample, we include managers from multi-facility hospital systems as well as stand-alone facilities. Figure 5 presents the baseline relationship between *NS* and the *Hospital Price Index* separately for the system-level and facility-level samples. There is a clear positive relationship between negotiation skill and the price index in the system sample, consistent with more skilled negotiators extracting higher prices from insurers. The positive relationship is weaker, however, in the facility-level sample. These patterns reflect raw correlations without controlling for hospital or market characteristics that may influence negotiated prices. To rigorously examine whether individual managers' negotiation skill affect hospital prices at both the system and facility level, we adopt the following empirical specification:

$$Y_{ihkt} = \beta_1 NS_i + \beta_2 Hospital\ Char_{ht} + Insurer\ FE + Hospital\ FE + Year\ FE + \varepsilon_{ihkt} \qquad (2)$$

where Y_{ihkt} is the natural logarithm of the negotiated price index between hospital h with manager i and insurer k in year t. NS_i is manager i's negotiation skill. $Hospital\ Char_{ht}$ is a list of hospital (system) characteristics, including *Rural*, an indicator whether a hospital is located in rural area (a hospital system has at least one facility in rural area), *Teaching*, an indicator whether a hospital is a teaching hospital (a hospital system has at least one facility with the teaching hospital status), *For Profit*, an indicator whether a hospital is for-profit (a hospital system has at least one for-profit facility), *Hospital Size Quintile*, the quintile of the number of hospital beds (if it is a hospital system, we take the average across all facilities within a system), *Medicaid Ratio*, the fraction of total admission days that correspond to Medicaid patients (if it is a hospital system, we take the average across all facilities), and *Medicare Ratio*, the fraction of total admission days that correspond to Medicare patients (if it is a hospital system, we take the average across all facilities). These control variables capture a range of hospital characteristics which have been documented to affect prices, as discussed in Liu (2022). Also included are *Insurer FE*, *Hospital FE*, and *Year FE*, which represent insurer, hospital (system), and year fixed effects. Hospital facility or hospital system fixed effects absorb time-persistent characteristics, such as location or specialization. Year fixed effects account for any temporal trends in service prices. Lastly, insurer fixed effects absorb cross-sectional heterogeneity in the pricing policies across insurance companies.

Table 4 documents consistently positive coefficient estimates for *Negotiation Skill* as an explanatory variable of the *Hospital Price Index*, whether at the hospital system level (Columns 1 and 2) or the hospital facility level (Columns 3 and 4). Columns (1) and (3) include the hospital, insurer, and year fixed effects while Columns (2) and (4) also include control variables to capture hospital features which may affect prices. Across all specifications, a within-hospital change in negotiation skill significantly influences the prices negotiated with insurers. The economic impact is substantial. For example, Column (2) of Table 4 indicates that a 10% increase in a hospital system manager's bargaining ability is associated with an average 8.61% increase in negotiated service prices with insurers.

As discussed in Section 3.1, Table 4 uses *Negotiation Skill* from the earliest transaction of a manager if the individual purchases multiple vehicles during our event window. While Table 3 documents the within-manager persistence of bargaining skill measured across vehicles, we confirm that our results are not driven by the use of the earliest transaction. Online Appendix Table OA3.3 shows the baseline results are robust to using the manager's maximum *NS* in both the hospital system and hospital facility samples.

The baseline *Negotiation Skill* measure is calculated after controlling for demographic information following Chandra et al. (2017) which documents the role of such attributes in vehicle price negotiations. To confirm that the score is robust to this specification choice, we reconstruct the measure without the inclusion of demographic information such as gender and number of children. Online Appendix Table OA3.4 reveals this has no material impact on the coefficient estimates.

It should be noted that *Negotiation Skill* is a generated regressor (a la Pagan, 1984) which might lead to underestimated standard errors. While this is less of concern given the measure is constructed in an entirely distinct dataset, we nevertheless rerun our baseline analysis with bootstrapped standard errors. Table OA3.5 presents these results. The results are virtually unchanged and, in fact, become more statistically significant with the bootstrapped standard errors, relative to the original analysis which adjusted for clustering at the individual hospital manager level.

4.2 X-Ray Pricing: Controlling for Service Quality

Another concern is that the *Hospital Price Index* is an imperfect measure of negotiation outcomes. In particular, medical service prices reflect a confluence of difficult-to-observe contracting factors, such as service quality or the risk of claims decline. In this case, a higher price per unit of service could reflect better service quality rather than a superior negotiation outcome. To minimize the effects of these confounding factors, we limit our analysis to a subset of standardized medical imaging procedures that offer a homogeneous product (X-ray image). As discussed in Brown (2019) and Liu (2022), these are widely regarded as some of the least differentiated medical procedures.

The medical imaging procedure regression sample uses the ten most common X-ray procedures occurring in our sample, including X-ray chest for two views (CPT code 71020), X-ray exam of foot (CPT code 73630), X-ray exam of lower spine (CPT code 72100), X-ray exam of shoulder (CPT code 73030), X-ray chest for a single view (CPT code 71010), X-ray exam of hand (CPT code 73130), X-ray exam of ankle (CPT code 73610), X-ray exam of knee (CPT code 73562), X-ray exam of neck spine (CPT code 72040), X-ray exam of wrist (CPT code 73110). The dependent variable is the natural logarithm of the allowed amount (finally paid amount) for a procedure. We expand our controls to include patient observables such as gender, age, 3-digit zipcode, service-mix weights, and disease category (following Shepard, 2022) to group patient's ICD-10 (or ICD-9) diagnosis codes in medical claims into 285 mutually exclusive Clinical Classification Software, or CCS, single-level categories in addition to the standard hospital characteristics including the hospital size quintile, for-profit status, teaching status, whether it is a rural hospital (absorbed at facility level analysis by facility FEs), the ratio of Medicare patients stay days, and the ratio of Medicaid patients stay days. We also add the procedure FE which recognizes the procedure CPT codes and procedure modifier codes.

Table 5 examines the impact of hospital managers' negotiation skill on prices for standard X-ray procedures at the hospital system level (Panel A) and hospital facility level (Panel B). The results reveal a positive and significant relationship between a manager's *Negotiation Skill* and higher negotiated prices for the same procedure at the same hospital across insurers.[14] Notably, the effect is most pronounced for the most frequently performed procedures, such as the top 3 X-rays, and diminishes slightly as the analysis incorporates less common procedures, expanding to the top 10. This pattern is consistent with the theory of optimal allocation of constrained managerial effort (Radner and Rothschild, 1975) and parallels prior evidence that agents prioritize activities with the highest financial impact (Fich et al., 2015).

5 Addressing Selection Concerns

Since the matching between managers and hospitals is clearly not random, this section aims to distinguish the effects of managerial negotiation skill from potential confounding factors. For instance, managers with better negotiation skill may systematically match with higher-quality hospitals due to unobserved factors, such as a preference for prestige or better institutional quality. In such cases, negotiation outcomes may reflect the influence of hospital-level factors rather than the manager's bargaining

[14] As a robustness check, we include imaging procedure-by-year fixed effects to control for time-varying demand across medical procedures and re-estimate our model. As shown in Table OA3.6, our main results remain robust.

skill. Our baseline specification addresses the time invariant component of the match with the inclusion of hospital fixed effects. Thus, our identification hinges on within-hospital changes in negotiation skill (changes in the hospital manager). Further, insurer fixed effects are included to ensure changes in the composition of payers does not affect the estimates. In Table OA3.7 of the Online Appendix, we directly test whether hospital manager turnover leads to changes in the composition of insurers contracting with the hospital. At both the system and facility levels, we find no clear evidence of such a correlation.

To further address the concern that hospitals matched with managers of varying negotiation skill (NS) may differ along other dimensions that could influence service prices, we perform additional tests. In Figure OA2.2 of the Online Appendix, we report correlations between hospital quality measures and managers' *NS*. The majority of these measures show no significant correlation with managers' *NS*. Table OA3.8 also examines the correlation between hospital patient volumes—in both outpatient and inpatient settings—and managers' *NS*. Across all specifications, we find no clear evidence of a relationship between patient volume and managerial skill.

That said, selection concerns remain. For example, a deterioration in the hospital's financial condition could affect its bargaining position as well as management turnover and the skillset of the new hire. To buttress the link between bargaining skill and negotiated hospital prices, we present two sets of alternative empirical specifications. First, we examine management separations for idiosyncratic reasons that induce a change in the negotiation skill within the same hospital. Second, we exploit variation in the insurer market power to identify shocks to the hospital manager's relative bargaining position.

5.1 Plausibly Exogenous Turnover and Negotiated Hospital Prices

We begin by focusing on management turnovers that are plausibly unrelated to hospital performance. Specifically, we examine management departures resulting from deaths, terminal health issues, and age-related retirements. To identify the first two categories, we utilize administrative data from the Social Security Administration (SSA). Individual records in Lexis Nexis Public Records (LNPR) are linked via social security numbers to the SSA's administrative Death Master File, a central repository that aggregates death records from U.S. states and is updated weekly in LNPR. For individuals who have experienced a death event, LNPR includes a deceased indicator along with the date of death, as recorded by the SSA. We classify a departure as related to death or terminal health issues if a manager's death event occurs within the same year as their separation from the hospital. To identify age-based retirements, we analyze hospital press releases that announce management changes. A departure is classified as an age-based retirement if the outgoing manager is over 62 years old (the minimum threshold for social security) and the press release explicitly cites retirement as the reason for the departure. Following this algorithm, we identify 130 management turnover events from natural causes across both the hospital facility and system levels.

Panels A and B of Table 6 provide more summary statistics for these turnovers. At the system level, approximately half of all manager turnovers are attributed to natural causes. While the proportion is lower at the facility level, more than a quarter of turnovers still fall into this category. Reassuringly, the differences in negotiation skill between incoming and departing managers appear to be fairly random, with changes occurring in both directions. In fact, the distribution of increases and decreases in *NS* is roughly even at both levels.

Panel C of Table 6 investigates the association between the natural turnover of hospital managers and their hospital's negotiated prices. The sample includes hospitals with management turnovers due to the exogenous natural causes and all regressions include hospital facility or hospital system fixed effects so we estimate within-hospital variation in the *Hospital Price Index* after a shock to their manager's negotiation skill due to natural turnover. We find that a change in management bargaining skill as a result of natural turnover affects negotiated prices. This conclusion is statistically significant for both hospital systems (Columns 1 and 2) and hospital facilities (Columns 3 and 4) and the economic magnitudes are material. For instance, Column (1) suggests that a 10% increase in managers' bargaining ability corresponds to an average 8.53% increase in the hospital negotiated prices. The estimates remain comparable after we saturate the regressions with controls at the level of the hospital system (Column 2) and hospital facility (Column 4). These additional controls account for time-varying hospital characteristics, such as the hospital size quintile and the fraction of Medicare patients, and show that the effect of negotiation skill is incremental to changes in these hospital fundamentals.

We corroborate these findings with additional evidence on changes in hospital prices around management turnover events that involve an increase or decrease in the incoming manager's negotiation skill.

Specifically, we distinguish turnovers where the incoming manager has higher (lower) negotiation skill, denoted by the indicator variables *Increase-NS Turnover* (*Decrease-NS Turnover*). In the regression analysis, we interact these indicators with *NS*. The results are reported in Table OA3.9 in the Online Appendix. Across all specifications at both the hospital system and facility levels, the interaction term between *Increase-NS Turnover* and *NS* is significantly positive, indicating that replacing a departing manager due to natural causes with a higher-NS manager leads to a substantial increase in negotiated hospital prices. In contrast, for hospitals experiencing a turnover associated with a decrease in *NS*, the estimated coefficients ahead of *Decrease-NS Turnover* and *NS* are either significantly negative at the facility level or statistically insignificant at the system level. This pattern is intuitive, as it is generally slower and more difficult to negotiate prices downward once higher price precedents have been established.

To validate that managers' exogenous departures are truly "exogenous" and not systematically related to hospital characteristics, Table OA3.10 in the Online Appendix examines whether hospitals' financial and operational conditions predict managers' exogenous departures or changes in managers' negotiation skills within the exogenous departure sample at both the hospital facility and system levels. The analysis includes a range of hospital-level variables, such as profit margin, the logarithm of the number of beds, the logarithm of patient volumes, and quality measures. The regression results show that these financial and operational indicators generally do not significantly predict either the likelihood of a managerial exogenous departure or changes in managers' negotiation skills, supporting the identifying assumption that such departures are independent of underlying hospital performance or conditions.

5.2 Insurer Bargaining Position

Another important source of variation in price negotiations would be changes in insurers' relative bargaining positions. Building on the intuition that consolidation between health insurers in local markets can affect their market power and alter their bargaining positions when negotiating prices with hospitals (Dafny et al., 2012), we evaluate the impact of insurer consolidation on negotiated prices. Specifically, we evaluate whether the impact of a more concentrated local insurance market varies depending on the level of negotiation skill (*NS*) of hospital managers.

Using American Medical Association (AMA) insurance market annual reports (American Medical Association, 2018), we manually collect the Herfindahl-Hirschman Index (HHI) for the 25 largest Metropolitan Statistical Areas (MSAs) in Texas. This measure of MSA-level insurer concentration spans the years 2017, 2018, 2019, 2020, and 2022.[15] Some MSAs experienced dramatic increases in insurance market concentration over this period. For example, the College Station MSA's insurance market HHI rises from 2,578 to 4,300, while other MSAs, such as Killeen, remain relatively stable. Figure 6 illustrates the variation in time series of HHI with the three largest (Dallas, Houston, San Antonio) and three smallest (Texarkana, San Angelo, Victoria) Texas MSAs.

Motivated by this heterogeneity in changes in insurer market power, we evaluate whether changes in the local insurer landscape impact hospital prices. We define Δ*Concentration* to equal one if the MSA's insurer HHI increases between the sample's initial year (2017) and the current year by more than 100 in Columns (1) and (2), by more than 200 in Columns (3) and (4), and by more than 300 in Columns (5) and (6). We split the hospital facility sample[16] into two groups: *High-NS Hospital* and *Low-NS Hospital*. Hospitals are categorized as *High-NS Hospital* if their managers' *NS* in the earliest year of the sample period is above the median, and *Low-NS Hospital* otherwise. Then we run regressions on the full sample by including the interaction term of *High-NS Hospital* and Δ*Concentration* to examine how pricing patterns differ across hospitals with varying levels of managerial negotiation skill when faced with a dramatic increase in insurer market concentration.

