Expectation, Disappointment, and Exit

Evidence on Reference Point Formation from an Online Marketplace

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Reference points

– a component of prospect theory, following Kahneman and Tversky (1979), that modify the value of an outcome:

$$v = y + \mu(y - p)$$

- if p is the status quo then losses needn't be the reflection of gains
- if p is my expectation then subpar gains may disappoint
- alternatively, p may be a target combining elements of both

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This paper uses data from a real market to shed light on expectations in reference point formation

From Barberis (2013),

"It is curious, then, that so many years after the publication of the 1979 paper, there are relatively few well-known and broadly accepted applications of prospect theory in economics. On might be tempted to conclude that, even if prospect theory is an excellent description of behavior in experimental settings, it is less relevant outside the laboratory. In my view, this lesson would be incorrect... the main reason it has taken so long... is that it is hard to know exactly *how* to apply it... it is not ready-made for economic applications."

Related Work

- Empirics of reference points: Camerer, Babcock, Lowenstein, and Thaler (1997), Crawford and Meng (2011), Farber (2015), **Card and Dahl (2011)**
- Market Design and Behavioral Economics: Roth and Ockenfels (2002), Ariely and Simonson (2003), Wolf, Arkes, and Muhanna (2005), Cotton (2009), Filiz-Ozbay and Ozbay (2007)
- Platform exit: Israel (2005), Ascarza, Iyengar, and Schleicher (2016), Backus, Blake, Masterov, and Tadelis (2015), Nosko and Tadelis (2015), Masterov, Mayer, and Tadelis (2015)

Our Setting

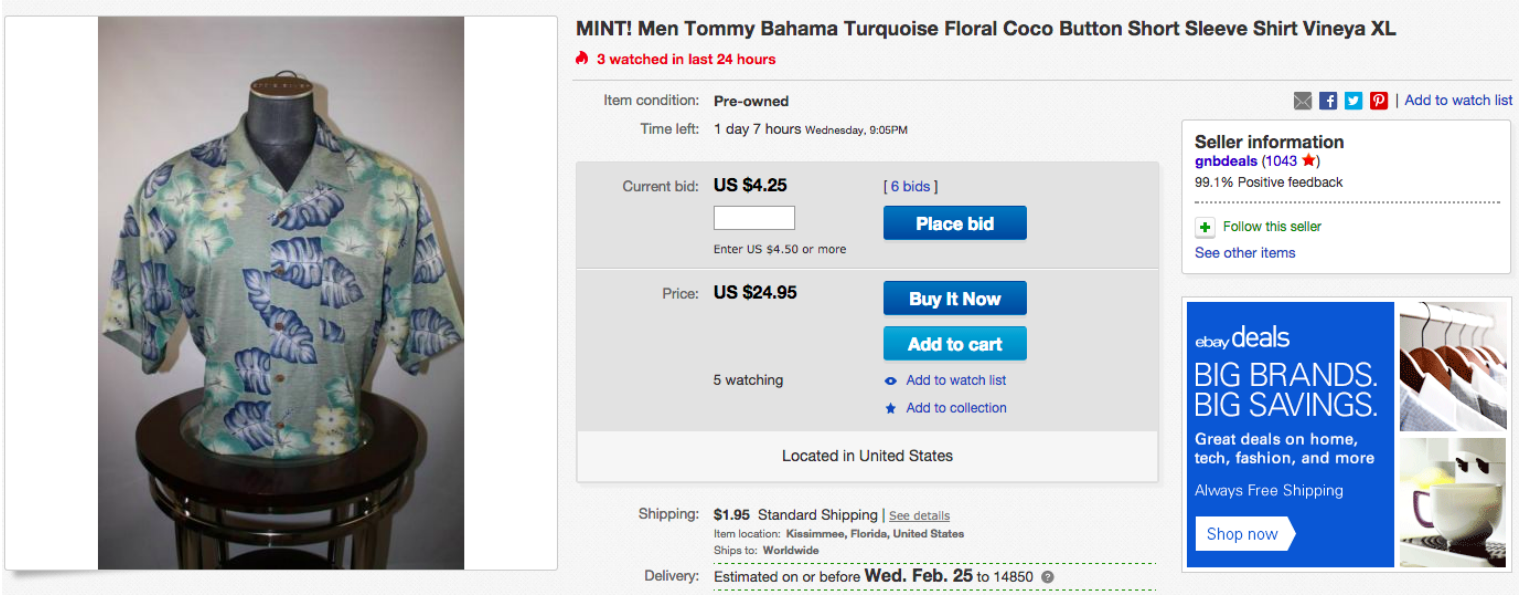
We study losers in eBay auctions

Everyone has the same material outcome

However, the *means* by which one loses could affect one's expectations

- is the loss a disappointment?
- is it expected?

Auctions with Buy-It-Now



In cell phones and accessories; clothing, shoes, and accessories; event tickets and experiences, and motor parts and accessories.

(a Very Stylized) Model of a Bidders Experience

You hold the standing high bid in an internet auction

You might win the auction, or you might lose

Along the way, you form expectations about the likelihood of winning

At the end of the auction you may be surprised – even disappointed – at the outcome

Based on your experience, you choose whether to try again

The Bidder

- Time t passes from 0 to 1, where 1 is the scheduled end of the auction
- At a point $s < 1$ take the standing high bidder.
- Normalize their payoff in the event that they win to 1, so the material outcome y is

$$y = \begin{cases} 0 & \text{if the bidder loses} \\ 1 & \text{if the bidder wins} \end{cases}$$

Surplus and Reference Points

- In our model, expectations about the material outcome enter as a *reference point*
- Let $p(t)$, for $t \in [s, 1]$ denote the bidder's expected likelihood of winning
- Then, the bidder's gains-loss utility at the end of the auction is:

$$\pi = y + \mu(y - p)$$

  – and for simplicity,

$$\mu = \begin{cases} \alpha \cdot (y - p) & \text{if } y - p \leq 0 \\ \beta \cdot (y - p) & \text{if } y - p > 0 \end{cases}$$

- Disappointment aversion: $\alpha > 0$

Expectations

ASSUMPTION 1 (evolution of p):

At the end of the auction,

$$p = \begin{cases} 0 & \text{if the bidder is outbid at } t \leq 1 \\ p_s \leq 1 & \text{if the bidder holds the high bid at } t = 1 \\ p(t) < p_s & \text{if the bidder loses to a BIN} \end{cases}$$

– moreover, $p(t)$ is increasing.

