Pricing and Fees in Auction Platforms with Two-Sided Entry

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Discussion Paper

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SCIENCES PO ECONOMICS DISCUSSION PAPER

No. 2020-02

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December 2019

Abstract

This paper presents, solves, and estimates the first structural auction model with seller selection. This allows me to quantify network effects arising from endogenous bidder and seller entry into auction platforms, facilitating the estimation of theoretically ambiguous fee impacts by tracing them through the game. Relevant model primitives are identified from variation in second-highest bids and reserve prices. My estimator builds off the discrete choice literature to address the double nested fixed point characterization of the entry equilibrium. Using new wine auction data, I estimate that this platform's revenues increase up to 60% when introducing a bidder discount and simultaneously increasing seller fees. More bidders enter when the platform is populated with lower-reserve setting sellers, driving up prices. Moreover, I show that meaningful antitrust damages *can* be estimated in a platform setting despite this two-sidedness. (JEL codes: D44, C52, C57, L81)

KEYWORDS: auctions with entry, two-sided markets, nonparametric identification, estimation, nested fixed point

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* *Sciences Po, Department of Economics. E-mail: marleen.marra@sciencespo.fr.* I am indebted to Andrew Chesher, Phil Haile, Lars Nesheim, Adam Rosen and Áureo de Paula for fruitful discussions and continued guidance. I also thank Dan Ackerberg, Larry Ausubel, Matt Backus, Dirk Bergemann, Natalie Cox, Martin Cripps, Matt Gentry, Emel Filiz-Ozbay, Ken Hendricks, Tom Hoe, Hyejin Ku, Kevin Lang, Guy Laroque, Brad Larsen, Thierry Mayer, Konrad Mierendorff, Rob Porter, Imran Rasul, José-Antonio Espín-Sánchez, Andrew Sweeting, Michela Tincani, Jean Tirole, Frank Verboven, Daniel Vincent, Quang Vuong, Martin Weidner and seminar participants for helpful comments. All errors are my own. I am grateful for financial support from the Economic and Social Research Council (PhD Studentship).

1 Introduction

Auction platforms provide increasingly popular marketplaces for trading goods and services, and generate revenues from fees charged to users. The platform faces a "two-sided market" with network effects as it is more valuable to potential bidders when more sellers enter, and vice versa. The theoretical two-sided market literature highlights that both 1) the platform revenue-maximizing fee structure, and 2) welfare impacts of those fees are theoretically ambiguous and depend on the magnitude of network effects.[1] To study these two issues, I exploit an original data set of wine auctions and develop a structural model in which network effects arise from endogenous bidder and seller entry.

A key innovation relative to the two-sided market literature is to leverage the transparency of payoffs in the auction game to characterize its network effects. This allows me to provide a tight quantitative analysis of how fee changes affect both platform profitability and user welfare. The second novelty is that my auction model captures endogenous entry on both sides of the market; accounting for seller selection is new to the empirical auction literature. It generates an additional trade-off that is crucial for platform pricing. Bidders expect lower (reservation) prices when lower-value sellers are attracted to the platform, so bidder entry depends both on the expected number and type of sellers that enter.[2]

The resulting distributions of reserve prices, transaction prices and number of bidders are endogenous to the fee structure through optimal entry, bidding and reserve pricing strategies. Variation in outcomes allows for the estimation of model primitives needed to answer how fees affect user welfare in this market. As such, the wine auctions provide an opportune setting to understand the otherwise hard to quantify network effects by tracing fees through the auction platform game.

Moreover, certain institutional details of wine auctions facilitate tractability of the auction platform model, despite accounting for endogenous entry of both bidders and sellers. These "fine, rare, and vintage" wines are traded on a secondary market, among hobbyists, and with secret reserve prices. Listing pages include a wealth of information about the wine's characteristics, including on temperature-controlled storage, "ullage" or fill level, and delivery cost and conditions. Empirical patterns in

[1] See e.g. Evans (2003) or Rysman (2009)

[2] The importance of this dynamic was first postulated in Ellison et al. (2004).

the data are consistent with bidders facing significant listing inspection cost. Most notably given the platform setting is that listings turn out to be independent of each other: related listings do not affect transaction / reserve prices, number of bidders, or the number of bids per bidder. I show how inspection cost, and the resulting independence property, minimize the complexity of the auction platform game to facilitate empirical analysis of fee impacts.

