

The efficiency of real-world bargaining: evidence from wholesale used-auto auctions

Author: Bradley Larsen, presented by Louise Guillouët

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Motivation

- This paper: not exactly about auctions but a different kind of allocation rule, alternative offers bargaining.
- Bargaining theory: can reach efficient contracts under certain conditions.
- BUT not necessarily first-best when there is uncertainty. (Myerson-Satterthwaite 1983).
- What happens in real life? How far are outcomes from efficiency frontier?
- This paper is the first to quantify the efficiency of bargaining.

Empirical Context

- Wholesale of used cars sold through auction houses.
- Seller set a secret reserve price.
- Ascending auction, button style.
- If the final price is under reserve price, alternating offers bargaining between seller and highest bidder.
- Great context to study bargaining because get idea of valuation of players from the auction.
- And cars have a lot of characteristics that are valued in the market (blue book and beyond).
- Data used: starting from 6 auction houses, 2007-2010, 600,000 cars sold in 1m runs. Trim down to about 270,000 runs in two groups, used-car dealers vs fleet/lease.

Framework: backward induction

- Assumptions: Participants are risk neutral and their valuations follow symmetric IPV (one for sellers, one for buyers) that includes relevant common information about cars.
- During bargaining, players face a per offer disutility and auction house forbids bargaining price to go below auction price.
- Bargaining: for seller, accepting: get p , quitting: get s , counter-offer:

$$\max_p \left\{ p\delta Pr(D^B = A|H) + s(\delta Pr(D = Q|H) + 1 - \delta) \right. \\ \left. + \delta Pr(D = C|H)(\delta E[\max \dots] + s(1 - \delta)) \right\} - c_s$$

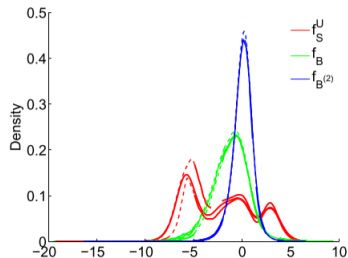
- Note that this is too complex to solve for analytically
- Button-style auction: truth-telling is the weakly dominant strategy.
- Setting the reserve price: find that it is strictly increasing in true valuation.

Estimating valuations

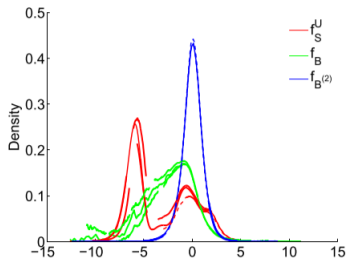
- Adjust for auction house fees and “auction-level heterogeneity” i.e. car characteristics. Too many?
- For buyers, use auction price = second order statistic of value distributions and assume distribution of number of bidders.
- For sellers, establish bounds based on reaction to auction price, using revealed preference argument (Haile and Tamer style): seller never accepts auction price below value and never walks away at an auction price above her value.
- Interpretation of figure 1: enables to establish distribution of seller valuation.

Results: value distribution

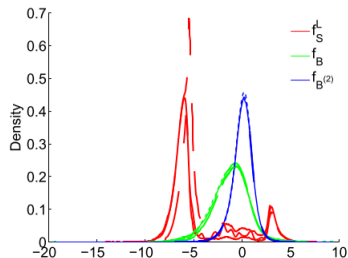
(a) Dealers, seller upper bound



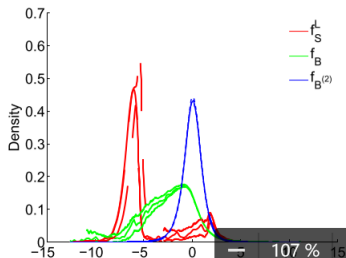
(b) Fleet/lease, seller upper bound



(c) Dealers, seller lower bound



(d) Fleet/lease, seller lower bound

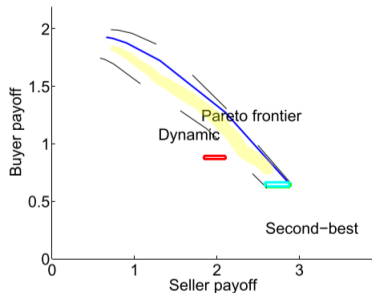


Efficiency of bargaining

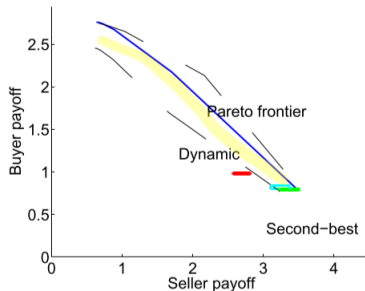
- First: what is the Pareto-frontier? Need to model the bargaining game.
- Assume there is a single equilibrium and there is a function separating buyers/sellers who trade from those who don't (sort of monotonicity)
- Can identify the probability of trade at the Pareto-frontier as a function of estimated valuation distributions.
- And compare it to observed probability of trade.
- Real-world bargaining is not too far from efficiency in this case (85% of first-best, 97% of second-best)

Results: bargaining efficiency

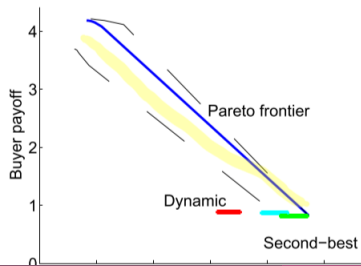
(a) Dealers, seller upper bound



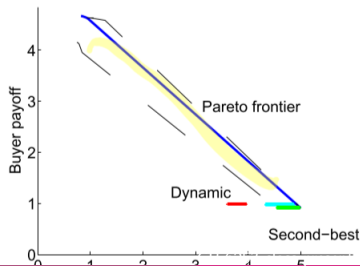
(b) Fleet/lease, seller upper bound



(c) Dealers, seller lower bound



(d) Fleet/lease, seller lower bound



Conclusion

- An interesting and innovative idea.
- Good use of empirical context, very careful implementation of all the tools.
- Real world bargaining seems to be doing pretty good.
- Counterfactuals are not completely satisfying: they are not real-world mechanisms: random bidder bargaining? When would that happen? Suggestions: different auction
- I don't understand why there are not more differences in the results for cars that go through the auction houses for the second or third time (learning)