Managing Bidder Learning in Retail Auctions

Simon Schulten (DICE, hhu) and Paul Schäfer (Uni Bonn)

Exploitation of Behavioral Biases and Learning

- Firms have an incentive to exploit consumer mistakes when consumers have behavioral biases.
- Overbidding is a well documented consumer mistake in auctions [Malmendier and Lee 2011]; [Malmendier and Szeidl 2020].
- In repeated interactions it is not unreasonable to think that consumers may learn from their mistakes.
  - This could "fix the market".
- It is, however, equally plausible that firms respond optimally to consumer learning.
- Firms may use their substantial control over the transaction environment to manage consumer learning to their benefit.

The Auction and Overbidding

Multi Unit Descending Auction

- Auctioneer announces number of units to be sold and start auction at a high starting price.
- The current price is lowered over time (discrete increments).
- Bidders can submit bids at the current price. Each bid claims one unit of the good.
- The auction ends when all units are claimed.
- All bidders pay the lowest bid in the auction, regardless of their own bid (uniform pricing rule).

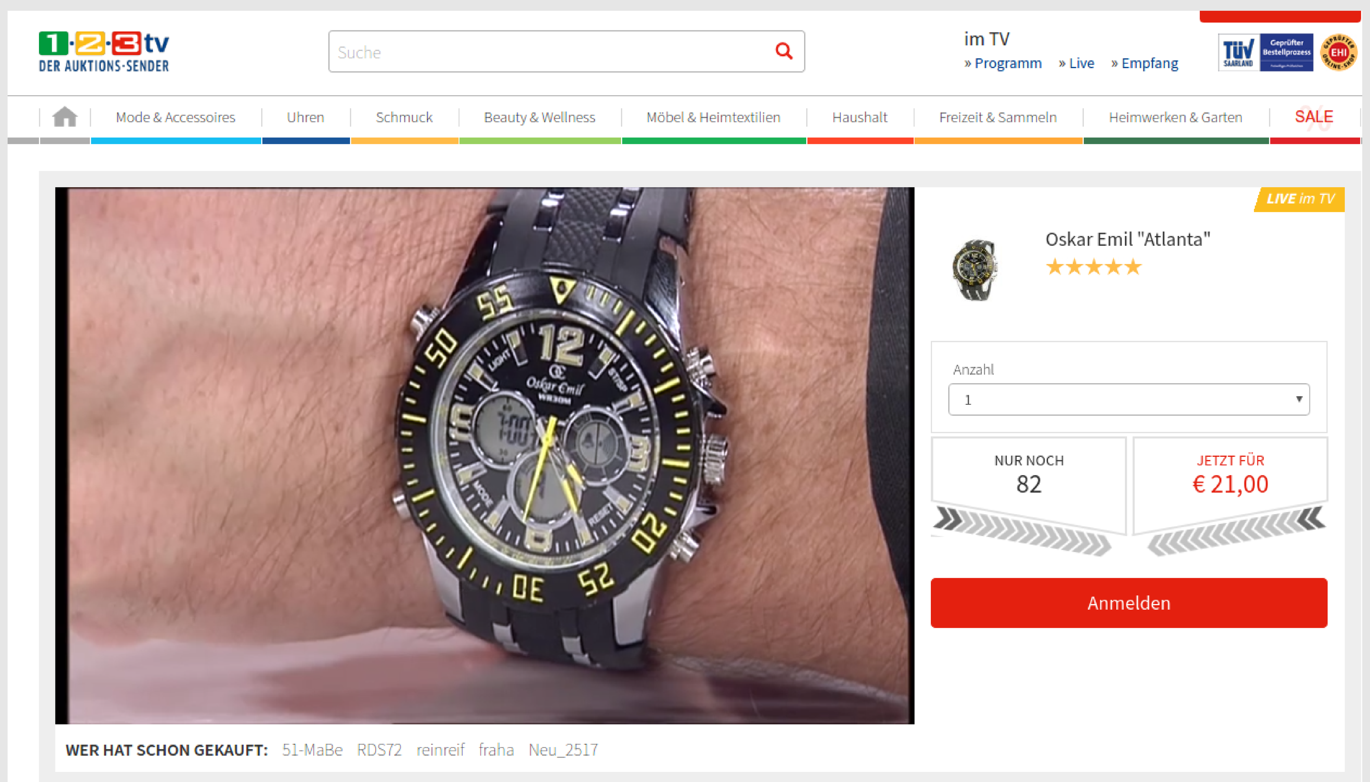

Figure 1. The Auction.

