Buy-It-Now prices in eBay auctions
– The Field in the Lab

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Motivation: The “Buy-It-Now” (BIN) option in eBay auctions

- BIN auction on eBay

  Object for sale can be bought at the BIN price before the auction. BIN price disappears when the first bid is submitted (start of the auction).

- BIN auctions are very popular – example BIN auctions in the US: 45% of all eBay auctions are BIN auctions. (2001) 28% (app. 4.4 Bil. USD) of all sales at the BIN price. (2004)

  eBay.com report: sales based on fixed prices in such mechanisms accounted for 34% of the gross merchandise volume (2005); 53% (2009); 63% (2011); 66% (2012).

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Theory (SIPV):

The use of the BIN-price before an auction can be explained by:

- Risk-aversion of buyers, \((Reynolds\ et\ al.,\ 2009)\)
  - of sellers, \((Mathews\ et\ al.,\ 2006)\)
  - and of buyers and sellers. \((Ivanova-Stenzel\ et\ al.,\ 2008)\)

- Time preferences. \((Mathews,\ 2004,\ Gallien\ et\ al.,\ 2007)\)

- Presence of transactions costs. \((Wang\ et\ al.,\ 2006)\)
Motivation: Empirical Studies

- BIN auction revenues are increasing in the BIN price. (Hendricks et al., 2005, Dodonova et al., 2004)

- Experience plays an important role.
  - Experienced sellers use the BIN option more frequently. (Durham et al., 2004)
  - BIN prices of experienced sellers with a high reputation are more often accepted. (Durham et al., 2004, Anderson et al., 2008)

- Focus mainly on goods (e.g., American silver Eagle coins, Palm computers) where
  - multiple items are offered simultaneously
  - a market price is easily recognizable.
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- Risk aversion:
  - Buyers behave as being risk averse. \((Shahriar \textit{et al.}, 2006, Peeters \textit{et al.}, 2007, Ivanova-Stenzel \textit{et al.}, 2008)\)
  - BIN prices reduce variance in seller revenue. \((Shahriar \textit{et al.}, 2006)\)
  - Risk-aversion of sellers seems not be able to explain BIN price setting. \((Ivanova-Stenzel \textit{et al.}, 2008)\)

- Use of different second-price auction formats; participants might not have experience with the chosen format.
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Motivation: Our Contribution

- We study how sellers set BIN prices in BIN auctions on eBay for single objects with independent private values (SIPV).
- Combine advantages of field and lab experiments.
- Experiment conducted
  - on eBay with experienced eBay traders.
    - Observe “natural” behavior of trading agents in an environment that they are familiar with.
    - Variation of participants’ experience with the institution.
    - Allows us to relate information available on eBay and personal characteristics to subjects’ behavior.
  - in the lab over items with induced values.
    - Control over basic model assumptions (e.g., private values).
    - Observe traders’ decisions over several rounds.
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Theoretical Predictions

- A seller (value and reservation price = 0) offers a single indivisible object for sale;
  two buyers with symmetric independent private valuations for the good: $V \sim U[0, 1]$.

- Sequence of events:
  1. Seller announces a BIN price.
  2. One (randomly selected) buyer (buyer 1) observes the BIN price and decides whether to accept it.
     - If acceptance: Transaction completed at the BIN-price.
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Solution:

- **Auction:**
  - In equilibrium: bid = value (Ockenfels & Roth, 2006).
  - Auction price: second-highest value.

- **BIN price acceptance (buyer 1):**
  \[ u(v_1 - p) \geq \int_0^{v_1} u(v_1 - x) \, dx \]
  \[ \Rightarrow p \leq \bar{p}(v_1, \alpha_B) = v_1 - (\frac{v_1^{2-\alpha_B}}{2-\alpha_B})(\frac{1}{1-\alpha_B}) \]
  \[ (\alpha_B: \text{buyer 1's CRRA parameter}) \]

- **BIN price (seller):**
  \[ \max_p (\Pr\{p \leq \bar{p}(v_1)\}u(p) + (1 - \Pr\{p \leq \bar{p}(v_1)\})E_{v_1,v_2}[u(R_A)|\bar{p}(v_1) < p]) \]
  \[ (R_A = \min\{v_1, v_2\}: \text{auction revenue}) \]

- **Risk neutrality (\(\alpha_S = \alpha_B = 0\)):**
  BIN price: \( p \in [0.5, 1] \); never accepted.