Rational Expectations Reference Points

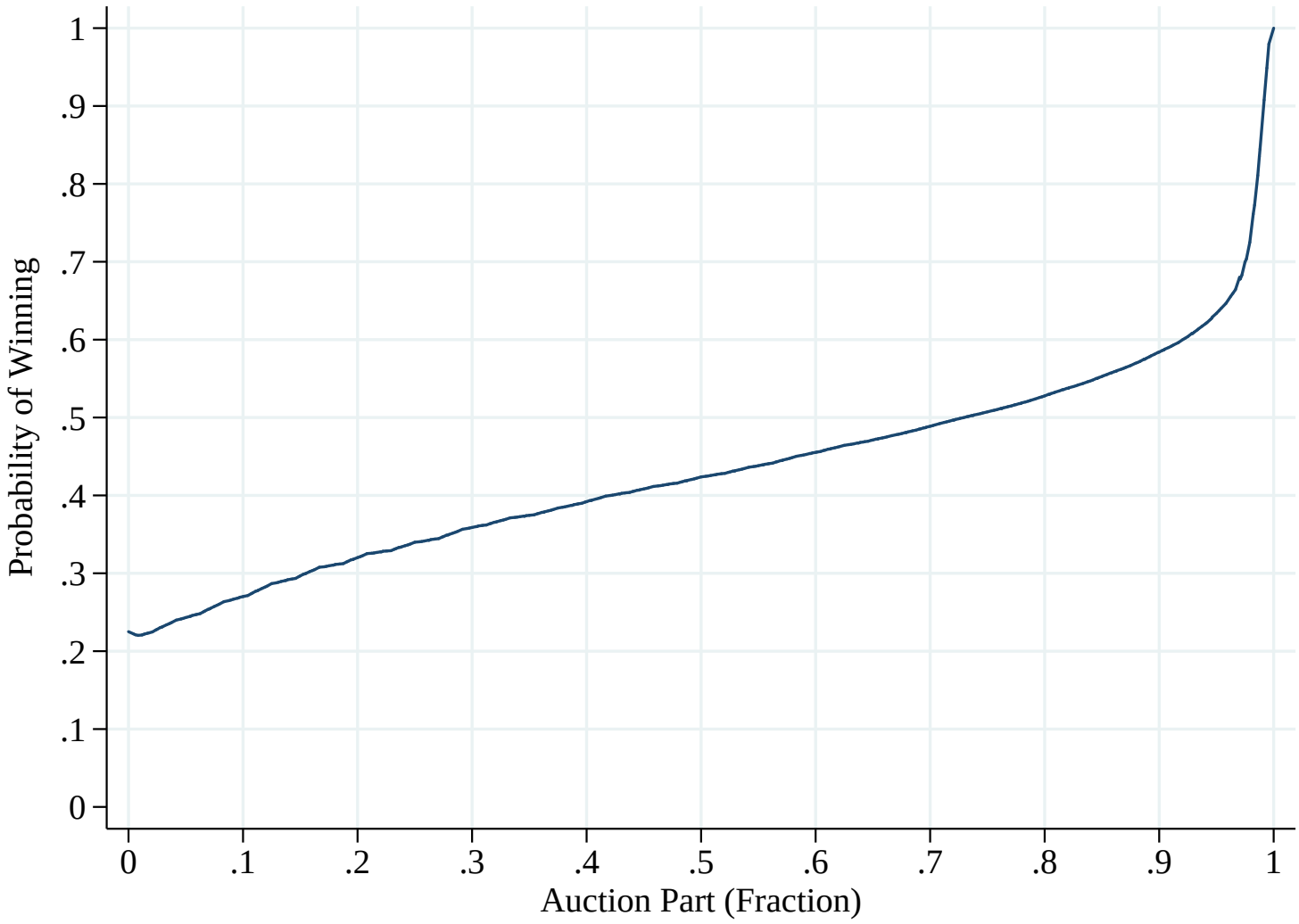
A1 yields reference points that are qualitatively consistent with rational expectations (Koszegi and Rabin 2006)

The longer I am in the lead, the more I believe I will win

- Consistent with models with random bidding opportunities (Ambrus, Burns, and Ishii 2014, Kapor and Moroni 2016, Hopenhayn and Saeedi 2016)

- Also consistent with our data

Evidence on Expectations



The Decision to Return

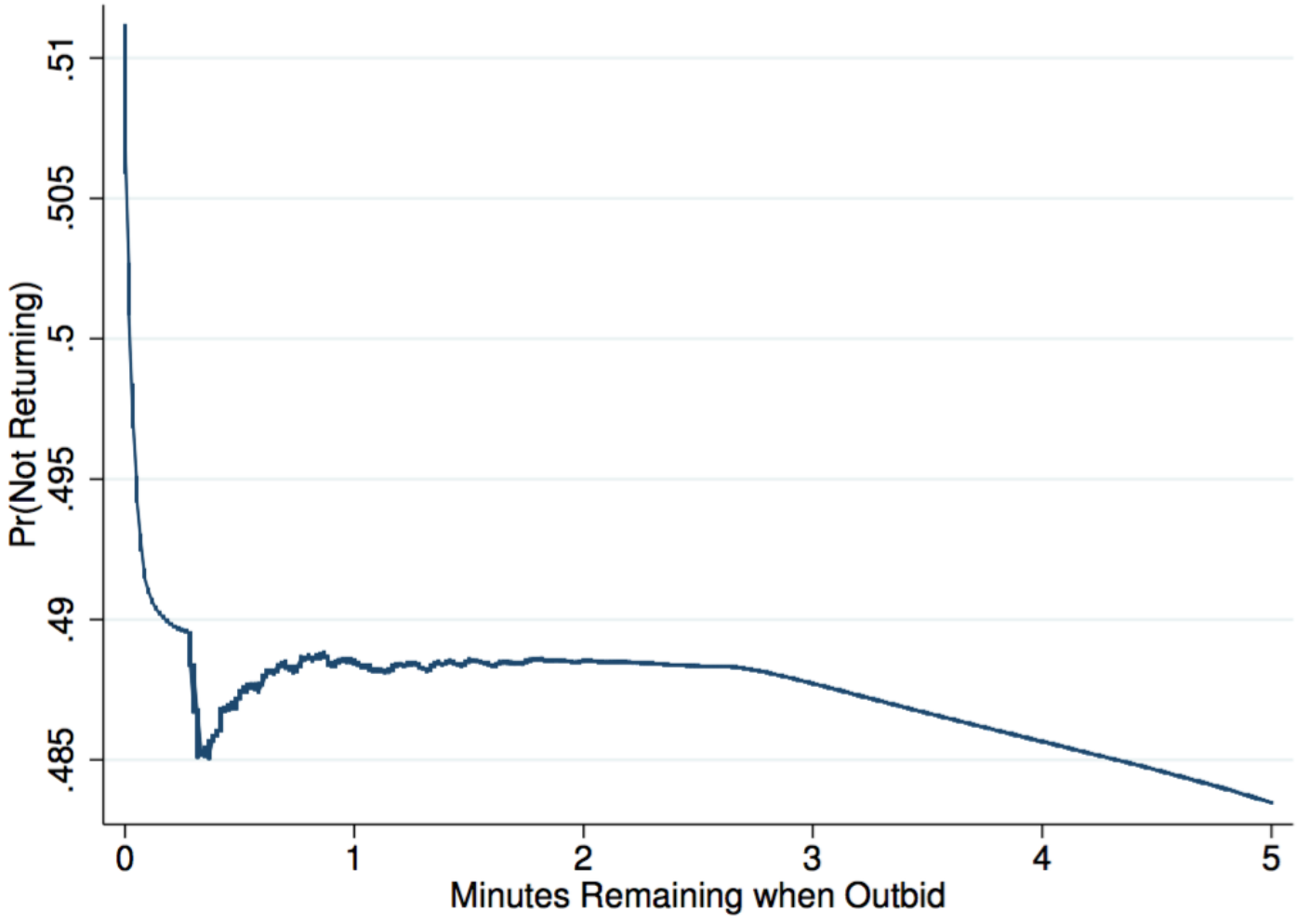
- Bidders form expectations about future surplus based on past experience
- They compare expected future surplus to their idiosyncratic outside option and **exit the platform** if

