"Driving a Bargain: Negotiation Skill and Price Dispersion" by Hankins, Liu, and Sosyura

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Context: Nash-in-Nash Bargaining

- Nash-in-Nash bargaining is a workhorse of empirical industrial organization
 - Crawford and Yurukoglu (2012), Grennan (2013), Ho and Lee (2017)
- Model of mulitlateral contracting determining contracting terms between upstream and downstream firms
- E.g., between hospitals h=1,...,H and insurers i=1,...,I, and if hospital h is in network for insurer i, then reimbursements maximize bilateral surplus

$$\max_{p_{hi}} (GFT_h)^{\beta_h} (GFT_i)^{1-\beta_h}$$

 With data on reimbursements AND marginal costs, can use the Nash-in-Nash FOC to invert for bargaining weights (think of regular IO FOC inversion to recover marginal costs)

This Paper: Where Does β_h Come From?

- Not much work exploring where β_h comes from
 - Grennan (2014), Lewis and Pflum (2015)
- Key idea for this paper: If hospital executives are better at negotiating in their personal lives, do they have larger bargaining weights when they negotiate hospital reimbursements with insurers?
- Specifically, authors match data on what hospital executives pay for their personal automobiles (relative to what others pay for the same make—model—trim) and ask whether execs that pay less for their cars negotiate higher hospital reimbursements
- This is a super cool idea

Outline

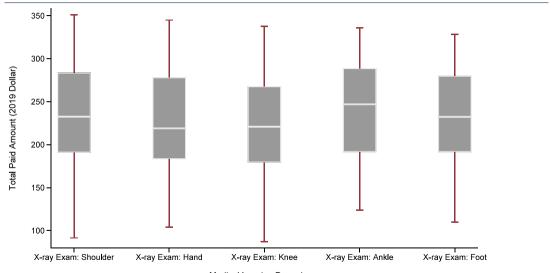
- 1. Data
- 2. Measuring Negotiation Skill
- 3. Negotiation Skill Matters
- 4. The Nash-in-Nash Model
- 5. Counterfactual
- 6. Takeaways

Data

Data Sources: Texas 2013 to 2021

- Outpatient hospital utilization and reimbursements (allowed amounts) from Clarivate Real World Data
 - 20 million outpatient hospital visits, 35% with allowed amounts
- Hospital executives from the American Hospital Association Annual Survey
 - Identify each hospital's highest ranking manager (President, CEO, etc)
 - 1,738 hospital managers at 711 facilities and 92 systems
- New and used vehicle transactions from Texas DMV
 - 50 million sales with buyer and seller names, dealer licenses (when applicable), and vehicle characteristics (model–make–trim, manufacturing year, odometer, VIN)
 - Restrict to dealer sales and retail customers and other restrictions (end up with 9 million sales)
- Data on hospital managers from Lexus Nexis Public Records
- Hospital costs from Healthcare Cost Report Information System

X-Ray Allowed Amounts



Hospital Manager Vehicles

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)



Negotiation Skill Measure $(-e_{ijdt})$

OLS of sales price for **customer** i buying vehicle j from dealer d at time t

$$y_{ijdt} = \alpha_1 \operatorname{CarChar}_{jt} + \alpha_2 \operatorname{Dem}_{it} + \alpha_3 \operatorname{NumComp}_{dt} + \alpha_4 \operatorname{Dist}_{id} + \operatorname{FE} + \varepsilon_{ijdt}$$

- y_{ijdt} : log of vehicle sale price
- ullet CarChar $_{jt}$: odometer reading group, engine displacement, country of manufacturing plant
- Dem $_{it}$: age group, marital status, number of children
- NumComp $_{dt}$: number of nearby dealers (50–mile radius)
- Dist $_{id}$: distance between buyer's residence and dealer's location
- **FE**: Vehicle Make×Model×Trim×Model-Year; Dealer; Year–Month; FIPS

Negotiation skill defined as first negative residual from this regression by manager

