Driving a Bargain: Negotiation Skill and Price Dispersion*

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Abstract

We develop a measure of managers' bargaining skill based on the price they negotiate when buying a car. We find that managers' bargaining skill contributes to price dispersion in business-to-business contracting. Using proprietary data on insurance claims between hospitals and private insurers, we find that hospital managers with higher bargaining skill achieve better negotiation outcomes for the average price per service as well as for the same procedure at the same hospital. Bargaining skill is manager-specific, and management turnovers for natural causes are followed by material changes in negotiation outcomes. In a structural model, we show that heterogeneity in managers' negotiation skill captures 5% of the dispersion in contracted prices.

*MIT COUHES Protocol #2406001338

1 Introduction

Bargaining, or negotiating the terms of trade, is central to many firm contracts 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. 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.

We develop a novel measure of a manager's negotiation skill and study its role in price negotiations between hospitals and insurance firms, a bargaining process that establishes transaction prices for the more than half of Americans with private health insurance. Due to these negotiations, prices for identical services can vary dramatically across and within hospitals (Cooper et al., 2019). Grennan (2014) attributes this price dispersion largely to unobservable bargaining ability, highlighting the need for its measurement and better understanding. Our paper opens the black box of bargaining outcomes by presenting evidence on the role of individuals in such negotiations.

To evaluate a person's negotiation skill (*NS*), 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 pervasive price dispersion for identical vehicles (Chandra et al., 2017). And, relative to their annual compensation, a vehicle purchase is a significant transaction for the managers in our sample. Leveraging individual-level vehicle purchase transaction data from administrative Department of Motor Vehicle (DMV) data on millions of sales transactions, we calculate whether an individual negotiated a low price relative to other individuals purchasing the same vehicle (make-model-year-trim) during the same month after controlling for the dealership, travel distance, and other market attributes.

We find that our measure of negotiation skill has several validating patterns. First, a person's ability to obtain a lower price is persistent over time, across vehicles, and across dealers. Second, consistent with existing evidence on the importance of familial experience on manager traits (Duchin et al., 2021), we document that family factors explain a large amount of a manager's bargaining skill. Third, we validate the measure out-of-sample. For those managers with available real estate transaction data, we find *NS* correlates with better returns in housing purchases.

To study the association between agents' bargaining skills and the terms of negotiated contracts, we focus on bilateral agreements between hospitals and insurance firms that establish transaction prices for standard medical procedures. This is an economically important driver of healthcare costs, a topic at the forefront of policy debate and academic research. To evaluate bargaining outcomes while accounting for variation in product quality, we collect data from insurance claims that offer transaction-level information on the hospital's charges and negotiated prices (Liu, 2022). These data contain a breakdown of negotiated rates, deductibles, and coinsurance payments that include the insurance company, medical procedure, diagnosis code, and patient demographics. The rich set of observables makes it possible to study both pecuniary and non-pecuniary negotiation outcomes, such as the reimbursement rate and the spectrum of covered procedures, respectively, and to estimate the economic effects for observably identical procedures and diagnoses. The insurance company identifier allows us to exploit variation in negotiation outcomes achieved by the same agents but across different counterparties, while holding constant the endogenous manager-hospital matches. 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 managers with higher negotiation skill (*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 8.7% increase in the negotiated reimbursement rate of a hospital system with insurance company. These economic estimates reflect marginal effects for the same medical procedure, the same diagnosis, and in the same geographic market (three-digit zip).

Of course, the matching between a manager and hospital is far from random and this could introduce serious selection concerns. We address this issue 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 skill. (As *NS* is measured using the manager's earliest vehicle purchase, the changes in *NS* are due to new managers not new transactions. Further, the negotiation skill measure often predates their employment tenure.) We also include insurer fixed effects to control for changes on the payer side that might be correlated with management turnover.

Next, we exploit a subset of managerial departures resulting from natural causes (death, illness, or age-based retirement) to show that the loss of a manager with high negotiating skill is followed by a significant drop in the hospital's future negotiation outcomes. For example, when the negotiation skill gap between an incoming manager and a departing manager is large enough, namely the incoming one is able to negotiate at least 10% lower vehicle price relative to the departing one, hospital systems on average witness a 23% increase in the future negotiated reimbursement rate for the same hospital-insurer pair.

Lastly, holding the manager-hospital match constant, we evaluate how negotiation skill affects the hospital bargaining in response to increased insurer market power. In general, the expectation is that a more consolidated insurance market will increase the bargaining power 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 material increases in market concentration. Those hospitals led by high *NS* managers see no change in negotiated prices. However, those hospitals with less skilled negotiators experience a significant decline in negotiated prices when there is local insurer consolidation.

Further, building on the frameworks in Gowrisankaran et al. (2015) and Ho and Lee (2017), we estimate a model incorporating patient demand for outpatient service 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 commonly-deemed determinants of bargaining power such as market share and hospital system membership. A horse-race test highlights that *NS* actually is one of the most important determinants: a one standard deviation increase in *NS* raises hospital bargaining power by approximately 0.06, representing a 15% increase relative to the sample mean of 0.40.

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, market price dispersion would decrease by more than 5% if all hospitals had managers with homogeneous *NS*.

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

This finding suggests that heterogeneity in managers' skills explains a substantial portion of the observed price dispersion in the data.

One central contribution of this article is to develop a novel measure of an agent's bargaining skill which can be estimated for many agents and applied to a variety of negotiation settings. Our findings suggest that a manager's bargaining skill is a persistent personal characteristic associated with better negotiation outcomes. However, another critical component of this research is to highlight the role of individual agents in observed price dispersion. The literature in economics and industrial organization that examines vertical 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, prior literature has discussed the role of firm conditions (Lewis and Pflum, 2015), market structures (Gowrisankaran et al., 2015; Ho and Lee, 2017; Dafny et al., 2019; Cooper et al., 2020; Barrette et al., 2022; and Dubois et al., 2022), ownership changes (Liu, 2022 and Arnold et al., 2024), as well as information and search costs (Sorensen, 2000; Brown, 2019; and 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 two 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 trait, we develop a concrete out of sample measure of this skill and study its origins.

Our paper also is related to the growing literature on public sector organizations, particularly the healthcare industry, to examine the impact of top managers and corporate governance associated with various ownership types on organization performance. Close to our work, Bloom et al. (2020) and Otero and Munoz (2024) document the impact of hospital managers on hospital productivity and patient mortality. Lewellen (2022) examines the impact of female CEOs as well as hospital board structure on hospital management practices and Liu (2022) shows that strong principals (private equity firms) can extract large improvements in hospital performance. Recently, Lewellen et al. (2024) provides a comprehensive analysis of the non-profit hospitals' governance structure. Our paper extends this research by providing micro-evidence on the role of hospital managers in contract negotiations and quantitatively estimating the effects of their bargaining skill.

More broadly, our paper extends the governance literature on managerial traits. Managers vary in skill and style in ways that materially impact corporate outcomes (Bertrand and Schoar, 2003; Schoar and Zuo, 2016). Adams et al. (2018) find that non-cognitive skills are the strongest predictor of future CEOs, and Kaplan et al. (2012) show 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 is challenging. This paper introduces a unique measure of individual bargaining skill which can be calculated for a large number of managers and documents its importance to negotiated prices.

Our data-driven 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 paper offers a novel quantifiable measure of negotiation skill based on the observed division of surplus in comparable transactions controlling for the counterparty.

2 Data

This paper leverages a number of unique proprietary 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 negotiated prices 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 how we measure negotiation skill (*NS*) using administrative data on vehicle purchases. 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. This dataset covers over 300 million longitudinal patient records in the United States, drawing from multiple payer sources and a variety of insurance plans. The dataset 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*). The additional details on the index construction appear in Section OA-1.1 of the Online Appendix.

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 top 10 X-ray procedures occurring in our sample.[2] Figure 1 reveals the wide dispersion in the prices for the same medical services charged by different hospitals. This figure also highlights 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. The AHA sample covers 1,738 hospital managers for 711 hospital facilities and 92 hospital 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, and Aghamolla et al., 2024).

[2] 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).

Table 1 Panel A provides summary statistics for Texas hospital facilities included in our final analysis sample (following the matching process with managers' DMV records). 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 physicians. In fact, the median hospital employees zero physicians while the mean is 9 and the standard deviation is over 71. This reflects the historical norm of physicians not being employed directly by hospitals (Scott et al., 2017 and Capps et al., 2018), not the actual presence of physicians working in hospitals.

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.

2.3 Characteristics of Hospital Managers

We start with the initial sample that contains 1,738 hospital managers. We hand-match these 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 (system) managers included in the final analysis sample. The majority of hospital managers are male (70%), and the average manager is 60 years old. While ethnicity is missing for approximately 29% of managers, 62% of the managers are white and Hispanic is 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 public firms. The median hospital manager earns $600,000 (Saini et al., 2022) and 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. These statistics align well with nationwide evidence on management compensation this industry in Lewellen (2022) and Lewellen et al. (2024). One third of hospital managers have professional backgrounds in medicine or pharmacy, as inferred from their professional licenses, such as a medical doctor, pharmacist, registered nurse, or physician assistant. A small minority of managers (7%) have licenses in business or law, such as a certified public accountant, real estate broker, or attorney. 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 summary, the typical hospital manager is a 60-year-old white male with a Republican leaning. A large fraction of managers come from the local population and have backgrounds in medicine or pharmacy. 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).[3] 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., 2024). 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., 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[4], marital status, mailing address,

[3] 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.

