The Efficiency of Real-World Bargaining: Evidence from Wholesale Used-Auto Auctions

Bradley Larsen, 2014

GR6255 class presentation, Spring 2018

Motivation

Research Question

How efficient is real-world bargaining?

- Evaluates this question in the context of used-auto auctions
- Setting is convenient because it allows for non-parametric estimation of valuation distributions of both sellers and buyers (from the auction part)
- Efficiency loss comes from both asymmetric information and allocation mechanism choice

Setting

Wholesale used-auto auction industry

- 15 million used cars pass through one of the 320 wholesale auction houses (almost 1/2 of the total US used-car market)
- Around 60% of the cars are sold, for \$8k-9k per car, for a total revenue of over \$80 billion per year
- Majority of auction house revenue comes from fees paid by the buyer and seller when trade occurs
- Buyers - new and used car dealers; sellers - new or used car dealers ("dealers") or large institutions such as banks, manufacturers, or rental companies ("fleet/lease")

The Model (Timing)

Timing of the model:

- Seller sets a secret reservation price
- N bidders bid in an ascending auction
- A car is sold if the second highest bid exceeds the secret reservation price
- If not, the winning bidder can enter negotiation with the seller, starting from the auction price
- If the bidder enters bargaining, then the seller and the bidder make alternating offers (in each stage of bargaining game, bidder/seller can *accept*, *quit*, or *make a counteroffer*)

The Model (Assumptions)

1. Ascending button auction with N bidders, where bidders have private values $\tilde{B}_i = W + B_i$, with $B_i \sim F_B$.
2. Risk-neutral seller has private valuation $\tilde{S} = W + S$, with $S \sim F_S$.
3. In the bargaining game:
    - Players incur costs from making an offer (c_S, c_B), but quitting is costless
    - Bargained price cannot fall below the auction price

Conditional on W (auction-level heterogeneity), buyers and sellers have independent private values.

Results derived from the model are used for identification.

Data

Data from six auctions houses with high market share in "different regions"

- January 2007 to March 2010
- Over 600,000 cars with 1 million records (on average each car goes 1.67 times through lanes)
- Huge list of auction characteristics
- Elimination of the outliers:
  - less than 1 year and more than 16 years old
  - less than 100 or greater than 300,000 miles
- Two samples: dealers and fleet/lease cars
  - Fleet/lease cars tend to be newer with lower reservation prices and more likely to sell
- 77% of deals end with the auction or immediately after
  - Few deals reach 5th period of bargaining (average price $600 above auction price)
  - These latter period observations have higher reservation prices

Estimation strategy

Five-step estimation procedure

- Accounting for auction house fees
- Controlling for observed heterogeneity
- Controlling for unobserved heterogeneity
- Estimating the distribution of buyer valuations through on an order statistic inversion
- Estimating bounds on the distribution of seller valuations using revealed preferences arguments

Estimation strategy (steps 1-3)

Accounting for auction house fees

- Buyers and sellers pay fees when transactions are completed
- Linear regression models: $h^t(p) = \alpha_0^t + \alpha_1^t p$, where $t \in \{S, B\}$

Controlling for observed heterogeneity

- The model implies that auction-level heterogeneity valued equally by buyers and sellers is additive
- Joint regression of reserve and auction prices on many observables, e.g. odometer reading, car-make dummies

Controlling for unobserved heterogeneity

- Identification of the densities of unobserved heterogeneity, reservation price, and the buyer's second order statistic by Kotlarski (1967)
- Densities are approximated by Hermite polynomials and estimated with maximum likelihood

Estimation strategy (steps 4-5)

Distribution of Buyer Valuations F_B

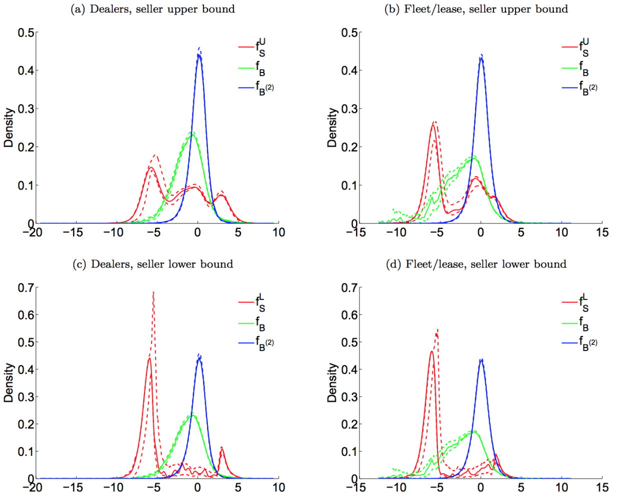
- Proposition 1 (BNE in button auction): the auction price is the second order statistic of buyer valuations $B^{(2)}$
- Assume a known distribution for N. Poisson distribution, $\lambda = 7, 10$ for dealer and fleet/lease sales respectively
- We obtain the distribution of buyer valuations F_B from the CDF of the 2nd order statistic $F_{B^{(2)}}$ and the distribution of bidders

Distribution of Seller Valuations

- Bounds of F_S are obtained from the observation of sellers' initial responses to the auction price (first phone call)
  $Pr(Accept|\cdot) \leq Pr(\tilde{S} + X'\gamma \leq \text{net bid value})$ [never accept if $<\tilde{S}$]
  $Pr(Quit|\cdot) \leq Pr(\tilde{S} + X'\gamma \geq \text{net bid value})$ [never reject if $>\tilde{S}$]
- Upper and lower bounds on F_S for realization v are estimated as $\tilde{L}(v) \equiv Pr(A|v) \leq F_{\tilde{S}} \leq Pr(\neg Q|v) \equiv \tilde{U}(v)$

Estimation results

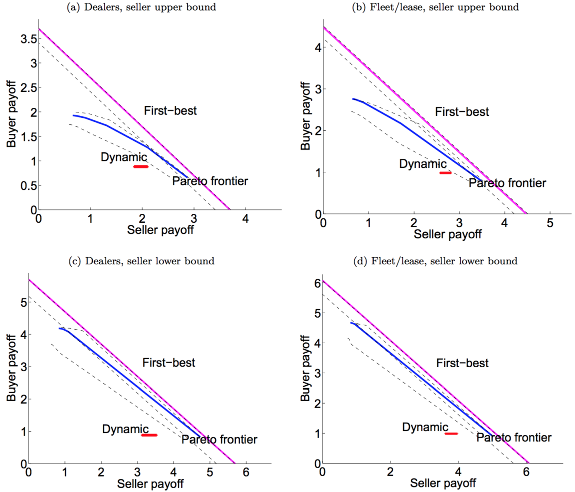
Figure 2: Densities of seller valuations, buyer valuations, and auction price



Notes: Densities of seller valuations (in red), buyer valuations (in green), and auction price (in blue). Panels (a) and (b) display seller distribution upper bound. Panels (c) and (d) display lower bound. Dashed lines mark pointwise 95% confidence bands from 200 bootstrap replications of full estimation procedure. Units = $1,000.

Counterfactuals

Figure 5: Expected gains from trade in dynamic mechanism, on Pareto frontier, and on first-best efficient frontier.



Notes: Expected gains from trade, in buyer and seller payoff space, for Pareto frontier (in blue), current dynamic mechanism (in red), and first-best efficient frontier (in magenta). Dashed lines surrounding the frontiers, and solid lines about dynamic mechanism, mark pointwise 95% confidence bands from 200 bootstrap replications of full estimation procedure. Units = $1,000.