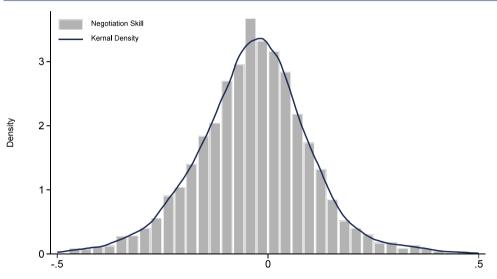
$$NS_i = -\min_t e_{ijdt}$$

 $NS_i=0.1$ means that for manager i's first vehicle purchase in the data, they got a price 10% lower than we would predict based off the OLS

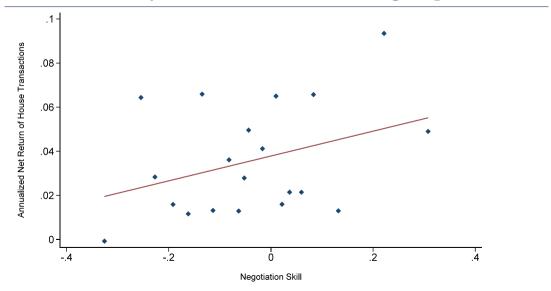
Which Controls Do We Want?

- Residuals are orthogonal to all controls by the OLS normal equations
- Vehicle make–model–trim–year fixed effects mean NS_i is calculated within make, model, trim, and year
- I.e., NS_i picks up extent to which a hospital exec gets lower prices than other customers of the same make, model, trim, and year
- If the OLS regression includes any covariate that is correlated with true negotiation skill, then NS_i will be purged of that part of negotiation skill
- Challenging: goal is to control for determinants of price that are uncorrelated with true negotiation skill, while not controlling for variables that are correlated with true negotiation skill

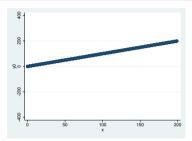
Distribution of NS_i for Hospital Managers

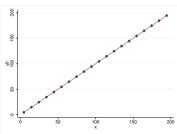


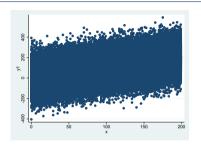
NS_i Is Positively Correlated with Housing Capital Gains

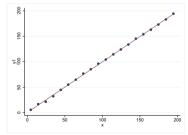


Binned Scatter Plots



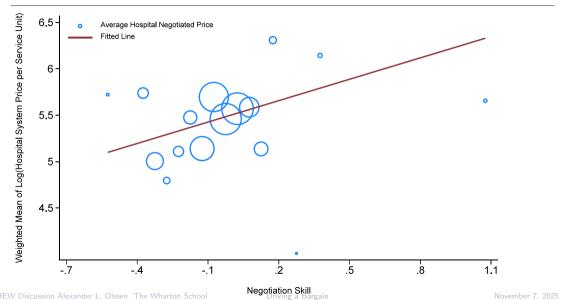








NS_i and Outpatient Hospital Prices



Regression Model

OLS of the price index that manager i negotiates for hospital h with insurer k in year t

$$Y_{ihkt} = \beta_1 \text{ NS}_i + \beta_2 \text{ Hospital Char}_{ht} + \text{Insurer FE} + \text{Hospital FE} + \text{Year FE} + \varepsilon_{ihkt}$$

- Y_{ihkt} : Log of hospital price index
- NS_i : Manager i's negotiation skill
- HospitalChar $_{ht}$: rural, teaching, for-profit, number of beds, fractions of Medicaid/Medicare patients
- Standard errors are clustered at the manager level
- If each hospital only ever had a single hospital manager associated with it in the data, then β_1 could not be estimated; estimation of β_1 relies on manager turnover

Regression Results

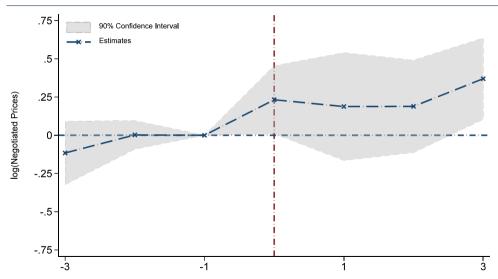
	DV: Hospital Price Index			
	System Level		Facility Level	
	(1)	(2)	(3)	(4)
Negotiation Skill	0.565*** (2.68)	0.545** (2.58)	0.384*** (2.90)	0.339** (2.48)
Insurer FE	Y	Y	Y	Y
Year FE	Y	Y	\mathbf{Y}	Y
Hospital System FE	Y	Y	N	N
Hospital Facility FE	N	N	Y	Y
Controls	N	Y	N	Y
N	1,301	1,301	2,854	2,854
adj - R^2	0.616	0.618	0.659	0.664

