

# Sustainable Intermediation: Using Market Design to Improve the Provision of Sanitation<sup>1</sup>

Jean-François Houde<sup>a</sup>   Terence Johnson<sup>b</sup>  
Molly Lipscomb<sup>c</sup>   Laura Schechter<sup>d</sup>

<sup>a</sup>UW-Madison & NBER

<sup>b</sup>University of Notre Dame

<sup>c</sup>University of Virginia

<sup>d</sup>UW-Madison

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# Sanitation in Senegal

- Despite rapid urbanization, Senegal *under-invested* in public infrastructure
- On average, every 6-12 months households need to *desludge* their pit
- Three technologies:
  - ▶ *Mechanized*: Truck + Pump + Treatment center (?)
  - ▶ *Family*: Family member + Street or open water
  - ▶ *Baaypell*: Hired worker + Street or open water
- Both manual options are *illegal* (rarely enforced)
- 47% of desludging in Dakar are performed with a truck, 27% by a family member, and 25% by a hired manual

# What explains the low take-up for Mechanized desludging?

- **Our focus:** Mechanized Prices are 60% Higher than *Baaypell*
- **Key market frictions:**
  - 1 Decentralized market with search frictions
  - 2 Trade association and collusion
  - 3 Renegotiation and price discrimination

# Intervention: Just-in-time Auction Platform

- Experimental auction platform:
  - ① Frequent, centralized, anonymous auctions reduce search times, undermine collusion, and mitigate price discrimination
    - ★ Desludgers know the neighborhood and how many opponents they face (for half the auctions), but not who they are bidding against
  - ② Implement just-in-time procurement auctions for desludging services: invite 8-20 desludgers to over 5,000 between 2013-2016
  - ③ The platform randomizes how many and which desludgers are invited: auction “laboratory”, but is not socially optimal
- **Summary:** Less than 30% of calls end in a successful transaction, and the average clearing price is comparable to market price. Can we improve on this?

# Market Design Question

- **Houde et al. (2024):** Exploit random variation in invitations and auction formats to
  - ① Test the null hypothesis of competitive bidding
  - ② Back-of-the-envelope measure of the effect of increasing competition
- **Key takeaways:**
  - ▶ Roughly 3/4 of active bidders behave non-competitively
  - ▶ How? Rely on “coarse” bidding strategy resulting in ties and higher bids
- **This paper:** What would be the take-up rate under an improved auction design?
  - ▶ Non-random invitations
  - ▶ Competitive bidding
- **How?**
  - ▶ Estimation distribution of WTP and cost
  - ▶ Simulate counter-factual equilibrium with *maximal* competition

# Outline

- 1 Auction Platform
- 2 Model Estimation
  - Demand
  - Desludging Cost
  - Outside Option
- 3 Platform (re)-design
- 4 Conclusion

# Auction Platform Design: Sequence of Actions

- ① Client  $t$  calls the platform
- ② Auction format (50%): (i) open, or (ii) sealed-bid.
- ③ Random set of bidders are invited (8-21)
- ④ Reminders: (i) time left to bid, and (ii) current lowest bid (open)
- ⑤ Duration = 65 minutes
- ⑥ Client is offered the lowest bid, and decides to accept or reject.
- ⑦ All bidders are notified of the winning bid (not the identity)



# Model: Bidding in the Sealed-bid Auction

- Information available to bidders regarding client  $t$  ( $I_t$ ):
  - ▶ *Location*: Nearest landmark
  - ▶ *Competition*: Number of invited bidders
  - ▶ *Time*: Hour, day, month, etc.
- Bidder  $i$ 's expected profits from submitting a bid  $b_i$ :

$$\pi_{it}(c_{it}) = \max_{b_i \in \mathcal{B}} (b_i - c_{it}) D(b_i | I_t) \Pr(\text{Win} | b_i, I_t)$$

Where,

- ▶  $c_{it}$  is the (private) marginal cost of performing job  $t$  for bidder  $i$
  - ▶  $D(b_k | I_t)$  is the prob. that  $b_k$  is accepted (i.e. demand)
  - ▶  $\Pr(\text{Win} | b_k, I_t)$  is the probability of winning the auction (i.e. beliefs)
- Conditional on being invited, bidder  $i$  submits an offer if:

$$E_{\gamma_{it}} [\pi_{it}(\bar{c}_{it} + \gamma_{it}) | I_t, \bar{c}_{it}] > \kappa_{it} + \epsilon_{it}$$

where  $\gamma_{it}$  and  $\epsilon_{it}$  are IPV.



