ONLINE APPENDIX

Auctions versus Posted Prices in Online Markets

by Einav, Farronato, Levin and Sundaresan

This online appendix contains four sections. Appendix A provides a more general version of the model from Section 2. Appendix B includes additional charts and tables that are referenced in the main paper. Appendix C reports alternative specifications for our main results, using different matching criteria, as discussed in Section 3. Appendix D provides cross-country evidence on the decline on eBay auctions. A separate document, Appendix E, contains the survey we sent to eBay sellers, and complete responses.

Appendix A. Extended Model

The model in Section 2 assumes that all buyers have the same value v. We mention in the text that allowing heterogeneity in buyer valuations would not change the main results. Here we describe this extension.

There are $n \geq 1$ potential buyers, indexed by $i = 1, ..., n$. Buyer i has a value $v_i = v + w_i$, where v is a common value for all buyers drawn from a distribution f, and each w_i is an idiosyncratic value drawn independently from a distribution g. The distributions f and g are both log-concave. Let $w^{(1)}, ..., w^{(n)}$ denote the order statistics of the idiosyncratic value draws, and $v^{(k)} = v + w^{(k)}$ be the kth order statistic of the buyer valuations. All buyers have a common reservation value u, and auction disutility λ.

If the seller offers a posted price p, the probability of sale is

$$Q_F(p) = \Pr\left[v^{(1)} - u \geq p\right].$$

If the seller offers an auction with reserve price r, the probability of sale is

$$Q_A(r) = \Pr\left[v^{(1)} - \lambda - u \geq r\right].$$

Therefore (as in Figure 5) the posted price demand curve is a vertical translation of the auction sales curve: $Q_F(r + \lambda) = Q_A(r)$. That is, setting a posted price of $r + \lambda$ gives an equivalent probability of sale as running an auction with reserve price r.

Next, the expected auction price given reserve price r is

$$p_A(r) = r + \mathbb{E}\left[\max\left\{v^{(2)} - \lambda - u - r, 0\right\} \mid v^{(1)} - \lambda - u - r \geq 0\right].$$

We claim that the second term is decreasing in r. This is because

$$\begin{aligned}
&\mathbb{E}\left[\max\left\{v^{(2)}-\lambda-u-r,0\right\} \mid v^{(1)}-\lambda-u-r\geq 0\right] \\
&\quad= \mathbb{E}\left[v^{(2)}-\lambda-u-r \mid v^{(2)}-\lambda-u-r\geq 0\right] \\
&\qquad\times \Pr\left[v^{(2)}-\lambda-u-r\geq 0 \mid v^{(1)}-\lambda-u-r\geq 0\right].
\end{aligned}$$

Log-concavity of the distributions $f(v)$ and $g(w_i)$ is preserved for the distribution of $v+w_i$, and for the corresponding order statistics (Barlow and Proschan, 1966).[1] Moreover, the mean residual lifetime $\mathbb{E}\left[v_i \mid v_i \geq r'\right]-r'$ of a random variable whose distribution is log-concave is decreasing in r'. So $\mathbb{E}\left[v^{(2)}-\lambda-u-r \mid v^{(2)}-\lambda-u-r\geq 0\right]$ is decreasing in r.

It remains to be proven that $\Pr\left[v^{(2)}-\lambda-u-r\geq 0 \mid v^{(1)}-\lambda-u-r\geq 0\right]$ is also decreasing in r. Let H be the cumulative distribution function of $v_i=v+w_i$ and n the number of bidders. Then

$$\begin{aligned}
\Pr\left[v^{(2)}-\lambda-u-r\geq 0 \mid v^{(1)}-\lambda-u-r\geq 0\right] &= \frac{\Pr\left[v^{(2)}-\lambda-u-r\geq 0\right]}{\Pr\left[v^{(1)}-\lambda-u-r\geq 0\right]} \\
&= 1-\frac{nH^{n-1}(r+\lambda+u)\left[1-H(r+\lambda+u)\right]}{\left[1-H^{n}(r+\lambda+u)\right]} \\
&= 1-\frac{nH^{n-1}(r+\lambda+u)}{1+\sum_{k=1}^{n-1}H^{k}(r+\lambda+u)}.
\end{aligned}$$

The last term is an increasing function of r, so $\Pr\left[v^{(2)}-\lambda-u-r\geq 0 \mid v^{(1)}-\lambda-u-r\geq 0\right]$ is decreasing in the reserve price.