Overbidding and Overpaying

- Every item in the auction can also be purchased in the online shop at a fixed price.
- We call a bid that is larger than the fixed price an **overbid**.
- We define an auction that ends above the fixed price as **overpaid**.
- Overpaying leads to a negative transaction utility.
  - It is plausible that experience a negative transaction utility leads bidders to rethink their actions.
- Uniform pricing rule: overbidding does not imply overpaying.

Data

- We scraped the auction website for 2 years.
- Information on bids (with Username) and product prices at the time of the auction.
- Long-term panel data that allows us to follow bidders as well as the institution over time.

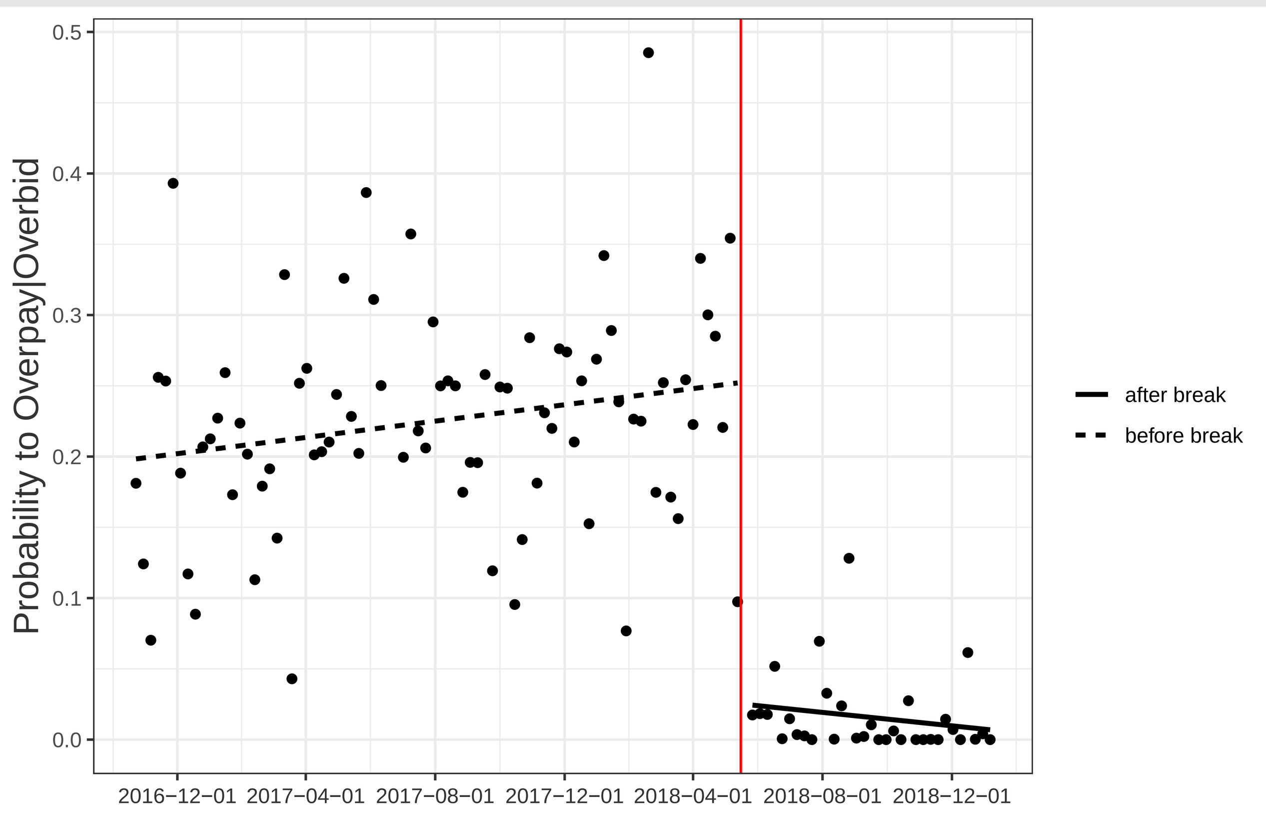

Figure 2. Weekly averages of overpaying probabilities conditional on overbidding.