Table 7 presents the regression results. The negative coefficient on Δ*Concentration* is consistent with the notion that more concentrated insurance markets weaken hospitals' bargaining positions, thereby leading to lower negotiated hospital prices. However, notable differences emerge between high-*NS* and low-*NS* hospitals. Specifically, the interaction term *High-NS Hospital*$\times\Delta$*Concentration* is significantly positive across all columns (often at the 1% level), indicating that hospitals with high-*NS* managers are able to negotiate better prices than those managed by low-*NS* counterparts when insurer markets become more concentrated. When summing the estimated coefficients on *High-NS Hospital*$\times\Delta$*Concentration* and Δ*Concentration*, the combined effect is close to zero, suggesting that high-*NS* hospitals experience no meaningful change in negotiated prices. In contrast, hospitals with low-*NS* managers face a signifi-

[15] We begin with 2017 because a change in MSA definitions in the AMA's "Competition in Health Insurance" update that year renders earlier data incompatible with the subsequent years.

[16] We focus on hospital facilities rather than systems, as systems often span multiple MSAs.

cantly larger decline, with negotiated prices falling by an average of 17%.

Leveraging variation in insurer market concentration, we conduct a placebo test to assess the extent to which potential hospital-manager sorting might influence our baseline results in Section 4.1. The underlying hypothesis is that, if such sorting exists, hospitals in more concentrated insurer markets may have stronger incentives to hire managers with higher bargaining ability to counteract increased price pressure from insurers.

In Table OA3.11 of the Online Appendix, we test this hypothesis by regressing an indicator variable, equal to one if a hospital hires a new manager with higher *NS* than the departing manager, on changes in insurer market concentration, $\Delta Concentration$. The regression results indicate that changes in insurer market concentration are not significantly associated with changes in the negotiation skills of newly hired managers. This finding is reassuring, as it suggests that hospital-manager sorting is unlikely to meaningfully bias our main estimates.

6 Structural Approach

In this section, we estimate a hospital-insurer price bargaining model built on Gowrisankaran et al. (2015) and Ho and Lee (2017). We associate our *NS* measure with the recovered bargaining power parameters from the model and explore the extent to which hospital managers' *NS* affects hospital bargaining power and hospital price dispersion.

6.1 Model

6.1.1 Patient Hospital Choice

Within a local market (defined as a hospital referral region, or HRR), there is a set of hospitals (systems) indexed by $h = 1, \cdots, H$, and a set of insurers $i = 1, \cdots, I$. A hospital (system) h may own one or multiple facilities, denoted by $h(k)$ with $k \in 1, \cdots, K_h$. There is a set of enrollees denoted by $j = 1, \cdots, J$, each of which has a health plan managed by insurer i. Let $i(j)$ denote enrollee j of insurer i. The subset of hospitals that insurer i includes in its network is denoted by N_i. Each insurer i and hospital h negotiate a benchmark price p_{hi}. $\mathbf{p}_i$ is the vector of all negotiated prices between insurer i and hospitals in its network N_i. Let M_h be the set of insurers that include hospital h in their networks, so for each $m \in M_h$ it always has $h \in N_m$.

Each enrollee $i(j)$ who is stricken by illness with CCS category $d = 0, 1, \cdots, D$ where $d = 0$ represents the status of no illness, picks a hospital in the network of i to visit. 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 h by insurer i is $w_d \times p_{hi}$. For each illness $d = 0, 1, \cdots, D$, patients seek hospital care at the hospital that gives them the highest utility. The ex-post utility of patient j insured by insurer i receiving care from hospital $h(k)$ is given by

$$U_{ijkd} = \alpha_1 \cdot d_{jk} + \alpha_2 \cdot d_{jk}^2 + \alpha_3 \cdot \mathbf{X_{jd}} \cdot \mathbf{Y_k} + \alpha_4 \cdot \mathbf{CCS_{jd}} \cdot \mathbf{Z_k} + \eta_k + e_{jk}$$

where d_{jk} is the travel time (in hours) between patient j's residence and hospital facility $k \in h$'s location, and d_{jk}^2 is the squared travel time. The indirect utility also depends on interaction terms involving a vector of patient-specific characteristics, $\mathbf{X_{jd}}$, such as patient age, gender, relative service-mix weights, dummy for prior hospital visits in the past year, and travel time, as well as a vector of hospital-specific characteristics, $\mathbf{Y_k}$, including the number of hospital beds, for-profit status, teaching status, and dummy for rural location. Additionally, the covariates include interactions between the patient's major diagnoses indicators, represented by CCS code dummies $\mathbf{CCS_{jd}}$, and corresponding hospital service availability indicators, $\mathbf{Z_k}$. Finally, η_k denotes hospital fixed effects, and e_{jk} represents the idiosyncratic error with i.i.d. type 1 extreme value distribution that is known by the patient at the time of choosing hospitals.

The patient may visit a hospital in their network, $h(k) \in N_i$, within an HRR. The outside option is modeled as choice 0, which corresponds to patients going to a facility outside of the local market, and the delivered utility is normalized as $U_{ij0d} = e_{j0}$.

Define $\delta_{ijkd} = U_{ijkd} - e_{jk}$ 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

$$s_{ijkd}(N_i) = \frac{exp(\delta_{ijkd})}{\sum_{\kappa \in \{0, N_i\}} exp(\delta_{ij\kappa d})}.$$

The expected utility for a patient of disease d in need of outpatient service is

$$CS_{ijd}(N_i) = \ln\left(\sum_{\kappa\in\{0,N_i\}} exp(\delta_{ij\kappa d})\right).$$

6.1.2 Price Bargaining

Let us consider the general form of the Nash-in-Nash bargaining problem between a hospital and an insurer:

$$\max_{p_{hi}} \left(\Pi_h(M_h) - \Pi_h(M_h \setminus i)\right)^{\beta_h} \times \left(\Pi_i(N_i) - \Pi_i(N_i \setminus h)\right)^{1-\beta_h}$$

in which $\Pi(\cdot)$ refers to the payoff function of either a hospital or an insurer, N_i and M_h represent the set of contracts with hospitals and insurers maintained by i and h, $M_h \setminus i$ denotes the state for hospital h where it exits insurer i's network, and $N_i \setminus h$ refers to the state for insurer i to exclude hospital h from its network. β_h is the bargaining power parameter of hospital h which does not vary across insurers.

The payoff function for hospital h can be characterized as

$$\Pi_h(M_h) = \sum_{m\in M_h} (p_{hm} - c_h) \times D_{hm}(M_h)$$

where p_{hm} is the derived price index per unit of APC weight of service between insurer m and hospital h, c_h is the marginal cost of hospital h per unit of APC weight service provided, and $D_{hm}(M_h)$ is the total expected patient volume (in unit of APC weights) from insurer m to visit hospital h.

If hospital h is excluded from insurer i's network, the payoff function becomes

$$\Pi_h(M_h \setminus i) = \sum_{m\in\{M_h\setminus i\}} (p_{hm} - c_h) \times D_{hm}(M_h \setminus i).$$

Since the reallocation of patients who originally would have visited hospital h to other hospitals would only affect hospitals that are not hospital h, and the enrollees of other insurers are not affected by hospital h's removal from i's network. This means that the hospital gains-from-trade (GFT) can be simplified as

$$\Pi_h(M_h) - \Pi_h(M_h \setminus i) = (p_{hi} - c_h)D_{hi}(M_h).$$

The payoff for insurer i is modeled as following: we follow Gowrisankaran et al. (2015), Liu (2022), and Arnold et al. (2024) to model the insurer as an agent that maximizes all enrollees' welfare. So it can be characterized as

$$\Pi_i(N_i) = \gamma \mathbf{CS_i}(N_i) - \sum_{k \in N_i} p_{ki} D_{ki}(N_i)$$

where $\mathbf{CS_i}(N_i)$ is the sum of all enrollees' willingness-to-pay given the network N_i, γ is a parameter to be estimated and it governs how much the insurer cares about enrollees' welfare and converts the willing-to-pay of enrollees from utils to dollars, and D_{ki} represents the total patient volume from insurer i to hospital k.

The payoff for insurer i when hospital h is excluded from its network becomes

$$\Pi_i(N_i \setminus h) = \gamma \mathbf{CS_i}(N_i \setminus h) - \sum_{k \in \{N_i \setminus h\}} p_{ki} D_{ki}(N_i \setminus h).$$

Therefore, the insurer's GFT is

$$\Pi_i(N_i) - \Pi_i(N_i \setminus h) = \gamma \Delta_h \mathbf{CS_i}(N_i) - p_{hi} D_{hi}(N_i) - \sum_{k \in \{N_i \setminus h\}} p_{ki} \Delta_h D_{ki}(N_i)$$

where

$$\Delta_h \mathbf{CS_i}(N_i) = \mathbf{CS_i}(N_i) - \mathbf{CS_i}(N_i \setminus h)$$

and

$$\Delta_h D_{ki}(N_i) = D_{ki}(N_i) - D_{ki}(N_i \setminus h).$$

Plugging these expressions into the bargaining problem and taking the first-order conditions, we can obtain

$$\beta_h \left(\underbrace{\gamma \Delta_h \mathbf{CS_i}(N_i)}_{\text{Marginal WTP}} - \underbrace{\sum_{k \in \{N_i \setminus h\}} p_{ki} \Delta_h D_{ki}(N_i)}_{\text{Demand reallocation}} - \underbrace{c_h D_{hi}(N_i)}_{\text{Hospital costs}} \right) = \underbrace{(p_{hi} - c_h) D_{hi}(N_i)}_{\text{Hospital profits}} \tag{3}$$

The above equation indicates that the hospital gains-from-trade from contracting with insurer i, on the RHS, are β_h-proportional to the total gains-from-trade (on the LHS in parentheses). Denote the RHS of

Equation (3) as GFT_t^{hi}, representing the gain from trade of hospital h with insurer i in year t. Denote the LHS of Equation (3) inside of the parentheses as $GFT_t(\gamma)$, representing the total gain from trade. Then we are able to calculate hospital h's bargaining power when negotiating with insurer i based on the following estimating equation:

$$\frac{GFT_t^{hi}}{GFT_t(\gamma)} = \beta_h(t). \tag{4}$$

6.2 Estimation Results

6.2.1 Demand Estimates

The patient demand is estimated separately for each HRR in a year by maximum likelihood using the patient claims data. Panel A of Table 8 summarizes the estimates by reporting the visit-number-weighted coefficients and standard errors of all HRR-years in Texas.

The first set of coefficients highlights the impact of travel time on patient utility. 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 on average increasing in the size of hospitals and for-profit status, and decreasing in teaching status and rural hospital status.

The second set of coefficients examines how other hospital characteristics influence patient preferences. For example, interaction terms involving teaching hospital status reveal a positive association with female and older patients, indicating a stronger preference for teaching hospitals among these groups. Additionally, patients with a history of previous visits are significantly more likely to choose teaching hospitals. Similarly, interaction terms between hospital size, as measured by the number of hospital beds, and patient characteristics suggest that female and older patients, as well as those requiring greater medical resources, tend to prefer larger hospitals.

Finally, the interaction of diagnoses with hospital services demonstrates that patients in need of specific medical services are more likely to choose hospitals that are able to accommodate their needs. For instance, patients with psychological or cancer diagnoses are significantly more likely to choose a hospital offering psychological and oncological services, respectively.

6.2.2 Supply Estimates

On the supply side, we directly estimate hospitals' marginal costs (c_h) from the data following Ho and Lee (2017), which gives us empirical flexibility to recover hospitals' bargaining power parameters. Specifically, we source detailed cost items from HCRIS and carefully select cost components related to patient-relevant variable costs. To calculate the proportional outpatient variable costs for hospital h in year t, VC^{out}_{ht}, we multiply the total variable costs by the ratio of outpatient revenues to total patient revenues. We then divide this value by the total volume of outpatient visits and the average service-mix weight per visit at a hospital. The process is summarized in the following equation:

$$\text{MC}_{ht} = \frac{\text{VC}_{ht} \times \frac{\text{Rev}^{out}_{ht}}{\text{Rev}^{tot}_{ht}}}{D_{ht} \times w_{ht}} \tag{5}$$

in which VC_{ht} is the total variable costs for hospital h in fiscal year t, Rev^{s}_{ht} with $s \in \{out, tot\}$ denotes the net outpatient or total patient revenues of hospital h in fiscal year t, D_{ht} is hospital h's total outpatient volume in year t, and w_{ht} is the average APC weights per outpatient visit for hospital h in year t, derived from Clarivate DRG claims data. Further details on the procedure for constructing the marginal cost per unit of service are provided in Section OA-1.3 of the Online Appendix .

With the marginal costs estimated, the remaining parameter to identify in the model is insurers' price sensitivity, γ, which reflects how insurers value their enrollees' expected utility. Following Arnold et al. (2024), we introduce an additional moment that equates the medical loss ratios (MLRs) implied by the model with their empirical counterparts:

$$\mathbf{E}\left[MLR_t - \sum_{i \in \{0,\cdots,I\}} \theta_{it} \frac{\sum_{k \in N_i} p_{kit} D_{kit}(N_{i(t)})}{\gamma \mathbf{CS_{it}}(N_{i(t)})}\right] = 0$$

where θ_{it} represents enrollment-based weights summing to one. More details on the empirical procedure to construct this moment can be found in Section OA-1.4 of the Online Appendix.

Panel B of Table 8 reports our estimate of γ as 595.26, implying that insurers, on average, equate one unit of utility to approximately \$595 in revenue. This magnitude aligns with other studies' findings in the outpatient setting, including Arnold et al. (2024), Liu (2022), and Prager and Tilipman (2020).

6.3 Counterfactual

With estimated γ, we recover hospital h's bargaining power (weight), $\beta_h(t)$, when negotiating with insurer i within a hospital referral region (HRR, defined as a market) in year t, using Equation 4. Based on the theoretical properties of β, we winsorize the estimated bargaining weight to fall between zero and one. This process yields a sample of 1,175 bargaining power estimates by hospital, insurer, year, and HRR. The mean bargaining weight in our sample is 0.419, with a standard deviation of 0.402.

6.3.1 Determinants of Bargaining Power

To investigate the factors influencing hospitals' bargaining weights, we follow Grennan (2014) and Lewis and Pflum (2015) and estimate the following equation:

$$\beta_h(t) = \alpha_1 \times \textit{Hospital Characteristics} + \delta_i + \gamma_h + \tau_{hrr,t} + \varepsilon_{hit} \tag{6}$$

where δ_i represents insurer fixed effects, γ_h is hospital system fixed effects, and $\tau_{hrr,t}$ is HRR-by-year fixed effects. We cluster standard errors at the level of the hospital system by year.

