# Sustainable Intermediation: Using Market Design to Improve the Provision of Sanitation[1]

Jean-François Houde[a] Terence Johnson[b]
Molly Lipscomb[c] Laura Schechter[d]

[a]UW-Madison & NBER

[b]University of Notre Dame

[c]University of Virginia

[d]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 Platorm

- 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

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  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" biding strategy resulting in ties and higher bids

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- **Key takeaways:**
  - Roughly 3/4 of active bidders behave non-competitively
  - How? Rely on "coarse" biding 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 $t$ ($I_t$):
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  - *Competition:* Number of invited bidders
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$$\pi_{it}(c_{it}) = \max_{b_i \in \mathcal{B}} \quad (b_i - c_{it}) D(b_i | I_t) \Pr(Win | b_i, I_t)$$

Where,

- $c_{it}$ is the (private) marginal cost of performing job $t$ for bidder $i$
- $D(b_k | I_i)$ is the prob. that $b_k$ is accepted (i.e. demand)
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- Conditional on being invited, bidder $i$ submits an offer if:

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

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

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  - **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

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

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

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

# Cost Estimation: Beliefs Calculation

- **Belief estimation:** Calculate the frequency, $\widehat{\Pr}[\text{Win}|b', I_t]$, by re-sampling rivals' bids/participation decisions in other auctions with *similar* attributes $I_{t'}$. How?

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  - Let $I_t = \{\text{lat}_t, \text{long}_t, \text{hour}_t, \text{date}_t, \text{Nb. invitees}_t\}$
  - We sample bids from auctions $t'$ with probability:

$$w(I_t', I_t) = \frac{K(I_{t'}, I_t)}{\sum_l K(I_l, I_t)}$$

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

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- 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)

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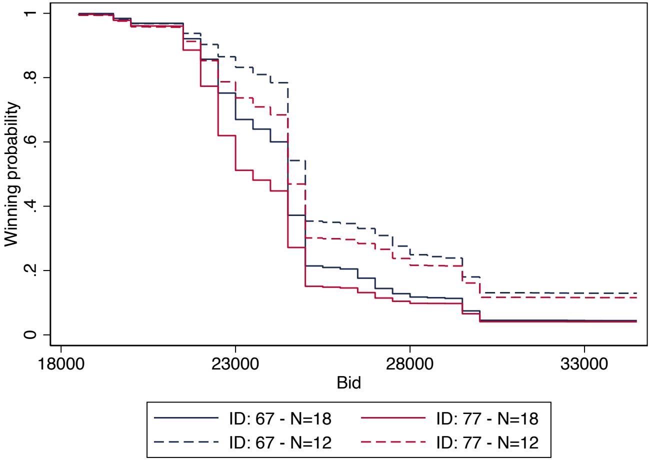
- **Motivation:**
  - (1) and (2): Consistent with Bayes-Nash beliefs
  - (3): Bidders observe $\approx$ 2nd-lowest **only** in the open auction

# Example: Win probability for two bidders and two auctions

Beliefs = Heterogenous




Ex. 2: Variation in Demand
Ex. 3: Variation in Beliefs

# Cost Estimation: Revealed Preference Inequalities

- Profit maximization implies:

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

- **Round bids and ties:** If consideration set is very rich (e.g. $\mathcal{B}=\Re_+$), some bids $b_{it}$ are *dominated* for any $c_{it}\geq 0$ (e.g. $b_{it}=25K$).

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- **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 \\
&\to 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} \\
&\to 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}
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- 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 $\mathcal{B}_{it} = \{b_1 < \cdots < b_k < \cdots < b_{K_i}\}$ 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

| | Beliefs: Heterogeneous | | Beliefs: Revisable auction | |
|---|---|---|---|---|
| VARABLES | (1) | (2) | (3) | (4) |
| Distance (km) | 0.020 | 0.020 | 0.021 | 0.021 |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| Association | 0.261 | 0.261 | 0.215 | 0.214 |
| | (0.020) | (0.020) | (0.020) | (0.020) |
| 1(Single truck) | 0.088 | 0.087 | 0.081 | 0.081 |
| | (0.011) | (0.011) | (0.011) | (0.011) |
| Nb. Trucks | 0.058 | 0.058 | 0.062 | 0.062 |
| | (0.005) | (0.006) | (0.006) | (0.006) |
| Nb. bidders invited | | 0.001 | | 0.002 |
| | | (0.001) | | (0.001) |
| % invitees same garage | | -0.034 | | -0.070 |
| | | (0.027) | | (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 $b_{it}$