Introducing seller selection in my structural auction model turns out to be important to capture first-order effects of fees, but it does not come without empirical challenges. The population distribution of seller values is nonparametrically identified using the equilibrium mapping from values to reserves, but only on the part of the support for which platform entry is optimal for sellers. Complications for parametric estimation are that the distribution of observed reserve prices 1) relates to seller values in the population through the model's entry equilibrium, which is a computationally costly (double) nested fixed point problem, and 2) its support depends on the parameters to estimate. I propose an estimator that combines a concentrated likelihood function with the iterative updating of the equilibrium seller entry threshold.[3] This delivers consistent estimates for any number of iterations given demonstrated uniqueness of the entry equilibrium.

Model estimates reveal significant network effects on this platform, which can be harnessed to improve platform profitability without harming user welfare. I estimate that platform revenues increases by more than 60 percent when implementing fee structures that subsidize buyers (more) while increasing the seller commission and/or listing fee, attracting more serious (lower marginal cost) sellers while increasing transaction prices. It requires providing winning bidders with a *discount* on the transaction price. This fully agrees with the idea that businesses in two-sided markets should subsidize the side that contributes most to profits, even if this results in negative fees. Platform revenues would also be 20 percent higher when pairing a substantial 10-pound hike in listing fee with halving the seller commission, attracting more high-end wines.

My framework allows for the estimation of currently hard to measure antitrust damages from (anti-competitive) fee changes. Results show that impacts are hetero-

[3]This algorithm is inspired by the Aguirregabiria and Mira (2002) nested pseudo likelihood method to solve estimation problems involving fixed point characterizations in (static) games. In my case, the algorithm uses the auction structure to obtain seller parameters from a first order condition.

geneous and larger than those obtained using more simple analysis without network effects. For example, the average seller is 13 percent worse off after increasing the seller commission by 5 percentage points and the newly marginal seller (entrant) is 37 percent worse off in the higher-commission world. Clearly, much more than the status-quo "pro-rata" damages of 5 percent would be justified if this concerned an antitrust case. Furthermore, while most of the loss falls on sellers (total seller surplus decreases by 17 percent), also winning bidders are worse off (7 percent) in the higher seller commission world.

Relation to the literature. This paper brings together research on auctions and two-sided markets. I build on the large and influential literature on nonparametric identification and estimation of auction models, starting with Guerre et al. (2000) for first-price auctions and Athey and Haile (2002) for English auctions. My paper relates most to recent papers that account for endogenous bidder entry in various bidding markets, including Roberts and Sweeting (2010), Moreno and Wooders (2011), Krasnokutskaya and Seim (2011), Li and Zheng (2009, 2012), Fang and Tang (2014), Marmer et al. (2013), Gentry and Li (2014) and Gentry et al. (2015, 2017). Distinctively, I address endogenous seller entry as well and show how equilibrium entry decisions of bidders and sellers are interconnected in an auction platform. Also important are recent papers accounting for search and/or dynamics in auction platforms (e.g. Backus and Lewis (2019), Hendricks and Sorensen (2018), Bodoh-Creed et al. (forthcoming), and Coey et al. (2019)). While these papers rely on steady-state requirements for tractability of their platform models, I instead exploit the sizeable listing inspection cost inherent to the idiosyncratic nature of the auctioned goods and a large population assumption. Other related work uses eBay data to research economic phenomena (e.g. Anwar et al. (2006), Nekipelov (2007), and Dinerstein et al. (2018)), but none structurally estimate impacts of auction platform fees.

The second literature studies network effects and pricing in two-sided markets, (e.g. Rysman (2007), Lee (2013), Song (2013), and Bresnahan et al. (2015)), building on an influential theoretical literature (e.g. Baye and Morgan (2001), Rochet and Tirole (2003, 2006), Evans (2003), Wright (2004), and Armstrong (2006)). A fundamental difference is that I use the auction structure to quantify the platform's attractiveness to bidders when there are more sellers, and vice versa. As such, payoffs from the auction platform game provide a micro-foundation of its network effects. Two other papers that also bring a two-sided market perspective to auction data are

Athey and Ellison (2011) and Gomes (2014), both focusing on position auctions.