Table 9 presents the estimated coefficients for Equation 6. In Column (1), we include only hospital managers' *NS* as the sole hospital characteristic. The positive coefficient suggests that managers' *NS* significantly enhance hospitals' bargaining power. Specifically, if a hospital manager demonstrates the ability to negotiate a 10% lower price when purchasing vehicles, the hospital she manages would experience an increase in bargaining power of approximately $0.06(\approx 10\% \times 0.643)$ when negotiating medical prices with insurers. Column (2) of Table 9 extends the analysis by incorporating additional hospital characteristics. The coefficient on *NS* remains positive and statistically significant at 1% level, with a magnitude comparable to that in Column (1). The inclusion of other hospital characteristics related to bargaining such as a larger patient share from the insurer (measured as the fraction of the insurer's patients treated by the system in an HRR-year), operating multiple facilities within a local market (HRR), being wholly owned by, partially owned by, or operating as a joint venture with a physician group, and for-profit ownership status does not materially attenuate the economic magnitude or statistical significance of the *NS* coefficient.

To assess the relative importance of bargaining ability to other characteristics, we conduct a "horse race" analysis by evaluating the change in hospitals' bargaining weights when each characteristic increases by one standard deviation. The results are illustrated in Figure 7. Among the characteristics analyzed, hospital managers' *NS* emerges as the most influential determinant of bargaining power. A one standard deviation increase in *NS* corresponds to a bargaining weight increase of approximately 0.08—roughly twice the effect of insurer-specific patient share (denote it as market share) and physician group affiliation, and nearly twelve times larger than the effect of operating multiple facilities within a local market.

6.3.2 Impact on Price Dispersion

To what extent does the heterogeneity in hospital managers' *NS* explain the price dispersion observed in the data? While the literature has reached a consensus that variation in bargaining power accounts for a nontrivial portion of price dispersion, the opaque nature of bargaining power parameters limits a more quantitative understanding of this question.

To this end, we conduct a counterfactual in which all heterogeneity in managers' *NS* is removed and assess how market price variance changes as a result. We measure price dispersion by following Grennan (2014) and calculating the variance of the natural logarithm of the gap between hospital prices and marginal costs (markups), $var(\log(p_{hi} - c_h))$, where $h \in N_i$ represents hospitals within insurer i's network. This measure aligns with the concept of observed price dispersion depicted in Figure 1, accounting for heterogeneity in hospital marginal costs. We then compute the mean of $var(\log(p_{hi} - c_h))$ across hospital-insurers in an HRR of a year to derive the market-average price dispersion.

First, we compute the market-average price dispersion in the model-implied equilibrium, where all hospital prices are determined through a linear system of equations governed by the first-order Equation 3, based on a set of winsorized bargaining power parameters from Table 9.[17] Column (1) of Table 10 reports the average price dispersion for the equilibrium prices implied by the model.

Next, we consider two counterfactual scenarios. The first one is our focal counterfactual (*Counterfactual: Equal NS*), in which we eliminate differences in hospital managers' *NS* by constructing a

[17] For certain hospital-insurer-year combinations, negotiated prices are imputed using prices observed in other years. These imputed prices are treated as exogenous in this counterfactual.

new set of bargaining power parameters ($\beta_h^c(t)$), based on the specification in Column (2) of Table 9. Specifically, we compute

$$\beta_h^c(t) = \beta_h(t) - \hat{\alpha}_1 \times NS_{ht} + \hat{\alpha}_1 \times \overline{\mathrm{NS}}$$

where $\beta_h(t)$ is the estimated bargaining weights in equilibrium, $\hat{\alpha}_1$ is the estimated coefficient on *NS* from Column (2) of Table 9 (0.650), NS_{ht} is the negotiation skill of the manager at hospital h in year t, and $\overline{NS}$ is the sample mean of managers' *NS*. The second counterfactual serves as a benchmark (*Counterfactual: Equal Beta*), in which all hospitals are directly assigned the same bargaining weight, equal to the sample average ($\overline{\beta}_h$). The difference in average price dispersion between the model equilibrium and this counterfactual reflects the total price dispersion explained by heterogeneity in hospitals' bargaining weights.

Using the counterfactual bargaining power parameters, we recompute the equilibrium negotiated prices and the corresponding average price dispersion. As shown in Column (2) of Table 10, the average price dispersion in the *Equal NS* counterfactual decreases to 1.1, compared to 1.328 in the model equilibrium. In contrast, the *Equal Beta* counterfactual, intuitively, leads to a larger reduction in the average price dispersion—about 0.608—as shown in Column (3) of the same table. These results suggest that differences in hospital managers' *NS* account for approximately $37.5\% (= 0.228/0.608)$ of the total price dispersion explained by heterogeneity in hospitals' bargaining weights in our sample. It is important to note that our sample is a subset of the full population of hospitals in Texas, as it includes only those with non-missing data on managers' *NS* and negotiated prices. Consequently, the estimated impact of *NS* on price dispersion is likely a lower bound of the true effect.

7 Conclusion

This paper develops a measure of managers' negotiation skill inferred from their personal transactions. Our evidence suggests that bargaining skill is a persistent individual characteristic that contributes to price dispersion in contract outcomes. In contrast to most prior work, which has viewed bargaining outcomes by focusing on the firm as a unit of observation, our evidence highlights the critical role of individual agents negotiating on behalf of their organizations. Moreover, this paper quantifies the importance of negotiation skill for observed price dispersion in business-to-business contracting.

While we use the healthcare industry as a laboratory to study contract outcomes, the concept of bargaining skill extends beyond our empirical setting. Negotiations are an integral part of a diverse scope of economic transactions ranging from microeconomics to macro policy. Examples of negotiation-driven transactions in microeconomics include employment agreements, collective bargaining with labor unions, and mergers and acquisitions. Examples from macroeconomics range from international trade agreements to negotiations between political parties in shaping economic and social policies.

Our study makes a step towards understanding the foundations of human capital in bargaining outcomes, but leaves many open questions. One of the lingering questions deals with the origins of the bargaining skill and the factors that explain its wide dispersion, ranging from formative experiences to specialized training. We hope that the growing interest in the role of individual agents in industrial organization will continue to yield novel insights on this topic.

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Figures

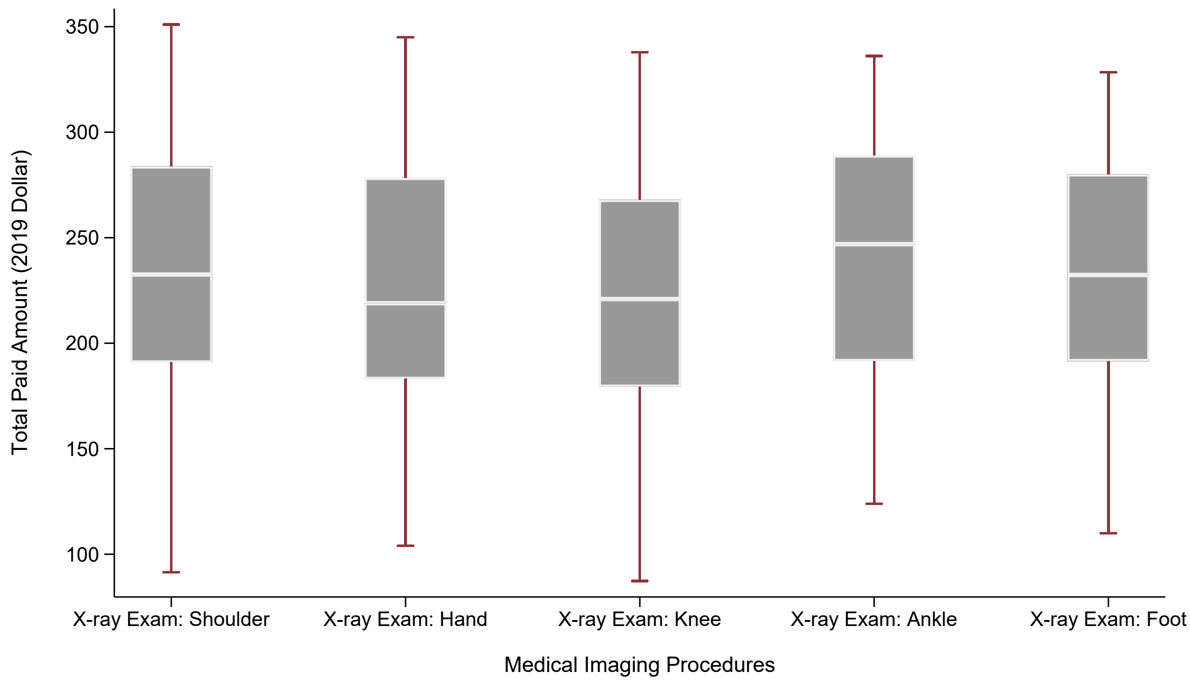


Figure 1: Price Dispersion of Medical Imaging Procedures

This presents the paid amounts (allowed amount) of one large insurer for five common medical imaging procedures across hospital providers in TX in 2019. The gray bars represent 25th and 75th percentile prices. The capped spikes represent 10th and 90th percentile prices.

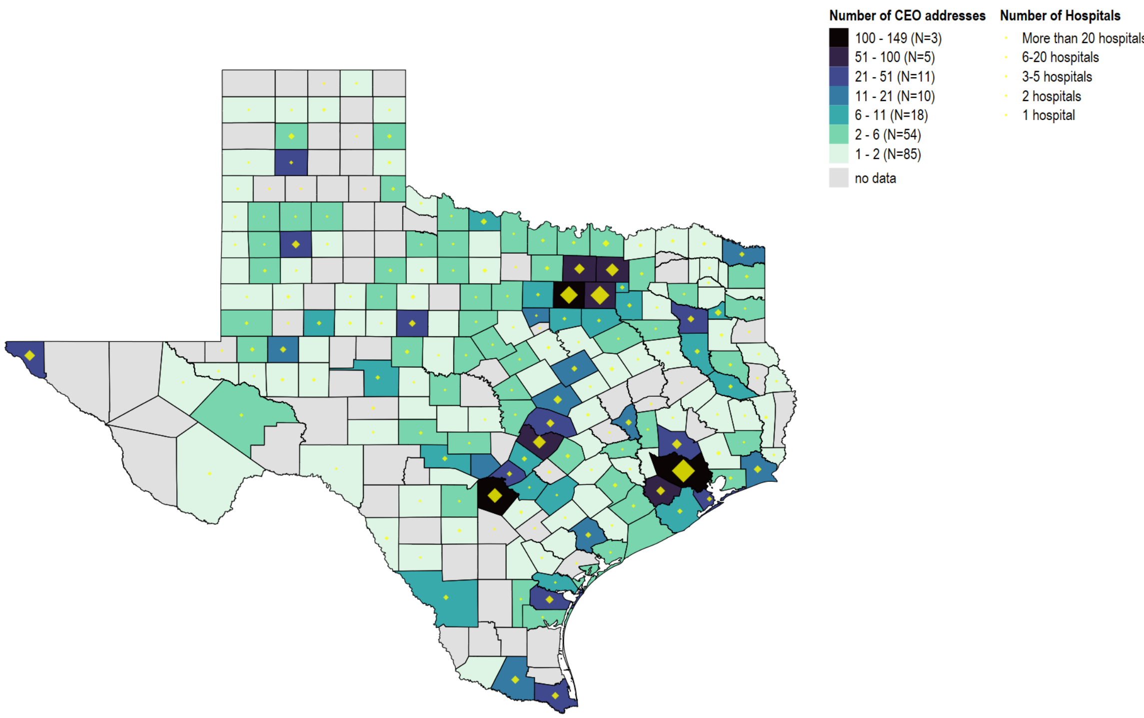


Figure 2: Geographic Distribution of Hospitals and Managers

This figures illustrates the geographic distribution of hospitals and their respective managers included the sample.