$$\mathbb{E}[\pi_{m+1}|\pi_1, \ldots, \pi_m] \leq \theta$$

  – where θ is bidder-specific and drawn from $F(\cdot)$

An Aside on Exit

From Backus, Blake, Masterov, and Tadelis (2015),



Return

ASSUMPTION 2 (beliefs):

$\mathbb{E}[\pi_{m+1}|\pi_1, \ldots, \pi_m]$ is strictly increasing in $\pi_1, \ldots, \pi_m$

- Weak assumption on updating process
- However, strong implication is that it rules out bidders learning structure

Predictions

From our model we derive a number of empirically testable hypotheses

- H1 First-time bidders, lose to BIN
- H2 First-time bidders, outbid
- H3 Experienced bidders, lose to BIN

Hypothesis (First-time, lost to BIN)

The longer a first-time bidder has been in the lead, the more likely they are to exit the platform after experiencing a BIN event

From the model, the probability of return is given by $F(\mathbb{E}[\pi_2|\pi_1])$, but $\pi_1 = -\alpha p(t)$. By A1, $p(t)$ is increasing in t, so by A2, the expectation is decreasing in t. □

Hypothesis (First-time, outbid)

Among first-time bidders who are outbid at $t < 1$, time spent in the lead is unrelated to exit.

From the model, the probability of return is given by $F(\mathbb{E}[\pi_2|\pi_1])$, but by A1, $\pi_1 = 0$. Therefore the probability of return is invariant to t. □

Hypothesis (Experienced, BIN)

Among experienced bidders bidders who lose to a BIN event, the relationship between time spent in the lead and exit is weaker than for inexperienced bidders

Intuition 1: θ is negatively selected on survival, so these bidders are more likely to return

Intuition 2: If one also assumes Bayesian updating, bidders' posterior variance on π_{m+1} shrinks as m grows large

NB: Similar to List 2003, WITHOUT assuming different preferences!

Empirics

Our three hypotheses are testable predictions for the relationship between time in the lead and exit

- H1 First-time bidders, lose to BIN
- H2 First-time bidders, outbid
- H3 Experienced bidders, lose to BIN

Define exit to be 0 if a bidder returns to bid in another auction within one year and 1 otherwise

H1: Empirical Strategy

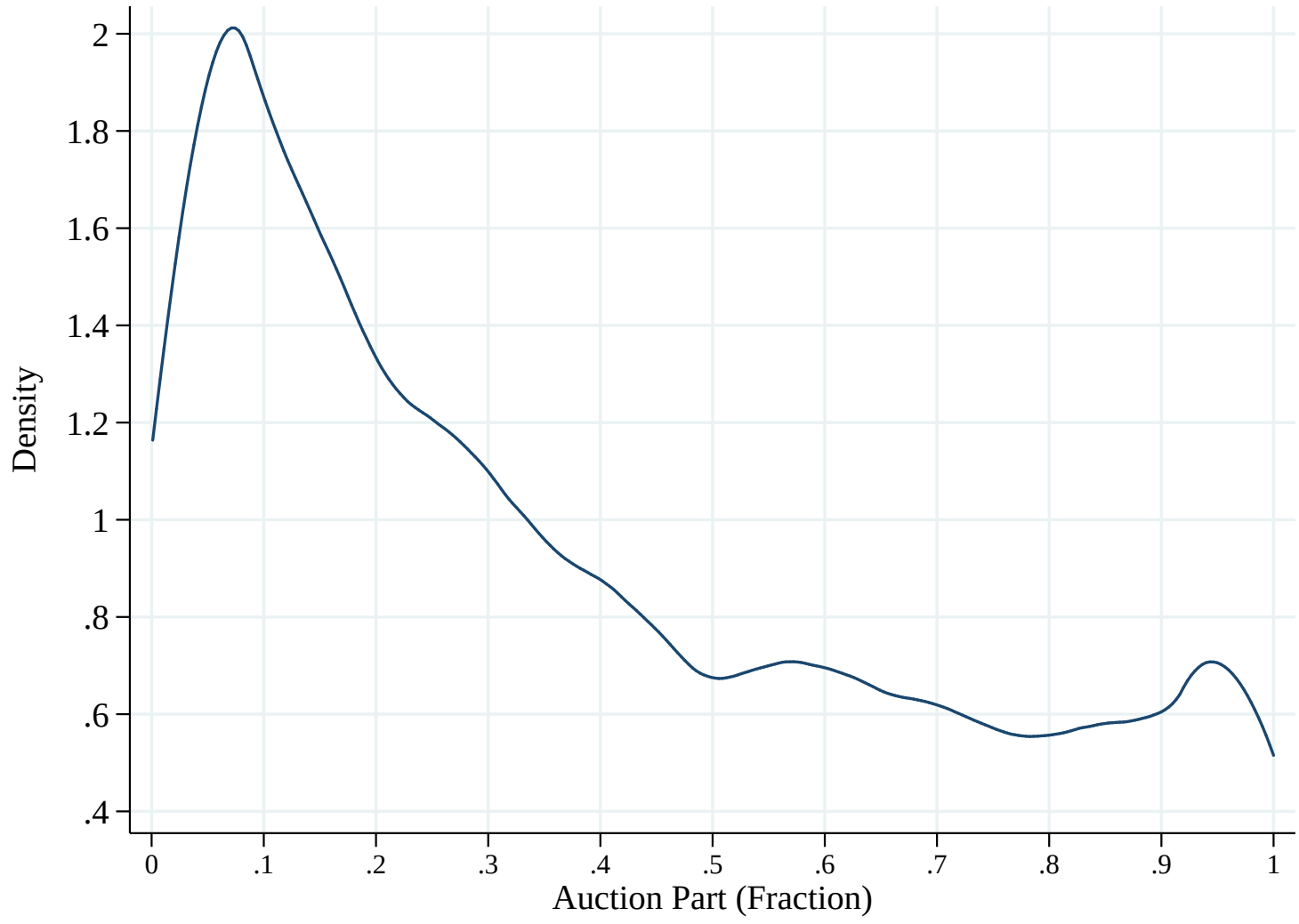
Out identification argument in three parts:

1. Careful sample construction
   - First time bidders (created account between June 2009 and October 2013),
   - whose first bid is an ABIN auction in our four categories
   - who lose to a BIN
2. time in the lead = time at BIN - time of bid
   - many plausible confounds, but most are observable
3. Robustness: Altonji et al. 2005, Oster (2015)
   - Put structure on the unobservables
   - What do we need to believe to qualitatively overturn the results?

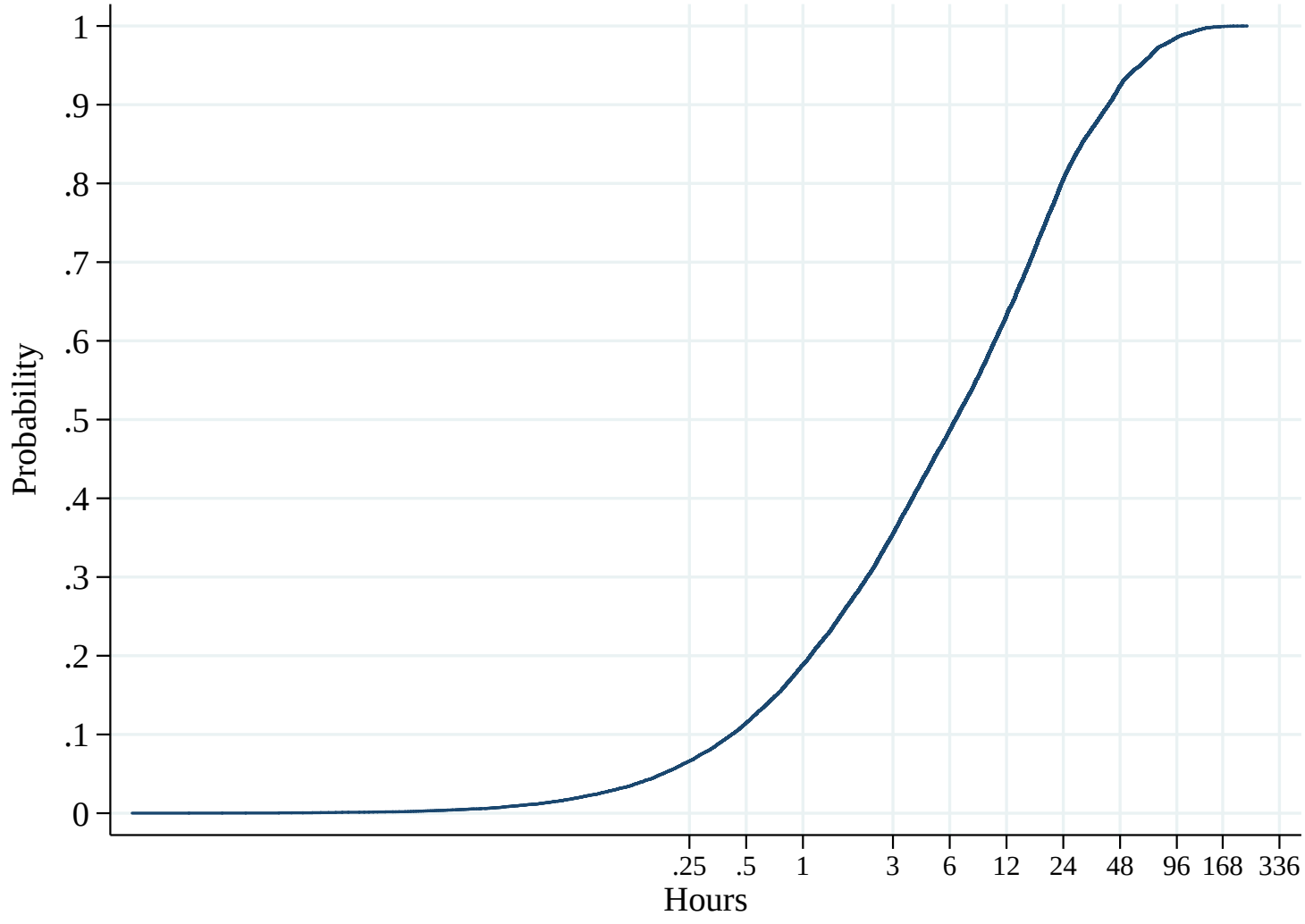
	Mean	Std. Dev	Min	Max	N
Abandoned Auctions After Losing	0.28	0.45	0	1	23,439
Abandoned eBay After Losing	0.23	0.42	0	1	23,439
Number of Distinct-Auction Bids In the Year Since Losing	20.1	116.99	0	8770	23,439
Number of BINs In the Year Since Losing	3.15	10.32	0	367	23,439
Perc. Diff. B/W Subseqent Attempt and Losing Bid	1764.1	29300.02	-99.9	999900	2,093
Attempted to Buy Same Product ID	0.29	0.45	0	1	7,294
Time in the Lead (24 Hours)	0.61	0.91	0.000012	9.42	23,439
Time in the Lead Intervals	1.13	0.49	1	11	23,439
Losing Bid-BIN Price Ratio	34.6	20.13	0.0024	100.0	23,439
Seller's Previous Transaction Count (1Ks)	32.9	276.16	0	4183.5	23,439
Item Page Views Per Day Up	105.7	329.22	0.29	18078.3	23,439
Events Before Auction Was Up (Normalized)	176.2	11146.98	0.00010	1589760	22,390
Sessions Before Auction Was Up (Normalized)	2.04	69.76	0.00010	8640	22,390
Item in Product Catalog	0.31	0.46	0	1	23,439
Listings Within 1 Year for Losing Product ID	2541.2	9209.17	1	154947	7,294
First Bid Normalized By Duration	0.26	0.27	0.00014	1.00	23,439
Scheduled Time Remaining When Outbid (Hours)	95.7	54.38	0.0011	240.0	23,439
Intended Lost Auction Duration (Days)	5.52	2.22	1	10	23,439
Intended Auction End Day:					
Sun	0.15	0.35	0	1	23,439
Mon	0.15	0.36	0	1	23,439
Tue	0.15	0.36	0	1	23,439
Wed	0.15	0.36	0	1	23,439
Thu	0.14	0.35	0	1	23,439
Fri	0.13	0.34	0	1	23,439
Sat	0.13	0.33	0	1	23,439
Vertical:					
Clothes	0.46	0.50	0	1	23,439
Phones	0.46	0.50	0	1	23,439
Auto Parts	0.063	0.24	0	1	23,439
Tickets	0.022	0.15	0	1	23,439
Item Condition:					
New	0.42	0.49	0	1	23,439
Refurbished	0.017	0.13	0	1	23,439
Used	0.53	0.50	0	1	23,439
Unknown	0.032	0.18	0	1	23,439

