Efficiency in Dynamic Auctions with Endogenous Matching

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June 2025

Introduction

- Many goods are traded online in decentralized, dynamic auction markets.
  - Decentralized: sellers sell their goods in separate auctions
  - Dynamic: buyers who fail to puchase - and sellers who fail to sell - can return to the market to try again
- Trade may be inhibited by information and matching frictions:
  - But opportunity to trade many times can mitigate these frictions (Satterthwaite & Shneyerov (2007, 2008))
  - Theoretical result: prices, allocations converge to Walrasian equilibrium as number of trading opportunities get large
- Research questions:
  - How close to efficient is a real-world market like eBay?
  - What can the platform do to increase efficiency and revenues?

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- Research questions:
  - How close to efficient is a real-world market like eBay?
  - What can the platform do to increase efficiency and revenues?
- We study these questions using eBay data on 16GB iPad Mini.

Auction Environment

- Sellers randomly arrive over time to sell identical goods in separate, ascending price auctions of fixed duration
  - Generates an infinite sequence of **overlapping** auctions.
- Buyers randomly arrive over time to buy one unit.
  - Observe "state of play": closing time and current highest losing bid in each auction (but not the high bid)
  - Choose in **which** auction to bid and **how much** to bid
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    - Choose in **which** auction to bid and **how much** to bid
    - If they lose, they can return later and try again
- Key feature: auction choice depends on state of play.
    - Leads to sorting: high-value bidders tend to bid in soon-to-close auctions, low-value bidders in later-to-close.
    - Main challenge: bidder needs to consider how his actions affects decisions of subsequent buyers and, as a result, his re-entry payoff if and when he returns.

What We Do

- **Theoretically:** provide a large market approximation result that makes the model empirically tractable.
  - Prove that, as market thickens, a buyer's expected re-entry payoff depends only on his type, not on previous actions or losing state
  - Show that it is nearly optimal (in $\varepsilon-$equilibrium sense) for each buyer to bid her type minus her expected re-entry payoff
  - Bid is invariant to auction choice, strictly increasing in type.

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  - Bid is invariant to auction choice, strictly increasing in type.
- **Empirically:** provide identification result and estimation strategy.
  - Invariance and monotonicity properties of the (inverse) bid function implies that model can be identified from bid data
  - Estimate distribution of buyer values accounting for the selection effect of auction choice.

Main Results

- Accounting for auction selection is empirically important.
  - Previous studies assumed buyers choose the soonest-to-close auction $\Rightarrow$ matching to sellers is randomly determined by arrival times
  - We show that this choice rule leads to substantial overestimates of buyer values
  - Also inconsistent with data, leads to violations of the model's steady state conditions.

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  - We show that this choice rule leads to substantial overestimates of buyer values
  - Also inconsistent with data, leads to violations of the model's steady state conditions.
- The eBay auctions are not close to being efficient.
  - Significantly more eficient than a static benchmark in which buyers have only one chance to bid
  - But fall well short of achieving the Walrasian benchmark,

Two Counterfactuals

- Sealed Bid Auctions: does disclosure of highest losing bid increase efficiency?
  - Examine this issue by considering a counterfactual in which platform does not post highest losing bid $\Rightarrow$ sealed bid auction
  - Result: posting highest losing bid tends to **increase** prices but **reduces** efficiency.

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  - Result: posting highest losing bid tends to **increase** prices but **reduces** efficiency.
- Posted Price Mechanism: can platform improve efficiency by setting a single price at which each seller must sell?
  - Result: can implement the efficient, revenue-maximizing allocation and does so in our data.

Contributions

- Theory literature on Dynamic Auctions:
    - McAfee (1983), Satterthwaite & Shneyerov (2007, 2008), Bodoh-Creed, Boehnke & Hickman (2021)
    - Setting: a large number of buyers and sellers arrive each period, each buyer randomly matched to a single seller.
    - Feature: in steady state, actions of any single buyer today has negligible impact on state of market tomorrow $\Rightarrow$ continuation value depends only on buyer's type.
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  - Our contribution: provide an analogous result in dynamic auction models where matching is in real-time and endogenous.
- Empirical literature on Dynamic Auctions:
  - Adachi (2016), Bodoh-Creed et al (2021), Backus & Lewis (2023)
  - They assume buyers are matched to soonest-to-close sellers based on their random arrival times
  - Our contribution: extends structural program of auctions to dynamic environments with endogenous matching

Road Map

- Data, key facts that motivate our modeling choices, and evidence on how bidders choose auctions.
- Theoretical model and results
- Identification, model tests, and estimation.
- Efficiency results
- Counterfactuals
- Conclusions