With this established, it follows that the posted price demand curve is steeper than the auction demand curve. To see this, for any q define r such that $q=Q_A(r)$. Then the vertical distance between the auction demand curve and the posted price demand curve at q is $p_A(r)-(r+\lambda)$, which is decreasing in r, and hence increasing in q. Furthermore, at $q=0$, we have $p_A(r)=r<r+\lambda$. So the auction demand curve starts below the posted price demand curve. At $q=1$, we have $p(r)=\mathbb{E}\left[v+w^{(1)}\right]-\lambda-u$, whereas the relevant posted price is $\underline{v}+\underline{w}-u$, so provided $\lambda<\mathbb{E}\left[v+w^{(1)}\right]-(\underline{v}+\underline{w})$, the auction demand curve ends higher.

Therefore the posted price demand curve crosses the auction demand curve once from above as in Figure 5. Under this condition, the comparative statics in the main text with respect to c, u, and λ are straightforward. In particular, an increase in any of these parameters makes it more likely that the best posted price will dominate an auction with an optimal reserve price.

[1] Barlow, Richard E., and Frank Proschan (1966). "Inequalities for Linear Combinations of Order Statistics from Restricted Families." *Annals of Mathematical Statistics* 37(6), 1574-1592.

Appendix B. Additional Tables and Figures

This Appendix includes Additional Tables and Figures that were referenced but not included in the main text.

Appendix B Figures

Appendix B Tables

Appendix C. Alternative Matching Criteria

In the paper, we define a set of matched listings to be the same item sold by the same seller within the same calendar year. A potential concern with this definition is that a full calendar year is a long period: demand conditions may change, the seller's information about the item value may change, or the seller's listing strategy may evolve. Such time-varying changes within a matched set of listings could affect the causal interpretation of our main results.

To address these types of concerns, in this appendix we replicate our main results (Figure 8, Figure 10, Table 2, and the key numbers from Figure 7) using seven alternative criteria for matching listings. *Matching Definition I* shortens the time period for matching listings to a calendar-quarter, so that we identify matched listings as being listings of the same item by the same seller offered within a calendar quarter (that is, within January-March, within April-June, and so on). This provides less comparable listings for any given listing in the sample, but arguably demand conditions and seller information are more likely to be stable within a quarter than within a year.

We next explore the possibility that there might be life-cycle effects in for any given item, and these life-cycle effects or time trends in the demand for the item could confound our results. Such a confounding problem might arise if, for example, demand for the item fell over time and the seller also shifted sale format from posted price toward auctions. We use two alternative methods to identify and address possible time trend or product life-cycle issue. For both methods we start with our baseline sample (same item, same seller, same year) or matched listings.

The first of the two approaches relies on the regression model

$$p_{ij} = a_j + \beta_j t_{ij} + \varepsilon_{ij}.$$

Here j indicates a matched set, i indicates a posted-price listing within the set, p_{ij} is the normalized posted price associated with the listing, and t_{ij} is a calendar time indicator (measured in weeks). We run this regression separately for each matched set. The coefficient β_j, which is estimated separately for each matched set, captures a time trend in the listed price for the item. The idea in this regression is that if demand for the item is changing systematically over time due to product life-cycle or because the supply of potential buyers begins to be exhausted, and the seller is responsive in terms of selling approach (which might confound our results), we should be able to pick this up as well from seeing changes in the listing price.

The table below reports the resultant distribution of the estimated β_j's across matched sets, separately for 2003 and 2009. For the median item in our sample, there is no trend in the posted price over time (the median β_j in both 2003 and 2009 is zero). However, some items do exhibit systematic price trends, including some items with sizeable price decreases over time. The average β_j is negative although relatively small (corresponding to a 0.7% per week price decrease in 2003 and 0.3% decrease per week in 2009, with the average matched set covering about 8-9 weeks).