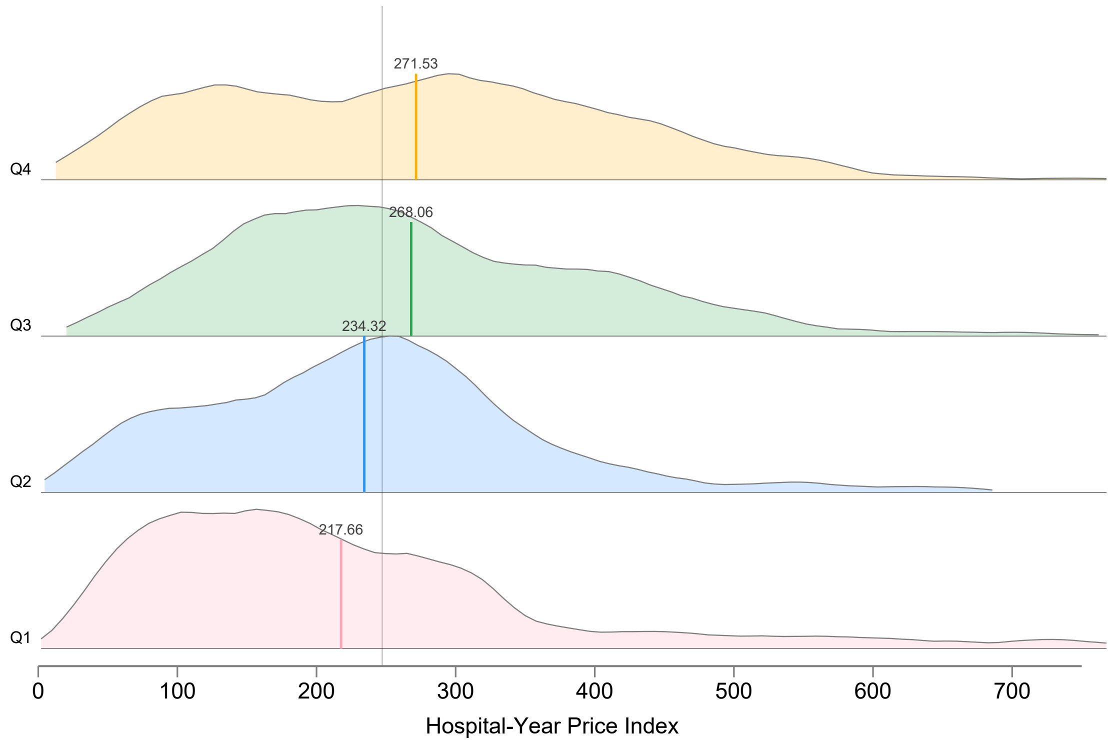
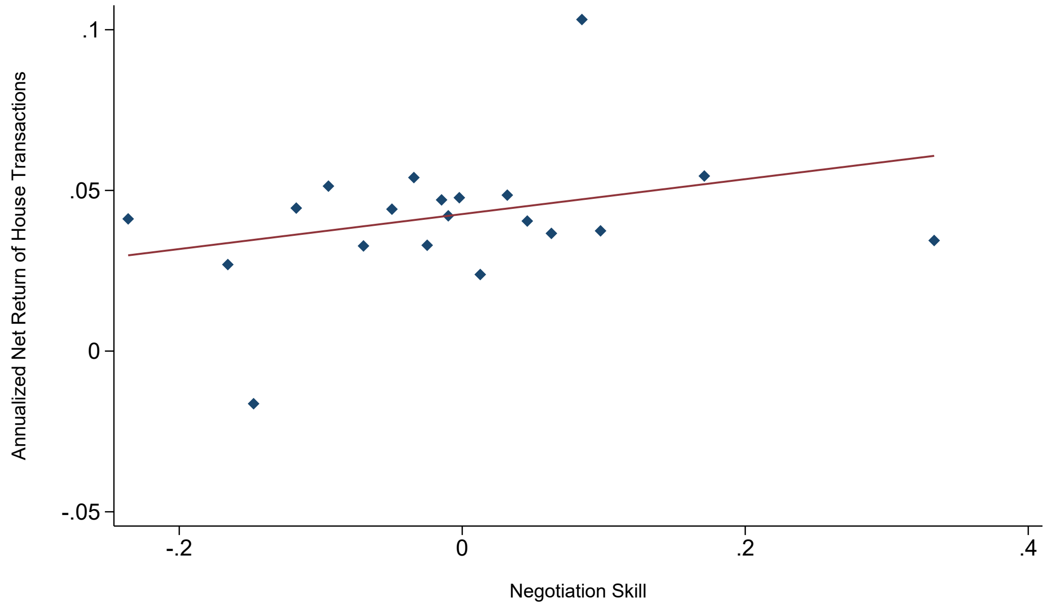
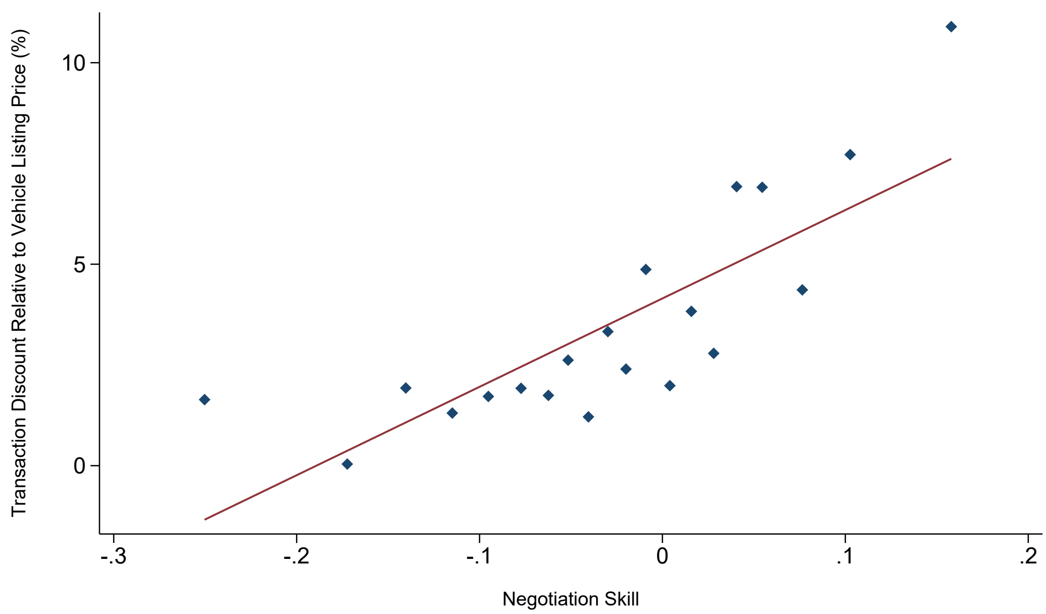


Figure 3: Distribution of Hospital Price Index

This figure presents the distribution of hospital price indices across the sample. The sample is divided into quartiles based on the Herfindahl-Hirschman Index (HHI) of hospital beds at the HRR-year level. Q1 represents the lowest HHI quartile (least concentrated markets), while Q4 represents the highest HHI quartile (most concentrated markets). The vertical colored line in each panel indicates the mean hospital price index for that quartile, and the vertical gray line represents the overall sample mean across all panels.



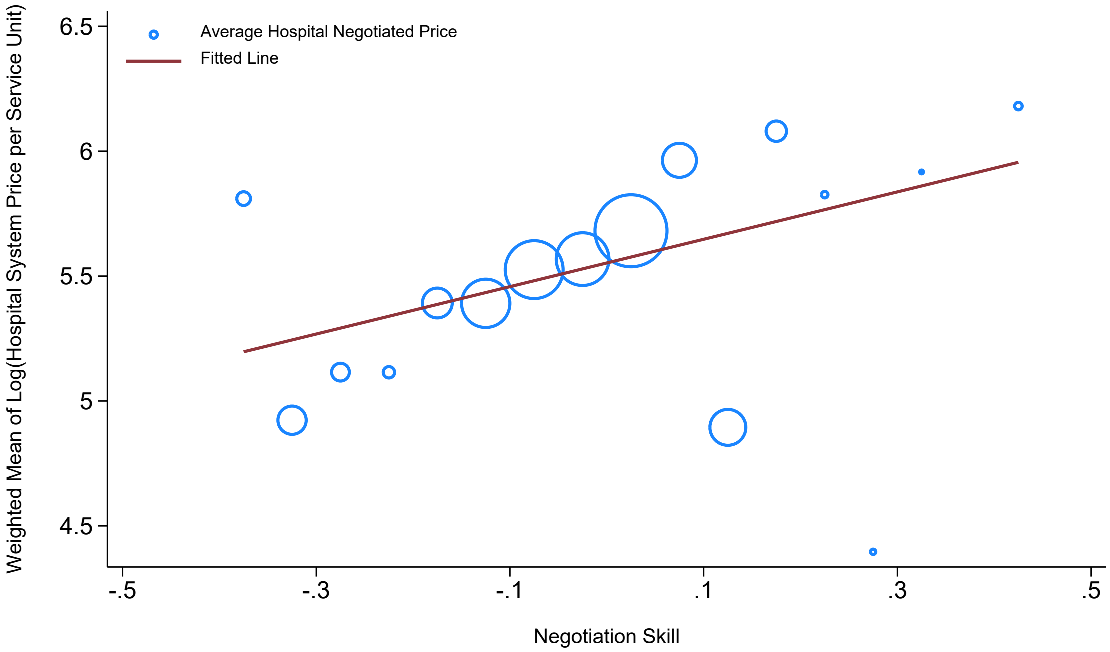
(a) Housing Returns



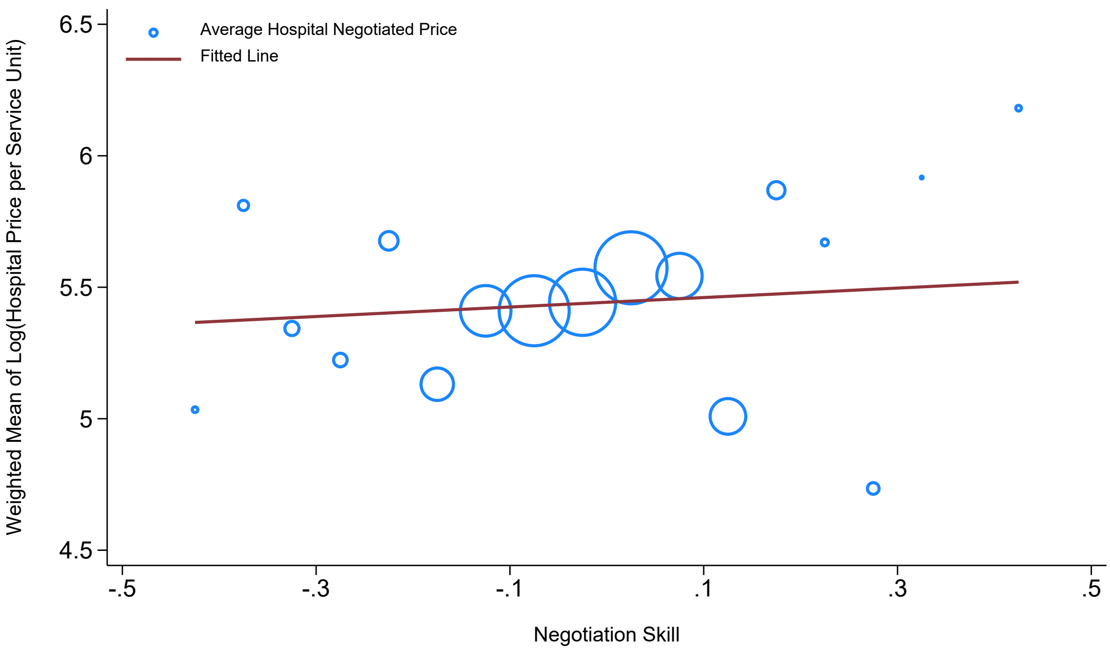
(b) New Vehicle Transaction Discount

Figure 4: Alternative Returns and Manager Negotiation Skill

This figure relates hospital managers' *NS*, constructed from vehicle transaction records, to outcomes in two alternative markets. Panel A plots managers annualized net returns on housing transactions against *NS*, adjusting for observable property characteristics (bathrooms, bedrooms, square footage, lot size, and Zillows current price estimate). Panel B plots the vehicle transaction discount ratio for new vehicles purchased by hospital managers against *NS*; list prices are manually collected from VehicleHistory.com using vehicles VIN numbers.



(a) Hospital System Level



(b) Hospital Facility Level

Figure 5: Correlation between Hospital Prices and Manager Negotiation Skill

This figure exhibits the correlation between the hospital price index and managers' negotiation skill (NS) at the hospital system level (Panel A) and hospital facility level (Panel B). Each circle corresponds to the weighted mean of log(Hospital Price per Unit of Service) in a bin, with the size of the circle indicating the number of hospitals (or systems) included in that bin. The red line denotes the best-fit line.

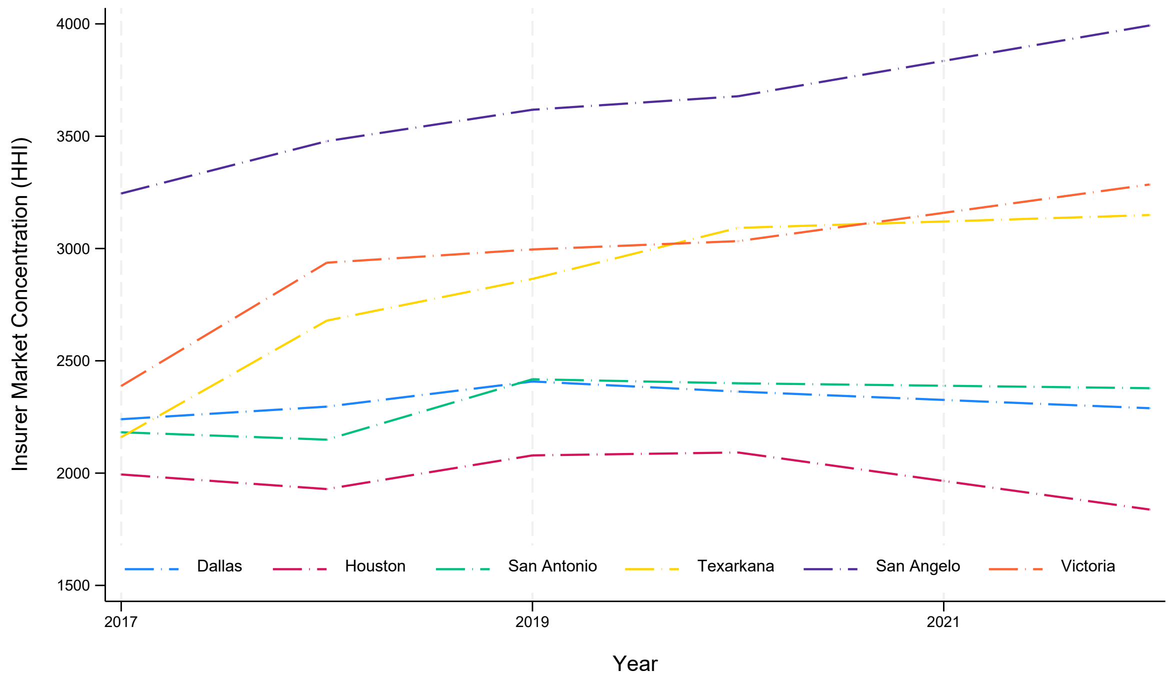


Figure 6: Insurance Market Concentration (HHI) in Texas MSAs

This figure plots health insurance market concentration, measured by the Herfindahl-Hirschman Index (HHI), across six Texas Metropolitan Statistical Areas (MSAs) from 2017 to 2022 (2017, 2018, 2019, 2020, and 2022, in which we impute HHI for year 2021 by taking average of years 2020 and 2022). The sample includes the three largest MSAs (Dallas, Houston, and San Antonio) and the three smallest MSAs (Texarkana, San Angelo, and Victoria). The data is sourced from from Table 1 of the American Medical Association's Annual Report, "Competition in Health Insurance: A Comprehensive Study of U.S. Markets." The product market is defined as the combined HMO, PPO, POS, and EXCH market.