[4] We follow the US Census Bureau to categorize race and ethnicity into nine diversity groups, including 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.

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 information of hospital managers using Lexis Nexis Public Records.

In our final step, we drop transactions that miss the sale price, the characteristics of the core vehicle, or the demographics of the customer. This filter drops about 2.8 million observations from our sample. Next, 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*.[5] We also drop any make-model-trim in a year with the average transaction prices above $100,000, which shrinks our sample size by another 2,000 observations. After applying these data restrictions, we arrive at our final dataset of about 9 million vehicle transactions.

2.6 Which Cars do Managers Drive? Descriptive Evidence

We identify 3,151 vehicle transactions by 1,303 hospital managers in our matched sample. Table 2 provides summary statistics comparing hospital managers' vehicle transactions with those of the general public in Texas, highlighting notable differences in transaction characteristics and vehicle attributes. Panel A reveals several patterns. First, hospital managers tend to purchase more expensive vehicles, with an average sale price of $57,662 compared to $37,337 for the general public. They also exhibit higher purchasing activity, averaging approximately 4.3 transactions within the 2014-2023 event window, compared to 2.4 transactions by the general public. Additionally, hospital managers travel further for vehicle purchases, averaging 64.7 kilometers compared to 44.1 kilometers for the general public. This

[5] Tesla, a vehicle manufacturer which does not permit price negotiations, does not sell directly to customers in Texas.

pattern may reflect the relative scarcity of premium brand dealerships or greater willingness to travel for favorable deals. Timing of transactions also differ. Hospital managers are more likely to purchase vehicles at the end of the year (5.4% vs. 4.0%) and at the end of the month (20.5% vs. 20.2%), though the latter difference is not statistically significant. The higher likelihood of end-of-year purchases may reflect managers' preferences for taking advantage of year-end deals or tax-related considerations.

There also are differences in vehicle attributes. Hospital managers are more likely to purchase new vehicles (51.8% vs. 42.9%) compared to the general public. Their transactions involve vehicles with considerably lower odometer readings (14,377 vs. 25,031 miles) and newer average vehicle age (1.4 vs. 2.5 years). While they favor vehicles with larger engine displacements (3.6 vs. 3.4 liters) and foreign brands (55.4% vs. 47.9%), there is no notable difference in the preference for U.S.-manufactured cars between the two groups.

Table 2 Panel B lists the top five vehicle brands preferred by hospital managers and the general public. While Ford, Toyota, and Chevrolet are the most common brands purchased in Texas, these three account for only one-third of hospital managers' purchases compared to 43% for the general public. Notably, BMW is the next most popular choice for managers but is not in the top 5 for the broader population, reflecting managers' stronger preference for luxury brands. Untabulated results further reveal hospital managers' preferences across vehicle types. SUVs are the most common choice, accounting for 48% of purchases, followed by pickups (20%), sedans (18%), and coupes (5%). This aligns broadly with the purchasing trends observed in the Texas population.

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 (make-model-trim-year) 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.[6]

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

$$
\begin{aligned}
\ln(\mathit{Sale\ Price}_{ijdt}) = & \alpha_1 \mathit{Veh\ Char}_{jt} + \alpha_2 \mathit{Demographics}_{it} + \alpha_3 \mathit{Mkt\ Comp}_{dt} + \alpha_4 \mathit{Travel\ Distance}_{id} + \\
& \mathit{Make\text{-}Model\ (Year)\text{-}Trim\ FE} + \mathit{YearMonth\ FE} + \mathit{Dealer\ FE} + \mathit{FIPS\ FE} + \varepsilon_{ijdt}
\end{aligned}
\tag{1}
$$

where $\mathit{Sale\ Price}_{ijdt}$ is the sale price of a transaction initiated by buyer i from dealer d for vehicle j at time t. $\mathit{Veh\ Char}_{jt}$ represents vehicle odometer reading group at the time of transaction.[7] $\mathit{Demographics}_{it}$ is a list of demographic variables of buyer i at time t, including their age group, marital status, and number of children.[8] $\mathit{Mkt\ Comp}_{dt}$ 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).[9] $\mathit{Travel\ Distance}_{id}$ is the travel distance between buyer i's residency and dealer d's location. *Make-Model (Year)-Trim FE* is make-model plus model year-trim fixed effects. *YearMonth FE* is the transaction year-month fixed effects. *Dealer FE* and *FIPS FE* are dealer and buyer state-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. These initial transactions often occurred before they assumed their roles as hospital managers, mitigating concerns about potential mismeasurement due to reduced attention to personal vehicle purchases during their tenure. In Section 4.1, we confirm that our results are robust to alternative measures as well as the inclusion of demographic controls in the

[6] While the Texas DMV data does not include the list price, we manually collect this for hospital managers's new vehicle purchases by searching their individual VINs on vehiclehistory.com. We then calculate the transaction price discount relative to the specific vehicle list price. Figure OA2.1 shows a positive relationship between our *NS* measure and this alternative measure of vehicle negotiation skill. However, data access limitations do not allow us to replicate the measure for the universe of vehicle sales.

[7] 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.

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

[9] 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.

construction of the *NS* measure.

3.2 Validating the *NS* Measure

Table 3 Panels A, B, and C present multiple tests to validate our negotiation skill measure. We confirm that *NS* is an individual persistent across multiple vehicle purchases. We present evidence that it has origins in familial experience. Lastly, we validate the measure of skill in another transaction setting—real estate purchases.

First, 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. Theoretically, since *NS* is an intrinsic trait, we should 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 45% 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, with the inclusion of additional controls increase the explanatory power to 42% (Column 4). These findings indicate that individual-specific traits play a crucial role in shaping negotiation skills, with other contextual and demographic variations adding limited incremental explanatory power.

If *NS* is an intrinsic trait, 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 0.144 in Column (1) and remains nearly unchanged when controlling for time (0.143 in Column 2), both highly statistically significant. For the manager subsample, the persistence of *NS* is weaker but still significant, with coefficients of 0.059 (Column 3) and 0.056 (Column 4). These results confirm that negotiation skill is a persistent trait over time, with the time elapsed since the initial transaction having no significant effect on its persistence.

Given *NS* persists as an individual trait, a natural question is why some managers differ from others in their negotiation skills. The literature on the determinants of personality traits 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 traits (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, including parents and siblings of hospital managers. Columns (1) and (2) replicate the individual fixed effects analysis from Panel A for this subsample, 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 22 to 27 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 validation in a distinct and orthogonal context, we also assess how a manager's negotiation skill correlates with the return in their real estate transactions.[10] 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

[10] While real estate transactions also involve bargaining, 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.

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 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). Figure 3 plots these observations (y-axis) against the manager's *NS* measure derived from motor vehicle transactions (x-axis). The scatterplot in Panel A reveals a positive relationship, with most observations distributed along an upward-trending line. Panel B replicates the scatterplot but controls for observable property features (e.g., number of bathrooms and bedrooms, square footage, etc.) and the positive relationship between managers' NS and their real estate returns is still robust. These results suggest that a manager's negotiation outcomes are positively correlated across different bargaining settings, consistent with the theory of behavioral consistency (Allport, 1937; Epstein, 1979).

In sum, the empirical evidence suggests that our measure of a manager's negotiation skill derived from vehicle purchase history captures a persistent trait 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 delve 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) and Cooper et al. (2019). Cross-sectional evidence in

Figure 4 shows the correlation between a hospital manager's bargaining skill and this index. Regardless of whether we evaluate this relationship at the individual hospital facility or the hospital system level, these figures highlight a positive relationship between bargaining ability and the prices negotiated with insurers.

To explore how managers' bargaining skill affect hospital prices in a more formal framework, we adopt the following empirical specification:

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

where Y_{ihkt} is the negotiated price index between hospital h whose manager being 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), *Beds*, the number of hospital beds in hundreds (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 corresponding 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 corresponding to Medicare patients (if it is a hospital system, we take the average across all facilities). These controls variables capture a range of hospital characteristics which have been documented to affect prices, as discussed in Cooper et al. (2019). 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* when regressed on 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 5.45% increase in negotiated medical 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 OA3.2 replicates the baseline table using two alternative measures of negotiation skill for managers with multiple transactions. Panel A presents the results using the manager's maximum *Negotiation Skill* while those in Panel B use the manager's median *Negotiation Skill* score. Both alternative measures are economically and statistically significant determinants of the *Hospital Price Index* 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 OA3.3 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 OA3.4 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.

Lastly, we rerun the analysis dropping all make-model-trims with fewer than twenty vehicle sales in a year. The concern is that there would be more noise in these purchases' *Negotiation Skill* measure. Online Appendix Table OA3.5 documents that the results continue to be robust.

4.2 X-Ray Pricing: Controlling for Service Quality

Another concern is that contract prices are 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 non-payment. 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 number of hospital beds in hundreds, 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 $NegotiationSkill$ and higher negotiated prices for the same procedure, with the same insurer, at the same hospital. For example, Column (1) in Panel A indicates that a 10% increase in a hospital system manager's NS is associated with a 6.99% average increase in negotiated prices for the top 3 X-ray procedures. 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.[11] In such cases, negotiation outcomes may reflect the influence of hospital-level factors rather than the manager's bargaining skill. Our baseline specification addresses this 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.