Data Overview

- All eBay listings for iPad.from Feb-Sept 2013
  - Focus on auction listings
  - Drop fixed price listings and any "Buy-it-Now" listings sold at BIN price.
- Listing data:
  - Seller identity and feedback rating,
  - Auction start and closing times, starting bid, secret reserve
  - Product characteristics: case, keyboard, screen protector, stylus, headphones, charger, color, shipping fee.
- Bidding data:
  - Amounts and times of all bids submitted for each listing, including the high bid
  - Identities of all bidders $\Rightarrow$ track individual bidders across auctions

Product Market

Used 16GB WiFi-only iPad Mini (new retail price = $329)

- Not much substitution between used and new
  - After losing an auction for a used item, 79% of returning bidders bid on another used item
  - Two most common sequences for bidders bidding three times: used-used-used, new-new-new.
- Not much substitution between used 16 GB WiFi model and other models (e.g., 32 GB or 64 GB)
  - After losing an auction for this model, 83% of returning bidders bid on same model.
- Sample: 5,002 auctions, 27,381 unique bidders, 51,668 bids
  - Normalize bids based on regression of prices on item characteristics, month dummies
  - Assumes characteristics are valued uniformly across bidders.

Sellers

- Our model treats sellers as non-strategic players
  - Over 90% of sellers set low, non-binding start prices with no reserve price (Hendricks and Wiseman (2021))
  - Few sellers fail to sell, and even fewer return.
- Our model assumes that the period between seller arrivals (or equivalently auction closings) is constant.
  - Arrival rate of buyers is measured relative to this period.
  - In reality, arrival rates of sellers and buyers fluctuate by time of day, but number of bidder arrivals per closing period is approximately constant.
  - Assuming constant arrival rates is thus a useful normalization.
- Auction duration can be 1, 3 or 7 days but most sellers choose 7 days.

Buyers

- Buyers are assumed to have unit demands.
    - In our sample, 94% of buyers (auction winners) purchased only one unit.
- Buyers are assumed to bid only once (i.e., proxy bidding) in the auction they choose.
    - True for most bidders but roughly 40% bid more than once (incremental bidders).
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- Return bidding:
  - Roughly half of losing bidders return to bid again in **another** auction (repeat bidders)
  - Return time = (time of return) - (time at which bidder loses)
  - Some return quickly - one third come back within an hour - but mean return time is 8 hours, median is 12 hours..

Market Thickness

- An average of 23 items are posted for auction each day.
  - Sellers arrive at an average rate of one per hour
  - An average of 5.47 new bidders and 4.86 returning bidders arrive per period.
  - At any point in time, an arriving bidder can choose from over 100 auctions, most of which have no bids.

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- There is typically an auction that closes within a day that has no bids and a low start price
  - Assume every arriving buyer submits a bid (no censoring).
- When a losing bidder returns, on average eight auctions have closed and over 60 other buyers have bid.

Bidding Patterns

- Rank auctions by their closing time.
- Posted price of auction with rank j is highest losing bid when it becomes the j^{th} auction.

Table 1: Bids and prices by auction rank

Auction rank	Average posted bid	Std. dev. posted bid	Fraction of all bids submitted	Frac. of winning bids submitted
1	259.54	59.11	.152	.601
2	228.69	81.43	.054	.099
3	215.40	87.86	.039	.056
4	204.88	92.11	.032	.036
5	196.42	94.57	.029	.024
6	188.08	96.81	.025	.019
7	181.55	98.08	.023	.012
8	175.21	99.14	.020	.011
9	169.39	100.01	.020	.008
10+	72.96	74.14	.607	.134

Bidding Activity

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  - Most are bidders who are already outbid.
  - But almost 20% submit bids in later-to-close auctions higher than the posted bid in the soonest-to-close auction
  - And almost 10% submit bids that are even higher than the eventual price in the soonest-to-close auction.
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- Serious bidding occurs well before the end of the auction.
  - Almost 40% of the winning bids are submitted **before** the auction is soonest-to-close.
  - Over 13% are submitted in auctions ranked 10 or above.

Model

We discretize time, values, and bids with arbitrarily fine grids.

- Time: each hour is divided into T periods of length $\Delta \equiv 1/T$.
- Infinite sequence of sellers arrive exogenously, one every hour.
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- New buyers arrive at Poisson rate $\lambda\Delta$ each period
  - Unit demand, i.i.d., positive value $x \sim F_E$, density f_E
  - Observes state of market, chooses an open auction, submits bid $b \in B = \{0, \underline{b}, .., \overline{b}\}$ where 0 denotes no bid.
- Auction rule: proxy bidding, platform bids on buyer's behalf up to b.