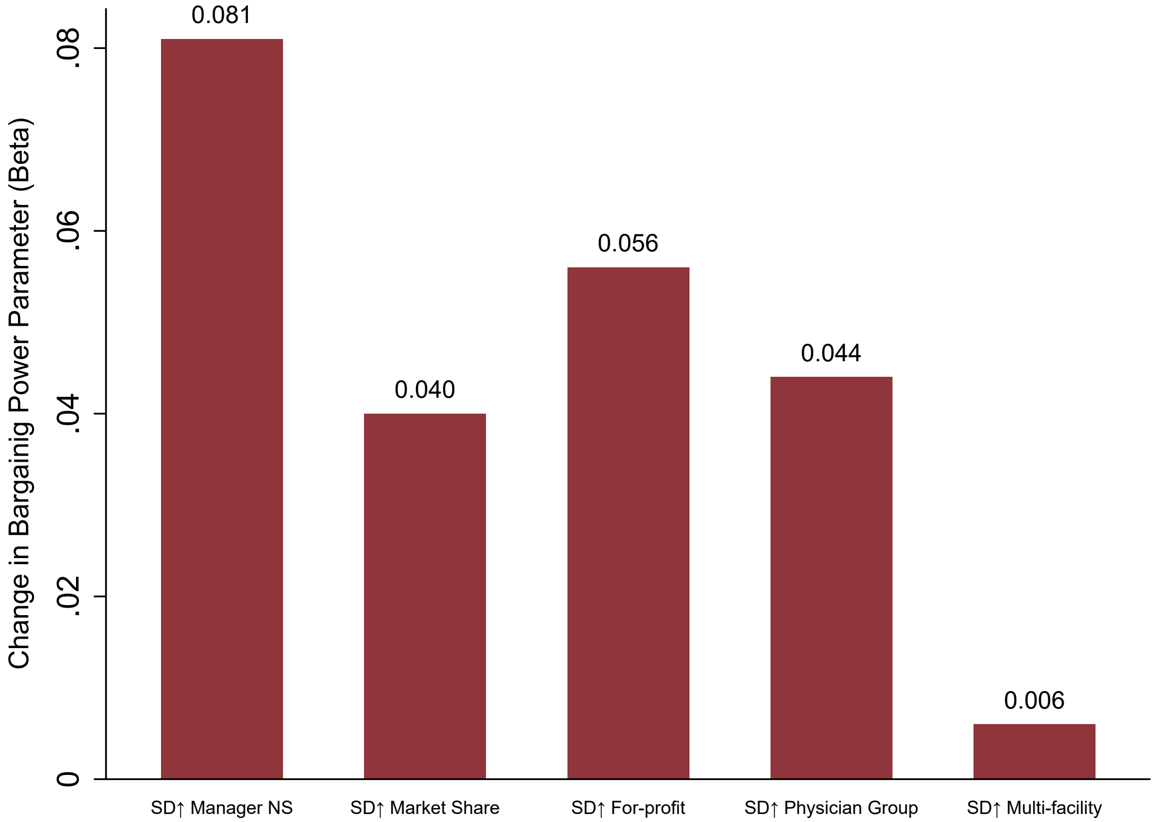


Figure 7: Relative Contribution of NS to Estimated Hospital Bargaining Power

This figure exhibits how various hospital characteristics influence the estimated hospital bargaining power parameters (β). Each bar represents the change in bargaining power parameter asscoiated with a one-standard-deviation increase in a specific hospital characteristic, including manager NS, within-insurer market share, for-profit status, physician-group involvement, and multi-facility indicator.

Tables

Table 1: Summary Statistics

This table shows summary statistics for the main sample of hospitals and their managers. The reported values are time-series averages over the sample period of 2014 to 2021. Panel A describes the sample of hospital facilities located in the state of Texas, where the managers' vehicle purchases have been matched with Texas DMV data. Information on **Hospital Type** is sourced from the American Hospital Association (AHA) Annual Survey. **Hospital Operation** variables, such as *Num Beds (in 100)*, *Total Personnel*, and *Medicaid Ratio*, are also obtained from the AHA Annual Survey. **Hospital Financials** information is from the Healthcare Cost Report Information System (HCRIS) database (any hospital-year with negative total assets is dropped. All exhibited financial variables are winsorized at the 1st and 99th percentiles). **Patient and Service Prices** data come from the Clarivate DRG claims data, and the *Price Index* is constructed at the facility-insurer-year level. Panel B describes a sample of 1,279 hospital managers (matched with Texas DMV data), defined as the highest ranking executives with a direct responsibility for a hospital or hospital system in AHA. Additional manager data come from Lexis Nexis Public Records, Data Axle, LinkedIn, Zillow, and management biographies. Detailed variable definitions are provided in Table OA3.1 of the Online Appendix. All financial and price-related variables are adjusted to 2023 dollars using annual GDP deflators.

Panel A: Hospital Characteristics

Variable	Mean	Median	SD
Hospital Type			
For Profit	0.487	0.000	0.500
Teaching	0.030	0.000	0.170
Critical Access	0.149	0.000	0.356
Rural	0.154	0.000	0.361
Part of a System	0.636	1.000	0.481
Operation and Financials			
Num Beds (*in*100)	1.390	0.570	2.025
Total Personnel	687.322	183.000	1499.455
Total Registered Nurses	215.432	46.000	411.479
log(*Total Income*)	17.966	17.697	1.454
Revenue Growth	0.067	0.023	0.392
Profit Margin	0.069	0.072	0.173
Leverage	0.460	0.457	1.121
Medicaid Ratio	0.114	0.074	0.138
Medicare Ratio	0.528	0.543	0.239
Patient and Service Prices (from DRG Claims)			
Patient Age	43.672	45.000	13.851
Patient Gender	0.672	1.000	0.470
Charge per Visit ($100)	54.914	13.277	151.597
Total Paid Amount ($100)	18.063	4.524	59.266
Payer Paid Amount ($100)	13.454	3.214	44.281
Patient Paid Amount ($100)	4.609	0.000	37.061
Serivce Mix Weight per Visit	7.513	2.093	19.878
Price Index	241.460	226.124	150.154

Summary Statistics (cont.)

Panel B: Hospital Managers

Variable	Mean	Median	SD
Demographics			
$Age\ (in\ 2023)$	60.544	61.000	11.700
$Female$	0.296	0.000	0.457
$Num\ of\ Children\ under\ 18$	0.633	0.000	1.150
$White$	0.868	1.000	0.339
$Hispanic$	0.091	0.000	0.288
$Black$	0.015	0.000	0.122
$Asian$	0.018	0.000	0.135
$Born\ Out\ of\ TX$	0.481	0.000	0.500
$Foreign\ Born$	0.008	0.000	0.088
Socioeconomic Status			
$Primary\ Home\ Purchase\ Price\ (\$1,000)$	1069.077	699.346	1329.901
Advanced Degree			
MBA	0.317	0.000	0.466
JD	0.022	0.000	0.146
PhD	0.031	0.000	0.175
MD	0.040	0.000	0.195

Table 2: Correlation between NS and Managers' Traits

This table reports univariate regressions of managers' negotiation skill (NS) on observable personal characteristics, educational credentials, and LinkedIn-based skill indicators. Columns (1)-(4) report results for personal background measures, including a female indicator, a non-white indicator, an IQ proxy measured by the manager's undergraduate institution's average SAT score, and an Ivy League indicator for the manager's undergraduate institution. Columns (5)-(8) report results for advanced degrees: each indicator equals one if the manager holds an MBA, JD, PhD, or MD. Columns (9)-(12) report results for LinkedIn-based skill indicators. The "Skills" group includes indicators constructed from managers' LinkedIn profiles, equal to one if the manager self-reports or is endorsed for skills related to negotiation, management, leadership, or research. Detailed definitions are provided in Table OA3.1. *t*-values are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	DV: Negotiation Skill											
	Personal Background				Advanced Degree				Skills			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Female	-0.015**											
	(-2.00)											
Non-White		-0.003										
		(-0.26)										
Avg SAT			-0.000									
			(-1.54)									
Ivy League				0.012								
				(0.29)								
MBA					-0.002							
					(-0.24)							
JD						0.057*						
						(1.89)						
PhD							0.010					
							(0.42)					
MD								0.024				
								(1.07)				
Negotiation									0.025**			
									(2.02)			
Management										-0.006		
										(-0.75)		
Leadership											-0.003	
											(-0.39)	
Research												0.032
												(0.66)
N	1,279	837	666	672	731	731	731	731	984	984	984	984
adj-R^2	0.002	-0.001	0.002	-0.001	-0.001	0.004	-0.001	0.000	0.003	-0.000	-0.001	-0.001

Table 3: Validating Negotiation Skill Measure

This table exhibits three validation exercises of our negotiation skill (NS) measure. Panel A exhibits the variance decomposition results by reporting the R-squares after regressing NS on fixed effects and individual demographic characteristics. Columns (1) and (2) of Panel A report the regression results for a sample of vehicle buyers with more than one transactions in the full sample. Columns (3) and (4) of Panel A report the regression results for the hospital manager sample. *Controls* include all individual demographic characteristics included in the regression to construct the bargaining skill measures. Panel B reports the estimation results by regressing individual i's negotiation skill derived from the current transaction on i's negotiation skill derived from their initial transaction ($Negotiation\ Skill_0$). $Month\ Gap_0$ measures the number of months between the current vehicle transaction date and the initial transaction date. Fixed effects are indicated in the bottom rows. *Controls* include all individual characteristics included in the regression to construct the bargaining skill measures as well as buyers' gender and ethnicity. Panel C reports the variance decomposition results for a sample of hospital managers and their relatives (parents and siblings). Fixed effects are indicated in the bottom rows. *Controls* includes buyers' age group, marital status, and number of children in Columns (1) and (2). In Columns (3) and (4), where individual FE are omitted, *Controls* also include ethnicity group and gender. Standard errors are cluster at the individual level. t-values are reported in parentheses. ***, **, and * represent the statistical significance level at 1%, 5%, and 10% respectively.

Panel A: Variance Decomposition

	DV: Negotiation Skill			
	Full Sample		**Manager Sample**	
	(1)	(2)	(3)	(4)
R^2	0.44	0.45	0.34	0.43
Indiv FE	Y	Y	Y	Y
Yr-Month FE	N	Y	N	Y
County FE	N	Y	N	Y
Controls	N	Y	N	Y
N	4,545,666	4,545,666	2,406	2,386

Panel B: Persistence in NS

	DV: Negotiation Skill (t)			
	Full Sample		**Manager Sample**	
	(1)	(2)	(3)	(4)
Negotiation Skill_0	0.098***	0.096***	0.049*	0.053*
	(116.07)	(114.52)	(1.78)	(1.88)
Month Gap_0		0.000***		-0.000
		(6.62)		(-0.35)
Yr-Month FE	N	Y	N	Y
County FE	N	Y	N	Y
Controls	N	Y	N	Y
N	2,832,000	2,832,000	1,648	1,609

Validating Negotiation Skill Measure (cont.)

Panel C: Variance Decomposition (Parents and Siblings)

	DV: Negotiation Skill			
	Individual FE		**Family FE**	
	(1)	**(2)**	**(3)**	**(4)**
R^2	0.42	0.47	0.26	0.39
Individual FE	Y	Y	N	N
Family FE	N	N	Y	Y
County FE	N	Y	N	Y
Controls	N	Y	N	Y
N	1,025	1,013	1,286	1,266

Table 4: Hospital Negotiated Prices and Negotiation Skill

This table reports the coefficient estimates for *Negotiation Skill* regressed on *Hospital Price Index* at the hospital system level and hospital facility level with the inclusion of hospital, insurer, and time fixed effects. Control variables include the Medicaid ratio, Medicare ratio, hospital size quintile, and indicators for rural, teaching hospital, and for-profit status. Standard errors are clustered at the manager level. t-values are reported in parentheses. ***, **, and * represent the statistical significance level at 1%, 5%, and 10% respectively.

	DV: Hospital Price Index			
	System Level		Facility Level	
	(1)	(2)	(3)	(4)
Negotiation Skill	0.932***	0.861**	0.429*	0.386*
	(2.70)	(2.50)	(1.93)	(1.73)
Insurer FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Hospital System FE	Y	Y	N	N
Hospital Facility FE	N	N	Y	Y
Controls	N	Y	N	Y
N	1,295	1,295	2,788	2,788
adj-R^2	0.622	0.623	0.659	0.664

Table 5: Medical Imaging Procedure Prices and Negotiation Skill

This table reports the coefficient estimates for *Negotiation Skill* regressed on the natural logarithm of the allowed amount (finally paid amount) for a procedure. Column (1) limits the sample to the top 3 most common X-ray procedures while Column (2) uses the top 5 and Column (3) uses the top 10. These include X-ray chest for two views (CPT code 71020), X-ray exam of foot (CPT code 73630), X-ray exam of lower spine (CPT code 72100), X-ray exam of shoulder (CPT code 73030), X-ray chest for a single view (CPT code 71010), X-ray exam of hand (CPT code 73130), X-ray exam of ankle (CPT code 73610), X-ray exam of knee (CPT code 73562), X-ray exam of neck spine (CPT code 72040), X-ray exam of wrist (CPT code 73110). Control variables include patient observables such as gender, age, 3-digit zipcode, service-mix weights, disease category (following Shepard (2022)) to group patient's ICD-10 (or ICD-9) diagnosis codes in medical claims into 285 mutually exclusive Clinical Classification Software, or CCS, single-level categories, and hospital characteristics including the Medicare ratio, Medicaid ratio, hospital size quintile, and indicators for rural, teaching hospital, and for-profit status. In addition to hospital, insurer, and time fixed effects, we add the procedure FE which recognizes the procedure CPT codes and procedure modifier codes. Standard errors are clustered at the manager level. *t*-values are reported in parentheses. ***, **, and * represent the statistical significance level at 1%, 5%, and 10% respectively.

Panel A: Hospital System Level

	DV: Procedure Price		
	Top 3 X-ray	Top 5 X-ray	Top 10 X-ray
	(1)	(2)	(3)
Negotiation Skill	0.971***	0.768***	0.790***
	(5.36)	(3.38)	(3.66)
Procedure FE	Y	Y	Y
Insurer FE	Y	Y	Y
Hospital System FE	Y	Y	Y
Year FE	Y	Y	Y
Controls	Y	Y	Y
N	63,028	90,894	151,338
adj-R^2	0.585	0.560	0.532

Panel B: Hospital Facility Level

	DV: Procedure Price		
	Top 3 X-ray	Top 5 X-ray	Top 10 X-ray
	(1)	(2)	(3)
Negotiation Skill	0.534***	0.471***	0.359**
	(3.28)	(2.86)	(2.38)
Procedure FE	Y	Y	Y
Insurer FE	Y	Y	Y
Hospital Facility FE	Y	Y	Y
Year FE	Y	Y	Y
Controls	Y	Y	Y
N	72,595	108,578	177,898
adj-R^2	0.555	0.535	0.506

Table 6: Hospital Negotiated Prices and Negotiation Skill: Exogenous Departures

This table reports summary statistics on hospital manager turnover and coefficient estimates from regressions of *NS* on the *Hospital Price Index*, conducted at both the hospital system and facility levels in a sample including only hospitals with manager turnovers arising from exogenous causes (medical leave, age-related retirement, or death). Panel A summarizes manager turnover events at the hospital system level. Column (1) reports all turnover events in the full sample, while Columns (2) and (3) separately present turnovers due to exogenous (natural causes) and non-exogenous reasons, respectively. Panel B summarizes turnover events at the hospital facility level. *Count of Turnovers with* $\Delta NS \geq 0$ denotes the number of cases in which the incoming manager's negotiation skill (NS) is equal to or greater than that of the departing manager, while *Count of Turnovers with* $\Delta NS < 0$ refers to cases where the incoming manager has lower NS. Panel C presents the coefficient estimates from regressions of *Negotiation Skill* on the *Hospital Price Index* at both the system and facility levels, restricted to hospitals experiencing exogenous manager turnovers. The regressions include hospital, insurer, and time fixed effects. Control variables include the Medicaid ratio, Medicare ratio, hospital size quintile, and indicators for rural location, teaching-hospital status, and for-profit ownership. Standard errors are clustered at the manager level. *t*-values are reported in parentheses. ***, **, and * represent the statistical significance level at 1%, 5%, and 10% respectively.