Sample	N	Mean	Std. Dev.	10th pctile	25th pctile	50th pctile	75th pctile	90th pctile
2003	23,057	-0.007	0.059	-0.031	-0.010	0.000	0.002	0.015
2009	83,685	-0.003	0.036	-0.019	-0.006	0.000	0.002	0.010

These results motivate a set of robustness checks where we restrict the sample to items that exhibited stable posted prices over time. For *Matching Definition IIa* we trim the items in the bottom 10% and top 10% of the β_j distribution, and focus on the 80% of the matched sets that have β_j estimates between the 10th and 90th percentiles. For 2009, none of these items have a posted price trend greater than 0.1% per week or less than -0.3% per week. For *Matching Definition IIb*, we restrict attention to matched sets with an absolute value of β_j that is less than 0.01. For *Matching Definition IIc*, we restrict attention to matched sets with an absolute value of β_j that is less than 0.005. These last two definitions mean that for any item that makes the sample, its price trend over ten weeks (a relatively long time for a matched listing in our sample) was no more than plus or minus one percent.

Our last approach relies on a similar regression model

$$A_{ij} = \gamma_j + \delta_j t_{ij} + u_{ij}.$$

Again j index matched sets and i listings, except that now we include both auction and posted price listins and the dependent variable A_{ij} is an indicator for whether the listing is an auction listing. The idea here is that if sellers are responding to systematic trends in demand and changing their mix of auctions and posted price listings accordingly, it will show up in the time trend of their sale composition. Similarly, if sellers start listing an item using auctions to gain information, then switch to posted prices as they learn more about the item value, we will pick this up as a systematic trend in sale format. In principle, either of these mechanisms might confound our interpretation of the results in the paper. As in the above regression, we estimate a separate δ_j for each matched set of listings.

The table below reports the distribution of the estimated δ_j's across matched sets, separately for 2003 and 2009. For the median item, there a slight trend away from auctions in 2003 (0.6% per week), and essentially no trend at all in 2009 (0.1% per week fall in auctions).

However, as with the posted price trend estimates, we do see some items where the seller moved more significantly in one direction or the other.

Sample	N	Mean	Std. Dev.	10th pctile	25th pctile	50th pctile	75th pctile	90th pctile
2003	23,057	-0.012	0.083	-0.082	-0.036	-0.006	0.017	0.049
2009	83,685	-0.005	0.070	-0.055	-0.023	-0.001	0.015	0.041

The presence of some matched sets that exhibit a systematic trend toward or away from auctions motivates our next robustness check, in which we focus only on matched listings with a relatively stable mix of auction and posted price listings over time. For *Matching Definition IIIa*, we trim items with estimated δ_js in the bottom 10% and top 10% of the distribution, and focus on the 80% of the matched sets that have δ_j estimates between the 10th and 90th percentiles. This restricts us to items where the composition of listings is shifting toward auctions by less than 5% over a ten week period, and shifting away from auctions by no more than 5-8 percent over the same ten week period. For *Matching Definitions IIIb and IIIc*, we adopt even more stringent criteria and restrict attention to matched sets whose estimated δ_j have an absolute value less than 0.03, and less than 0.015 respectively. For the items that survive into these samples, the mix of auctions to posted prices is highly stable over the observed time period.

The results from all seven alternative matching definitions, as well the baseline results from the main text, are presented in the following Appendix Tables C1 and C2, and in Appendix Figures C1-C3. The striking feature of these tables and figures is that although there are some small variations in the exact estimates as we try different matching definitions, the results reported in the paper are highly robust to restricting to matched listings that appeared in short time windows, exhibited stable posted pricing, or a stable format mix. This suggests that while we certainly cannot rule out the types of life-cycle or shifting demand or learning effects that plausibly might be present in the data, they do not seem to play a major role in driving our main empirical results.

Appendix D. Cross-Country Evidence

The figures on the following pages replicate Figure 1 in the paper for different countries. Figure 1 showed the share of active auction listings relative to the combined auction and posted price (Buy-It-Now) active listings, and similarly the share of auction transaction volume in dollars relative to the combined auction and posted price transaction volume, for eBay.com, which is eBay's US-based platform. Here we construct the same Figure for ten additional countries where eBay operates a separate marketplace.

The countries are

- Germany
- United Kingdom
- Italy
- France
- Spain
- Austria
- Canada
- India
- Philippines
- Australia

For all the European countries, Canada and Australia, we have data back to January 2004. These country patterns look very similar to the United States. The one possible exception is auction revenue in Austria, which has remained relatively high although auctions have diminished greatly in their listing share. In India, the data starts in January 2005. Here the auction share of revenue starts below 40%., and declines sharply but not until 2011. In the Philippines, the data starts at the end of 2007, and shows a steady decline in the auction share.