Payoffs and dynamics

- Seller's payoff: second highest bid received, or 0 if item is not sold
  - Highest bid w
  - Highest losing bid r.
- Buyer's payoff: $x - r$ if wins. If loses,
  - exits with probability α (constant in application, but can depend on type)
  - otherwise enters losers' pool, returns at exponential rate γ
  - no discounting (unimportant).
- If there are n buyers in the losers' pool, then number of returning buyers each period is approx. Poisson with rate $n\gamma\Delta$.

State of the market

- Observable: for each open auction,
  - closing time
  - highest losing bid r : "posted bid"
- Unobservable:
  - highest bid w in the auction
  - size n of losers' pool; in steady state,

$$\gamma n \approx \frac{(\lambda - q)(1 - \alpha)}{\alpha}$$

    where q is the endogenous probability that an auction ends with sale.
  - distribution F_L of values in losers' pool: endogenous.

Outcomes

- Strategy σ : maps value x and observable state $\widetilde{\omega}$ into choice of auction j, bid b.
  - σ induces ergodic Markov process over (finite) state ω
- Beliefs p: maps observable state $\widetilde{\omega}$ into beliefs over state ω.
- Equilibrium: (σ^*, p^*) such that
  - σ^* is best response to (σ^*, p^*)
  - p^* is consistent with σ^*.
- **Proposition:** an equilibrium exists.

Thick Markets

- For identification, we look for conditions under which the bidding rule $b(x, \widetilde{\omega})$ does not depend on observable state $\widetilde{\omega}$.
- Leverage the fact that losing buyers do not return immediately.
  - Takes time for them to learn and respond to news that they have lost.
- If arrival rates of buyers and sellers are high, then market may have undergone many transitions before buyer returns.
- In that case, a buyer's re-entry payoff may be largely independent of his previous actions and the losing state

Constant bidding

Let $V(x; \omega; \sigma, p)$ denote expected re-entry payoff to a bidder with value x who loses at state ω.

- If $V(x, \omega; \sigma, p)$ is given by $V(x; \sigma, p)$, then the following bid is weakly dominant:

$$b^*(x) = x - (1 - \alpha) V(x; \sigma, p)$$

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- Proof extends standard weak dominance argument for second-price auctions
  - Buyer's bid can influence decisions of subsequent buyers.
  - But can only do so when the buyer loses, in which case it no longer matters to the buyer.

Approximation Result

Theorem

For any $\varepsilon > 0$, in the limit as we increase the arrival rates of sellers and new buyers, keeping the average number of new buyers per auction and expected return time fixed, there is an $\varepsilon-$ equilibrium in which (i) each type-x bidder submits a constant bid $b^*(x)$ and (ii) $b^*(x)$ is strictly increasing.

- Isometric to letting $\gamma \to 0, J \to \infty$, with γJ (fraction of open auctions that close before return) constant.
- Why $\varepsilon-$equilibrium? two types of mistakes:
  - Current $\widetilde{\omega}$ has small effect on expected V, so may want to fine tune (high prob of small mistake)
  - At unlikely extreme $\widetilde{\omega}$ (e.g., all auctions filled or none), want to change bid (small prob of big mistake).
  - Nearly optimal nearly all the time!

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  - Taking expectations over $\widetilde{\omega}$,the Bellman equation can be solved to obtain

$$V(x;\sigma^*,p^*) = \frac{\sum_{m\in\{0,\ldots,b^*\}}(x-m)g_{\sigma^*,p^*}(m|b^*)}{[1-(1-\alpha)(1-G_{\sigma^*,p^*}(b^*|b^*))]}$$

  - $g_{\sigma^*,p^*}(m|b^*)$ is the probability that b^* pays m in the set of auctions in which b^* bids and wins;
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- b^* plays two roles: it accounts for set of auctions that type x selects and the bid that he submits in those auctions.

Inverse Bid Function

We use closed form expression for V to solve for the inverse bid function:

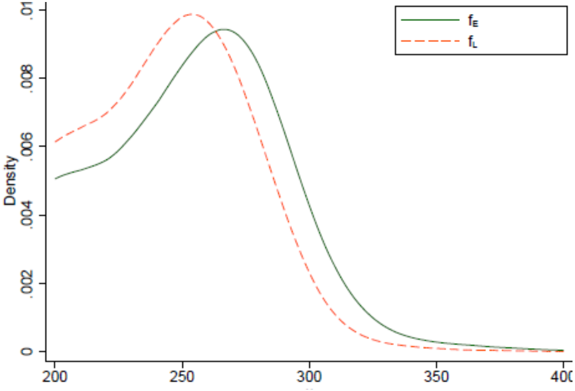
$$\eta(b^*) = b^* + \left(\frac{1-\alpha}{\alpha}\right) G_{\sigma^*,p^*}(b^*|b^*)(b - E[M|M < b^*, b^*])$$

- To recover values from bids, obtain estimates of α, G_{σ^*,p^*} and $E[M|M < b^*, b^*]$ directly from data on bids
- F_E, F_L separately identified.