	Mean	Std. Dev	Min	Max	N
Female User	0.62	0.49	0	1	18,836
User Age (2 Year Increments)	35.0	14.42	18	99	13,650
Annual Household Income:					
<15K	0.15	0.35	0	1	23,316
15-19K	0.066	0.25	0	1	23,316
20-29K	0.12	0.33	0	1	23,316
30-39K	0.11	0.32	0	1	23,316
40-49K	0.098	0.30	0	1	23,316
50-74K	0.21	0.40	0	1	23,316
75-99K	0.10	0.31	0	1	23,316
100-124K	0.055	0.23	0	1	23,316
125K+	0.086	0.28	0	1	23,316

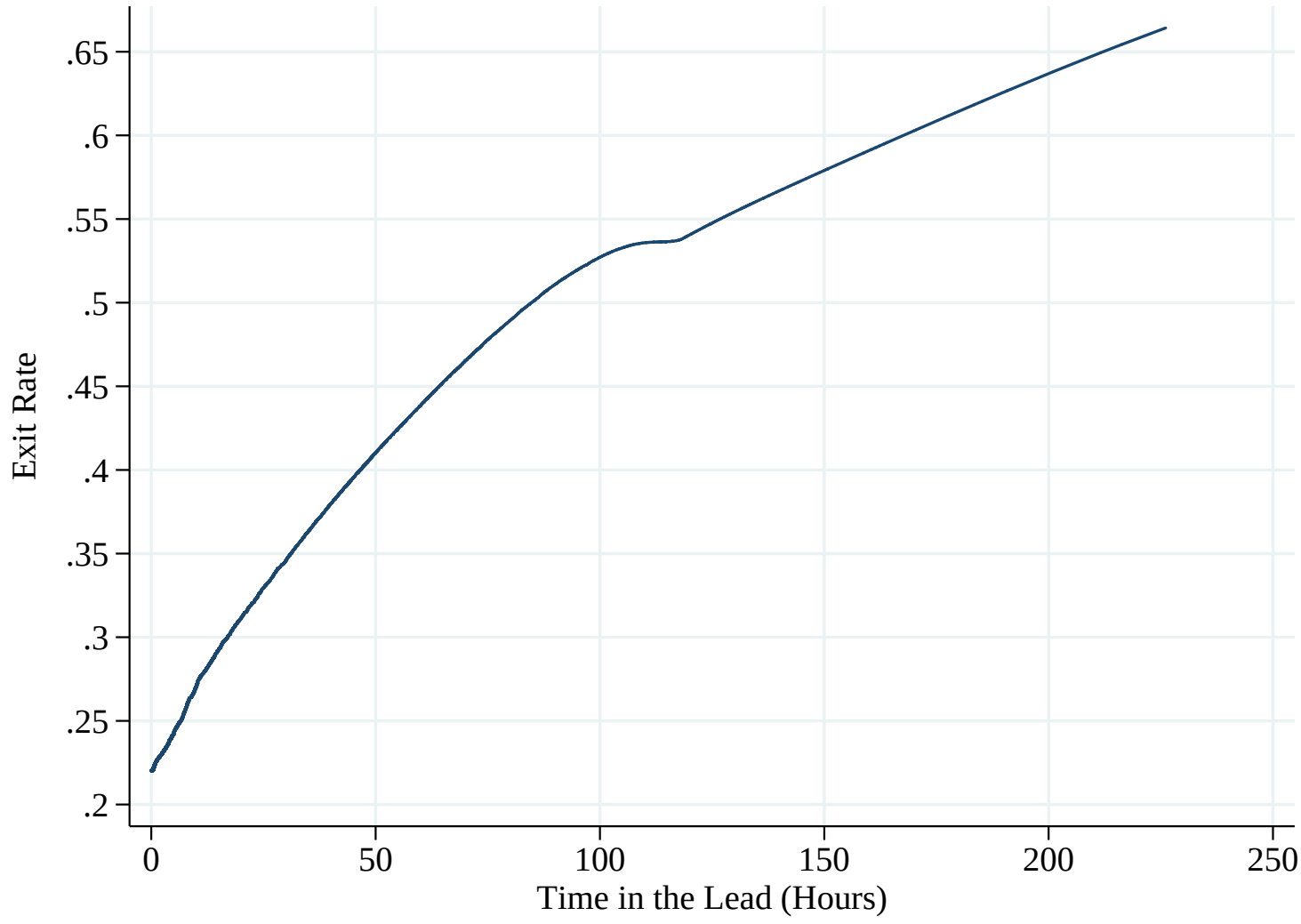
Distribution of BIN Option



CDF of Time in the Lead (in $\log_2$ Hours)



H1: Exit Rate By Time in the Lead



Observables

- Bid-Bin Ratio in deciles and number of spells as leader.
- Auction attributes
  - Product category
  - Duration and ending day of the week
  - Page views, seller experience, condition, productized
- Time variables
  - Deciles of scheduled time remaining at BIN
  - Quintiles of scheduled time remaining at first bid
- Site visits by bidder
- Demographics
  - Household income
  - gender
  - age

Main Results

	(1) AME	(2) AME	(3) AME	(4) AME	(5) AME	(6) AME
Time in the Lead (24 Hours)	0.073***	0.069***	0.065***	0.067***	0.064***	0.064***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.005)
Bid-Bin Ratio and Spells		Yes	Yes	Yes	Yes	Yes
Auction Attributes			Yes	Yes	Yes	Yes
Time Variables				Yes	Yes	Yes
Site Visits					Yes	Yes
Demographics						Yes
N	23,439	23,439	23,439	23,439	22,390	12,068

Another Alternative

Perhaps bidders are simply annoyed at time wasted

H2 disambiguates this by comparing "normal" to "BIN" losers

"Normal" losers expect to lose, so face no disappointment

(NB: Careful to exclude sniped losers)