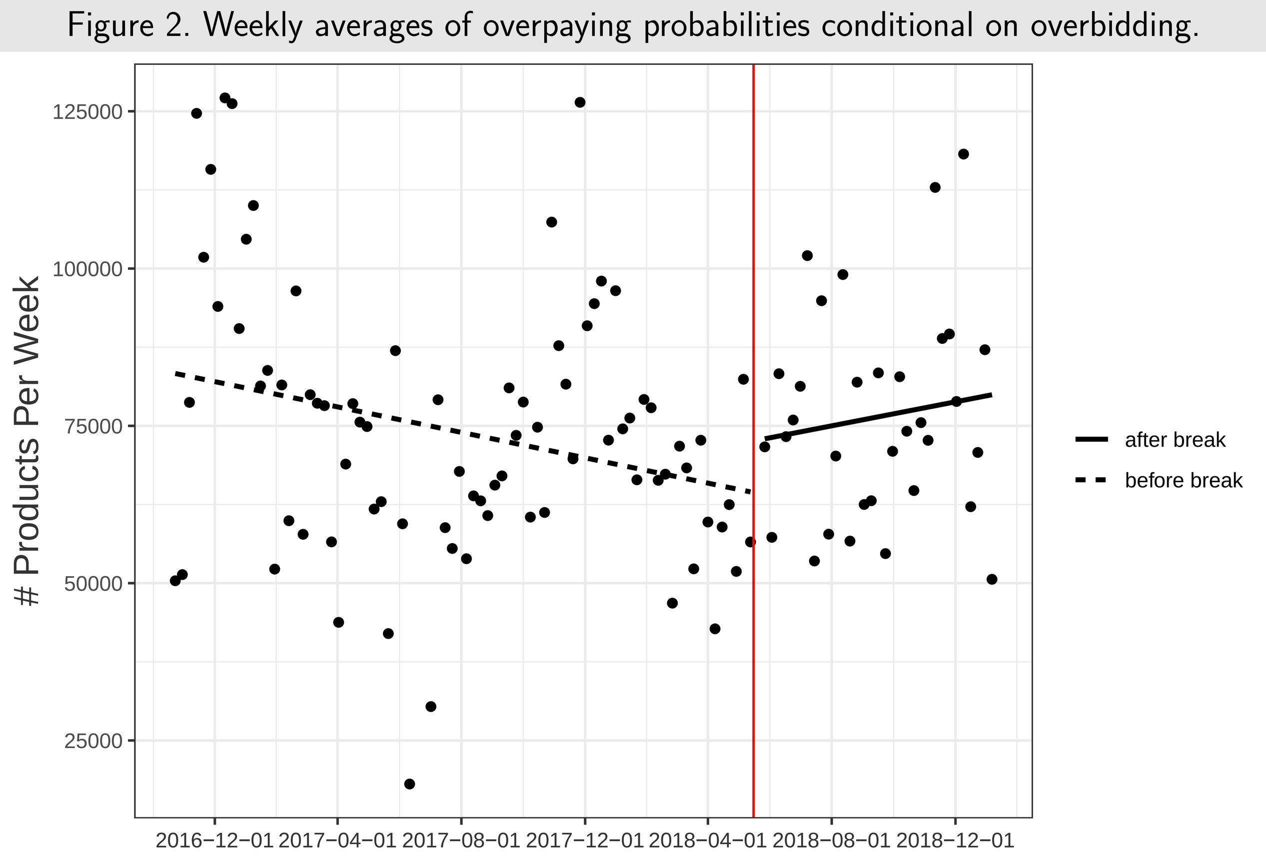

Figure 3. Number of Products sold each week.

Intensive and Extensive Margin Learning

- In our case, bidders may learn not to overbid again. We call this the **intensive margin learning**.
  - After making a mistake one may narrowly learn to avoid exactly that same mistake [Haselhuhn et al. 2012]; [Agarwal et al. 2013]; [Ater and Landsman 2013].
- Bidders may learn not to participate in the auction. We call this the **extensive margin learning**.
  - Bidders may think they are bad or unlucky at bidding. Or that the auctions do not provide a lot of value [Anderson and Simester 2010]; [Backus et al. 2021].
- We model bidders three types: overbidder, sophisticate and non-bidder.
- We capture learning as a transition from being an overbidder to being a sophisticate or non-bidder.

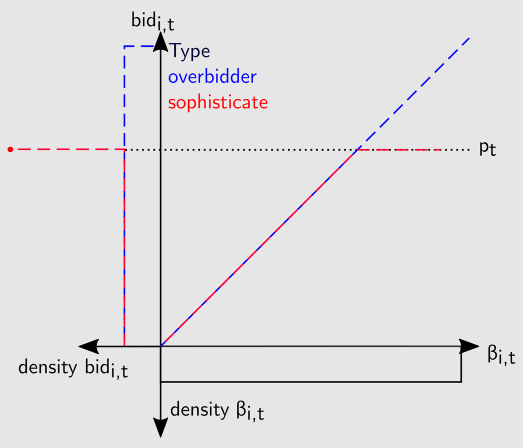

Figure 4. Bids as a function of latent bids. Marginal distribution of bids and latent bids for uniformly distributed latent bids.