# Roadmap

We'll work backwards through the game/estimation, then discuss the counterfactuals:

- 1 Demand:  $D(b|I_t)$
- 2 Desludging cost:  $\bar{c}_{it}, F(\gamma_{it})$
- 3 Outside option:  $\kappa_i, G(\epsilon_{it})$
- 4 Counter-factual: Platform (re)-design

## Step 1: Demand Estimation

- **Goal:** Estimate the distribution of WTP from Accept/Reject decisions of clients:

$$w_t = x_t\beta + u_t/\alpha, \quad u_t \sim \mathcal{N}(0, 1)$$

$$\Rightarrow \Pr(\text{Accept} | b_t^*, x_t) = 1 - \Phi\left(\alpha \ln b_t^* - x_t\tilde{\beta}\right)$$

- **Identification problem:** In equilibrium, the winning bid can be correlated with  $u_t$ 
  - ▶ Solution: Rivers and Vuong (1988)
  - ▶ **IV:** Any variable that shifts the clearing prices but is unobserved by the household is a valid instrument: We use number of *active* bidders for that neighborhood
- **Summary of demand results:**
  - ▶ Cannot reject the null hypothesis of exogenous bids (i.e. no auction unobserved heterogeneity)
  - ▶ Very steep platform demand curve: Average elasticity of -3.77

## Step 2: Desludging Cost Estimation

- **Expected profits:** Bidder  $i$ 's expected profits from submitting a bid  $b$  with cost  $c_{it}$  with information set  $I_{it}$ :

$$\pi_i(b, c_{it}, I_{it}) = \underbrace{\Pr[\text{Win}|b, I_{it}]}_{\text{Pr(Winning)}} \underbrace{D[b|I_{it}]}_{\text{Demand}} \underbrace{(b - c_{it})}_{\text{Margin}}$$

- **Probability of winning:** Let  $\tilde{A}_{-i}$  be the number of active bidders besides  $i$ , so

$$\begin{aligned} \Pr[\text{Win}|b, I_{it}] &= \underbrace{\Pr[\tilde{A}_{-i} = 0|I_{it}]}_{\text{Monopolist}} \\ &+ \underbrace{(1 - \Pr[\tilde{A}_{-i} = 0|I_{it}])}_{\text{Contested auction}} \underbrace{\Pr[\min b_{-i} > b | \tilde{A}_{-i} > 0, I_{it}]}_{\text{Lowest bidder}} \end{aligned}$$

- Traditional approach (Guerre, Perrigne and Vuong, 2000):

$$\frac{b_{it} - \hat{c}_{it}}{b_{it}} = - \left[ \frac{d\text{Prob. Transaction}}{dBid} \right]^{-1} \frac{\hat{\Pr}[\text{Win}|b_{it}, I_{it}] \hat{D}[b_{it}|I_{it}]}{b_{it}}$$

# Cost Estimation: Beliefs Calculation

- **Belief estimation:** Calculate the frequency,  $\hat{\Pr}[\text{Win}|b', l_t]$ , by re-sampling rivals' bids/participation decisions in other auctions with *similar* attributes  $l_{t'}$ . How?
  - ▶ Let  $l_t = \{\text{lat}_t, \text{long}_t, \text{hour}_t, \text{date}_t, \text{Nb. invitees}_t\}$
  - ▶ We sample bids from auctions  $t'$  with probability:

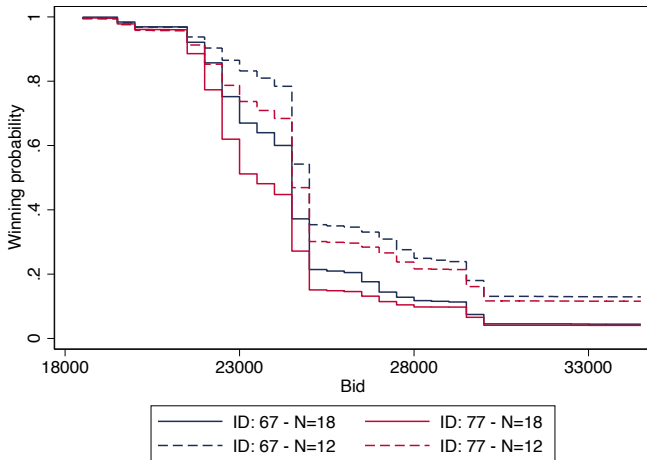
$$w(l'_t, l_t) = \frac{K(l'_t, l_t)}{\sum_l K(l_l, l_t)}$$

where  $K(l_s, l_t)$  is the product of four kernels: distance, hours, date and number of invited bidders. Density of auction characteristics

- Three alternative belief models:
  - ① *Heterogenous:* Sample **rivals'** bids from dist. of sealed-bid auctions
  - ② *Symmetric:* Sample **2nd-lowest** bids from dist. of sealed-bid auctions
  - ③ *Revisable:* Sample **current lowest-bid** from open auctions (at minute 50)
- **Motivation:**
  - ▶ (1) and (2): Consistent with Bayes-Nash beliefs
  - ▶ (3): Bidders observe  $\approx$  2nd-lowest **only** in the open auction

# Example: Win probability for two bidders and two auctions

Beliefs = Heterogenous



# Cost Estimation: Revealed Preference Inequalities

- Profit maximization implies:

$$\begin{aligned}\hat{H}(b_{it}|I_t)(b_{it} - c_{it}) &= \hat{\Pr}[\text{Win}|b_{it}, I_t] \hat{D}[b_{it}|I_t](b_{it} - c_{it}) \\ &\geq \hat{\Pr}[\text{Win}|b', I_t] \hat{D}[b'|I_t](b' - c_{it}) = \hat{H}(b'|I_t)(b' - c_{it}), b' \in \mathcal{B}\end{aligned}$$

- **Round bids and ties:** If consideration set is very rich (e.g.  $\mathcal{B} = \mathbb{R}_+$ ), some bids  $b_{it}$  are *dominated* for any  $c_{it} \geq 0$  (e.g.  $b_{it} = 25K$ ).
- **Solution:** Heterogeneous consideration sets
  - ▶ *Inattentive/collusive bidders:*  $\mathcal{B}^0 =$  Bids chosen more frequently than 5% (6)
  - ▶ *Competitive bidders:*  $\mathcal{B}_i = \mathcal{B}^0 +$  Bids chosen more frequently than 5% by bidder  $i$  (6-29)
  - \* Sample selection: Bidders who submit at least 20 bids (46 bidders)

CS and Experience

Ex: Small CS

Ex: Large CS

# Cost Estimation: Revealed Preference Inequalities

- For each chosen bid  $b_{it}$ :

$$\begin{aligned}\hat{H}(b_{it}|I_t)(b_{it} - c_{it}) &\geq \hat{H}(b'|I_t)(b' - c_{it}), b' \in \mathcal{B}_i \\ \rightarrow c_{it} &\leq \frac{\hat{H}(b_{it}|I_t)b_{it} - \hat{H}(b'|I_t)b'}{H(b_{it}) - H(b')} = \mu_{it}(b_{it}, b'), \forall b' > b_{it} \\ \rightarrow c_{it} &\geq \frac{\hat{H}(b'|I_t)b' - \hat{H}(b_{it}|I_t)b_{it}}{H(b') - H(b_{it})} = \mu_{it}(b', b_{it}), \forall b' < b_{it}\end{aligned}$$

- If  $c_{it} = x_{it}\beta + \gamma_{it}$ , the likelihood can be formed as follows:

$$\Pr(b_{it} = b_k | I_t, x_{it}) = F(\mu_{it,k} - x_{it}\beta) - F(\mu_{it,k-1} - x_{it}\beta)$$

where  $\mathcal{B}_{it} = \{b_1 < \dots < b_k < \dots < b_{K_i}\}$  is the sorted set excl.  $b_{it}$ , and  $\mu_{it,k} = \mu_{it}(b_k, b_{k+1})$ .

- ▶ *Semi-parametric estimator*: In practice, we use a mixture-of-normals to approximate  $F(\gamma)$  (Coppenjans, JoE, 2001).