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

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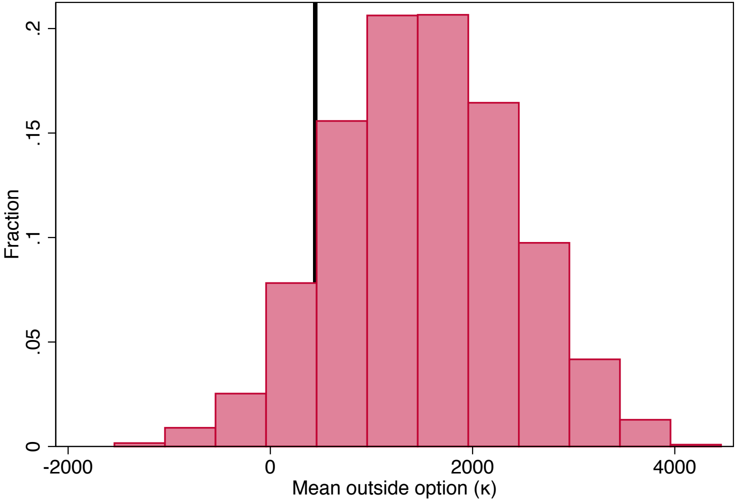
where $\bar{c}_{it} = x_{it}\hat{\beta}$.

- 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). Corr(k,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 $(w_{it}, \gamma_{it}, \epsilon_{it})$
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  - Firms decide to enter simultaneously and non-cooperatively
- Using the revelation principle (Myerson,1981), the incentive compatible expected payment to firm $i$ is:

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

- 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:

$$\bar{\pi}_{ij}(A_t) = E_{\tilde{A}_{it},\gamma_i,w_i}\left[\int_{\gamma_{ij}}^{\infty} P_{ij}(z,\gamma_{i,-j},w_i,\tilde{A}_{it})dz \middle| A_t\right] \text{ (Ass.: Efficient selection.)}$$

$$= E_{\tilde{A}_{it},\gamma_{it}}\left[\underbrace{\int_{\gamma_{ij}}^{\infty} D_i(\bar{c}_{ij}+\psi(z))\,\mathrm{Pr}\left(\min_{k\in\tilde{A}_{it}} \bar{c}_{kt}+\psi(\gamma_{kt}) > c_{it}+\psi(z)\right)dz}_{E(\pi_{it}|\gamma_{it},\tilde{A}_s)} \middle| A_t\right]$$

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

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

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$$= E_{\tilde{A}_{it},\gamma_{it}}\left[\underbrace{\int_{\gamma_{ij}}^{\infty} D_i(\bar{c}_{ij}+\psi(z))\Pr\left(\min_{k\in\tilde{A}_{it}} \bar{c}_{kt}+\psi(\gamma_{kt}) > c_{it}+\psi(z)\right)dz}_{E(\pi_{it}|\gamma_{it},\tilde{A}_s)} \middle| A_t\right]$$

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- **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 $\rho^{k-1}_{it}$
  - 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)

| | | Counter-factual | | | Observed platform (sealed) | | |
|---|---|---|---|---|---|---|---|
| Nbh. | N | 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 |
| **Total** | 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).