H2: Other Losers

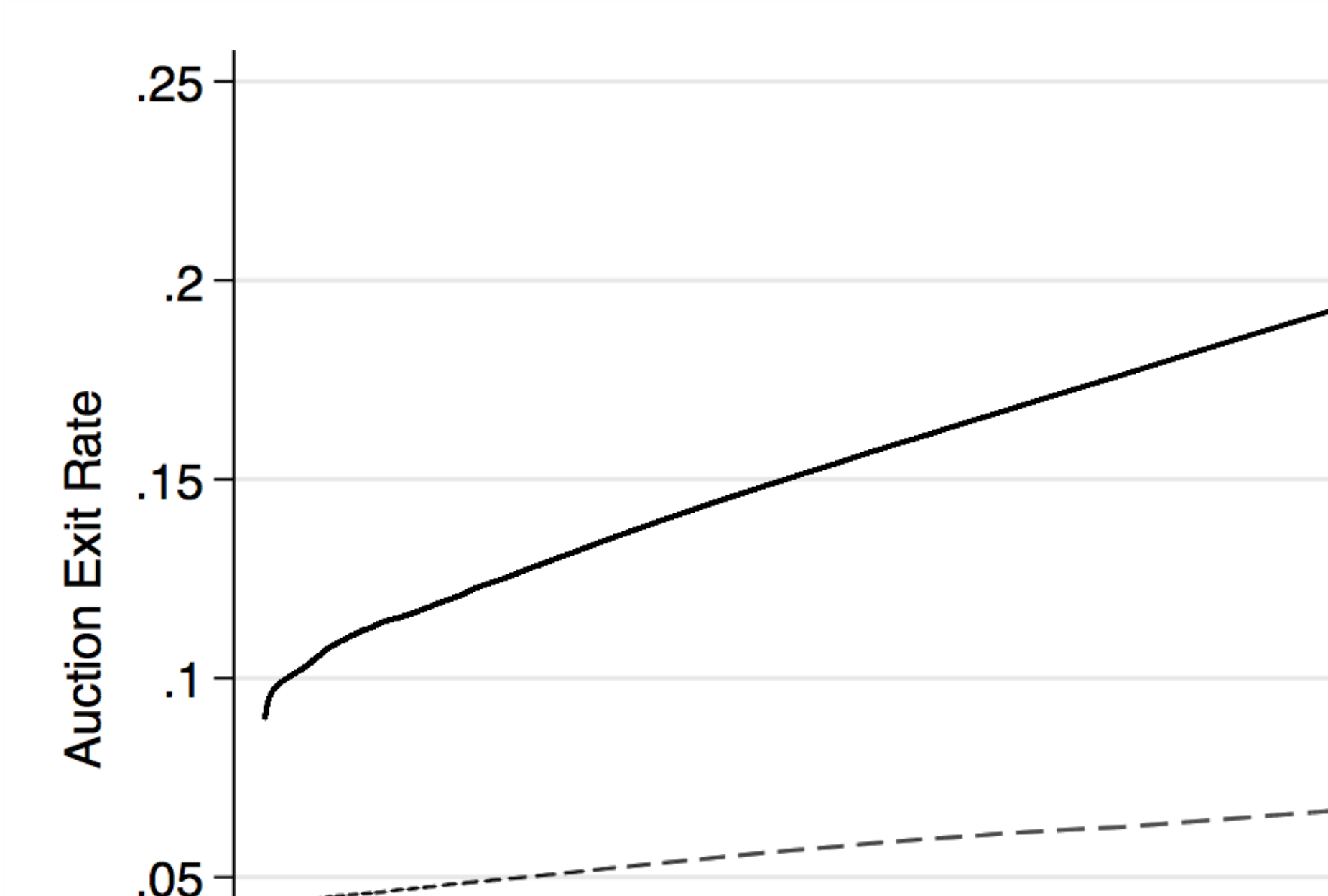
	(1) AME	(2) AME	(3) AME	(4) AME	(5) AME	(6) AME
AME:						
Binned Loser	0.075***	0.076***	0.073***	0.061***	0.058***	0.057***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
Non-Sniped Loser	0.011***	0.013***	0.009***	-0.010***	-0.011***	-0.005
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)
Bid-Bin Ratio and Spells		Yes	Yes	Yes	Yes	Yes
Auction Attributes			Yes	Yes	Yes	Yes
Time Variables				Yes	Yes	Yes
Site Visits					Yes	Yes
Demographics						Yes
N	142,481	142,481	142,476	142,476	82,459	27,980

Hypothesis H3

Our final hypothesis is a bit of a sanity check

H3 predicts that the cross effect of experience and time in the lead should be negative

H3: Exit Rate By Experience



Extensions and Robustness

- We worry about sensitivity in the spirit of Altonji et al. 2005 and Oster 2015
  - Intuition: adding structure to unobservables tells us about what we need to believe to kill the story with omitted variable bias ▸ robustness
- We consider other outcomes (e.g., eBay vs. auction exit, future bids) ▸ other outcomes
- We re-run the exercise with commodity products ▸ commodity products

Interesting Comparison with Card-Dahl

- Card and Dahl (2011) test for belief updating using the score at halftime and conclude that behavior is driven by the game outcome relative to expectations at the start of the game, with no updating of reference points based on halftime information.

- We find that individuals appear to update their reference points in two important ways.
  - Time in the lead seems to rapidly and rationally shift their beliefs about the likelihood of winning the object.
  - More striking, if they lose and have recourse to re-bid, and choose not to, then they update their reference point in an extreme way and seem to shed the expectation of winning the auction, regardless of how long they were in the lead beforehand.

Wrapping Up

We hope we did a few things:

- Offered empirical evidence from a real marketplace in favor of expectations as reference points
- Showed that the effects of expectations as reference points are important for the platform
- Offered an example of how rich data from online platforms can be used to study behavioral hypotheses

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Thanks!

Robustness

Recall, from our test of H1:

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Time in the Lead (24 Hours)	0.073***	0.069***	0.065***	0.067***	0.064***	0.064***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.005)
Bid-Bin Ratio and Spells		Yes	Yes	Yes	Yes	Yes
Auction Attributes			Yes	Yes	Yes	Yes
Time Variables				Yes	Yes	Yes
Site Visits					Yes	Yes
Demographics						Yes
N	23,439	23,439	23,439	23,439	22,390	12,068

Can we be more formal about the argument from observables?