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 a causal relationship 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 product market power to identify shocks to the hospital manager's bargaining position.

[11] In Figure OA2.3 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*.

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 134 management turnover events from natural causes.

Table 6 investigates the association between the natural turnover of hospital managers and their hospital's negotiated prices. The dependent variable is a hospital's service price index, defined as before. The main independent variable of interest is the change in the hospital manager's negotiation skill resulting from management replacement for natural causes (deaths, illness, or age-based retirement). The control group includes hospitals that do not experience a change in management. All regressions include hospital facility or hospital system fixed effects so we estimate within-hospital variation in the negotiated price index after a shock to their manager's negotiation skill due to natural turnover.

The results in Table 6 show that a change in management bargaining skill as a result of natural turnover affects negotiated prices. This conclusion is statistically significant at 1% across all specifications, with t-statistics between 2.56 and 3.51. These results persist whether we focus on hospital systems (Columns 1 and 2) or hospital facilities (Columns 3 and 4). The economic magnitudes are large and stable across specifications. For instance, Column (1) suggest that a 10% increase in managers' bargaining ability corresponds to an average 9.69% increase in the hospital negotiated prices. The estimates remain comparable after we saturate the regressions with dynamic 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 number of beds 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 event-time evidence on changes in hospital prices around management turnovers for natural causes. The source of variation comes from turnover events associated with a significant increase in the manager's negotiation skill, defined as an improvement of at least 0.1 in absolute magnitude. This threshold corresponds to an incoming manager able to negotiate at least 10 percent lower price than the outgoing manager in comparable private transactions on the same vehicles. Hospitals experiencing these turnovers with significant *NS* improvements form the treated group, while hospitals without any management turnovers serve as the control group. The analysis employs a standard event-study framework, interacting event-time dummies with a treatment indicator. Year zero represents the year of management turnover, and the analysis examines a time window spanning four years before and after the event.

Panel A in Figure 5 presents the event-study results for hospital systems, while Panel B displays the pattern for hospital facilities. The x-axis represents the event time in years relative to the manager's turnover year (year zero), while the y-axis shows the hospital's average price per service unit. Shaded regions denote 95% confidence intervals. By exploiting variation in bargaining skill within the same hospital, these figures net out the effects of their time-persistent unobservable characteristics and reveal three patterns.

First, there is no significant pre-trend in the dependent variable before the manager's departure, as expected in cases where departures for natural causes are systematically unrelated to hospital pricing policies. The absence of a pre-trend supports the validity of the identification strategy. Second, an increase in the manager's negotiation skill is followed by a corresponding increase in the hospital's negotiated prices. The effect unfolds gradually, with a slight uptick in the negotiated prices during the turnover year, followed by a predominantly upward trend. This pattern is consistent with the idea that prices take time to renegotiate, as many agreements are fixed in the short term. Third, the increase in hospital prices shows no reversal within the four-year event horizon. Instead, the upward trend in prices becomes steeper three to four years after the manager's replacement, underscoring the enduring impact of improved managerial negotiation skill on hospital pricing.

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, thereby altering their bargaining positions when negotiating prices with hospitals (Dafny et al., 2012), we examine how this impacts hospital prices. We evaluate how hospital-insurer negotiated outcomes vary in response to changes in market concentration among insurers 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.[12] Figure 6 illustrates the time series of HHI for each MSA between 2017 and 2022. Notably, some MSAs experienced dramatic increases in insurance market concentration during this period. For example, the College Station MSA insurance market HHI rises from 2578 to 4300 while other MSAs, such as Kileen, are relatively stable.

Motivated by this heterogeneity in changes in insurer market power, we conduct a regression analysis of the hospital price index on an indicator, Δ*Concentration*, which equals one if an MSA experiences an increase in HHI of over 100 between the current and prior year. We split the hospital facility sample[13] into two groups: *high-NS* and *low-NS*. Hospitals are categorized as *high-NS* if their managers' *NS* in the earliest year of the sample period is above the median, and *low-NS* otherwise. Separate regressions are run for these subsamples 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. Notable differences exist between the two subsamples. In Columns (1) and (2), hospitals with high-*NS* managers experience no material change in negotiated prices. In contrast, hospitals with low-*NS* managers experience a significantly larger decline, with ne-

[12] 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.

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

gotiated prices dropping by an average of 15%, significant at the 1% level. The negative coefficient on Δ*Concentration* aligns with the notion that more concentrated insurance markets weaken hospitals' bargaining positions if there manager is not a more able negotiator. These findings provide further validation, helping to address concerns about endogeneity by demonstrating how the impact of insurance market concentration varies with managerial negotiation skill.

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 (system) 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 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. Addtionally, the covariates include interactions between the patient's major diagnoses indicators, representd 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 delievered 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 probablity 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 consier 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 affects 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 costs 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_{ht}^{out}, 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:

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

in which VC_{ht} is the total variable costs for hospital h in fiscal year t, Rev_{ht}^{s} 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-1.2 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-1.3 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 findings in other studies, including Arnold et al. (2024), Liu (2022), and Prager and Tilipman (2020), within outpatient setting.

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 1,234 bargaining power estimates by hospital, insurer, year, and HRR. The mean bargaining weight in our sample is 0.404, with a standard deviation of 0.401.

6.3.1 Determinants of Bargaining Power

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

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

where δ_i represents insurer fixed effects and $\tau_{hrr,t}$ is HRR-by-year fixed effects.

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 $0.05 (\approx 10\% \times 0.481)$ 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, with a magnitude comparable to that in Column (1). Furthermore, other characteristics positively associated with hospitals' bargaining weights include larger market share measured by the number of hospital beds, being part of a hospital system, and accommodating a higher proportion of Medicaid patients.

To assess the relative importance of NS 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 0.06, which is double the effect of hospital market share and Medicaid patient ratios, and nearly six times greater than the impact of hospital system membership.

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 insurers 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.[14] Row 1 of Table 10 reports the average price dispersion for the equilibrium prices implied by the model.

In the counterfactual scenario, we eliminate differences in hospital managers' *NS* by constructing a new set of bargaining power parameters ($\beta_h^c(t)$) using the specification in Column (2) of Table 9. Specifically, we compute

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

where $\beta_h(t)$ is the estimated bargaining weights in equilibrium, $\hat{\alpha}_1$ is the coefficient for *NS* from Column (2) of Table 9 (0.404), NS_{ht} denotes the managers' *NS* for hospital h in year t, and $\overline{NS}$ is the sample mean of managers' *NS*.

Using the counterfactual bargaining power parameters, we recompute the equilibrium negotiated prices and the corresponding average price dispersion. As shown in Row 2 of Table 10, the counterfactual average price dispersion decreases to 1.08, compared to 1.14 in the equilibrium scenario. This suggests

[14] 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.

that heterogeneity in hospital managers' NS accounts for approximately 5.1% of the total price dispersion observed 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 has developed a measure of managers' negotiation skill inferred from their personal transactions. Our evidence suggests that bargaining skill is a persistent individual characteristic, which 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 decision agents endowed with signatory rights 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 convenient 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

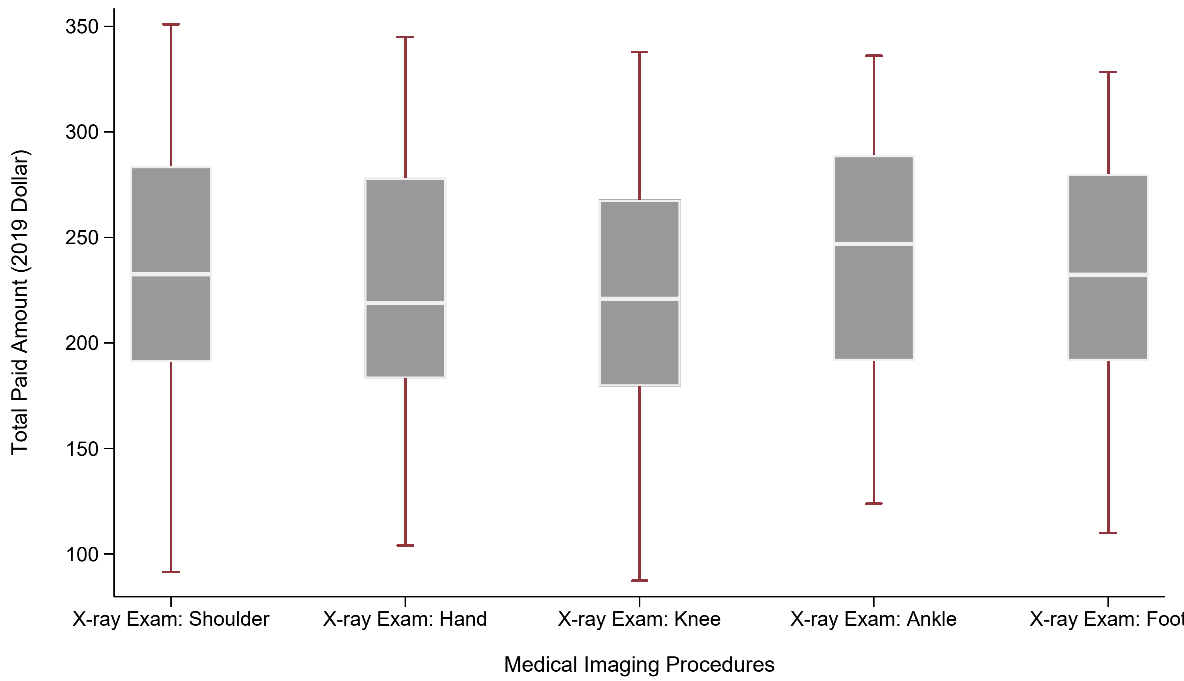


Figure 1: Price Dispersion of Medical Imaging Procedures

This presents the paid amounts (allowed amount) of one large insurer for five 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.