## Estimation Results: Desludging Cost Distribution

VARIABLES	Beliefs: Heterogeneous		Beliefs: Revisable auction	
	(1)	(2)	(3)	(4)
Distance (km)	0.020 (0.001)	0.020 (0.001)	0.021 (0.001)	0.021 (0.001)
Association	0.261 (0.020)	0.261 (0.020)	0.215 (0.020)	0.214 (0.020)
1(Single truck)	0.088 (0.011)	0.087 (0.011)	0.081 (0.011)	0.081 (0.011)
Nb. Trucks	0.058 (0.005)	0.058 (0.006)	0.062 (0.006)	0.062 (0.006)
Nb. bidders invited		0.001 (0.001)		0.002 (0.001)
% invitees same garage		-0.034 (0.027)		-0.070 (0.027)
Mixture weight: type 1	0.796	0.197	0.865	0.880
Location: type 2	-0.031	-0.028	-0.005	0.048
Std-deviation: type 1	0.230	0.231	0.256	0.279
Std-deviation: type 2	0.504	0.509	0.575	0.585
% violations	0.063	0.063	0.037	0.037
LLF/N	-2.334	-2.334	-2.156	-2.156

Control variables (FE): neighborhood, garage, company, month, year, dow, and client lat/long coordinates (continuous). Mean bid: 2.71.



## Step 3: Participation Probability Model

- Timing assumption:
  - 1 Bidders observe:  $I_t, \bar{c}_{it}, \kappa_{it}, \epsilon_{it}$
  - 2 Entry decision:  $a_{it} = 1$  if  $E(\pi_{it}|\bar{c}_{it}, I_t) > \kappa_{it} + \epsilon_{it}$
  - 3 If  $a_{it} = 1$ , each bidder observes  $\gamma_{it}$  and submits  $b_{it}$
- Expected profits based on the limited attention model:

$$E(\pi_{it}|\bar{c}_{it}, I_t) = \int \max_{b' \in \mathcal{B}_i} \hat{H}(b')(b' - \bar{c}_{it} - \gamma) f(\gamma|\hat{\theta}) d\gamma$$

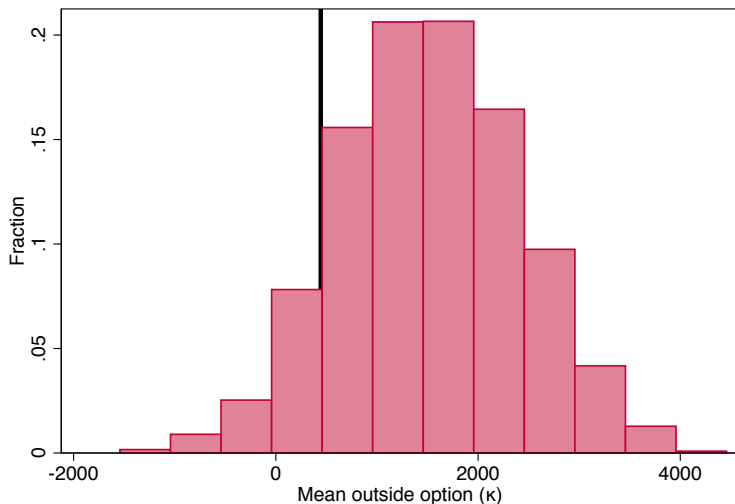
where  $\bar{c}_{it} = x_{it}\hat{\beta}$ .

- If  $\epsilon_{it} \sim N(0, \sigma_\epsilon^2)$  and  $\kappa_i = z_i\delta$ , this leads to a Probit model:

$$\Pr(a_{it} = 1|I_{it}, x_{it}, z_{it}) = \Phi\left(\frac{E(\pi_{it}|\bar{c}_{it}, I_t) - z_{it}\delta}{\sigma_\epsilon}\right)$$

# Average Outside Options – $\kappa_{it}$ (Units: CFA)

Vertical line = Expected platform profits (450)



Variance decomposition: (i) hour and day (.02), (ii) hour, day and month (.28).  $\text{Corr}(\kappa, c) = -.21$ .