- **Risk aversion (\(\alpha_S, \alpha_B\) elicited in the experiment):**
  BIN price: \( p \in [0.42, 0.59] \); acceptance rate: 26%.
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Experiment

- eBay internet platform in the lab.
- Participants: Persons with valid eBay accounts.
  - Buyers used their own accounts.
  - Sellers used accounts licensed to the experimenters.
- Items for sale: second hand books with induced values: iid uniform \{1, 1.5, \ldots, 50\}.
- One trading group: 1 seller, 2 buyers.
  - Randomly assigned role; kept throughout the experiment.
  - Random matching of traders in each round.
  - 1 seller (sets BIN price)
  - 1 buyer can accept or reject
    when accepting: item sold at this price and end of the transaction.
    otherwise (rejection): eBay auction (5min) with an additional bidder.
- Profits:
  - Seller: final price.
  - Winning buyer: induced value - final price.
  - Loosing buyer: 0.
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Experiment and Data

- Data 20 sellers and 40 buyers for 6 rounds = 120 transactions. (BIN prices, acceptance rates, bidding behavior, auction prices, and final prices)

- Approximation on traders’ experience: Number of completed and evaluated transactions collected at the beginning of the experiment. median: 11; interquartile range: [2, 31]

- Information on traders’ risk preferences: Elicitation of risk preferences via lottery choice tasks at the end of the experiment (similar to Holt and Laury, 2002). CRRA: median: 0.5; interquartile range: [0.2, 0.8].
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Results: Data vs. Predictions

- **Bidding in the eBay Auction:**
  - Price determining bid on average 13.5% below valuation. (65% of the losing bids are below bidder’s valuation).
  - Caused by combined use of two bidding strategies: multiple bidding and last-minute bidding. ([Roth and Ockenfels, 2006](#)).
    - Multiple (incremental) bidding: 4 bids on average
    - Sniping (bids submitted within the last 30 Seconds): in 75% of the auctions

- **BIN prices:**

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Comparing data and predictions of a modified model (taking the underbidding into account).

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⇒ Model 2 is 11\% more accurate than model 1.

Insight from Model 2: Optimal BIN price increases when the relative deviation from true value bidding decreases.

Could a seller infer the relative deviation?

OLS-regression of information about buyers available on eBay on the relative deviation.

⇒ Significant correlation between level of price deviation and number of bids, buyers’ experience and last-minute bidding.
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OLS-regression of information about buyers available on eBay on the relative deviation.
⇒ Significant correlation between level of price deviation and number of bids, buyers’ experience and last-minute bidding
Results: Setting BIN prices

- Do sellers react to the variables that are correlated with the relative deviation?

- Panel data model (N=100: 20 sellers over 5 periods):

\[
bin_{it} = \beta_0 + \overline{bc}_{it-1}'\beta_1 + \beta_2 D_{it-1} \\
+ \beta_3 bin_{it-1} D_{Rit-1} + \beta_4 bin_{it-1} D_{Ait-1} \\
+ \mu_i + \varepsilon_{it}, \quad \text{with } t = (2, \ldots, 6).
\]

Vector \(\overline{bc}_{it-1}\): empirical averages of buyer characteristics observed by seller \(i\) in previous periods. \(\overline{bc}_{it-1} = (\overline{nb}_{it-1}, \overline{exB}_{it-1}, \overline{exB}^2_{it-1}, \overline{sn1}_{it-1}, \overline{sn2}_{it-1})'\).

\(\mu_i\): individual fixed effects.

- Relate individual characteristics of sellers (risk aversion and experience) to the estimated fixed effects:

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Estimation results: Sellers’ reaction to information on eBay:
Sellers increase their BIN price ...

- ... when the number of submitted bids increases. ✓
  (The higher the number of bids, the closer the bid is to its true value and the smaller the deviation from the price compared to standard second-price auctions.)
- ... when the experience in the buyer population increases. ✓
  (Experienced bidders bid closer to their true value.)
- ... when the probability of sniping decreases. ✓
  (Last minute bidding decreases the auction price.)