Estimates

- $\widehat{\lambda} = 5.47 =$ average number of new buyers per auction closing.
- $\widehat{\alpha} = .502 =$ fraction of losers who do not return.
- $\widehat{q} =?$
- $\widehat{\gamma} = 0.12 =$ inverse of mean number of auctions before a losing bidder returns
- $G_{\sigma^*,p^*}(m|b^*)$: a semi-parametric ML method of Gallant & Nychka, 6$^{\text{th}}$-order polynomial
- $E[M|M < b^*, b^*]$: run a local polynomial regression of prices on associated winning bid.

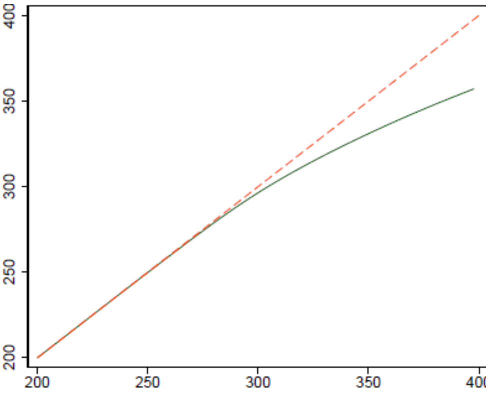
Result



- Distribution of loser valuations is a resampling of new bidder valuations, with less density in upper tail.

Tests

- Monotonicity of bid function:



- Constant bidding: bidders tend to bid more aggressively when they return, but effect is insignificant, 35 cents on average.

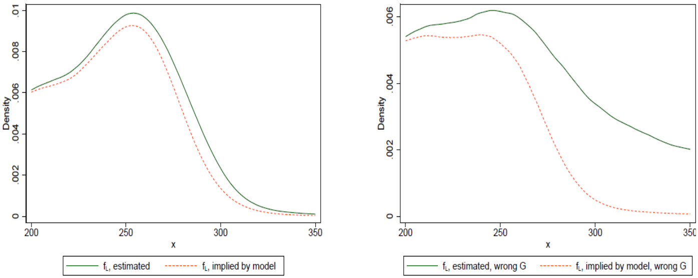
Steady State Restrictions

- Flow of types x out of loser pool must on average equal flow of types into the losers' pool

$$f_L(x) = \frac{\lambda\alpha(1 - G_{\sigma^*,p^*}(b^*|b^*))}{(\lambda - q)[1 - (1-\alpha)(1 - G_{\sigma^*,p^*}(b^*|b^*)]} f_E(x)$$

  - Left panel compares f_L we estimate directly from data to f_L implied by steady state restrictions - remarkably similar!

Figure 2: Test of restriction on f_L



Random Matching

- Suppose the set of auctions chosen by bidders is a random sample (i.e., not based on state of play, as assumed in literature).
  - Then we can equivalently use distribution of of the highest rival bid in set of *all* auctions to compute a bidder's re-entry payoffs.
- Using this distribution as our estimate of G, we find that it overestimates the probability of winning for high-value buyers.
  - Implies a substantial oversestimate of their values.
  - It also leads to a violation of the steady state restrictions (see right panel).

Efficiency Counterfactuals

- Uniform price auction: weakly dominant to bid value.
  - Number of sellers $N_s = 5,002$, number of unique buyers $N_b = 27,380$.
  - Market-clearing price P^* is given by

$$\left(1 - \frac{N_s}{N_b}\right) = 81.7^{th} \text{ percentile of } F_E$$

- One shot auctions with random matching (simulated)
  - Randomly assign N_b buyers with valuations drawn from F_E to the N_S sellers
  - Each buyer has only one chance to bid, weakly dominant to bid value.

Results

Table 3: Prices and efficiency compared to counterfactual benchmarks

	Simultaneous auctions, static bidding	Sequential auctions, dynamic bidding (i.e., data)	Uniform price auction
Avg. price	231.22	275.39	279.45
SD of prices	70.88	26.85	0.00
Avg. gross surplus	283.39	293.84	307.73
$\Pr(\text{win} \mid x > P^*)$	.305	.594	1.000

Notes: Average gross surplus is the average valuation (x) of the winning bidders. $\Pr(\text{win} \mid x > P^*)$ is the probability that a buyer whose x is greater than the market-clearing price P^* wins an auction before exiting.