## Step 4: Counter-factual Platform Design

- **Assumptions:**

- ▶ Platform designer select bidders to invite,  $A_t$ , and allocate the contract to the most efficient provider
  - ▶ Platform designer observes  $(\bar{c}_{it}, \kappa_{it})$ , and the distribution of private values  $(w_{it}, \gamma_{it}, \epsilon_{it})$
  - ▶ Firms decide to enter simultaneously and non-cooperatively
- Using the revelation principle (Myerson, 1981), the incentive compatible expected payment to firm  $i$  is:

$$E_{\tilde{A}_t, \gamma_t, w_t} \left[ P_{it}(\gamma_{it}, \gamma_{-i,t}, w_t, \tilde{A}_t) (\bar{c}_{ij} + \psi(\gamma_{it})) \mid A_t \right]$$

- Where,

- ▶  $P_{it}(\gamma_{it}, \gamma_{-i,t}, w_t, \tilde{A}_t)$  is a (decreasing) probability of selecting firm  $i$
- ▶  $\tilde{A}_t$  is the set of bidders competing for client  $t$
- ▶  $\bar{c}_{ij} + \psi(\gamma_{it}) = \bar{c}_{it} + \gamma_{it} + \frac{F(\gamma_{it})}{f(\gamma_{it})}$  is the *informationally* adjusted cost of  $i$

## Step 4: Counter-factual Platform Design

- The expected profit conditional on participating is:

$$\begin{aligned}\bar{\pi}_{ij}(A_t) &= E_{\tilde{A}_{it}, \gamma_{it}, w_i} \left[ \int_{\gamma_{ij}}^{\infty} P_{ij}(z, \gamma_{i,-j}, w_i, \tilde{A}_{it}) dz \middle| A_t \right] \quad (\text{Ass.: Efficient selection.}) \\ &= E_{\tilde{A}_{it}, \gamma_{it}} \left[ \underbrace{\int_{\gamma_{ij}}^{\infty} D_i(\bar{c}_{ij} + \psi(z)) \Pr \left( \min_{k \in \tilde{A}_{it}} \bar{c}_{kt} + \psi(\gamma_{kt}) > c_{it} + \psi(z) \right) dz}_{E(\pi_{it} | \gamma_{it}, \tilde{A}_s)} \middle| A_t \right]\end{aligned}$$

where the distribution of  $\tilde{A}_{it}$  is derived from the entry prob. of rivals.

- Bayes-Nash equilibrium:** Participation is consistent with  $\bar{\pi}_{it}(A_t)$ ,

$$\rho_{it}(I_t, A_t) = \Phi \left( \frac{\bar{\pi}_{in}^{\rho}(A_t) - \kappa_j}{\sigma_{\epsilon}} \right).$$

- Solution algorithm:** (Importance sampling)
  - ▶ Compute  $E_{\gamma_{it}}(\pi_{it} | \tilde{A}_s)$  for random list  $s = 1, \dots, S$  (independent of  $\rho$ ).
  - ▶ At iteration  $k$ , evaluate the probability of observing each  $\tilde{A}_s$  using  $\rho_{it}^{k-1}$
  - ▶ Update the best-response of each player until convergence

BNE entry prob.

# Counter-Factual Results: Comparison to Current Platform

Invitation list: Every active bidders (46)

Nbh.	N	Counter-factual			Observed platform (sealed)		
		Offers	Entry Freq.	Accept Freq.	Offers	Entry Freq.	Accept Freq.
Almadies	81	16.82	0.25	0.76	24.60	0.16	0.42
Dakar Plateau	23	20.03	0.21	0.67	27.95	0.13	0.30
Grand Dakar	34	17.33	0.23	0.62	23.38	0.18	0.21
Parcelles	68	14.50	0.27	0.89	22.05	0.19	0.46
Guediawaye	296	17.91	0.30	0.62	24.54	0.18	0.27
Niayes	631	21.32	0.27	0.47	28.17	0.13	0.25
Pikine	205	16.43	0.28	0.60	22.28	0.20	0.33
Rufisque	81	24.25	0.18	0.08	25.51	0.08	0.05
Thiaroye	683	18.02	0.28	0.67	24.98	0.18	0.33
<b>Total</b>	2102	18.93	0.27	0.58	25.53	0.16	0.29

**Notes:** Price units: 1,000 CFA. Sample: Sealed-bid auctions.  
Specification: Heterogenous belief model (1).

# Implementation

- The sealed-bid auction is a strategically complicated game to play...
  - ▶ Round numbers + Ties
- Relative to sealed-bid auctions, the revisable auction sample is (almost) revenue equivalent and leads to significantly fewer ties:

	Winning bid (log)	1(Winner Round)	1(Last 55min.)
ATE - Old	0.005 (0.005)	-0.096 (0.021)	0.233 (0.015)
ATE - Both	0.008 (0.004)	-0.096 (0.0115)	0.228 (0.0152)

- Feasible mechanism:
  - 1 Send invitation SMS to all potential bidders: Are you interested in client  $t$ , Y/N?
  - 2 Run revisable auction among interested bidders

# Conclusion

- **Estimation results:**

- ▶ Randomization provides great variation for measuring demand and cost
- ▶ Firms make low expected profits, driving low participation, but have high margins, and consumers are very elastic
- ▶ The lowest cost firms have high outside option value, drop out of the market relatively quickly

- **Counter-factual results:**

- ▶ Improving the auction design and eliminating non-competitive bidding would decrease prices by 25% and double the take-up rate
- ▶ Real-time auction platform = Market-based solution to a development problem

**THANK YOU!**

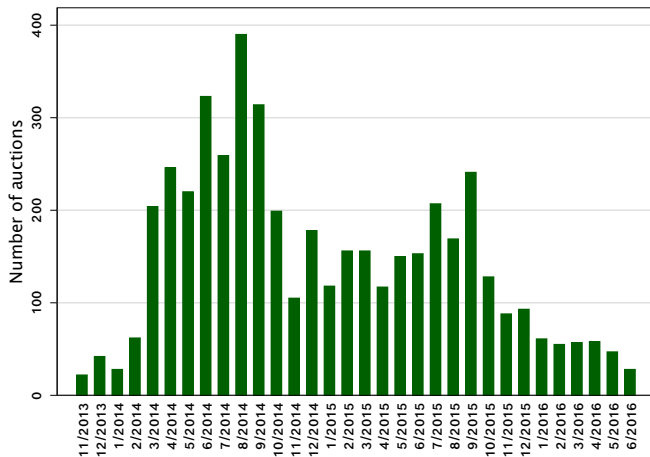


# Auction Platform: Summary Statistics

	Old platform		New platform	
	Average	SD	Average	SD
Nb. of auctions	2669		2005	
Nb. of clients	2488		1680	
Nb. of completed jobs	862		481	
Auction format = Open	0.501	0.500	0.495	0.500
Probability of bidding	0.115	0.153	0.102	0.140
Invited auctions per firm	352	240	239	102
Number of firms	109		92	
Number of potential bidders	14	2	11	2
Valid bids per successful auction	2.878	1.529	1.848	1.042
Auctions with zero bids (%)	0.069	0.254	0.283	0.450

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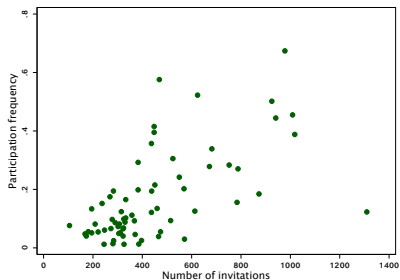
# Auction Platform: Number of Auctions per Month



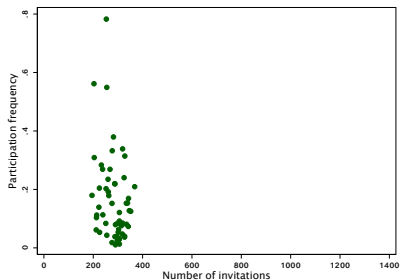
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# Auction Platform: Total Invitations per Desludger