Panel A: Manager Turnover (System Level)

	All Turnovers	Exogenous Turnovers	Non-exogenous Turnovers
	(1)	(2)	(3)
Count of Turnovers	102	47	55
Count of Turnovers with $\Delta NS \geq 0$	48	22	26
Count of Turnovers with $\Delta NS < 0$	54	25	29

Panel B: Manager Turnover (Facility Level)

	All Turnovers	Exogenous Turnovers	Non-exogenous Turnovers
	(1)	(2)	(3)
Count of Turnovers	301	79	222
Count of Turnovers with $\Delta NS \geq 0$	151	44	107
Count of Turnovers with $\Delta NS < 0$	150	35	115

Panel C: Negotiated Prices and NS

	DV: Hospital Price Index			
	System Level		Facility Level	
	(1)	(2)	(3)	(4)
Negotiation Skill	0.853***	0.763**	0.962***	0.744**
	(2.92)	(2.60)	(3.00)	(2.37)
Controls	N	Y	N	Y
Insurer FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Hospital System FE	Y	Y	N	N
Hospital Facility FE	N	N	Y	Y
N	337	337	452	452
adj-R^2	0.692	0.688	0.746	0.745

Table 7: Hospital Negotiated Prices and Negotiation Skill: Changes in Insurance Market Concentration

This table reports coefficient estimates from regressions of the *Hospital Price Index* on an interaction between *High-NS Hospital* and Δ*Concentration*, where Δ*Concentration* indicates whether a hospital's MSA experiences an increase in insurer market concentration, measured by HHI, of at least 100, 200, or 300 points relative to the sample baseline year 2017. Columns (1) and (2) use the $\Delta Concentration = 100$ threshold, Columns (3) and (4) use $\Delta Concentration = 200$, and Columns (5) and (6) use $\Delta Concentration = 300$. Within each threshold pair, odd-numbered columns exclude hospital controls while even-numbered columns include controls. All specifications include insurer fixed effects, year fixed effects, and hospital facility fixed effects. The sample spans 2017 to 2022 and includes 2017, 2018, 2019, 2020, and 2022, and HHI in 2021 is imputed as the average of 2020 and 2022. HHI data are from Table 1 of the American Medical Association's Annual Report *Competition in Health Insurance: A Comprehensive Study of U.S. Markets*, with the product market defined as the combined HMO, PPO, POS, and EXCH market. *High-NS Hospital* equals one if the hospital's manager in the first observed year has above-median negotiation skill NS, and zero otherwise. Control variables include the Medicare ratio, Medicaid ratio, hospital size quintile, and indicators for rural location, teaching-hospital status, and for-profit ownership. Standard errors are clustered at the manager level. t-values are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	DV: Hospital Price Index					
	ΔConcentration = 100		ΔConcentration = 200		ΔConcentration = 300	
	(1)	(2)	(3)	(4)	(5)	(6)
High-NS Hospital × ΔConcentration	0.152***	0.143***	0.248***	0.235***	0.178**	0.167**
	(2.68)	(2.62)	(2.85)	(2.83)	(2.01)	(1.98)
ΔConcentration	-0.133***	-0.140***	-0.221***	-0.228***	-0.162***	-0.167***
	(-2.78)	(-3.08)	(-2.83)	(-2.87)	(-2.64)	(-2.75)
Insurer FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Hospital Facility FE	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y
N	1,133	1,133	1,133	1,133	1,133	1,133
adj-R^2	0.728	0.728	0.729	0.728	0.728	0.727

Table 8: Model Estimation

This table exhibits the model estimates. Panel A shows the estimates for the multinomial logit hospital choice model. Since the patient choice is estimated separately for each HRR in a year, the panel reports the visit-number-weighted coefficients and standard errors. Panel B reports the estimates of insurers' price sensitivity γ on the supply side. Standard errors are in parentheses.

Panel A: Patient Choice Estimation

VARIABLE	Coeff.	Std. Error
Travel Time to Hospital		
Travel Time	-3.0701	(0.2637)
Travel Time Squared	-0.4767	(0.2607)
Travel Time Interactions		
$\times$Beds	0.0003	(0.0004)
$\times$Teaching	-0.4674	(0.1409)
$\times$For-profit	0.2656	(2.7588)
$\times$Rural	-1.1486	(77.9602)
Teaching Interactions		
$\times$Service Weight	-0.0089	(0.0005)
$\times$Female	0.0953	(0.0657)
$\times$Age	0.0015	(0.0005)
$\times$Visit Before	0.5156	(0.0130)
Num of Beds Interactions		
$\times$Service Weight	1.4329×10^{-6}	(5.3473×10^{-7})
$\times$Female	7.0646×10^{-5}	(2.0827×10^{-5})
$\times$Age	1.8351×10^{-5}	(7.5340×10^{-7})
$\times$Visit Before	0.0003	(2.0150×10^{-5})
For-profit Interactions		
$\times$Service Weight	0.0071	(0.0004)
$\times$Female	0.2386	(0.0140)
$\times$Age	0.0051	(0.0005)
$\times$Visit Before	-0.0209	(0.0133)
Rural Interactions		
$\times$Service Weight	-0.0631	(0.0116)
$\times$Female	0.2097	(0.1265)
$\times$Age	0.0013	(0.0046)
$\times$Visit Before	0.2520	(0.1270)
Diagnoses$\times$Hospital Services (top 3 largest coeffs)		
Pregnancy: Obstetrics Services	1.8059	(1.1407)
Mental: Psych. Services	1.1032	(0.7335)
Cancer: Oncology Services	0.8609	(0.0255)

Panel B: Insurer Objective Parameter

Insurer Price Sensitivity (γ)	595.2617	(7.3464)

Table 9: Correlation between Manager NS and Estimated Hospital Bargaining Power

This table reports the regression results of recovered hospital bargaining power parameters from the model on hospital managers' NS. All specifications include System fixed effects, HRR-by-year fixed effects and insurer fixed effects. Relative to Column (1), Column (2) includes other hospital characteristics in the regression: *Market Share* is the hospital system's within-insurer market share in an HRR-year (the fraction of insurer *i*'s patients treated by the system in the HRR-year). *Multi-Facility* is an indicator whether a system operates more than one facility in an HRR-year. *Physician Group Affiliation* is an indicator for whether the system is wholly owned by, partially owned by, or operates as a joint venture with a physician group. *Teaching Hospital*, *Rural Hospital*, and *For-profit* are the average ratio of hospital facilities of a system in an HRR having teaching, rural, or for-profit statuses. *Ratio of ER Visits* is the number of emergency department visits divided by the total number of outpatient visits to a hospital system in an HRR. Standard errors are clustered by hospital system by year. ***, **, and * represent the statistical significant level at 1%, 5%, and 10% respectively. t-values are in parentheses. The sample mean and standard deviation of the dependent variable (β) are reported at the bottom of the table.

	DV: Betas	
	(1)	(2)
Negotiation Skill	0.643**	0.650***
	(2.57)	(2.87)
Market Share		0.101**
		(2.47)
Multi-Facility		0.014
		(0.18)
Physician Group Affiliation		0.088
		(1.42)
Teaching Hospital		-0.193
		(-1.42)
Rural Hospital		-0.184
		(-1.27)
For-profit		0.121
		(0.80)
Medicare Patient Ratio		-0.190
		(-1.54)
Medicaid Patient Ratio		-0.533***
		(-2.77)
Ratio of ER Visits		-0.067
		(-0.56)
Insurer FE	Y	Y
System FE	Y	Y
HRR×Year FE	Y	Y
Size Quintile	N	Y
N	1,175	1,159
adj-R^2	0.412	0.434
DV Mean	0.419	
DV SD	0.402	

Table 10: Counterfactual: Homogeneous NS and Price Dispersion

This table shows presents the impact of hospital managers' negotiation skill (NS) on hospital price dispersion in the counterfactual. We examine three scenarios: (1) the model-implied equilibrium prices (*Model Equilibrium*), (2) a counterfactual in which all heterogeneity in managers'*NS* is eliminated (*Counterfactual: Equal NS*), and (3) a counterfactual in which all hospitals are assigned a common bargaining power parameter equal to the sample mean (*Counterfactual: Equal Beta*). The first row reports the average price dispersion, measured as the mean of $var(\log(p_{hi} - c_h))$, where $h \in N_i$ represents hospitals within insurer i's network, across markets (HRR-year) for each scenario. The second row reports the change in price dispersion for the two counterfactuals relative to the model equilibrium. The third row displays the percentage share of the change in price dispersion under the Equal *NS* Counterfactual relative to the change under the Equal Beta Counterfactual.

	Model Equilibrium	**Counterfactual: Equal NS**	**Counterfactual: Equal Beta**
Price Dispersion	1.328	1.100	0.720
Δ Dispersion Compared to Equ.	-	-0.228	-0.608
Share (%) Explained by NS		$(-0.228)/(-0.608) = 37.50\%$	

For Online Publication

Online Appendix for "Driving a Bargain: Negotiation Skill and Price Dispersion"

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This Online Appendix explains the sample construction process in detail and presents additional robustness checks mentioned in the paper.

OA-1 Data Appendix

OA-1.1 Constructing Hospital-insurer Price Index

In this section, we describe our procedure to derive the price index negotiated between hospitals and insurers. We follow a similar approach of Liu (2022), Gowrisankaran et al. (2015), Ho and Lee (2017), and others by recognizing the fact that hospitals and insurers do not negotiate over a full menu of prices for different items, but rather negotiate over a benchmark price (Dorn, 2024).

We start with our sample of hospital commercial outpatient claims and aggregate the total allowed amounts (or total paid amounts) Y_{ijmt} in a visit (claim encounter) for patient i from insurer m visiting hospital j in year t. Then we obtain the average price per unit of service-mix weight in a visit by dividing Y_{ijmt} by the relative service-mix weights, w_i, which measures the unit of medical resources used to treat patient i during his visit. Next, we run the following model:

$$\frac{Y_{ijmt}}{w_i} = \gamma_{jmt} + \beta X_{it} + \varepsilon_{ijmt},$$

where γ_{jmt} is the hospital-insurer-year fixed effects, X_{it} is a vector of patient characteristics including patients' gender and the natural logarithm of their age, and ε_{ijmt} is the stochastic error term.

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

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

OA-1.2 Matching Hospital Managers with Texas DMV Data

This section describes the process of matching hospital managers with their vehicle purchase records from the Texas DMV dataset. To begin, we prepare the data by extracting geographic coordinates for residential addresses. Using the ArcGIS package in Python, we obtain coordinates for hospital managers' residential addresses, which we manually collected from the Lexis Nexis Public Records (LNPR) database, as well as for buyers' residential addresses listed in the DMV dataset.

Another crucial preparation step involves cleaning buyer names in the DMV dataset, specifically owner_name1 and owner_name2 fields when multiple owners are listed. This cleaning process involves removing special characters such as parentheses, dots, and ampersands, and refining prefixes and suffixes using regexr patterns. After cleaning, we generate three name components—first, middle, and last names—by assessing the number of spaces in each owner_name string. If a name consists of a single word, it is mapped to the last name field, as such names typically represent company names like "Vault." For two-word names, we assign them to the first and last name fields. Names with three words are mapped in sequence to the first, middle, and last name fields. If a name contains more than three words, we retain the first and last words as the first and last names, respectively, and the remaining words as the middle name. One exception arises for a two-word last name in the manager sample, which we handle explicitly when constructing last names.

In the first round of matching, we link vehicle transaction records with hospital managers by identifying exact matches between the geographic coordinates of buyers' residential addresses and hospital managers' addresses. We also require an exact match on last names across both datasets. After obtaining a set of potential matches, we manually verify first names to confirm the accuracy of the matches.

The second round of matching expands the criteria by relaxing the geographical restriction. Instead of requiring exact coordinate matches, we allow matches within the same county. Here, vehicle transaction records are linked to hospital managers if the buyer has the same first and last names as the hospital manager and resides in the same county. Within this refined set of potential matches, we compute the geographic distance between the buyers and hospital managers based on their residential coordinates. Observations where middle names differ, provided they are available for both parties, are removed. We then apply a distance threshold of 5 kilometers, eliminating pairs where the distance exceeds this limit unless one of the addresses is a P.O. box. (If an address corresponds to a P.O. box, the geoprocessed coordinates are set to the midpoint of the ZIP code.) Finally, we manually verify these potential matched pairs by searching for their profiles online, ensuring that each match is indeed correct.

OA-1.3 Calculating Marginal Costs

This section outlines the methodology for estimating the marginal cost per unit of service for hospitals. The raw data are sourced from hospital-level cost reports, specifically Forms CMS-2552-96 and CMS-2552-10, available through the Healthcare Cost Report Information System (HCRIS) provided by CMS (publicly available at the CMS website). These reports contain detailed cost information for all Medicare-certified hospitals in the U.S. Due to changes in reporting structure in 2010, CMS-2552-10 includes cost reports for fiscal years beginning on or after May 1, 2010, while reports for earlier fiscal years are included in CMS-2552-96. We manually download and extract all files available from 1996 to 2024, although only data from 2013 to 2021 are used to estimate marginal costs).

Our objective is to calculate the **outpatient variable cost per unit of APC weight**, as described in Equation 5. Since HCRIS does not directly report hospital variable costs VC_{ht}, we approximate them by subtracting fixed costs—such as capital and interest expenses, which are invariant with respect to patient volume—from total expenses.