Sealed Bid Counterfactual

- Should platforms like eBay provide buyers with information about the state of play in the auctions?
  - Allows bidders to avoid selecting auctions where they have already been outbid.
  - Also allows them to respond to differences in expected payoffs across auctions.
  - But equilibrium effect on outcomes is less clear.
- To study this issue, we run a counterfactual in which the auctions are effectively sealed bid auctions.
  - But need to specify an auction choice rule,
- Our theoretical model provides a useful benchmark:
  - Show that soonest-to-close choice rule is an equilibrium.

Simulation

- Could simulate equilibrium outcomes of our model under the soonest-to-close choice rule.
- Instead, we simulate the entire sequence of auctions in the data under the soonest-to-close choice rule.
  - Observed arrival times of new and returning bidders are fixed but bidders at these times are re-assigned to soonest-to-close auctions
  - These reassignments change who participates, who wins, who loses in each auction, and composition of loser pool.

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  - These reassignments change who participates, who wins, who loses in each auction, and composition of loser pool.
- We treat new bidders and returning bidders differently.
  - The identities of the new bidders when they arrive are the same as in the data.
  - The identities of returning bidders at return times are randomly chosen from the simulated loser pool.
  - The determination of who wins is then based on actual values - sufficient for comparing efficiency.

Results

Table 4: Prices and efficiency compared to counterfactual benchmark

	Endogenous matching (i.e., data)	Random matching (simulation)
Pr(win $\mid x > P^*$)	.557	0.638
# of rival high bidders		
0	40.87	45.24
1	36.23	27.99
2+	22.90	26.77

Notes: Pr(win $\mid x > P^*$) is the probability that a buyer whose x is greater than the market-clearing price P^* wins an auction before exiting. The second column is based on a simulation in which bidders enter the next-to-close auction when they arrive, which means they are randomly assigned to auctions.

- Takeaway: real-time disclosure of highest losing bid reduces efficiency.
- Reason: increases the number of auctions with two high value bidders, causing more high value bidders to exit.

Posted Price Counterfactual

- In large markets, the platform can implement the efficient, revenue-maximizing allocation using a posted price mechanism
- Mechanism:
  - Each seller posts the market-clearing price P^*.
  - Each arriving buyer with valuation above P^* buys from the next-to-close seller.
  - Auction stays open until a buyer accepts, or ending time is reached after J periods.
  - A buyer who arrives when there are no open auctions is treated like a losing bidder.

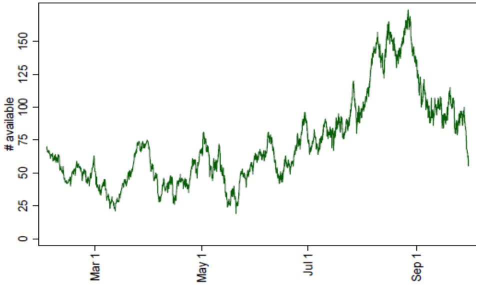
Equilibrium

- By definition, the expected # of new arriving buyers with values above P^* per auction is $\lambda(1 - F_E(P^*) = 1$.
  - Implies that the number of open auctions J_A follows a random walk with no drift, bounded by 0 and J.
  - For J large, probability a buyer can't buy ($J_A = 0$) is small
  - Probability a seller can't sell (fewer than $J_A + 1$ buyers arrive over J periods) is also small.
- So average seller revenue and average surplus approach their upper bounds P^* and $E[X|X \geq P^*]$.

Simulation

- We set $P^* = \$279.44$, $J = 140$ hours, $J_A(0) = 70$ and simulated the path of $J_A(t)$.

Figure H.4: Evolution of the number of available items



  - No stockouts, every bidder with a value above \$270.44 buys an item when he arrives.
  - A very small number of sellers fail to sell; average time to sell is 77 hours.

Summary

- Presented tractable model of auction choice and bidding in dynamic auction market
  - limit result for thick markets is crucial for identification.
  - applicable in other auction formats, bargaining settings (e.g., Freyberger and Larsen (2021))
- Demonstrated quantitative importance of accounting for endogenous auction choice.
- Findings suggest that endogenous matching with partial information about the state of play can reduce efficiency.
- Posted price mechanism would have achieved the Walrasian equilibrium in our data (Einav et al (2018)).