Old Platform

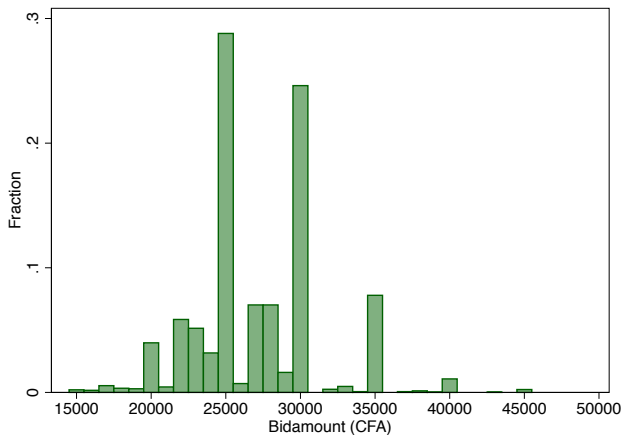


New Platform



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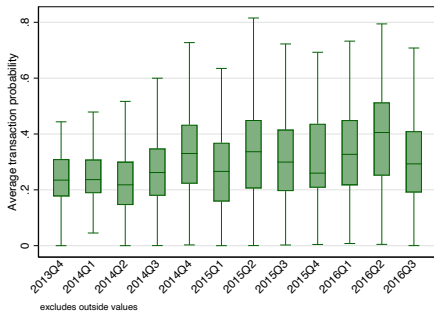
## Feature 3: Ties and round bids are very common



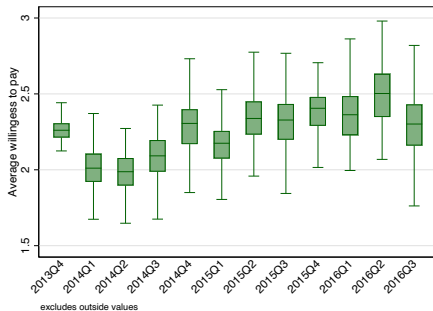
# ties	1	2	3+
%	0.77	0.19	0.04

# Demand Results: WTP and Acceptance Probability

## Acceptance Probability

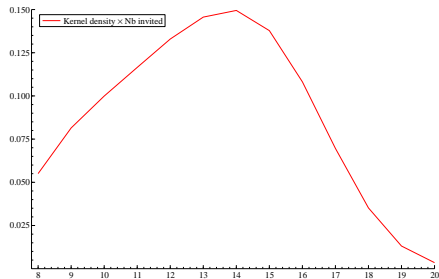
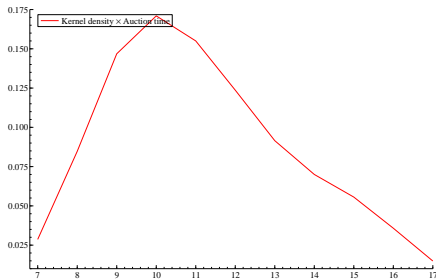
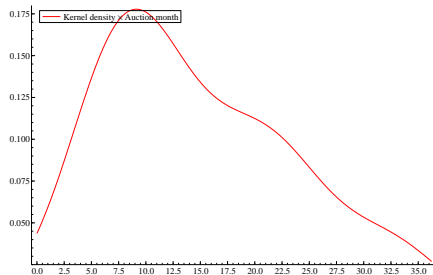
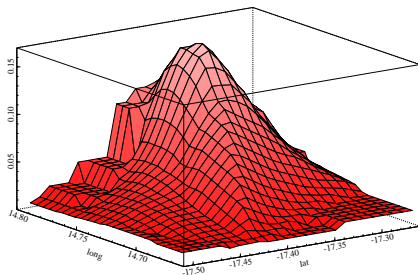


## Average WTP



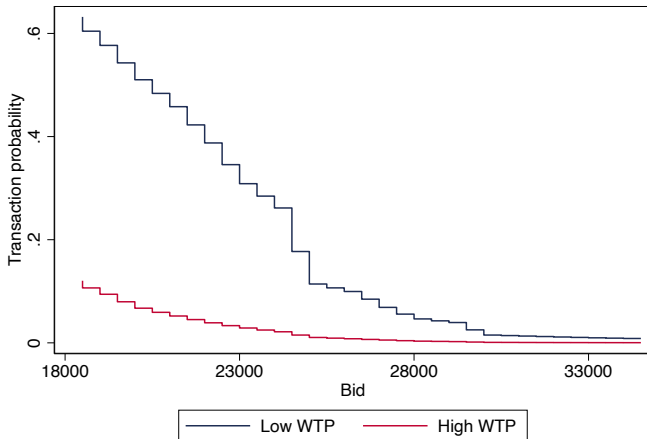
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# Density of Auctions Characteristics