LPM

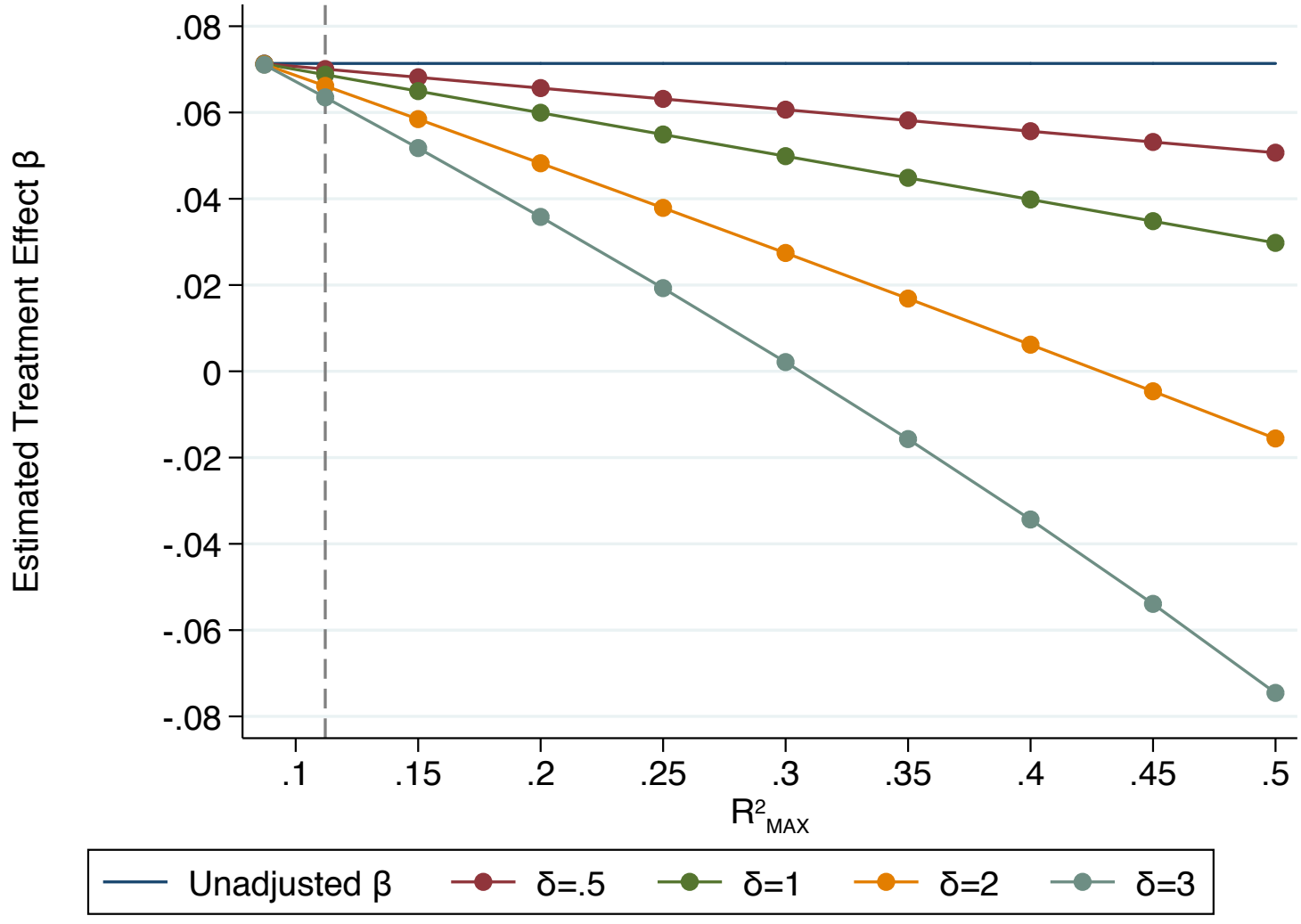
	(1) ME	(2) ME	(3) ME	(4) ME	(5) ME	(6) ME
Time in the Lead (24 Hours)	0.080***	0.076***	0.073***	0.075***	0.072***	0.071***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
Bid-Bin Ratio and Spells		Yes	Yes	Yes	Yes	Yes
Auction Attributes			Yes	Yes	Yes	Yes
Time Remaining				Yes	Yes	Yes
Site Visits					Yes	Yes
Demographics						Yes
N	23,439	23,439	23,439	23,439	22,390	12,068
R^2	0.03	0.04	0.05	0.05	0.08	0.09

Putting Structure on the Unobservables

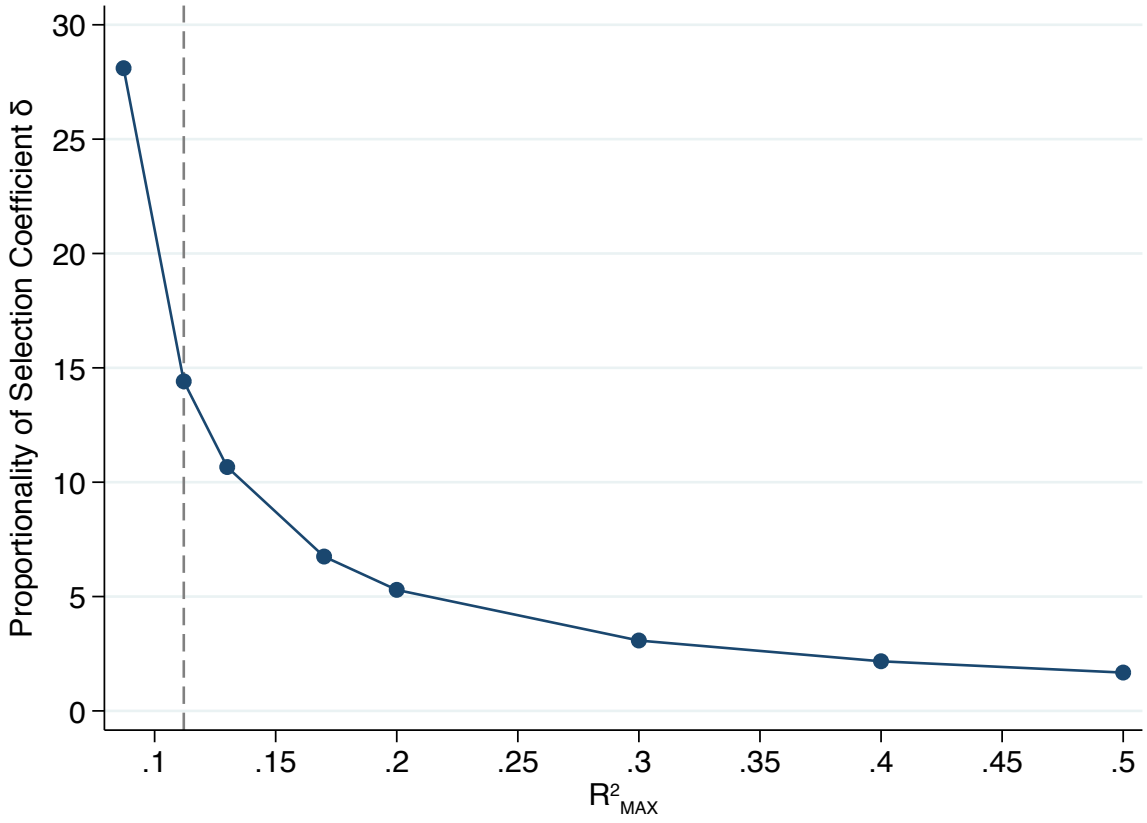
Following Altonji et al. (2005) and Oster (2015), we can write the potential omitted variable bias for β in terms of two variables:

- R^2_{MAX}, the R^2 of a regression including the unobservable confounds
- δ, the coefficient of proportionality, describing the correlation between the regressor of interest and the (un)observables

Adjusted Treatment Effect



Bounds for $\beta = 0$



Reasonable assumptions of R^2_{MAX} and δ (unobservables *twice* as important) still imply $\beta > 0$

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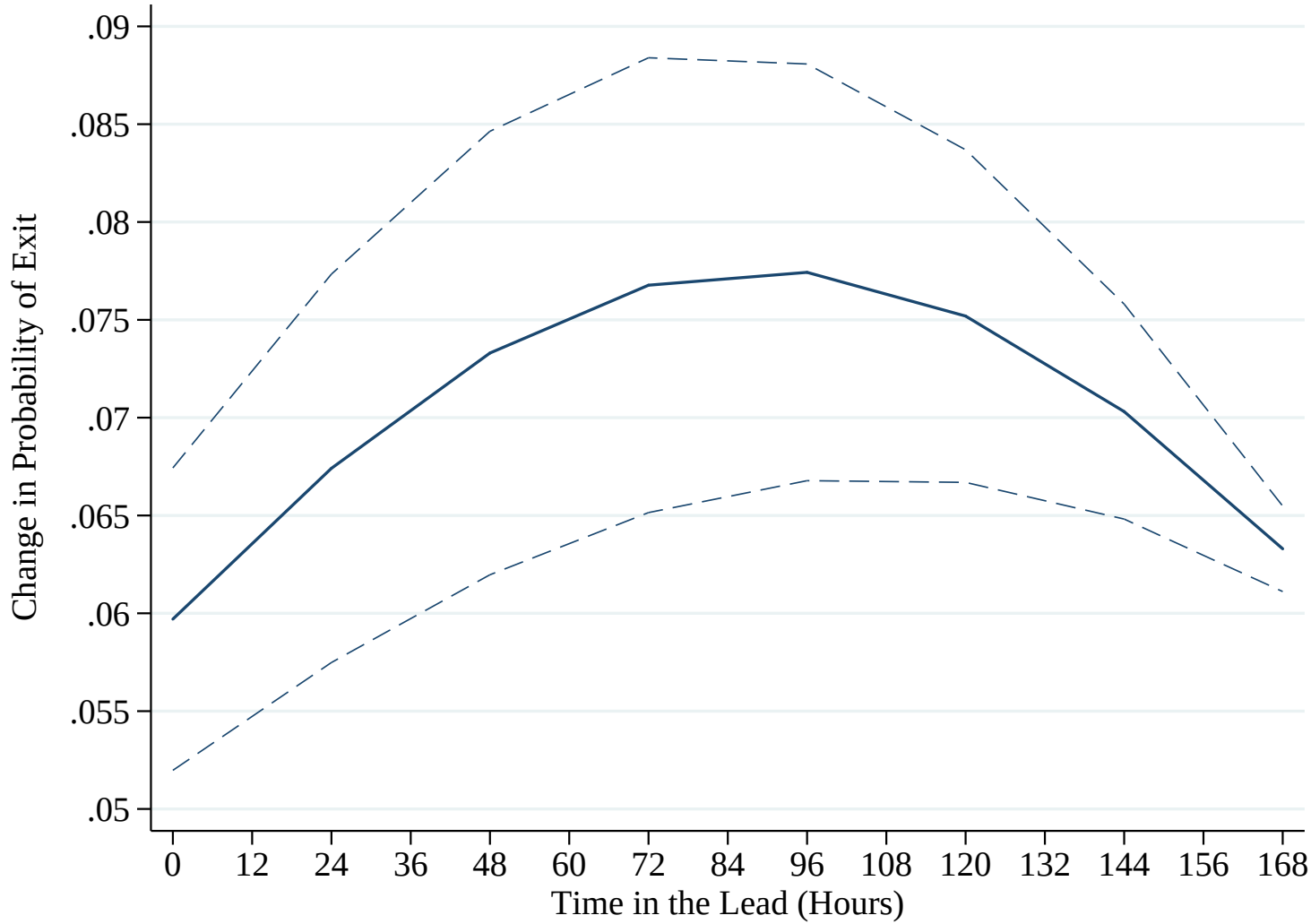
Marginal Effect at Different Values



An alternative model might involve a *pseudo-* or *quasi-* endowment effect (Wolf, Arkes, and Muhanna 2005, Bramsen 2008, Cotton 2009)

Perhaps bidders grow attachment over time as they lead the auction

These models predict re-bidding and higher bidding

Other Outcomes

	(1) Auct. Exit	(2) eBay Exit	(3) Same Product ID	(4) WTP Change
Spec. (1)	0.073***	0.060***	-0.044***	-7.026
	(0.003)	(0.003)	(0.009)	(5.018)
Spec. (2)	0.069***	0.057***	-0.050***	4.807
	(0.003)	(0.003)	(0.010)	(4.573)
Spec. (3)	0.065***	0.056***	-0.054***	3.400
	(0.003)	(0.003)	(0.011)	(5.332)
Spec. (4)	0.067***	0.058***	-0.055***	2.373
	(0.003)	(0.003)	(0.011)	(5.478)
Spec. (5)	0.064***	0.055***	-0.056***	2.534
	(0.003)	(0.003)	(0.011)	(5.564)
Spec. (6)	0.064***	0.054***	-0.043**	0.000
	(0.005)	(0.004)	(0.015)	(6.528)

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Commodity Products

	(1) AME	(2) AME	(3) AME	(4) AME	(5) AME	(6) AME
Time in Lead (24 Hours)	0.091***	0.084***	0.067***	0.072***	0.072***	0.078***
	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)	(0.013)
Bid-Bin Ratio and Spells		Yes	Yes	Yes	Yes	Yes
Auction Attributes			Yes	Yes	Yes	Yes
Time Variables				Yes	Yes	Yes
Site Visits					Yes	Yes
Demographics						Yes
N	7,006	7,006	7,006	7,006	6,509	3,167

A commodity is a product listing with at least ten appearances in the following year

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