Identifying Treatment Effects with a DAG

- We encode causal knowledge about the environment in a DAG or Causal Graph and use the backdoor-criterion to prove identification of treatment effects of overpaying.
- We are interested in the treatment effects on future number of overbids and future number of non-overbids.
  - These two treatment effects allow us to disentangle intensive and extensive margin learning.

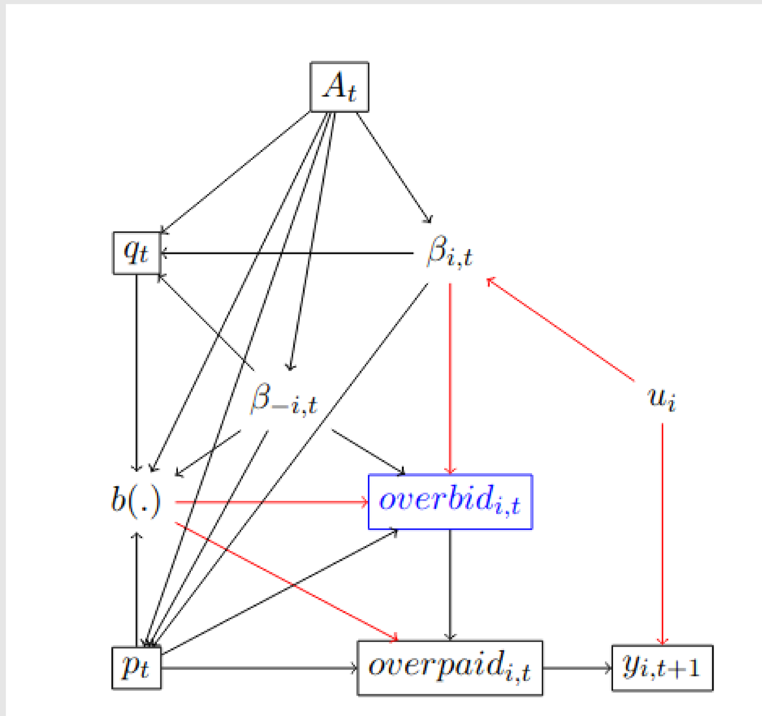

Figure 1: Collider Path

Results

- We find negative treatment effects for number of overbids and number of non-overbids, indicating that overpaying leads to fewer bids and fewer overbids.
- A stronger effect on number of non-overbids gives a first indication of extensive margin learning.

	# Overbids	# Non-Overbids
Overpaid	-0.154***	-0.343**
	(0.027)	(0.109)
Num.Obs.	117,973	117,973
R2	0.092	0.168
Counterfactual	1.213	6.387

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

- Treatment effects are learning effects scaled with the probability that we observe them
- We estimate this probability with the counterfactual mean

Simplified Example (no Heterogeneity in Learning, no Aggregation):

$$e = -\frac{\text{TE non-overbids}}{\text{non-overbids}(0)} = -\frac{-e \cdot P(\text{successful non-overbid})}{P(\text{successful non-overbid})}$$

- Probability of extensive margin learning ≈ 0.054
- Probability of intensive margin learning ≈ 0.07

References

- Backus, M., T. Blake, D. V. Masterov, and S. Tadelis (July 2021). "Expectation, Disappointment, and Exit: Evidence on Reference Point Formation from an Online Marketplace". In: *Journal of the European Economic Association*.
- Malmendier, U. and A. Szeidl (2020). "Fishing for fools". In: *Games and Economic Behavior*.
- Agarwal, S., J. C. Driscoll, X. Gabaix, and D. I. Laibson (2013). "Learning in the Credit Card Market". In: *SSRN Electronic Journal*.
- Ater, I. and V. Landsman (2013). "Do customers learn from experience? Evidence from retail banking". In: *Management Science* 59.9.
- Haselhuhn, M. P., D. G. Pope, M. E. Schweitzer, and P. Fishman (2012). "The impact of personal experience on behavior: Evidence from video-rental fines". In: *Management Science* 58.1.
- Malmendier, U. and Y. H. Lee (2011). "The bidder's curse". In: *American Economic Review* 101.2, pp. 749–787.
- Anderson, E. T. and D. I. Simester (2010). "Price stickiness and customer antagonism". In: *Quarterly Journal of Economics* 125.2, pp. 729–765.