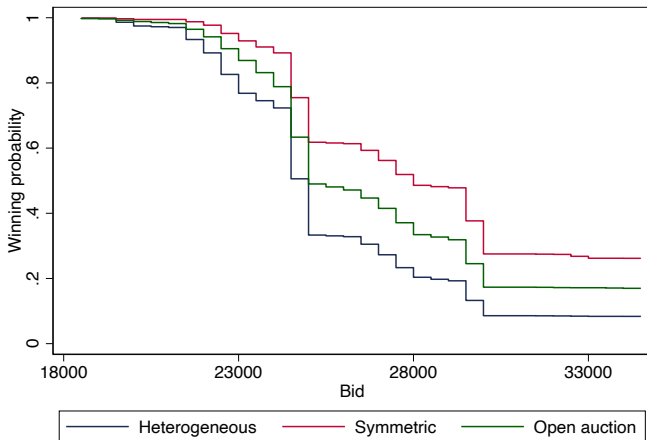
## Example 2: Expected Transaction Probability

$$P(b|I_t) = D(b|I_t) \times \Pr(\text{win}|b, I_t)$$



Bidder ID: 67

## Example 3: Win probability under three beliefs models

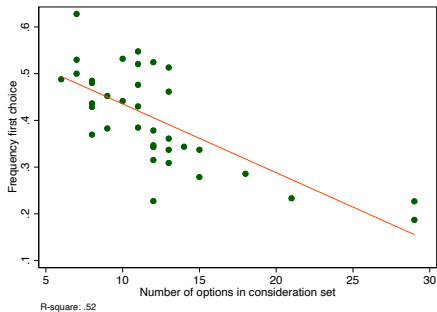
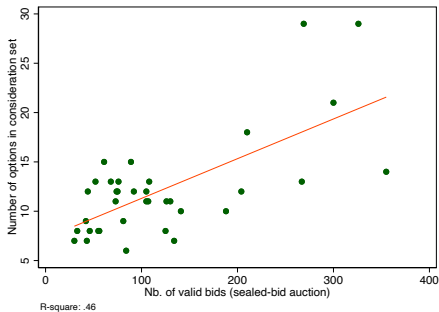


Bidder ID = 67

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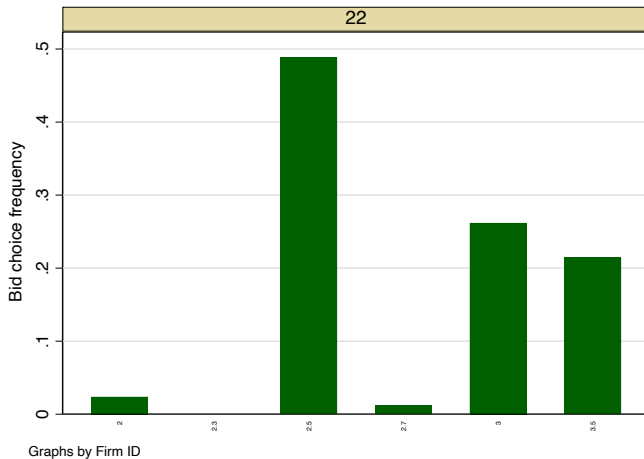


# Bid Consideration Sets: Experience and Sophistication



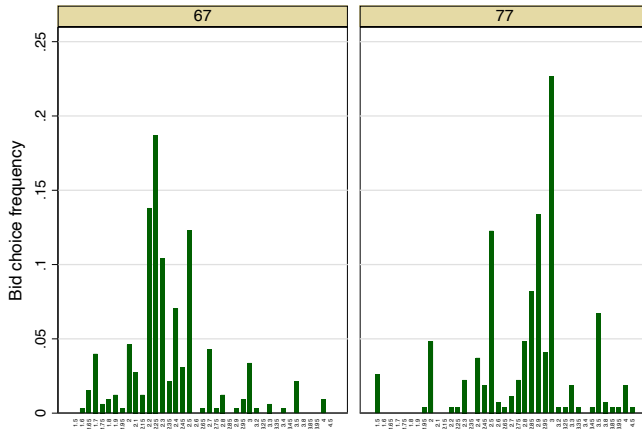
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## Example 1: Distribution of bids for small CS firms



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## Example 2: Distribution of bids for large CS firms



Graphs by Firm ID

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# Counter-Factual Results: Strategic Entry Probabilities

Invitation list: Every active bidders (46)