Additional results:

- Sellers do not adjust their BIN price in response to whether the BIN price in the previous period has been accepted or rejected.
- More experienced sellers set higher BIN prices.
- Sellers’ risk aversion does not explain setting of BIN prices.
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Summary and Conclusions

- Combine experimental methodology of field and lab to study how sellers set prices in eBay BIN auctions.
  (real traders on the real eBay platform with controlled valuations)

- Bids in eBay auctions deviate from those of standard second-price auctions. Bids on average below the true value resulting in auction prices below those of second-price auctions.

- We augment the baseline model of BIN auctions and allow bids to deviate from true values.
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Results: BIN auctions vs. NoBIN auctions

- Comparing data from our BIN auction treatment with data from a new eBay (without BIN) auction treatment (using in each period the exact same value draws and configuration of the trader groups)

<table>
<thead>
<tr>
<th></th>
<th>BIN auctions</th>
<th>No BIN auctions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Seller Profits</td>
<td>0.32</td>
<td>0.25</td>
</tr>
<tr>
<td>Buyer Profits</td>
<td>0.17</td>
<td>0.17</td>
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<tr>
<td>Final Auction Prices</td>
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<td>0.21</td>
</tr>
<tr>
<td>Efficiency</td>
<td>0.86</td>
<td>0.71</td>
</tr>
</tbody>
</table>
Predicted BIN by Model 1
Predicted BIN by Model 1 and Model 2
Table: Price deviation in eBay auctions

| Variable                  | \( \kappa \) | St.Dev | \( P > |z| \) |
|---------------------------|--------------|--------|--------------|
| \( \kappa_0 \)           | 0.064        | 0.037  | 0.088        |
| \( exB_0 \)              | 0.017        | 0.014  | 0.246        |
| \( (exB_0)^2 \)          | 0.000        | 0.001  | 0.919        |
| \( nb_0 \)               | -0.109       | 0.062  | 0.085        |
| \( nb_0^2 \)             | 0.045        | 0.024  | 0.066        |
| \( (nb_0 \cdot exB_0) \) | -0.043       | 0.039  | 0.272        |
| \( (nb_0 \cdot exB_0)^2 \) | 0.001       | 0.007  | 0.872        |
| sniping\_0 be            | 0.102        | 0.016  | 0.000        |
| \( exB_1 \)              | -0.049       | 0.022  | 0.032        |
| \( exB_1^2 \)            | 0.005        | 0.002  | 0.023        |
| \( nb_1 \)               | 0.056        | 0.151  | 0.711        |
| \( nb_1^2 \)             | 0.017        | 0.107  | 0.874        |
| \( (nb_1 \cdot exB_1) \) | 0.162        | 0.101  | 0.115        |
| \( (nb_1 \cdot exB_1)^2 \) | -0.117     | 0.049  | 0.020        |
| sniping\_1 be            | -0.016       | 0.017  | 0.327        |
| \( nb_0 \cdot nb_1 \)    | -0.094       | 0.096  | 0.331        |
Table: BIN price setting

| Variables | $\beta$ | St.Dev | $P > |z|$ |
|-----------|--------|--------|----------|
| $\beta_0$ | 0.469  | 0.071  | 0.000    |
| nb        | 0.025  | 0.009  | 0.009    |
| exB       | 0.042  | 0.016  | 0.012    |
| $(\text{exB})^2$ | -0.003 | 0.002  | 0.065    |
| sn1       | -0.143 | 0.066  | 0.033    |
| sn2       | 0.077  | 0.060  | 0.203    |
| D         | 0.054  | 0.060  | 0.376    |
| $\text{bin}_{t-1}D_R$ | -0.163 | 0.996  | 0.106    |
| $\text{bin}_{t-1}D_A$ | 0.008  | 0.120  | 0.947    |
| $\sigma_{\mu}$ | 0.183  |        |          |
| $\sigma_{\epsilon}$ | 0.088  |        |          |
| $\gamma$  |        |        |          |
| risk$_i$  | 0.095  |        | 1.25     |
| exS$_i$   | 0.016  |        | 2.14     |