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| | (0.005) | (0.021) | (0.015) |
| ATE - Both | 0.008 | -0.096 | 0.228 |
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- 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

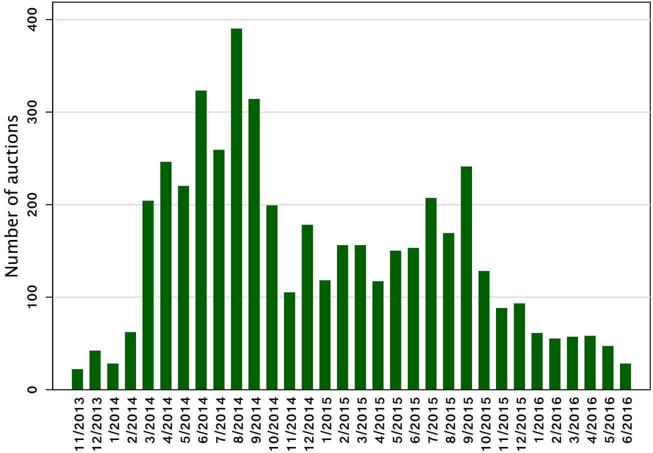
**THANK YOU!**

# Auction Platform: Summary Statistics

| | Old paltform | | 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 |

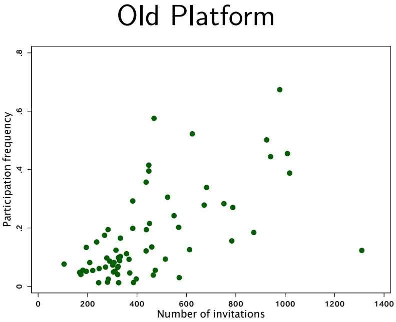
Return

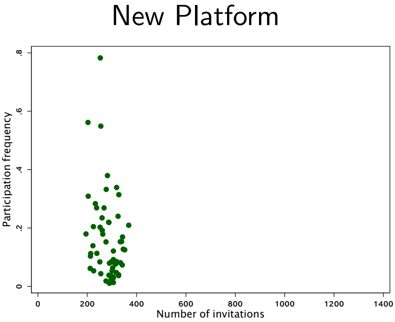
# Auction Platform: Number of Auctions per Month




Return

# Auction Platform: Total Invitations per Desludger

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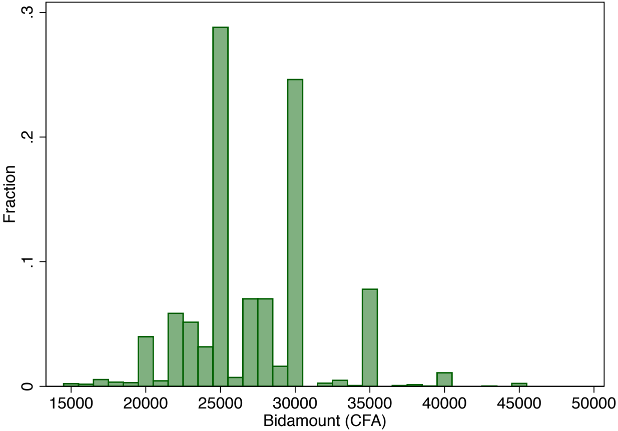
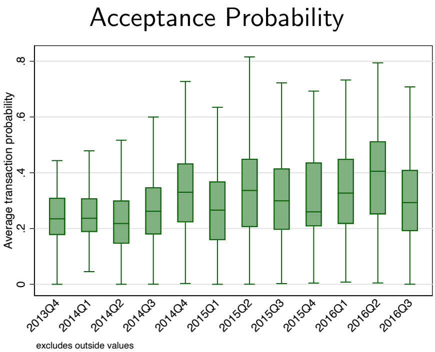
# Feature 3: Ties and round bids are very common