Finally, there is partial overlap with other papers that study wine (e.g. McAfee and Vincent (1993), Ashenfelter et al. (1995)), the incidence of commissions in wine auctions (Ashenfelter and Graddy (2003, 2005), Marks (2009)), theoretical properties of auctions with commissions and bidder entry (Ginsburgh et al. (2010)), theoretical listing fee impacts (Deltas and Jeitschko (2007)), transaction cost in posted-price platforms (e.g. Fradkin (2017), Ershov (2019)), and compositional impacts of fees in other markets (e.g. broadcasting: Sweeting (2013)).

The rest of this paper is organized as follows. Section 2 presents the auction platform model with two-sided entry, and solves for equilibrium strategies. Section 3 presents the wine auction data and highlights the role of listing inspection cost and seller selection. Section 4 discusses nonparametric identification of model primitives, and Section 5 presents a computationally-feasible estimation strategy. Estimation results, model fit and validation, and robustness analyses are discussed in Section 6. Structural estimates are used to evaluate counterfactual fee structures and their impacts on platform revenue, volume, and user welfare in Section 7. Section 8 concludes and provides directions for future research.

2 A model of auction platforms with idiosyncratic goods

This section presents a parsimonious and tractable structural auction platform model and solves for its equilibrium properties. The model is informed by empirical patterns in my wine auction data (especially independent listings) that are described further in section 3. I expect the model to also capture first-order aspects of other auction platforms with second-hand, used, or individualized goods.[4] Henceforth I use the generic term "idiosyncratic", as in Einav et al. (2018), to describe such items.

[4]Such as vintage cars on ClassicCarAuctions.co.uk or CarsontheWeb.com, individualized jobs at Upwork.com or uShip.com, and certain product categories on eBay.com.

2.1 Model assumptions and game structure

Consider a monopoly auction platform populated by listings that are generated by sellers, aimed at allocating indivisible goods among bidders with unit demands. Risk-neutral potential bidders and sellers face homogeneous opportunity cost of time spent on the platform, on top of any monetary fees charged. For bidders, these opportunity cost are referred to as "listing inspection cost". While more general Riley and Samuelson (1981) mechanism restrictions would suffice, to match the data and given my abstraction from inter-auction dynamics the allocation mechanism in each listing is taken to be a second-price sealed bid auction. Sellers set non-negative secret reserve prices. The presence of a positive reserve price is the only thing that bidders observe for free. This is motivated by highly visible "no reserve price" buttons attached to such listings on the platform's auction landing page.

I model this environment as a two-stage game. In the first stage potential bidders and sellers enter the platform simultaneously. For potential sellers, entry means paying the listing fee and creating a listing. For potential bidders, entry means opening the site and clicking on a listing. I allow for a positive entry fee for bidders although my platform does not have one. Listings are ex-ante identical up to whether or not they have a reserve price - so no additional listing selection takes place. Bidder entry is therefore modelled as opening the site and being allocated uniformly over available listings.

I let the second stage describe the usual auction behavior. Sellers that set a secret reserve price pay a reserve price fee. Bidders pay non-monetary listing inspection cost, learn their valuation, and bid. If the highest bid exceeds the reserve price, the good gets sold to the winning bidder for the hammer price. In that case the platform collects buyer premium and seller commission (both as shares of the hammer price).

Notation. The platform fee structure $f = \{c_B, c_S, e_B, e_S, e_R\}$ contains buyer's premium, seller commission, buyer entry fee, listing fee, and reserve price fee. Opportunity cost of time for potential bidders in zero and positive reserve price auctions equal $e^o_{B,r=0}$ and $e^o_{B,r>0}$. Opportunity cost of time for sellers equals e^o_S. Random vector $\mathbf{Z}$ contains auction covariates observed at the listing page. $N^B_{r=0}$, $N^B_{r>0}$, N^S, $T_{r=0}$, $T_{r>0}$ denote the number of: potential bidders for no reserve auctions, potential bidders for positive reserve auctions, potential sellers, and listings (sellers) in no and positive reserve auctions. $\mathcal{N}^B$ and $\mathcal{N}^S$ denote the sets of potential bidders and sellers,

$N^B = N^B_{r=0} + N^B_{r>0}$ the total number of potential bidders, and $T = T_{r=0} + T_{r>0}$ the total number of listings. $F_{V_0|\mathbf{Z}}$ and $F_{V|\mathbf{Z}}$ denote the conditional valuation distributions for potential sellers and bidders. Random variables are denoted in upper case and their realizations in lower case.

