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).

  "We believe that the mix of sales under our traditional auction-style listing format and fixed-price listing format will continue to shift towards our fixed-price format" (2013)

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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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Motivation: Experimental Studies

- Risk aversion:
  - Buyers behave as being risk averse. (*Shahriar et al., 2006, Peeters et al., 2007, Ivanova-Stenzel et al., 2008*)
  - BIN prices reduce variance in seller revenue. (*Shahriar et al., 2006*)
  - Risk-aversion of sellers seems not be able to explain BIN price setting. (*Ivanova-Stenzel 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

  $\Rightarrow$ 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.

  $\Rightarrow$ in the lab over items with induced values.

  - Control over basic model assumptions (e.g., private values).
  - Observe traders' decisions over several rounds.
  - Reliable test of theoretical predictions.

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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.
     - If rejection: Auction (two bidders).

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Solution:

- Auction:
  - In equilibrium: bid=value (Ockenfels & Roth, 2006).
  - Auction price: second-highest value.
- BIN price acceptance (buyer 1):

  $$u(v_1 - p) \geq \int_0^{v_1} u(v_1 - x)dx$$

  $$\Rightarrow p \leq \overline{p}(v_1, \alpha_B) = v_1 - \left(\frac{v_1^{(2-\alpha_B)}}{2-\alpha_B}\right)^{\left(\frac{1}{1-\alpha_B}\right)}$$

  (α_B: buyer 1's CRRA parameter)
- BIN price (seller):

  $$\max_p (\Pr\{p \leq \bar{p}(v_1)\} u(p) + (1 - \Pr\{p \leq \bar{p}(v_1)\}) E_{v_1,v_2}[u(R_A)|\bar{p}(v_1) < p])$$

  ($R_A = min\{v_1, v_2\}$: auction revenue)
- Risk neutrality ($\alpha_S = \alpha_B = 0$):
  BIN price: $p \in [0.5, 1]$; never accepted.
- Risk aversion (α_S, α_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) ▸ screenshot
    - 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

▸ BinNObin

- BIN prices:

▸ M1	Model 1 (true value bidding, $rdev = 0$)	Data
Acceptance Rate	26%	36%
BIN Price (Predicted/IQR) Range	$[0.42, 0.59]$	$[0.39, 0.60]$

(All numbers normalized to $[0, 1]$-range.)

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Results: Data vs. Predictions

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

‣ M1 & M2	Model 2 (with $rdev = 13.5\%$)	Data
Acceptance Rate	37%	36%
BIN Price (Predicted/IQR) Range	$[0.39, 0.55]$	$[0.39, 0.60]$

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$\Rightarrow$ 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.
  $\Rightarrow$ Siginificant correlation between level of price deviation and number of bids, buyers' experience and last-minute bidding ‣ Estimation results (OLS)

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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):

$$
\begin{aligned}
bin_{it} = \beta_0 \quad &+ \quad \overline{bc}'_{it-1}\beta_1 + \beta_2 D_{it-1} \\
&+ \quad \beta_3 bin_{it-1} D_{Rit-1} + \beta_4 bin_{it-1} D_{Ait-1} \\
&+ \quad \mu_i + \varepsilon_{it}, \qquad\qquad \text{with } t = (2, \ldots, 6).
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  Vector $\overline{bc}_{it-1}$: empirical averages of buyer characteristics observed by seller i in previous periods. $\overline{bc}_{it-1} = (\overline{nb}_{it-1}, \overline{ex}B_{it-1}, \overline{ex}B^2_{it-1}, \overline{sn}1_{it-1}, \overline{sn}2_{it-1})'$.
  μ_i individual fixed effects.

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

$$\widehat{\mu}_i = \gamma_0 + \gamma_1 risk_i + \gamma_2 exS_i + \varepsilon_i$$

▸ Estimation results (Panel)

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& + \quad \beta_3 bin_{it-1} D_{Rit-1} + \beta_4 bin_{it-1} D_{Ait-1} \\
& + \quad \mu_i + \varepsilon_{it}, \qquad \qquad \text{with } t = (2, \ldots, 6).
\end{aligned}
$$

  Vector $\overline{bc}_{it-1}$: empirical averages of buyer characteristics observed by seller i in previous periods. $\overline{bc}_{it-1} = (\overline{nb}_{it-1}, \overline{ex}B_{it-1}, \overline{ex}B^2_{it-1}, \overline{sn}1_{it-1}, \overline{sn}2_{it-1})'$.
  μ_i individual fixed effects.
- Relate individual characteristics of sellers (risk aversion and experience) to the estimated fixed effects:

$$\widehat{\mu}_i = \gamma_0 + \gamma_1 risk_i + \gamma_2 exS_i + \varepsilon_i$$

▸ Estimation results (Panel)

- Reminder of prediction:
  Optimal BIN price increases when the relative deviation from true value bidding decreases.
- 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.
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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.
  The modified model fits our data better and provides insight on the relation between the bid deviation and optimal BIN prices.