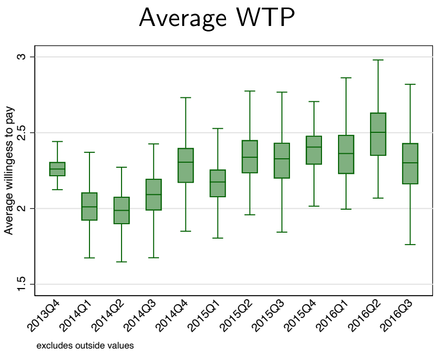



| # ties | 1 | 2 | 3+ |
|---|---|---|---|
| % | 0.77 | 0.19 | 0.04 |

Return

# Demand Results: WTP and Acceptance Probability

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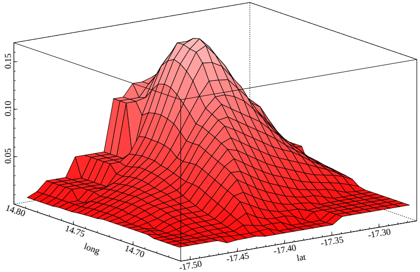
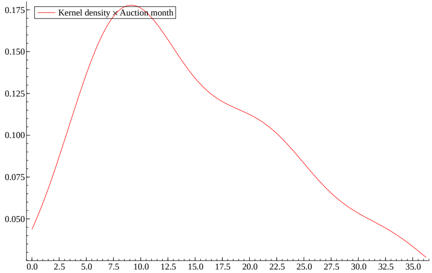
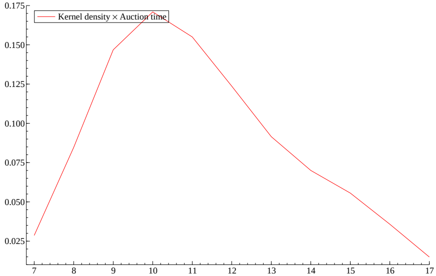
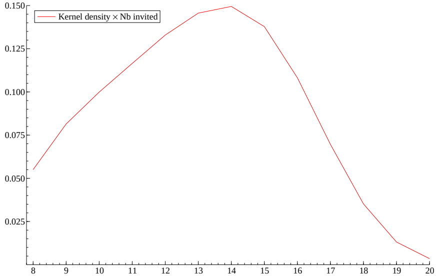
# Density of Auctions Characteristics

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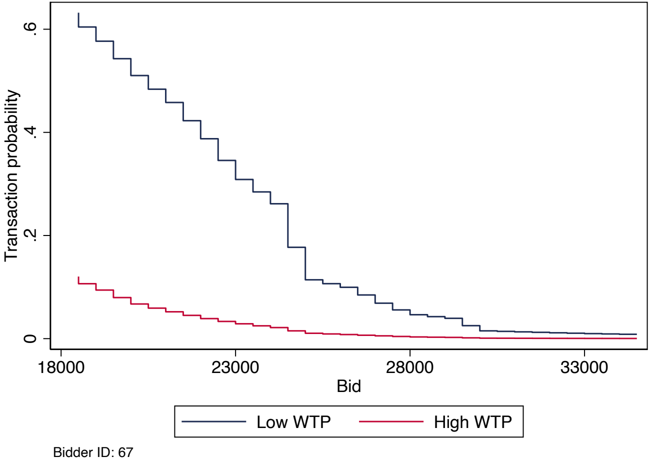
# Example 2: Expected Transaction Probability

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

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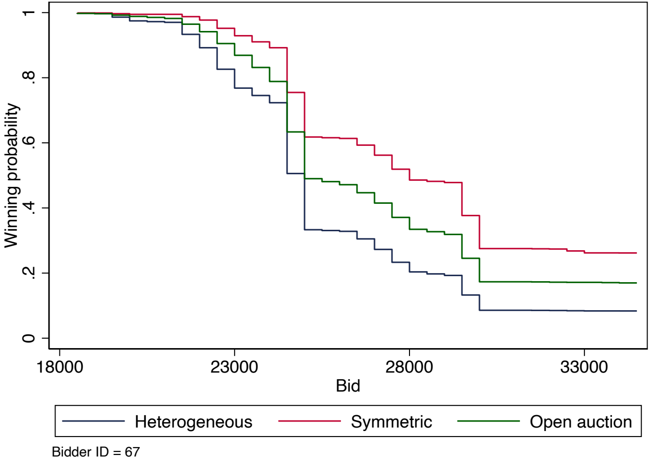
# Example 3: Win probability under three beliefs models