Sellers are endowed with a product with characteristics $\mathbf{z} \in \mathbf{Z}$. The two population value distributions are allowed to differ, and satisfy:

Assumption (two-sided IPV)**.** *All* $i = \{1, ..., N^B\}$ *potential bidders independently draw values* v_i *from* $V \sim F_{V|\mathbf{Z}}$ *and all* $k = \{1, ..., N^S\}$ *potential sellers independently draw values* v_{0k} *from* $V_0 \sim F_{V_0|\mathbf{Z}}$ *such that,* $\forall \mathbf{z} \in \mathbf{Z}$*:*
i) $(v_i \perp v_{i'})|\mathbf{z}, \forall i \neq i' \in \mathcal{N}^B$
ii)$(v_i \perp v_{0k})|\mathbf{z}, \forall i \in \mathcal{N}^B$ *and* $\forall k \in \mathcal{N}^S$
and $F_{V|\mathbf{Z}}$ *and* $F_{V_0|\mathbf{Z}}$ *satisfy regularity conditions:*
iii) supp$(V)=[\underline{v}, \bar{v}]$*, and supp*$(V_0)=[\underline{v_0}, \bar{v_0}]$
iv) $F_{V|\mathbf{Z}}$ *is absolutely continuous*
v) $\frac{f_{V|\mathbf{Z}}(x)}{1-F_{V|\mathbf{Z}}(x)} < 0 \; \forall x \in [\underline{v}, \bar{v}]$ *(Increasing Failure Rate)*

Most importantly, this assumption states that conditional on the vector of observed product attributes, variation in valuations across buyers and sellers is of a purely idiosyncratic -private values- nature. In addition, the idiosyncratic variation is independent.[5]

The valuation distributions, allocation mechanism, population sizes, and all cost (fees and opportunity cost) are common knowledge. The incomplete information structure and strategic interaction makes this suitable to study with the usual game-theoretic tools.

2.2 Equilibrium strategies

In this section, I solve for players equilibrium strategies focusing on two distinct stages of entry and auction. Any omitted proofs are delegated to the appendix. I restrict attention to symmetric Bayesian-Nash equilibria in weakly undominated strategies, requiring that strategies are best responses given competitors' strategies and that beliefs are consistent with those strategies in equilibrium.

[5]Independence and continuity are needed for identification of $F_{V|\mathbf{Z}}$ but can be omitted on the seller side. IFR guarantees uniqueness of the optimal reserve price and that listing-level bidder surplus decreases in the number of bidders (see Lemma 3).

2.2.1 Auction stage

Conditional on entry decisions and the matching of bidders to listings, the idiosyncratic-good auction platform is made up of independent second-price sealed bid auctions. I therefore derive standard reserve pricing (as in: Riley and Samuelson (1981)) and bidding (as in: Vickrey (1961)) strategies, up to the impact of buyer premium and seller commission.

Lemma 1. *A bidder with valuation v bids:*

$$b^*(v, f) \equiv \frac{v}{1 + c_B} \tag{1}$$

Proof. This follows directly from Vickrey (1961): bidding more may result in negative utility and bidding less decreases the probability of winning without affecting the transaction price. $\square$

Zero reserve price auctions attract more bidders, but the benefit of setting a positive reserve price increases in the seller's value. Combined with a positive reserve price fee, the set of sellers that sets a zero reserve price is determined by a threshold-crossing problem. I chose not to endogenize this "screening value" $v_{0,r=0}$, as doing so significantly complicates estimation of the game.

Lemma 2. *Sellers with valuation $v_0 \geq v^*_{0,r=0}$ set a reserve price solving:*

$$r^*(v_0, f) = \frac{v_0}{1 - c_S} + \frac{1 - F_{V|\mathbf{Z}}((1 + c_B)r^*(v_0, f))}{(1 + c_B)f_{V|\mathbf{Z}}((1 + c_B)r^*(v_0, f))} \tag{2}$$