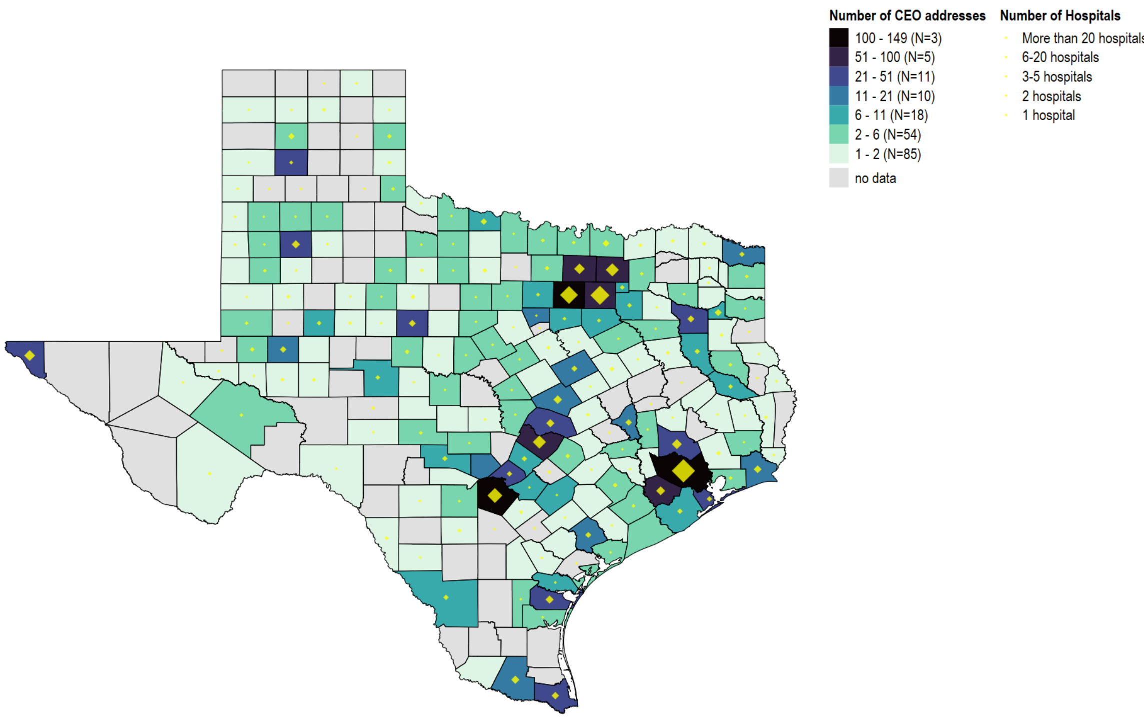
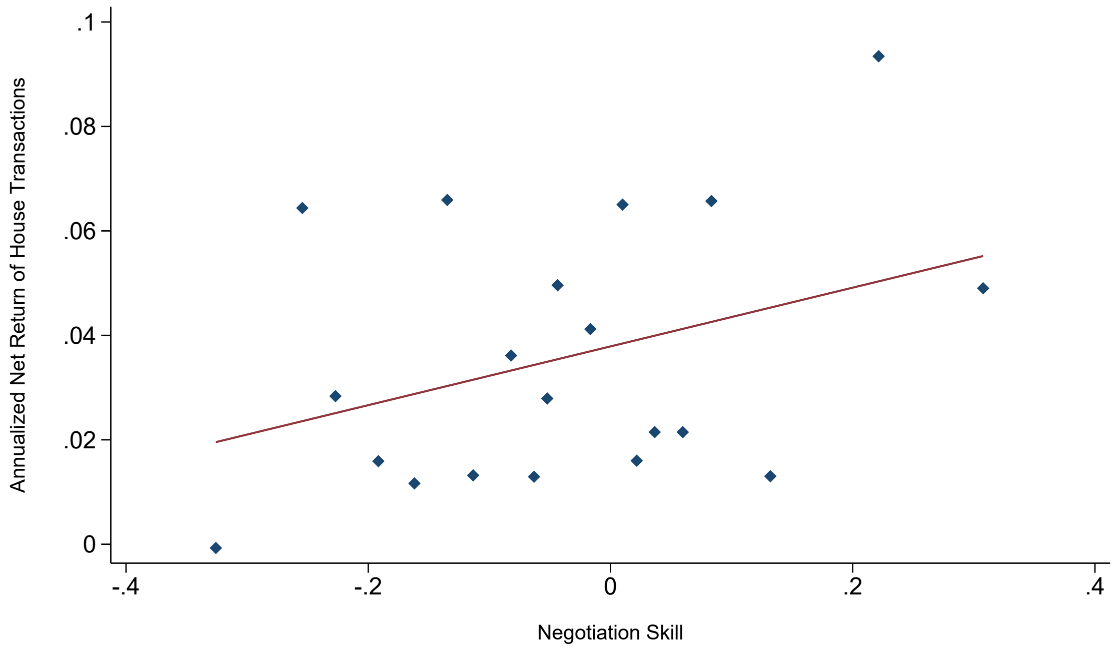
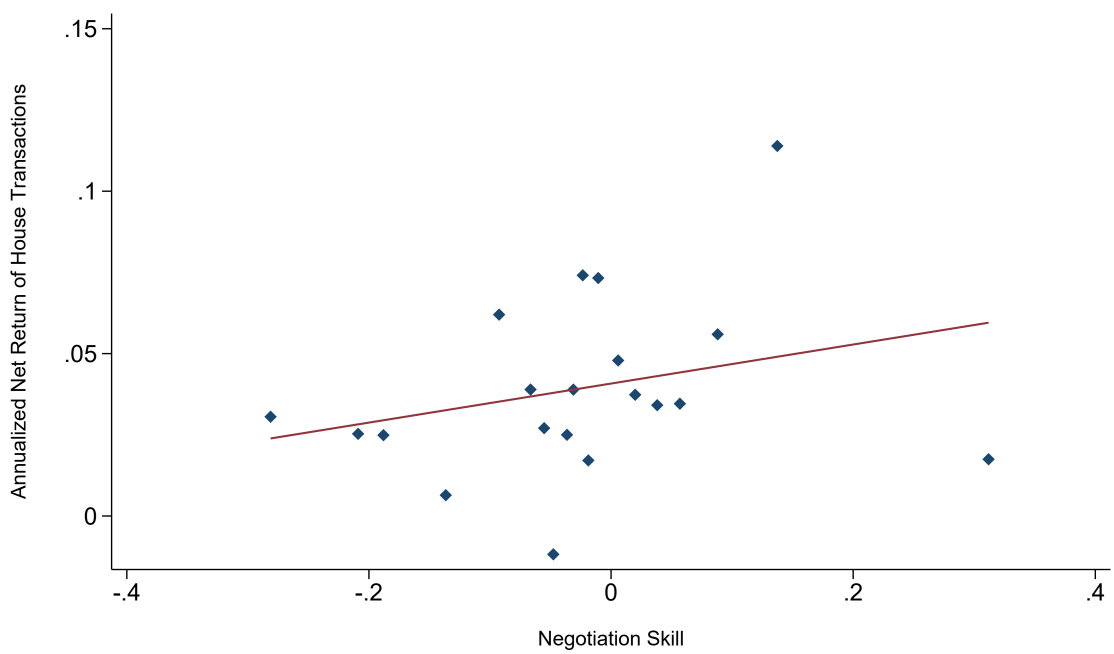