Regression Results X–Ray Sample

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	

Exogenous Separations Event Study





Nash-in-Nash Bargaining

Hospitals h=1,...,H and insurers i=1,...,I negotiate over networks with reimbursements chosen to maximize bilateral surplus

$$\max_{p_{hi}} (GFT_h)^{\beta_h} (GFT_i)^{1-\beta_h}$$

where

$$GFT_h = (p_{hi} - c_h) D_{hi}(N_i)$$

and

$$GFT_i = \underbrace{\gamma \, \Delta_h CS_i(N_i)}_{\text{Enrollees WTP}} - \underbrace{c_h \, D_{hi}(N_i)}_{\text{Hospital costs}} - \underbrace{\sum_{k \in N_i \setminus \{h\}} p_{ki} \, \Delta_h D_{ki}(N_i)}_{\text{Demand reallocation}}$$

First-Order Conditions

The Nash-in-Nash FOC is

$$\beta_h \left(\gamma \, \Delta_h CS_i(N_i) - c_h \, D_{hi}(N_i) - \sum_{k \in N_i \setminus \{h\}} p_{ki} \, \Delta_h D_{ki}(N_i) \right) = \underbrace{\left(p_{hi} - c_h \right) D_{hi}(N_i)}_{\text{Hospital profits}}$$

- Demand is estimated via a multinomial logit, and prices and costs are observed
- If we knew γ , then we could recover β_h directly from the FOCs, like when IO economists use an assumption of pricing conduct (e.g., Nash Bertrand) and FOCs to recover marginal costs

Estimating γ with an MLR Moment

Estimate γ (how much insurers care about enrollees' WTP) following Ho and Lee (2017) by adding a moment that matches the average medical loss ratio (MLR) of insurers in the data to the MLR from the model

$$\mathbb{E}\left[\mathrm{MLR}_{t} - \sum_{i \in \{0,\dots,I\}} \theta_{it} \frac{\sum_{k \in N_{i}} p_{kit} D_{kit}(N_{i}(t))}{\gamma CS_{it}(N_{i}(t))}\right] = 0$$

where θ_{it} are enrollment weights for insurer i at time t



Counterfactual Results

Following Grennan (2014), measure price dispersion by

$$var\left(\log(p_{hi}-c_h)\right)$$

where $h \in N_i$ represents hospitals within insurer i's network.

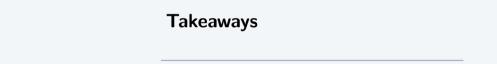
Counterfactual: Equal NS eliminates differences in managers' negotiation skills:

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

Counterfactual: Equal β eliminates differences in hospital bargaining power $\beta_h(t)$:

$$\beta_h^c(t) = \overline{\beta}$$

	Model Equilibrium	Counterfactual: Equal NS	Counterfactual: Equal Beta	
Price Dispersion	1.131	1.072	0.922	
Δ Dispersion Compared to Equ.	-	-0.059	-0.209	
Share (%) Explained by NS		${(-0.059)/(-0.209) = 28.23\%}$		



Which Managers Matter?

- Paper looked at vehicle purchases of hospital managers, not insurance managers
 - Good reasons for this
- Focusing on hospital managements, which managers matter for reimbursed prices?
 - Is it always the CEO? Might the CEO matter more for reimbursements in smaller systems?

Contributions to Remember

- Super cool idea that leverages super cool data
- Hospital managers that pay less for their cars work for outpatient hospitals that get reimbursed more for care
- This paper's measure of hospital managers' negotiation skill seems to explain a substantial proportion of price variation across outpatient hospitals

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