Note that, if $c_S = c_B = 0$, the optimal reserve price is identical to the Riley and Samuelson (1981) public reserve price in auctions with a fixed number of bidders. Because $r^*(v_0, f)$ is secret, it does not affect the number of bidders in the seller's listing. This is true for *any* reserve price strategy of competing sellers, and generally the entry equilibrium results are therefore valid as long as r^* is monotonically increasing in v_0. The optimal reserve price is increasing in c_S and (given IFR) decreasing in c_B. I denote a buyer premium-adjusted optimal reserve price by $\tilde{r}$:

$$\tilde{r} = \begin{cases} (1 + c_B)r^*(v_0, f) & \text{for } v_0 > v^*_{0,r=0} \\ 0 & \text{for } v_0 \leq v^*_{0,r=0} \end{cases}$$

2.2.2 Entry stage

Listing-level payoffs. Let $\pi_b(n, f, v_0)$ be the expected listing-level bidder surplus in an auction with $n-1$ competing bidders, fee structure f, when the seller has a value of v_0 (unknown to bidders, to be taken an expectation of), $\pi_b(n, f, 0)$and $\pi_s(n, f, v_0)$ the expected listing-level seller surplus in such an auction. I slightly abuse notation to let $\pi_b(n, f, 0)$ denote expected bidder surplus in a listing without a reserve price. Conditioning on $\mathbf{Z}$ is omitted, and flat fees and opportunity cost are ascribed to the entry stage.

$$\pi_b(n, f, v_0) = \frac{1}{n}\mathbb{E}[V_{(n:n)} - \max(V_{(n-1:n)}, \tilde{r})|V_{(n:n)} \geq \tilde{r}][1 - F_{V_{(n:n)}}(\tilde{r})] \quad (3)$$

$$= \int_{\tilde{r}}^{\bar{v}} v_n - \max(\tilde{r}, \int_{\underline{v}}^{v_n} v_{n-1} dF_{V_{n-1:n}|V_{n:n}=v_n}(v_{n-1}))dF_{V_{n:n}}(v_n)$$

$$\pi_s(n, f, v_0) = \left(\mathbb{E}[\max(\frac{V_{(n-1:n)}}{1+c_B}, r)|V_{(n:n)} \geq \tilde{r}](1 - c_S) - v_0\right)[1 - F_{V_{(n:n)}}(\tilde{r})] \quad (4)$$

$$= \left[\max(r, \frac{1}{1+c_B}\int_{\underline{v}}^{\bar{v}} v_{n-1} dF_{V_{n-1:n}|V_{n:n}\geq\tilde{r}}(v_{n-1}))(1 - c_S) - v_0\right][1 - F_{V_{(n:n)}}(\tilde{r})]$$

$$F_{V_{n:n}}(v_n) = \int_{\underline{v}}^{v_n} nF_V(x)^{n-1}f_V(x)dx \quad (5)$$

$$F_{V_{n-1:n}|V_{n:n}=v_n}(v_{n-1}) = \int_{\underline{v}}^{v_n} \frac{(n-1)F_V(y)^{n-2}f_V(y)}{F_V(v_n)^{n-1}}dy \quad (6)$$

The entry equilibrium relies on the following properties:

Lemma 3. *Bidder listing-level expected surplus $\pi_b(n, f, v_0)$ decreases in n and v_0. Seller listing-level expected surplus $\pi_s(n, f, v_0)$ increases in n and decreases in v_0.*

In line with empirical patterns in my data and motivated by listing inspection cost, bidders enter the platform randomly (before learning their valuation). Sellers on the other hand own the product and therefore know their value for it before they decide to list. Sellers' expected surplus decreases in v_0, so they adopt the pure strategy to enter only if their valuation is below a threshold value that in equilibrium makes the marginal seller indifferent between entering and staying out given that his opponents adopt the same threshold strategy. I denote the sellers' entry strategy by that threshold (v_0^*).[6]

[6]Unless it is optimal for *all* sellers on the platform to set no reserve, the seller who is indifferent between entering and staying out will set a positive reserve price: $\underline{v_0} \leq v_{0,r=0} \leq v_0^* \leq \bar{v_0}$. I restrict attention to the case where all these inequalities are strict.

Proposition 1. *The entry stage of the game results in a unique equilibrium for any fee structure. It is characterized by: i) a bidder entry probability for positive reserve price auctions and ii) a seller entry threshold,* $(p^*_{r>0}(f, v_0^*(f)), v_0^*(f))$*, and iii) a bidder entry probability for no reserve price auctions,* $p^*_{r=0}(f)$*.*

I first show that any candidate seller entry threshold ($\bar{v_0}$) maps to an equilibrium $p^*(f, \bar{v_0})_{r>0}$, and then I use that mapping to solve for $v_0^*(f)$. It turns out that because $p^*(f, \bar{v_0})_{r>0}$ is strictly decreasing in $\bar{v_0}$, sellers are strategic substitutes and the entry game reduces to a single agent discrete choice problem.