Figure 2: Price Dispersion of Medical Imaging Procedures

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



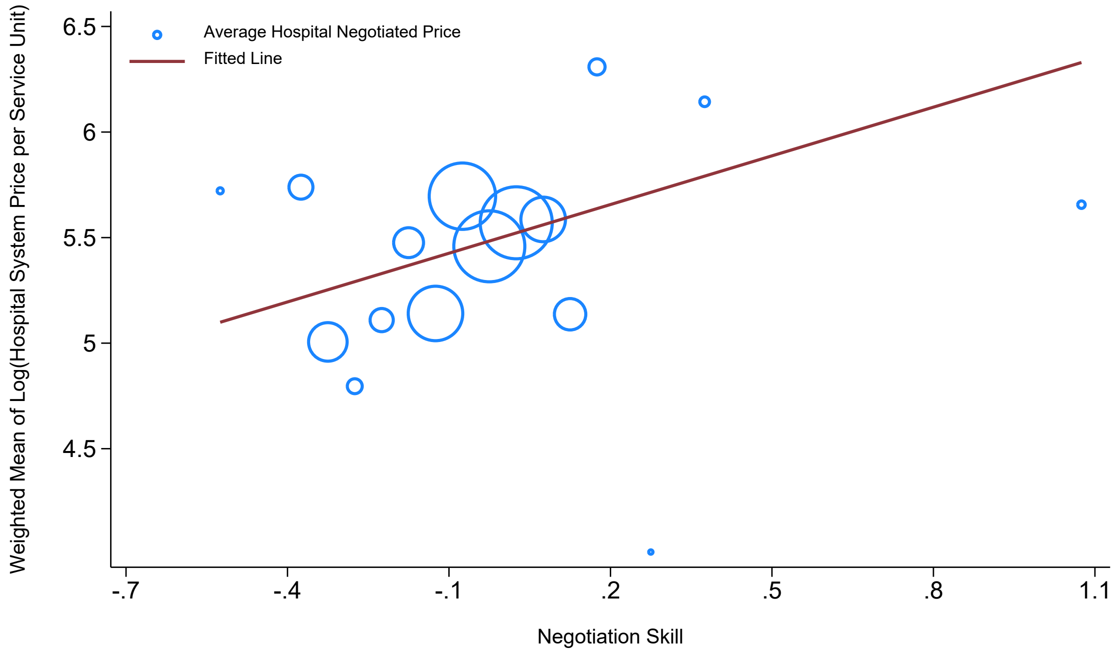
(a) W/O Controls



(b) With Controls

Figure 3: Annualized House Return and Manager Negotiation Skill

This figure plots managers' annualized returns on real estate transactions (y-axis) against their *NS* measure derived from vehicle transaction records (x-axis). Panel A presents the scatterplot without any controls, while Panel B adjusts for observable property features, including the number of bathrooms and bedrooms, square footage, lot size, and Zillow's current price estimate.

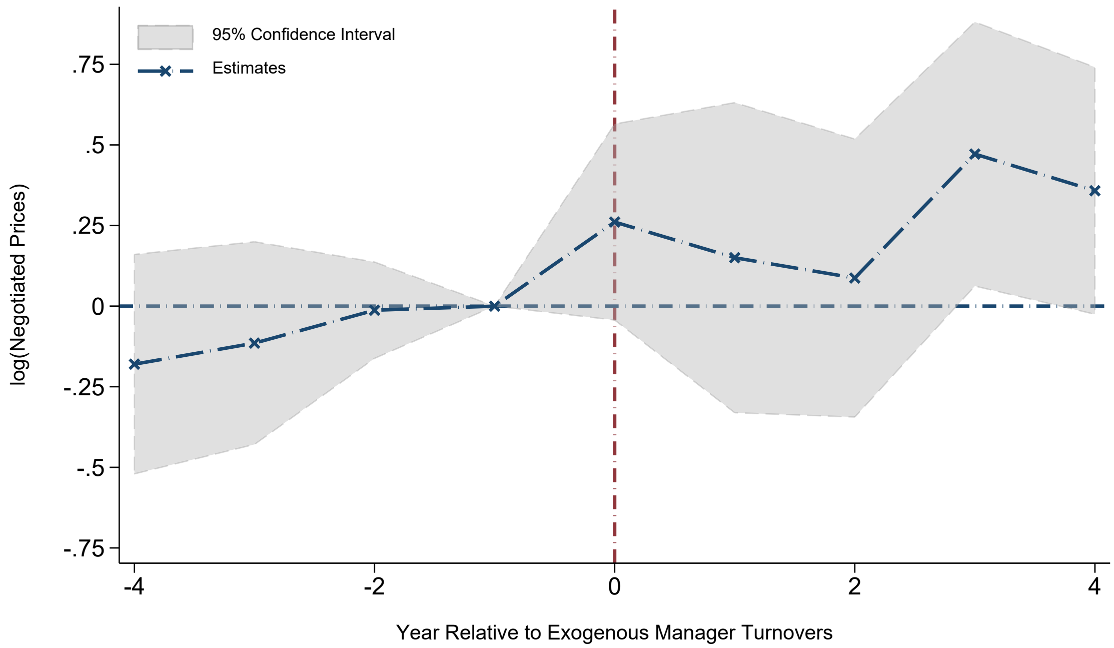


(a) Hospital System Level

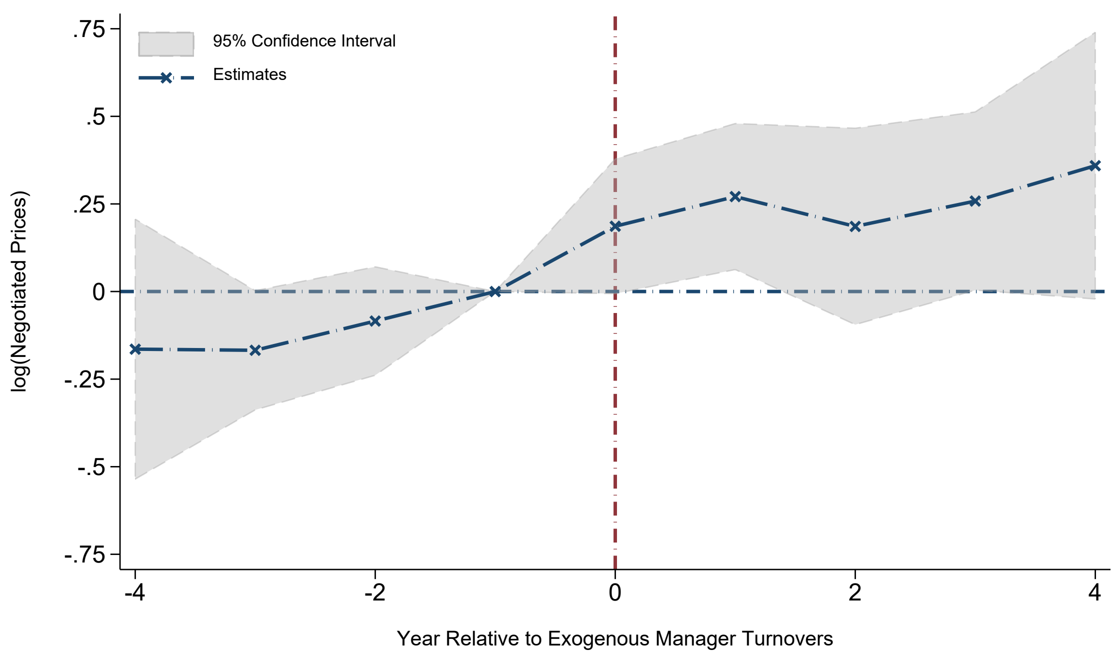
(b) Hospital Facility Level

Figure 4: 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.



(a) Hospital System Level



(b) Hospital Facility Level

Figure 5: Price Changes after Exogenous Departures

This figure exhibits the event-study regression results with manager turnovers. Panel A presents the results for hospital system while Panel B displays the pattern for hospital facilities. The x-axis indicates the event time in years relative to the manager's turnover year (year zero), while the y-axis shows the hospital's average pprice per service unit. Shaded regions denote 95% confidence intervals.

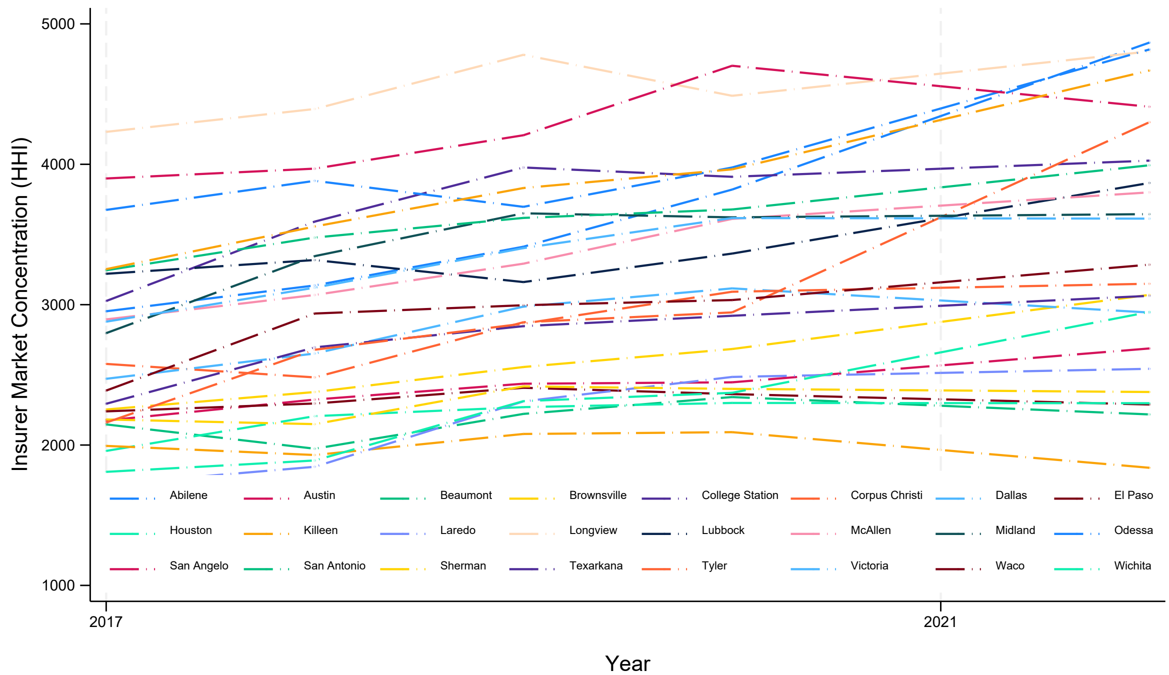


Figure 6: Insurance Market Concentration (HHI) in Texas MSAs

This figure exhibits the health insurance market concentration in terms of Herfindahl-Hirschman index (HHI) across Texas Metropolitan Statistical Areas (MSAs) between 2017 and 2022 (2017, 2018, 2019, 2020, and 2022). The data is sourced from Table 1 of 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.