In the first step, we calculate total expenses (TC_{ht}) by summing up "Total Operating Expenses" from Worksheet G-2 Part II, line 43 and "Total Other Expenses" from Worksheet G-3, line 28 (or line 30 in pre-2010 format). To address outliers, we exclude the lowest 1st percentile of total expenses.

Next, we construct variable costs by identifying fixed cost components (FC_{ht}) from Worksheet A, "Reclassification and Adjustment of Trial Balance of Expenses." We focus on cost items that are unlikey to vary with patient volume, as listed in Table OA1.1. After subtracting these fixed costs from total costs (TC_{ht}), we derive total variable costs (VC_{ht}).

Cost Item	Line # (2010 Format)	Column # (2010 format)
Capital Related Costs-Buildings and Fixtures	1	3
Capital Related Costs-Movable Equipment	2	3
Other Capital Related Costs	3	3
Intern & Res. Service-Salary & Fringes (Approved)	21	3
Intern & Res. Other Program Costs (Approved)	22	3
Paramedical Ed. Program (specify)	23	3
Durable Medical Equipment-Rented	96	3
Durable Medical Equipment-Sold	97	3
Intern-Resident Service (not appvd. tchng. prgm.)	100	3
Interest Expense	113	3
Research	191	3

Table OA1.1: Components Treated as Fixed Cost (Worksheet A, 2010 Format)

In the second step, we allocate a portion of total variable costs to outpatient services, based on the assumption that the distribution of costs between outpatient and inpatient departments is proportional to their respective revenues. We use data from Worksheet G-2, "Statement of Patient Revenues and Operating Expenses," to obtain outpatient revenues (Rev_{ht}^{out}) and total patient revenues (Rev_{ht}^{tot}). Specifically, outpatient revenues are calculated as the sum of Lines 18 through 25 in Column 2, while total patient revenues are sourced from Line 28 in Column 3 (see Table OA1.2 for details). The proportion of variable costs allocated to outpatient services is then calculated as

$$VC_{ht}^{out} = VC_{ht} \times \frac{Rev_{ht}^{out}}{Rev_{ht}^{tot}}.$$

All costs and revenues variables are adjusted for inflation using annual GDP deflators.

Outpatient components	Line # (2010 Format)	Column # (2010 format)
Ancillary services	18	2
Outpatient services	19	2
Rural Health Clinic (RHC)	20	2
Federally Qualified Health Center (FQHC)	21	2
Ambulance	23	2
Outpatient rehabilitation providers	24	2
ASC	25	2

Table OA1.2: Components Used in Outpatient Revenue Construction (worksheet G-2, 2010 format)

In the final step, we divide total outpatient variable costs (VC_{ht}^{out}) by the product of total outpatient visits (D_{ht})—sourced from the AHA survey—and the average APC weight per visit (w_{ht}), obtained from Clarivate DRG Claims data. The resulting measure is winsorized at the 1st and 99th percentiles to mitigate the impact of outliers. The final sample includes 3,735 hospital-year observations with non-missing values. Figure OA2.1 illustrates the distribution of estimated marginal costs across hospital facilities.

OA-1.4 Calculating MLRs

We sourced the Medical Loss Ratio (MLR) data from the CMS website, manually downloading all insurance company MLR reports in Texas covering the years 2013 to 2021. In cases where multiple versions of an MLR report were available for a given year, we consistently selected the latest version.

The MLR for each insurer in a market segment is calculated by dividing the total amount spent on medical claims and quality improvement initiatives by the total premiums collected. The raw data are categorized into three market segments: individual, small groups (companies with fewer than 50 employees), and large groups. To construct the numerator, we sum the total spending on medical claims across all three categories and insurance companies for a given year. Similarly, the denominator is calculated as the total premiums collected across these markets and insurers for the same year.

The average MLR for insurers operating in Texas in a given year is then computed by dividing the numerator by the denominator. Table OA1.3 presents the MLR values derived from this methodology.

Year	MLR
2013	0.868
2014	0.875
2015	0.909
2016	0.922
2017	0.905
2018	0.866
2019	0.855
2020	0.865
2021	0.897

Table OA1.3: MLRs by Year

OA-2 Additional Figures

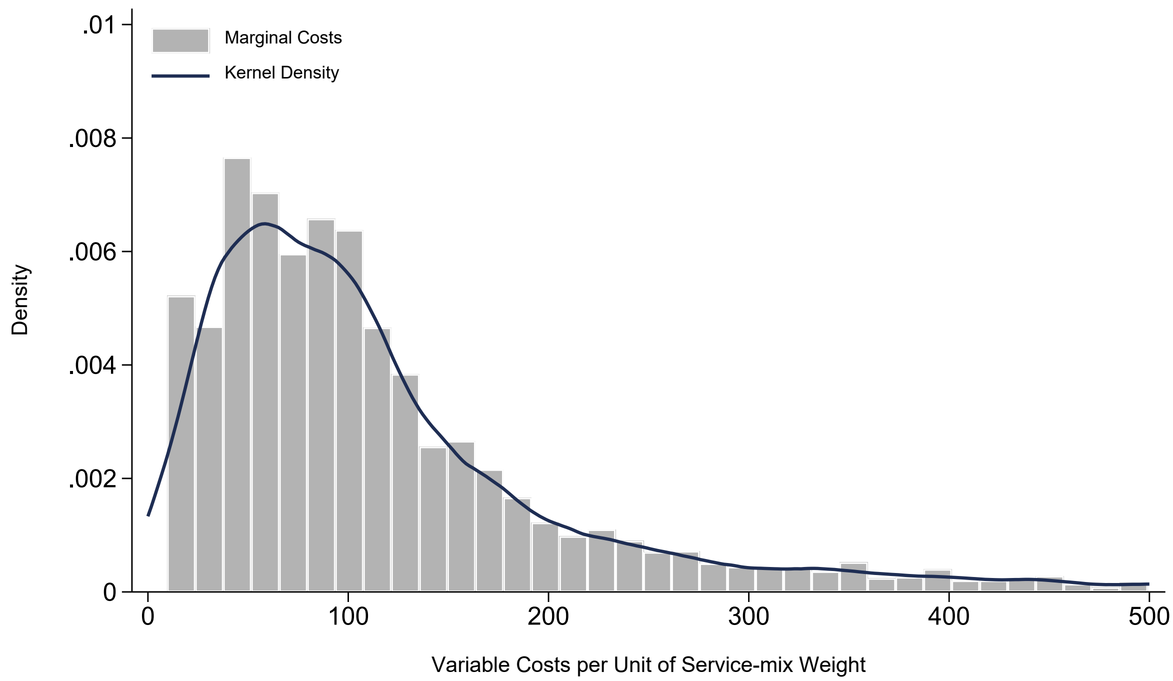

Figure OA2.1: Distribution of Marginal Costs

This figure exhibits the distribution of variable costs per unit of APC weight derived in Section OA-1.3.

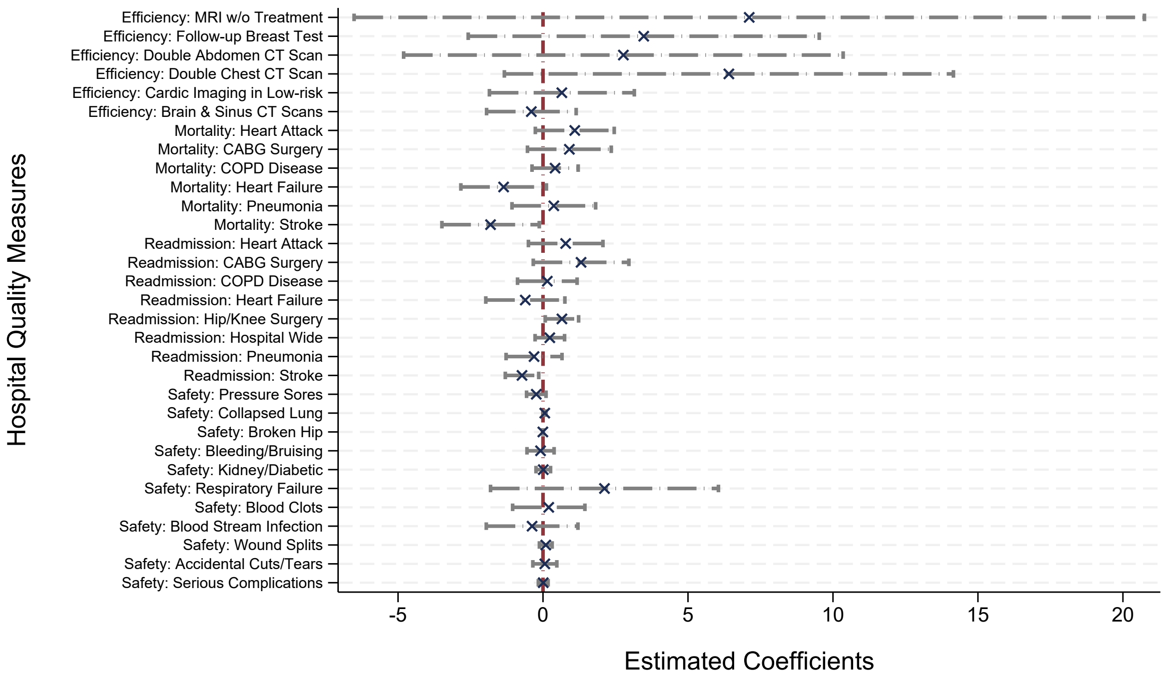

Figure OA2.2: Correlation Between Hospital Quality and Negotiation Skill

This figure exhibits the correlation between hospital manager negotiation skills and hospital service quality. We use four different sets of quality measures, including outpatient imaging efficiency, 30-day mortality rates, 30-day readmission rates, and patient safety indicators. The y-axis denotes the names of service quality measures. All standard errors are clustered at the hospital manager level. Capped spikes represent 95% confidence intervals.

OA-3 Additional Tables

Table OA3.1: Variable Definition and Descriptions

This table summarizes definitions and descriptions of all variables used in the paper.

Variable	**Description**
For Profit	Indicator for for-profit hospitals.
Teaching	Indicator for hospitals affiliated with medical teaching programs.
Critical Access	Indicator for hospitals designated as critical access facilities.
Rural	Indicator for hospitals located in rural areas.
Part of a System	Indicator for hospitals that are part of a larger hospital system.
Num Beds (*in* 100)	Number of beds in the hospital, expressed in hundreds.
Total Personnel	Total number of full-time personnel employed by the hospital.
Total Registered Nurses	Total number of full-time registered nurses employed by the hospital.
log(*Total Income*)	Natural logarithm of total hospital income, calculated as the sum of net patient revenue and total other income. All values are adjusted to 2023 dollars using annual GDP deflators.
Revenue Growth	Annual growth rate of the hospital's net patient revenue over the sample period.
Profit Margin	Annual profit margin of the hospital, defined as the ratio of total income minus total costs to total income. Total costs are the sum of operating expenses and total other expenses.
Leverage	Financial leverage of the hospital, defined as the ratio of total liabilities (long-term and current) to total assets.
Medicaid Ratio	Proportion of Medicaid patient visits in a year.
Medicare Ratio	Proportion of Medicare patient visits in a year.
Patient Age	Average age of patients at the time of their hospital visit.
Patient Gender	Proportion of hospital patients who are female.
Charge per Visit ($100)	Average charge per patient visit (from hospitals' chargemaster), expressed in $100. Prices are adjusted to 2023 dollars using annual GDP deflators.
Total Paid Amount ($100)	Average total amount (allowed amount) paid per visit, expressed in $100. Prices are adjusted to 2023 dollars using annual GDP deflators.
Payer Paid Amount ($100)	Average amount paid by private insurers per visit, expressed in $100. Prices are adjusted to 2023 dollars using annual GDP deflators.
Patient Paid Amount ($100)	Average amount paid by the patient per visit, expressed in $100. Prices are adjusted to 2023 dollars using annual GDP deflators.
Service Mix Weight per Visit	Average service-mix weight (APC weight) per visit calculated based on DRG claims.

Variable Definition and Descriptions (cont')

Variable	Description
Age (*in* 2023)	Age of hospital managers in 2023. For deceased managers, age is calculated up to the year of death.
Female	Indicator for managers who are female.
Num of Children under 18	Number of children under the age of 18 in the year of the manager's most recent vehicle transaction.
White	Indicator for managers identifying as White.
Hispanic	Indicator for managers identifying as Hispanic.
Black	Indicator for managers identifying as Black.
Asian	Indicator for managers identifying as Asian.
Born Out of TX	Indicator for managers born outside of Texas.
Foreign Born	Indicator for managers born outside of the United States.
Primary Home Purchase Price ($1,000)	Purchase price of the manager's primary home, expressed in $1,000. Purchase prices are adjusted to 2023 dollars using annual GDP deflators.
Married	Indicator for whether the manager is married.
Female	Indicator for whether the manager is female.
Minority	Indicator for whether the manager is non-white.
Avg SAT	Average SAT score of the manager's undergraduate institution (among enrolled students) from College Board (2013).
Ivy League	Indicator for whether the manager attended an Ivy League institution for undergraduate education.
MBA	Indicator for holding an MBA degree.
JD	Indicator for holding a JD degree.
PhD	Indicator for holding a PhD degree.
MD	Indicator for holding an MD degree.

Variable Definition and Descriptions (cont')

Variable	Description
Negotiation	An indicator of whether the manager's self-reported or endorsed skills on their LinkedIn profile include negotiation-related keywords, including "negotiation," "contract negotiation(s)," "contract renegotiations," "strategic negotiations," "mergers and acquisitions," "pricing," or "contract pricing."
Management	An indicator of whether the manager's self-reported or endorsed skills on their LinkedIn profile include management-related keywords, including "management," "healthcare management," "operations management," "practice management," "program management," "project management," "executive management," "change management," or "team management."
Leadership	An indicator of whether the manager's self-reported or endorsed skills on their LinkedIn profile include leadership-related keywords, including "leadership," "leadership development," "team leadership," "organizational leadership," "executive leadership," "team leadership," or "strategic leadership."
Research	An indicator of whether the manager's self-reported or endorsed skills on their LinkedIn profile include research-related keywords, including "market research," "marketing research," "quantitative research," or "legal research."
$Vehicle\ Sale\ Price\ (in\ \$1,000)$	Sale price of the vehicle, expressed in \$1,000. Sale prices are adjusted to 2023 dollars using annual GDP deflators.
Total Transactions	Total number of vehicle transactions.
$Travel\ Distance\ (km)$	Distance traveled to purchase the vehicle, measured as the distance between the buyer's residential addresses and the dealer's location, in kilometers.
#Competing Dealers	Number of competing vehicle dealers in the vicinity, defined as the count of distinct dealers within a 50-mile radius that have sales records for the same vehicle make during the current month (t) and the adjacent months ($t-1$ and $t+1$).
End of Month	Indicator for transactions occurring at the end of the month.
End of Year	Indicator for transactions occurring at the end of the year.
$Odometer\ Reading\ (1,000\ miles)$	Odometer reading of the vehicle at the time of purchase, expressed in 1,000 miles. (Excludes cases where odometer readings are exempt.)
$Vehicle\ Age\ (years)$	Age of the vehicle in years at the time of purchase, calculated as the difference between the sale year and the vehicle's model year.
New Vehicle	Indicator for new vehicles, defined as vehicles with an odometer reading of less than 200 miles.
Engine Displacement	Engine displacement of the vehicle, measured in liters.
Foreign Brand	Indicator for vehicles of foreign (Non-U.S.) brands.
US Manufacture	Indicator for vehicles manufactured in the United States.