Expected surplus from entering for $N^B_{r>0}$ potential bidders is the listing-level surplus $\pi_b(n, f, v_0)$ in expectation over seller-values V_0 and over the number of competing bidders they face in that listing. They only consider sellers that enter and set a positive reserve price, e.g. as $\mathbb{E}[\pi_b(n, f, v_0)|V_0 \in [v_{0,r=0}, \bar{v_0}]]$. With $v_{0,r=0}$ structural, I use $F_{V_0|\mathbf{Z},v_{0,r=0}}$ to denote the left-censored distribution of potential seller valuations, $\forall v_0 \in [v_{0,r=0}, \bar{v_0}]$:

$$F_{V_0|\mathbf{Z},v_{0,r=0}}(v_0) = \frac{F_{V_0|\mathbf{Z}}(v_0) - F_{V_0|\mathbf{Z}}(v_0, r=0)}{F_{V_0|\mathbf{Z}}(v_0, r=0)}, \tag{7}$$

The number of competing bidders follows a compound Binomial distribution. From the perspective of a bidder who enters the platform, $f_{N,r>0}(n; p, \bar{v_0})$ combines uncertainty about: 1) the stochastic number of positive-reserve price listings $T_{r>0}$ (with realization t) given entry threshold $\bar{v_0}$, and 2) how many of $N^B_{r>0} - 1$ competing bidders end up in his listing when they enter the platform with probability p and sort uniformly over available listings:

$$\begin{aligned} f_{N,r>0}(n; p, \bar{v_0}) = \sum_{t=0}^{N^S} & \binom{N^B_{r>0} - 1}{n} (\frac{p}{t})^n (1 - \frac{p}{t})^{N^B_{r>0}-1-n} \\ & \binom{N^S}{t} F_{V_0|\mathbf{Z},v_{0,r=0}}(\bar{v_0})^t (1 - F_{V_0|\mathbf{Z},v_{0,r=0}}(\bar{v_0}))^{N^S-t} \end{aligned} \tag{8}$$

Combined with entry and opportunity cost, $\Pi_b(f, \bar{v_0}; p)$ denotes potential bidders' expected surplus from entering the platform:

$$\Pi_b(f, \bar{v_0}; p) = \sum_{n=0}^{N^B_{r>0}-1} \mathbb{E}[\pi_b(n+1, f, v_0)|V_0 \in [v_{0,r=0}, \bar{v_0}]] f_{N,r>0}(n; p, \bar{v_0}) - e_B - e^o_{B,r>0} \tag{9}$$

Lemma 4. *For any candidate seller entry threshold $\bar{v_0}$, a unique equilibrium bidder entry probability solves potential bidders' zero profit condition in positive reserve auctions:*

$$p^*_{r>0}(f, \bar{v_0}) \equiv \arg_{p\in(0,1)}\{\Pi_b(f, \bar{v_0}; p) = 0\} \tag{10}$$

Proof. Listing-level surplus $\pi_b(n, f, v_0)$ strictly decreases in n (Lemma 3) and $f_{N,r>0}(n; p, \bar{v_0})$ increases in p, so a unique p solves $\Pi_b(f, \bar{v_0}; p) = 0$ for any $\bar{v_0}$. □

The above statement being conditional on the type (and therefore the expected number) of sellers on a platform, uniqueness of the bidder entry probability aligns with previous results in auctions with bidder entry such as Levin and Smith (1994). Central for my analysis of the two-sided entry equilibrium is the following, more striking, result.