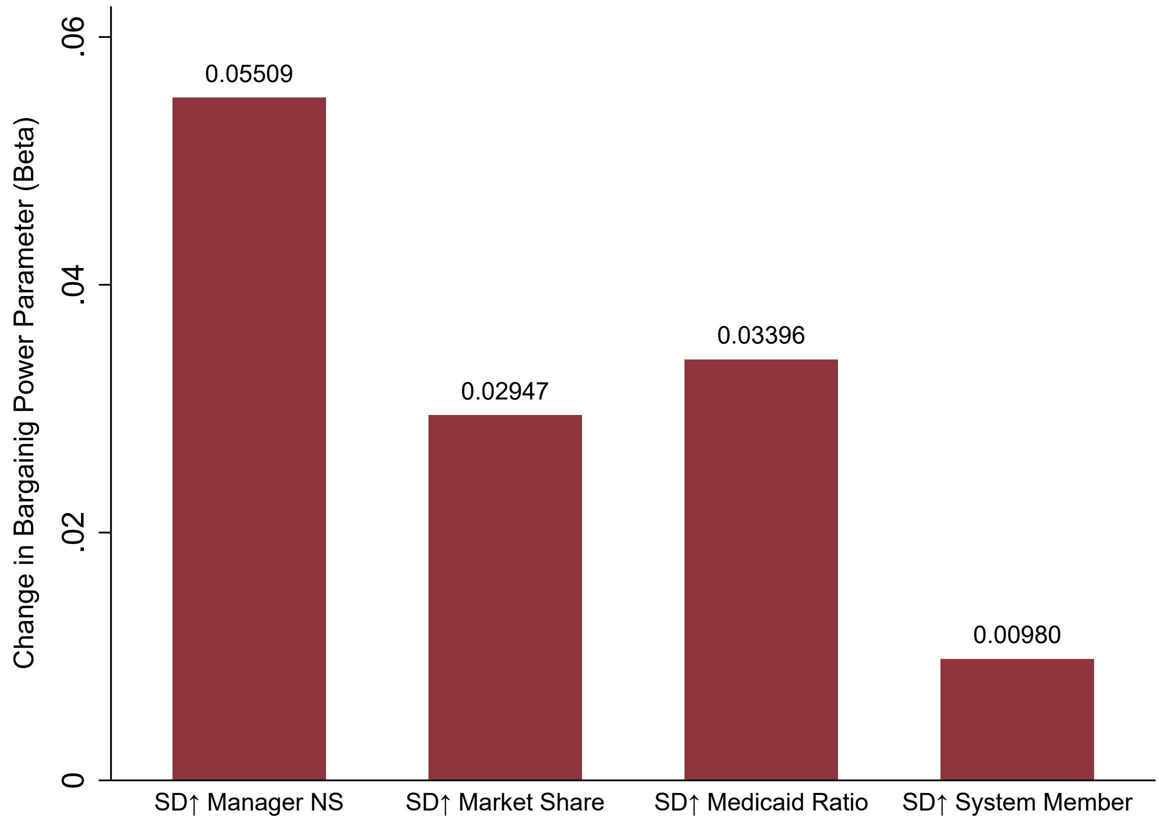


Figure 7: Relative Contribution of NS to Estimated Hospital Bargaining Power

This figure exhibits how various hospital characteristics influence the estimated hospital bargaining power parameters (β). Each bar represent the change in bargaining power parameter asscoiated with a one-standard-deviation increase in a specific hospital characteristic, including manager NS, market share in hospital beds, Medicaid ratio, and system membership.

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. Panel B describes a sample of 1,303 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, 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	0.493	0.000	0.500
Teaching	0.030	0.000	0.170
Critical Access	0.146	0.000	0.353
Rural	0.152	0.000	0.359
Part of a System	0.640	1.000	0.480
Operation and Financials			
Num Beds (in 100)	1.400	0.590	2.022
Total Personnel	693.108	188.000	1558.532
Total Physicians	9.461	0.000	71.372
Total Registered Nurses	214.386	47.000	410.782
log(*Total Income*)	17.979	17.727	1.456
Revenue Growth	0.070	0.023	0.397
Profit Margin	0.068	0.072	0.176
Leverage	0.460	0.454	1.131
Medicaid Ratio	0.114	0.074	0.138
Medicare Ratio	0.527	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

Summary Statistics (cont.)

Panel B: Hospital Managers

Variable	Mean	Median	SD
Demographics			
Age (*in* 2023)	60.630	61.000	11.716
Female	0.298	0.000	0.457
Num of Children under 18	0.619	0.000	1.142
White	0.619	1.000	0.486
Hispanic	0.067	0.000	0.250
Black	0.011	0.000	0.103
Asian	0.011	0.000	0.103
Born Out of TX	0.483	0.000	0.500
Foreign Born	0.008	0.000	0.092
Socioeconomic Status			
Num Current Properties	2.156	2.000	1.178
Primary Home Purchase Price ($1,000)	1,069.147	701.271	1,318.707
Professional Credentials			
Medical or Pharma License	0.327	0.000	0.469
Business Certification (*e.g., CPA*)	0.065	0.000	0.246
Legal Service License	0.010	0.000	0.099
Socal or Other License	0.048	0.000	0.213

Table 2: Vehicle Transactions of Hospital Managers and the General Public

This table compares the characteristics of motor vehicles purchased by hospital managers and the general public. The vehicle data includes about 9 million transactions in the state of Texas between 2014 and 2023, inclusive. The data come from the Texas Department of Motor Vehicles (DMV) and the vehicle identification number decoder service of the National Highway Traffic Safety Administration (NHTSA). Variable definitions appear in Table OA3.1 of the Online Appendix. Vehicle sale prices are adjusted to 2023 dollars using annual GDP deflators. The right-hand side column shows the absolute values of t-value for the tests of the differences of means.

Panel A: Vehicle Transaction

	Hospital Manager	**General Public**	**Diff**	**t-value**
Transaction Characteristics				
Vehicle Sale Price (*in* \$1,000)	57.662	37.337	20.325	(21.47)
Total Transactions	4.288	2.370	1.918	(24.18)
Travel Distance (*km*)	64.661	44.123	20.538	(10.66)
#Competing Dealers	4.271	5.568	-1.297	(-12.57)
End of Month	0.205	0.202	0.003	(0.44)
End of Year	0.054	0.040	0.013	(3.34)
Vehicle Attributes (at Purchase)				
Odometer Reading (1,000 *miles*)	14.377	25.031	10.654	(21.72)
Vehicle Age (*years*)	1.399	2.450	-1.051	(-20.11)
New Vehicle	0.518	0.429	0.089	(9.98)
Engine Displacement	3.637	3.437	0.200	(7.68)
Foreign Brand	0.554	0.479	0.076	(8.55)
US Manufacture	0.580	0.587	-0.007	(-0.84)

Panel B: Top Five Brands

	Hospital Manager		**General Public**	
Ranking	**Brand**	**Percent (%)**	**Brand**	**Percent (%)**
1.	FORD	15.26	FORD	17.30
2.	TOYOTA	9.55	CHEVROLET	14.07
3.	CHEVROLET	8.66	TOYOTA	12.24
4.	BMW	6.95	NISSAN	6.98
5.	JEEP	5.30	HONDA	5.66

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 his initial transaction ($Negotiation\ Skill_0$). $Month\ Gap_0$ measures the number of months between his current vehicle transaction date and his 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.