Table OA3.2: Variance Decomposition (Manager Sample with Non-missing Parents/Siblings)

This table replicates the variance decomposition exercise from Columns (3) and (4) of Table 3, Panel C, with two modifications. First, we restrict the sample to hospital managers who appear in Columns (3) and (4). Second, we control for individual fixed effects instead of family fixed effects. All other details remain the same as in Panel C of Table 3.

	DV: Negotiation Skill		
	(1)	(2)	(3)
R^2	0.00	0.34	0.40
Individual FE	N	Y	Y
County FE	N	N	Y
Controls	N	N	Y
N	623	531	511

Table OA3.3: Hospital Negotiated Prices and Negotiation Skill: Alternative NS

This table replicates Table 4 using an alternative negotiation skill measure. For managers with multiple transactions, the table defines NS as the maximum of the manager's transaction-level NS values, constructed as in Equation 1. All other specifications remain the same as in Table 4.

	DV: Hospital Price Index			
	System Level		Facility Level	
	(1)	(2)	(3)	(4)
Negotiation Skill	0.922***	0.819***	0.403**	0.381*
	(3.16)	(2.90)	(2.01)	(1.95)
Insurer FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Hospital System FE	Y	Y	N	N
Hospital Facility FE	N	N	Y	Y
Controls	N	Y	N	Y
N	1,295	1,295	2,788	2,788
adj-R^2	0.623	0.624	0.659	0.664

Table OA3.4: Robustness: Hospital Negotiated Prices and Negotiation Skill without Demographics

This table replicates Table 4, except that the NS measures are constructed according to Equation 1 after excluding buyers' demographics such as age group, marital status, and number of children. All other details remain the same as in Table 4.

	DV: Hospital Price Index			
	System Level		Facility Level	
	(1)	(2)	(3)	(4)
Negotiation Skill	0.899***	0.828**	0.435**	0.389*
	(2.66)	(2.44)	(1.99)	(1.78)
Insurer FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Hospital System FE	Y	Y	N	N
Hospital Facility FE	N	N	Y	Y
Controls	N	Y	N	Y
N	1,295	1,295	2,788	2,788
adj-R^2	0.622	0.623	0.659	0.664

Table OA3.5: Hospital Negotiated Prices and Negotiation Skill: Bootstrapped SE

This table replicates Table 4, except that the standard errors are obtained through bootstrapping. All other details remain the same as in Table 4.

	DV: Hospital Price Index			
	System Level		Facility Level	
	(1)	(2)	(3)	(4)
Negotiation Skill	0.932***	0.861***	0.429***	0.386***
	(5.45)	(4.70)	(3.98)	(3.79)
Insurer FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Hospital System FE	Y	Y	N	N
Hospital Facility FE	N	N	Y	Y
Controls	N	Y	N	Y
N	1,295	1,295	2,788	2,788
$adj\text{-}R^2$	0.622	0.623	0.659	0.664

Table OA3.6: Robustness of Table 5

This table replicates Table 5 with an alternative set of fixed effects. All other details remain the same as in Table 5

Panel A: Hospital System Level

	DV: Procedure Price		
	Top 3 X-ray	Top 5 X-ray	Top 10 X-ray
	(1)	(2)	(3)
Negotiation Skill	1.018***	0.830***	0.856***
	(5.82)	(4.08)	(4.52)
Procedure× Year FE	Y	Y	Y
Insurer FE	Y	Y	Y
Hospital System FE	Y	Y	Y
Controls	Y	Y	Y
N	62,981	90,797	151,101
adj-R^2	0.587	0.562	0.535

Panel B: Hospital Facility Level

	DV: Procedure Price		
	Top 3 X-ray	Top 5 X-ray	Top 10 X-ray
	(1)	(2)	(3)
Negotiation Skill	0.513***	0.442***	0.352**
	(3.03)	(2.60)	(2.22)
Procedure× Year FE	Y	Y	Y
Insurer FE	Y	Y	Y
Hospital Facility FE	Y	Y	Y
Controls	Y	Y	Y
N	72,522	108,439	177,579
adj-R^2	0.556	0.537	0.507

Table OA3.7: Hospital Manager Turnover and Insurer Compositions

This table presents the effect of hospital manager turnover on hospitals' insurer composition at the hospital system level (Columns 1 and 2) and hospital facility level (Columns 3 and 4). The dependent variable, *Inclusion of Insurer*, is an indicator equal to one if there is any claims with nonmissing payment information between a hospital and a payer. The independent variable, *Manager Turnover*, is an indicator equal to one if a hospital experiences managerial turnover in a year. *Controls* include the same covariates as in Table 4. Fixed effects are indicated at the bottom of the table. Standard errors are clustered by hospital facility or system. *t*-values are reported in parentheses. ***, **, and * represent the statistical significance level at 1%, 5%, and 10% respectively.

	DV: Inclusion of Insurer			
	System Level		Facility Level	
	(1)	(2)	(3)	(4)
Manager Turnover	-0.018	0.007	-0.010	-0.011
	(-0.26)	(0.14)	(-0.48)	(-0.53)
Insurer FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Hospital System FE	Y	Y	N	N
Hospital Facility FE	N	N	Y	Y
Controls	N	Y	N	Y
N	3,674	3,674	8,318	8,318
adj-R^2	0.183	0.198	0.182	0.193

Table OA3.8: Patient Volume and Negotiation Skill

This table presents the coefficient estimates for *Negotiation Skill* regressed on patient volume at the hospital system level (Columns 1 and 2) and hospital facility level (Columns 3 and 4). The dependent variable in Columns (1) and (3) is annual outpatient visits (in thousands); in Column (1), these visits are aggregated across facilities within each hospital system. The dependent variable in Columns (2) and (4) is annual total facility inpatient days (in thousands); in Column (2), inpatient days are similarly aggregated at the system level. *Controls* include the same covariates as in Table 4. Fixed effects are indicated at the bottom of the table. Standard errors are clustered at the manager level. *t*-values are reported in parentheses. ***, **, and * represent the statistical significance level at 1%, 5%, and 10% respectively.

	System Level		Facility Level	
DV:	**Outpatient Visits**	**Inpatient Days**	**Outpatient Visits**	**Inpatient Days**
	(1)	(2)	(3)	(4)
Negotiation Skill	9.414	35.812	-2.139	2.122
	(0.12)	(1.49)	(-0.06)	(0.39)
Year FE	Y	Y	Y	Y
Hospital System FE	Y	Y	N	N
Hospital Facility FE	N	N	Y	Y
Controls	Y	Y	Y	Y
N	888	888	2,106	2,120
adj-R^2	0.967	0.990	0.965	0.975

Table OA3.9: Hospital Negotiated Prices and Negotiation Skill: Exogenous Departures

This table replicates Table 6, except that it replaces *Negotiation Skill* with the interaction terms *Increase-NS Turnover*×*NS* and *Decrease-NS Turnover*×*NS*. Here, *Increase-NS Turnover* (*Decrease-NS Turnover*) is an indicator variable equal to one if the hospital experiences an exogenous manager turnover and the incoming manager possesses higher (lower) negotiation skills. *NS* denotes the manager's negotiation skill. *Controls* include the same covariates as in Table 4. Standard errors are clustered at the manager level, and *t*-values are reported in parentheses. ***, **, and * represent the statistical significance level at 1%, 5%, and 10% respectively.

	DV: Hospital Price Index			
	System Level		Facility Level	
	(1)	(2)	(3)	(4)
Increase-NS Turnover × NS	1.246**	1.224**	1.821***	1.668***
	(2.48)	(2.34)	(5.42)	(4.44)
Decrease-NS Turnover × NS	0.576	0.475	-0.774	-0.979*
	(1.26)	(1.00)	(-1.49)	(-1.80)
Controls	N	N	N	Y
Insurer FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Hospital System FE	Y	Y	N	N
Hospital Facility FE	N	Y	Y	Y
N	337	337	452	452
adj-R^2	0.691	0.688	0.752	0.750

Table OA3.10: Whether Hospital Characteristics Predict Manager Exogenous Departures and NS

This table investigates whether hospital financial and operational conditions predict managers' departures and changes in managers' negotiation skills within the sample of exogenous departures. Panels A and B present results at the hospital facility level, while Panels C and D report results at the system level. In Panels A and C, the dependent variable, *Exogenous Departure Indicator*, equals one if a hospital manager leaves within the following year due to natural causes (death, illness, or age-related retirement) and zero otherwise. In Panels B and D, the dependent variable, *Change in NS among Exogenous Departures*, is defined as the difference in negotiation skill (NS) between the incoming and departing manager when a turnover occurs, and zero otherwise. The independent variables include *Profit Margin*, the lagged annual profit margin calculated as the ratio of total income minus total costs to total income; *log(Beds Num)*, the lagged natural logarithm of total hospital beds; *log(Total Volume)*, the lagged natural logarithm of total annual outpatient visits; *log(Total Inpatient Days)*, the lagged natural logarithm of total annual inpatient days; and two measures of the average hospital-wide mortality rates. For the system-level analysis, all independent variables are averaged across all facilities within a system in a given year. Standard errors are clustered at the manager level. *t*-values are reported in parentheses. ***, **, and * represent the statistical significance level at 1%, 5%, and 10% respectively.

Panel A: Correlation between Hospital Characteristics and Exogenous Turnover (Facility Level)

	DV: Exogenous Departure Indicator					
	(1)	(2)	(3)	(4)	(5)	(6)
Profit Margin	0.060					
	(0.40)					
log(Beds Num)		-0.083				
		(-0.99)				
log(Total Volume)			0.017			
			(0.33)			
log(Total Inpatient Days)				-0.043		
				(-0.75)		
Mortality: Heart Attack					0.019	
					(1.04)	
Mortality: CABG Surgery						0.014
						(0.61)
Hospital Facility FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
N	304	418	391	418	246	153
adj-R^2	-0.097	-0.088	-0.088	-0.089	-0.020	-0.025

Whether Hospital Characteristics Predict Manager Exogenous Departures and NS (cont')

Panel B: Correlation between Hospital Characteristics and Change in NS (Facility Level)

	DV: Change in NS among Exogenous Departures					
	(1)	(2)	(3)	(4)	(5)	(6)
Profit Margin	-0.009					
	(-0.39)					
log(Beds Num)		0.004				
		(0.36)				
log(Total Volume)			-0.008			
			(-0.53)			
log(Total Inpatient Days)				-0.004		
				(-0.44)		
Mortality: Heart Attack					-0.000	
					(-0.09)	
Mortality: CABG Surgery						-0.005*
						(-1.82)
Hospital Facility FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
N	249	362	338	362	225	142
adj-R^2	0.120	0.046	0.051	0.046	0.135	0.133

Whether Hospital Characteristics Predict Manager Exogenous Departures and NS (cont')

Panel C: Correlation between Hospital Characteristics and Exogenous Turnover (System Level)

	DV: Exogenous Departure Indicator					
	(1)	(2)	(3)	(4)	(5)	(6)
Profit Margin	0.197					
	(0.73)					
log(Beds Num)		-0.056				
		(-0.29)				
log(Total Volume)			0.057			
			(1.04)			
log(Total Inpatient Days)				-0.110		
				(-0.88)		
Mortality: Heart Attack					-0.004	
					(-0.17)	
Mortality: CABG Surgery						0.012
						(0.39)
Hospital System FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
N	169	232	230	232	117	78
adj-R^2	-0.081	-0.067	-0.071	-0.062	0.097	0.105

Whether Hospital Characteristics Predict Manager Exogenous Departures and NS (cont')

Panel D: Correlation between Hospital Characteristics and Change in NS (System Level)

	DV: Change in NS among Exogenous Departures					
	(1)	(2)	(3)	(4)	(5)	(6)
Profit Margin	-0.028					
	(-0.75)					
log(Beds Num)		0.022				
		(0.79)				
log(Total Volume)			-0.003			
			(-0.19)			
log(Total Inpatient Days)				0.011		
				(0.54)		
Mortality: Heart Attack					-0.002	
					(-0.42)	
Mortality: CABG Surgery						-0.006
						(-1.16)
Hospital System FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
N	138	197	195	197	105	70
adj-R^2	0.116	0.123	0.116	0.122	0.146	0.232

Table OA3.11: NS of New Hires Following Changes in Insurer Market Concentration

This table examines whether hospitals are more likely to hire managers with higher negotiation skills (NS) after insurer markets become more concentrated, using the sample of hospital facilities used in Table 7. The dependent variable, *Higher NS Indicator*, equals one if a hospital's manager has higher NS than the hospital's manager in the previous year, and zero otherwise. The key independent variable, $\Delta Concentration$, is an indicator equal to one if a hospital's MSA witnesses an increase in insurance market HHI by over 100 (or 200 and 300 in columns 3 to 6) between the current year and sample initial year (2017). Control variables include the number of hospital beds binned in quintiles, Medicaid ratio, Medicare ratio, and indicators for rural, teaching hospital, and for-profit status. Standard errors are clustered at the manager level. *t*-values are reported in parentheses. ***, **, and * represent the statistical significance level at 1%, 5%, and 10% respectively.

	DV: Higher NS Indicator					
	ΔConcentrate = 100		ΔConentrate = 200		ΔConcentrate = 300	
	(1)	(2)	(3)	(4)	(5)	(6)
ΔConcentration	-0.057	-0.055	0.008	0.008	0.009	0.011
	(-1.12)	(-1.06)	(0.09)	(0.09)	(0.11)	(0.13)
Hospital FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y
N	416	416	416	416	416	416
adj-R^2	-0.014	-0.029	-0.020	-0.034	-0.020	-0.034