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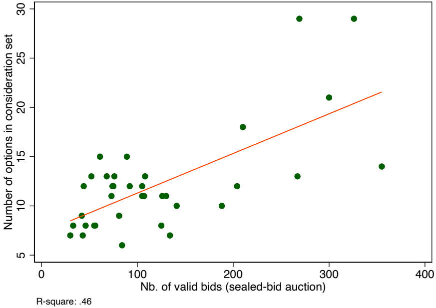
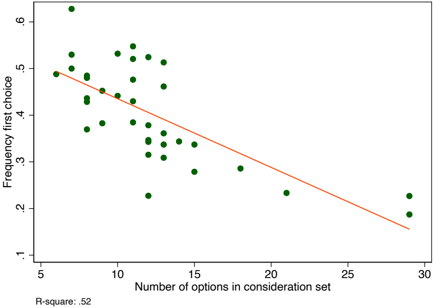
# Bid Consideration Sets: Experience and Sophistication

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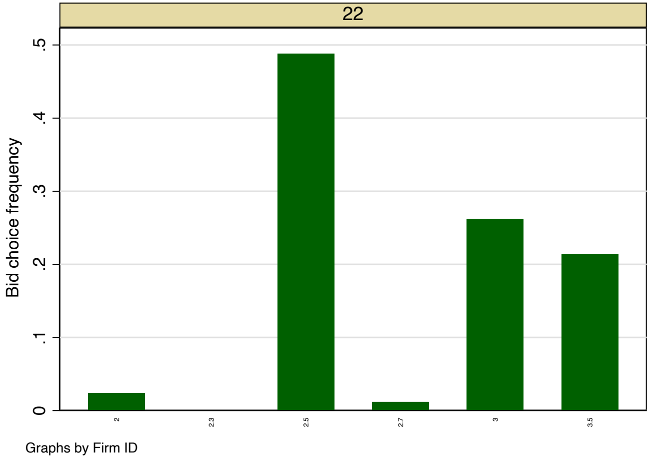
# Example 1: Distribution of bids for small CS firms

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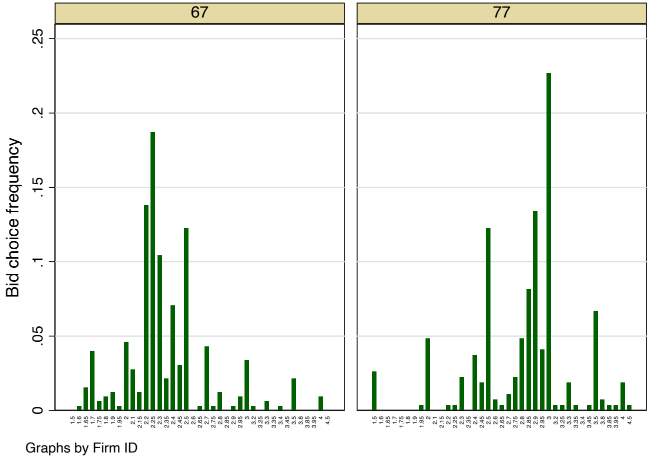
# Example 2: Distribution of bids for large CS firms

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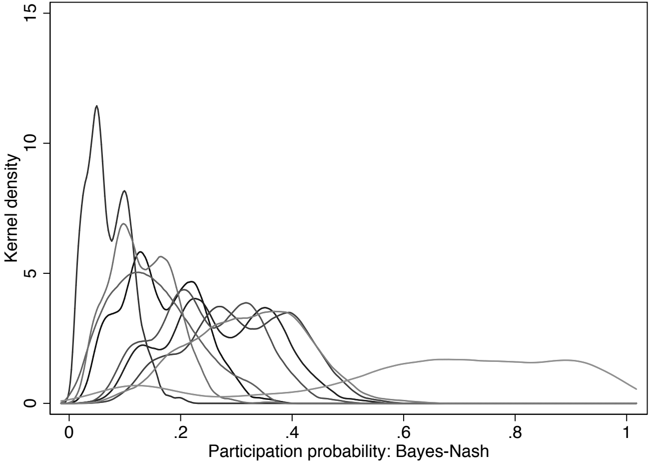
# Counter-Factual Results: Strategic Entry Probabilities

## Invitation list: Every active bidders (46)

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