Panel A: Variance Decomposition

	DV: Negotiation Skill			
	Full Sample		**Manager Sample**	
	(1)	(2)	(3)	(4)
R^2	0.45	0.45	0.34	0.42
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	4,986,956	4,986,956	2,635	2,611

Panel B: Persistence in NS

	DV: Negotiation Skill (t)			
	Full Sample		**Manager Sample**	
	(1)	(2)	(3)	(4)
$Negotiation\ Skill_0$	0.144***	0.143***	0.059**	0.056*
	(50.04)	(49.82)	(1.98)	(1.80)
$Month\ Gap_0$		-0.000		-0.000
		(-1.07)		(-1.17)
Yr-Month FE	N	Y	N	Y
County FE	N	Y	N	Y
Controls	N	Y	N	Y
N	3,135,753	3,135,753	1,848	1,809

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	0.31	0.33	0.21	0.27
Individual FE	Y	Y	N	N
Family FE	N	N	Y	Y
County FE	N	Y	N	Y
Controls	N	Y	N	Y
N	1,153	1,137	1,474	1,450

Table 4: Hospital Negotiated Prices and Negotiation Skill

This table reports the coefficient estimates for *NegotiationSkill* regressed on *HospitalPriceIndex* at the hospital system level and hospital facility level with the inclusion of hospital, insurer, and time fixed effects. Control variables include the number of hospital beds in hundreds, Medicaid ratio, Medicare ratio, and indicators for rural, teaching hospital, and for-profit status. Standard errors are clustered at the manager level. ***, **, 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	0.565***	0.545**	0.384***	0.339**
	(2.68)	(2.58)	(2.90)	(2.48)
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	1,301	1,301	2,854	2,854
adj-R^2	0.616	0.618	0.659	0.664

Table 5: Medical Imaging Procedure Prices and Negotiation Skill

This table reports the coefficient estimates for *NegotiationSkill* 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. Column 2 uses the top 5 and Column 3 uses the top 10, 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). 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 number of hospital beds, Medicare ratio, Medicaid ratio, 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. ***, **, 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	0.699***	0.651***	0.596***
	(3.35)	(3.12)	(2.61)
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	63,037	90,910	151,356
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	0.329**	0.331**	0.239*
	(2.21)	(2.49)	(1.96)
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	73,331	109,659	179,722
adj-R^2	0.554	0.534	0.505

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

This table reports the coefficient estimates for *NegotiationSkill* regressed on *HospitalPriceIndex* at the hospital system level and hospital facility level with the inclusion of hospital, insurer, and time fixed effects. Control variables include the number of hospital beds in hundreds, Medicaid ratio, Medicare ratio, and indicators for rural, teaching hospital, and for-profit status. Standard errors are clustered at the manager level. ***, **, 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	0.969***	0.937***	1.102***	0.879***
	(3.03)	(2.97)	(3.41)	(2.56)
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	1,081	1,081	1,838	1,838
adj-R^2	0.637	0.638	0.662	0.665

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

This table demonstrates how hospital negotiated prices change among hospitals with high-NS managers vs low-NS managers when health insurance markets become more concentrated. The health insurance market concentration is defined as the Herfindahl-Hirschman index (HHI) across Texas Metropolitan Statistical Areas (MSAs) between 2017 and 2022 (2017, 2018, 2019, 2020, and 2022, in which we impute HHI for year 2021 by taking average of years 2020 and 2022). The HHI data is sourced from Table 1 of 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. Our analysis is conducted at the hospital facility level. Columns (1) and (2) report the results of hospitals with high-NS managers, defined as a sample of hospitals whose managers in the earliest year of the sample period have above median NS, otherwise categorized as hospitals with low-NS managers. Columns (3) and (4) report the results for hospitals with low-NS managers. The key independent variable, ΔConcentration, is an indicator equal to one if a hospital's MSA witnesses an increase in insurance market HHI by over 100 between the current year and previous year. Control variables include the number of hospital beds in hundreds, Medicaid ratio, Medicare ratio, and indicators for rural, teaching hospital, and for-profit status. Standard errors are clustered at the manager level. ***, **, and * represent the statistical significance level at 1%, 5%, and 10% respectively.

	DV: Hospital Price Index			
	High-NS Hospital		Low-NS Hospital	
	(1)	(2)	(3)	(4)
ΔConcentration	0.014	-0.010	-0.151***	-0.144***
	(0.33)	(-0.27)	(-2.72)	(-2.67)
Insurer FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Hospital Facility FE	Y	Y	Y	Y
Controls	N	Y	N	Y
N	562	562	597	597
adj-R^2	0.693	0.693	0.776	0.775

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 HRR-by-year fixed effects and insurer fixed effects. Relative to Column (1), Column (2) includes other hospital characteristics in the regression: *Hosp. Market Share* is a hospital system's market share in total hospital beds in an HRR of a year. *System Member* is an indicator whether a hospital is affiliated with a system. *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. *Trauma Center* and *Psychiatric Care* are the average ratio of hospital facilities of a system in an HRR having trauma center and providing psychiatric care. *Outpatient Visits* is the total number of outpatient visits to a hospital system in an HRR. Standard errors are clustered by hospital system. ***, **, and * represent the statistical significant level at 1%, 5%, and 10% respectively. t-value is 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	0.481**	0.404***
	(2.58)	(2.70)
Hosp. Market Share		0.234
		(0.83)
System Member		0.020
		(0.36)
Teaching Hospital		-0.036
		(-0.36)
Rural Hospital		-0.137
		(-1.62)
For-profit		-0.012
		(-0.22)
Trauma Center		-0.113*
		(-1.94)
Psychiatric Care		-0.067
		(-1.34)
Outpatient Visits (in Million)		-0.192***
		(-3.40)
Medicare Patient Ratio		-0.204
		(-1.31)
Medicaid Patient Ratio		0.284
		(1.39)
Insurer FE	Y	Y
HRR×Year FE	Y	Y
N	1,208	1,192
adj-R^2	0.189	0.265
DV Mean	0.404	
DV SD	0.401	

Table 10: Counterfactual: Homogeneous NS and Price Dispersion

This table shows how hospital managers' NS affects hospital price dispersion in the counterfactual. The first row reports the market-average price dispersion, measured by the mean of $var(\log(p_{hi} - c_h))$, where $h \in N_i$ represents hospitals within insurer i's network, across insurers based on the model-implied prices. The second row reports the counterfactual price dispersion in which all heterogeneity in managers'NS is removed. The last row displays the percentage change in average price dispersion from the model implied equilibrium (row 1) to counterfactual with homogeneous NS (row 2).

	Mean Price Dispersion (Variance)
Model Implied Equilibrium	1.138
Counterfactual with Homogeneous NS	1.081
ΔDispersion (Percentage)	-5.066%

For Online Publication

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

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Denis Sosyura

November 2024

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. I 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 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.

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 OA2.2 illustrates the distribution of estimated marginal costs across hospital facilities.

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)

OA-1.3 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_All
2013	0.8675154
2014	0.8751399
2015	0.9091598
2016	0.9223365
2017	0.9046731
2018	0.8664892
2019	0.854748
2020	0.8651485
2021	0.8972428

Table OA1.3: MLRs by Year

OA-2 Additional Figures

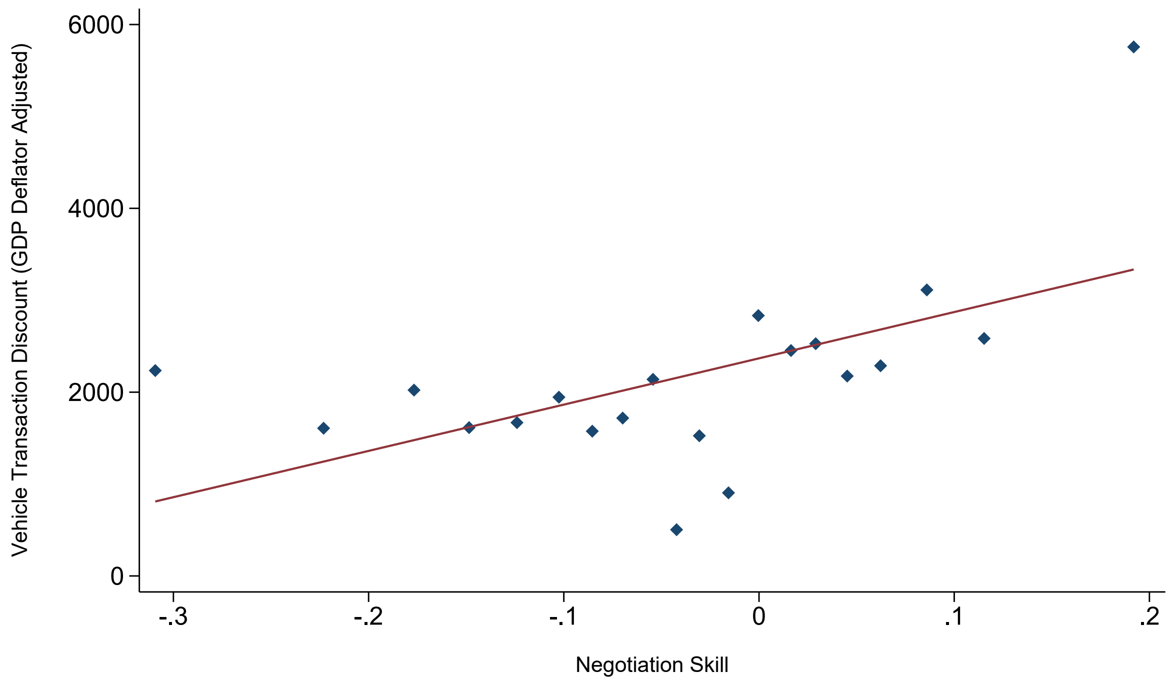

Figure OA2.1: New Vehicle Transaction Discount and Manager Negotiation Skill

This figure exhibits the correlation between vehicle transaction discounts—defined as the difference between a vehicle's invoice price (listing price) and its final sale price—and hospital managers' negotiation skills. The sample includes all new vehicles purchased by hospital managers. We manually collect invoice prices from VehicleHistory.com using the vehicles' VIN numbers. All discount are adjusted to 2023 dollars using annual GDP deflators.