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- Information available on the eBay platform - indicator for the relative deviation of bids from the true value and therefore of the price in the auction from the one in standard–second price auctions.
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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)

	BIN auctions	No BIN auctions
Seller Profits	0.32	0.25
Buyer Profits	0.17	0.17
Final Auction Prices	0.26	0.21
Efficiency	0.86	0.71

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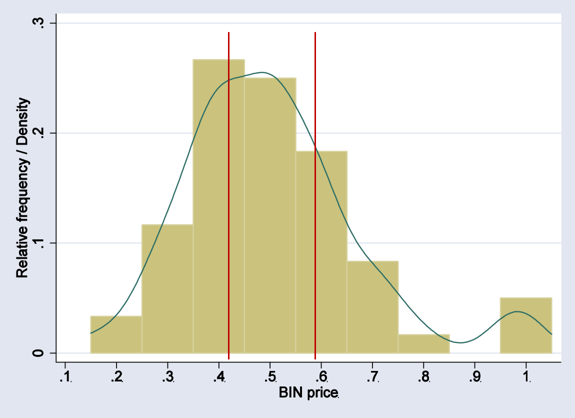
Predicted BIN by Model 1



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Predicted BIN by Model 1 and Model 2

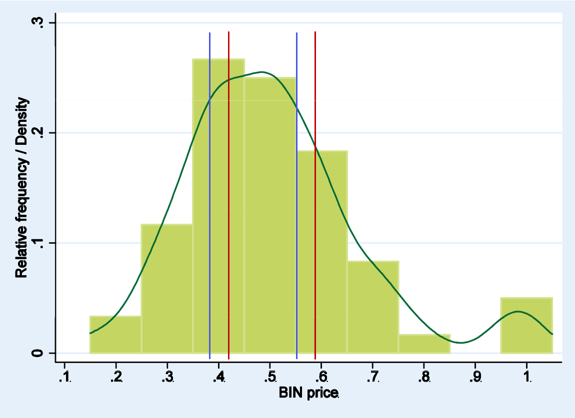

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Table: Price deviation in eBay auctions

Variable	κ	St.Dev	$P > \|z\|$
κ_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

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Table: BIN price setting

Variables	β	St.Dev	$P > \|z\|$
$\beta_{\mathbf{0}}$	0.469	0.071	0.000
nb	0.025	0.009	0.009
$\overline{\mathbf{exB}}$	0.042	0.016	0.012
$(\overline{\mathbf{exB}})^2$	-0.003	0.002	0.065
$\overline{\mathbf{sn}}\mathbf{1}$	-0.143	0.066	0.033
$\overline{sn}2$	0.077	0.060	0.203
D	0.054	0.060	0.376
$bin_{t-1}D_R$	-0.163	0.996	0.106
$bin_{t-1}D_A$	0.008	0.120	0.947
σ_μ	0.183		
σ_ε	0.088		
	γ		$t - value$
$risk_i$	0.095		1.25
$\mathbf{exS_i}$	0.016		2.14

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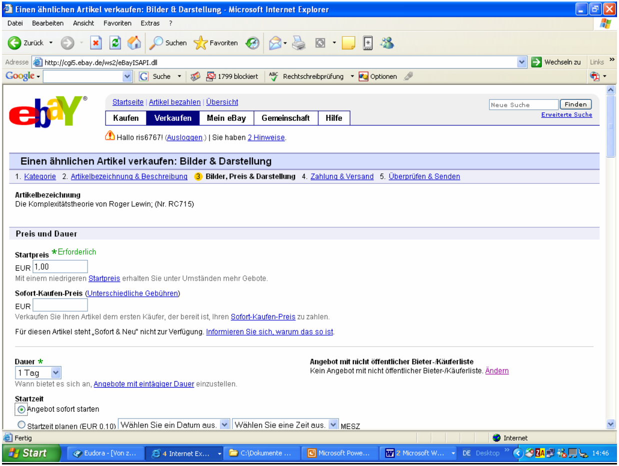
BIN-Price Screen Shot



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