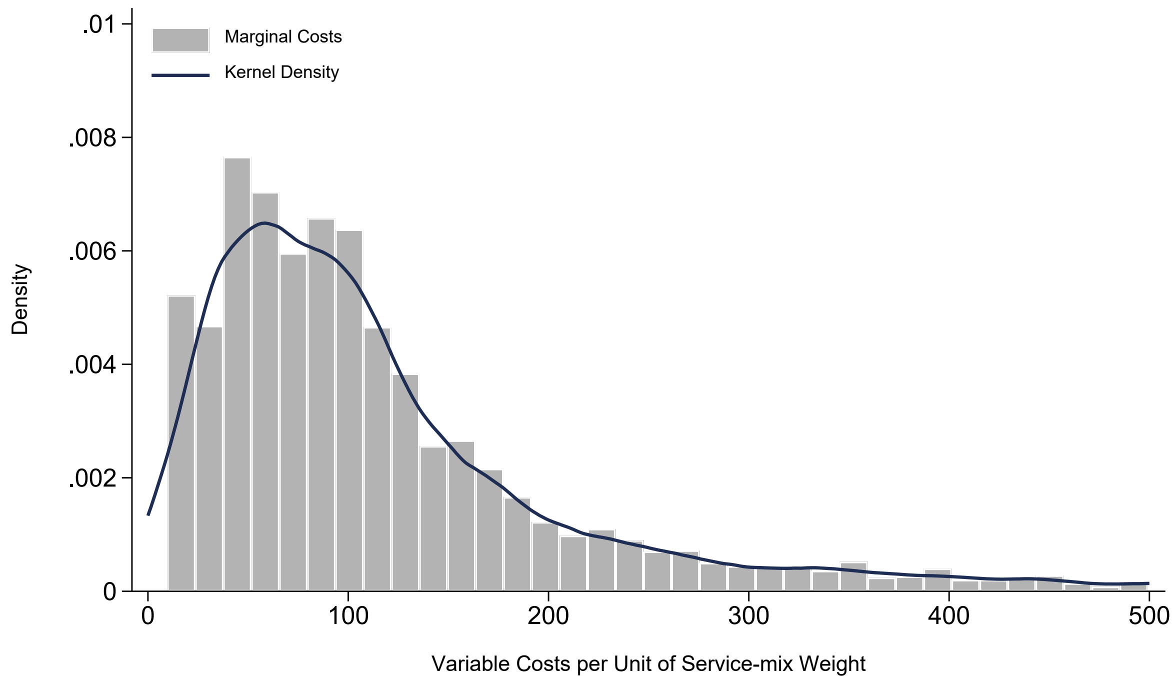

Figure OA2.2: Distribution of Marginal Costs

This figure exhibits the distribution of variable costs per unit of APC weight derived in Section OA-1.2.

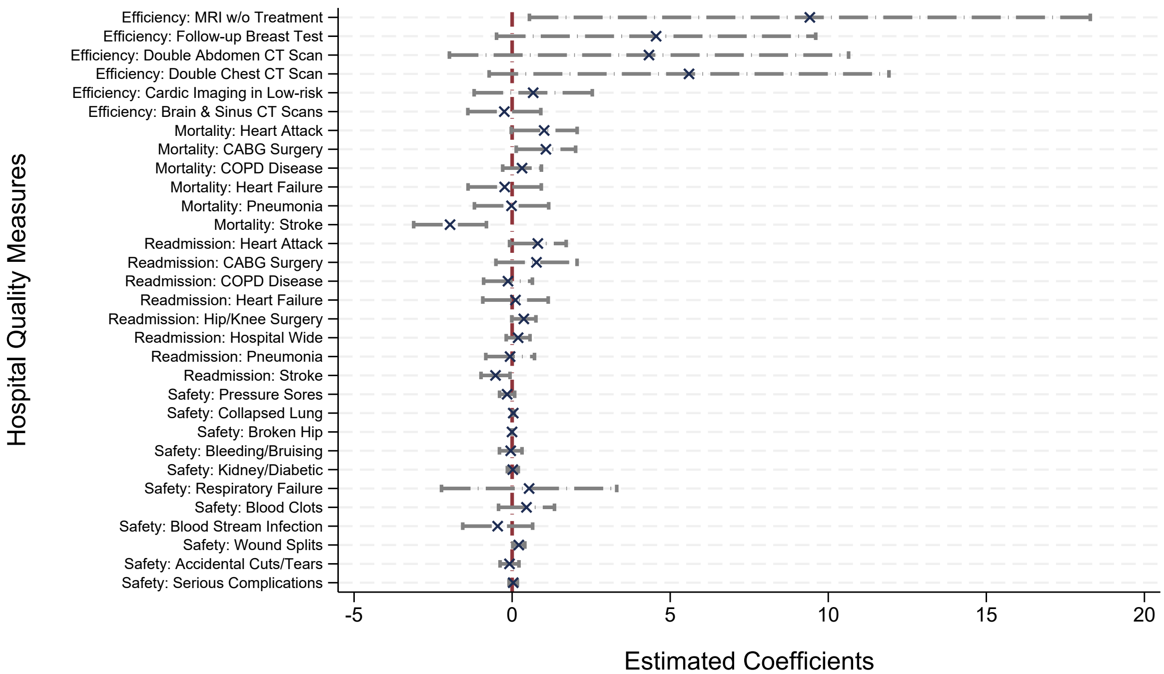

Figure OA2.3: Correlation Between Hospital Quality and Negotiation Skill

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 Physicians	Total number of full-time physicians 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.
$Num\ Current\ Properties$	Number of properties currently owned by the manager (as of December 2024, the data collection time).
$Primary\ Home\ Purchase\ Price\ (\$1,000)$	Purchase price of the manager's primary home, expressed in $1,000. Purchase prices are adjusted to 2023 dollars using annual GDP deflators.
$Medical\ or\ Pharma\ License$	Indicator for managers with a medical or pharmaceutical license.
$Business\ Certification\ (e.g.,\ CPA)$	Indicator for managers with a business-related certification, such as CPA.
$Legal\ Service\ License$	Indicator for managers with a license to provide legal services.
$Social\ or\ Other\ License$	Indicator for managers with a license in social work or other professional services.
$Vehicle\ Sale\ Price\ (in\ \$1,000)$	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: Hospital Negotiated Prices and Negotiation Skill: Alternative NS

This table reports the coefficient estimates for *NegotiationSkill* regressed on *HospitalPriceIndex* at the hospital system level and hospital facility level with the inclusion of hospital, insurer, and time fixed effects. Control variables include the number of hospital beds in hundreds, Medicaid ratio, Medicare ratio, and indicators for rural, teaching hospital, and for-profit status. Standard errors are bootstrapped. ***, **, and * represent the statistical significance level at 1%, 5%, and 10% respectively.

Panel A: Maximum NS

	DV: Hospital Price Index			
	System Level		Facility Level	
	(1)	(2)	(3)	(4)
Negotiation Skill	0.295**	0.253*	0.235**	0.206*
	(2.09)	(1.72)	(2.17)	(1.80)
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	1,301	1,301	2,854	2,854
adj-R^2	0.615	0.617	0.658	0.663

Panel B: Median NS

	System Level		Facility Level	
	(1)	(2)	(3)	(4)
Negotiation Skill	0.716**	0.661*	0.464**	0.415**
	(2.03)	(1.80)	(2.52)	(2.27)
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	1,301	1,301	2,854	2,854
adj-R^2	0.615	0.617	0.659	0.664

Table OA3.3: Robustness: Hospital Negotiated Prices and Negotiation Skill without Demographics

This table reports the coefficient estimates for *NegotiationSkill* regressed on *HospitalPriceIndex* at the hospital system level and hospital facility level with the inclusion of hospital, insurer, and time fixed effects. Control variables include the number of hospital beds in hundreds, Medicaid ratio, Medicare ratio, and indicators for rural, teaching hospital, and for-profit status. Standard errors are clustered at the manager level. ***, **, 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	0.564***	0.543**	0.395***	0.348**
	(2.69)	(2.58)	(2.98)	(2.56)
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	1,301	1,301	2,854	2,854
adj-R^2	0.616	0.618	0.659	0.664

Table OA3.4: Hospital Negotiated Prices and Negotiation Skill: Bootstrapped SE

This table reports the coefficient estimates for $NegotiationSkill$ regressed on $HospitalPriceIndex$ at the hospital system level and hospital facility level with the inclusion of hospital, insurer, and time fixed effects. Control variables include the number of hospital beds in hundreds, Medicaid ratio, Medicare ratio, and indicators for rural, teaching hospital, and for-profit status. Standard errors are bootstrapped. ***, **, 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	0.565***	0.545***	0.384***	0.339***
	(3.40)	(3.36)	(4.61)	(4.01)
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	1,301	1,301	2,854	2,854
adj-R^2	0.616	0.618	0.659	0.664

Table OA3.5: Robustness: Hospital Negotiated Prices and Negotiation Skill after Dropping Trims with Fewer Than 20 Transactions

This table reports the coefficient estimates for $NegotiationSkill$ regressed on $HospitalPriceIndex$ at the hospital system level and hospital facility level with the inclusion of hospital, insurer, and time fixed effects. Control variables include the number of hospital beds in hundreds, Medicaid ratio, Medicare ratio, and indicators for rural, teaching hospital, and for-profit status. Standard errors are clustered at the manager level. ***, **, 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	0.441***	0.425**	0.301***	0.237*
	(2.63)	(2.41)	(2.66)	(1.90)
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	1,242	1,242	2,840	2,840
$adj\text{-}R^2$	0.608	0.609	0.658	0.663