Lemma 5. *At the equilibrium $p^*_{r>0}(f, \bar{v_0})$, $f_{N,r>0}(n; p^*_{r>0}, \bar{v_0})$ decreases in the first-order stochastic dominance sense in $\bar{v_0}$.*

Proof. Candidate seller entry threshold $\bar{v_0}$ affects $\Pi_b(f, \bar{v_0}; p)$ in two ways; through the expected number of listings and the distribution of reserve prices in those listings. Supposing that the distribution of reserve prices would stay constant, then expected listing-level surplus would not be affected by a higher $\bar{v_0}$ so that $p^*_{r>0}(f, \bar{v_0})$ would adjust to keep the equilibrium distribution number of bidders per listing constant. However, higher $\bar{v_0}$ draws in sellers with higher v_0 that set higher reserve prices (Lemma 2), resulting in lower $\pi_b(n, f, v_0)$ (Lemma 3). The zero profit condition in (10) therefore dictates that the *equilibrium distribution* $f_{N,r>0}(n; p^*_{r>0}, \bar{v_0})$ places more weight on a lower number of bidders per listing for higher $\bar{v_0}$. □

By the same reasoning, *any factor* that does not affect listing-level expected surplus $\pi_b(n, f, v_0)$ won't affect the equilibrium distribution of number of bidders per listing. This holds true for example for populations sizes $N^B_{r>0}$ and N^S, which is useful for the large population approximation that follows.

Seller entry. Expected surplus from entering the platform for N^S potential sellers involves: 1) their listing-level expected surplus, and 2) an expectation over the number of bidders per listing, $N_{B,r>0}$, given $\bar{v_0}$ and bidders' equilibrium best-response to this threshold. Let $\Pi_s(f, v_0; p^*_{r>0}(f, \bar{v_0}), \bar{v_0})$ denote expected surplus for a seller with valuation v_0 when $N^S - 1$ competing sellers enter the platform if and only if their valuation is less than threshold $\bar{v_0}$:[7]

$$\Pi_s(f, v_0; p^*_{r>0}(f, \bar{v_0}), \bar{v_0}) = \sum_{n=0}^{N^B_{r>0}} \pi_s(n, f, v_0) f_{N,r>0}(n; p^*_{r>0}(f, \bar{v_0}), \bar{v_0}) - e_S - e^o_S \quad (11)$$

Lemma 6. *A unique equilibrium seller entry threshold solves the marginal seller's zero profit condition:*

$$v^*_0(f) \equiv \arg_{\bar{v_0} s.t. F_{V_0|\mathbf{Z}}(\bar{v_0}) \in (0,1)} \{\Pi_s(f, \bar{v_0}; p^*_{r>0}(f, \bar{v_0}), \bar{v_0}) = 0\} \quad (12)$$

with $p^*_{r>0}(f, \bar{v_0})$ solving (10).

Proof. The proof requires three parts. First, sellers have a unique best response for any competing $\bar{v_0}$, because $\Pi_s(f, v_0; p^*_{r>0}(f, \bar{v_0}), \bar{v_0})$ strictly decreases in their own v_0. Second, given that 1) $p^*_{r>0}(f, \bar{v_0})$ is strictly decreasing in $\bar{v_0}$, and 2) entry of competing sellers does not affect seller surplus in other ways, the best response function is strictly decreasing in competing sellers entry threshold. Third, symmetry then delivers a unique equilibrium threshold, $v^*_0(f)$, that is the fixed point in seller value space solving equation 12 i.e., making the marginal seller indifferent between entering and staying out. $\square$

This shows that Lemma 5 is key to accounting for seller entry in the auction platform.[8] In auctions without a reserve price there is no two-sidedness.

Lemma 7. *A unique equilibrium bidder entry probability ($p^*_{r=0}(f)$) solves potential bidders' zero profit condition in no-reserve price auctions.*

[7] Using $f_{N,r>0}(n; p^*_{r>0}(.)$ avoids introducing additional notation to capture that sellers care about that distribution of competing bidders +1. This distinction is irrelevant in the large-$N^B_{r>0}$ approximation as the two distributions are identical by the *environmental equivalence* property of the Poisson distribution (Myerson (1998)).

[8] More generally: any platform model that results in $f_{N,r>0}(n; p^*_{r>0}, \bar{v_0})$ FOSD decreasing in $\bar{v_0}$ delivers a unique equilibrium seller entry threshold. One could for instance allow for seller competition insofar as equilibrium reserve prices still FOSD increase in $\bar{v_0}$.

Large population approximation. The remainder of this section discusses an approximation of the entry equilibrium that is adopted for empirical tractability. Another benefit is that it relaxes the requirement that players know population sizes $N^B_{r=0}$, $N^B_{r>0}$, and N^S.

Assumption. *The population of potential bidders is large relative to the number of bidders on the platform:* $(N^B_{r>0}, N^B_{r=0}) \to \infty$ *and* $(p^*_{r>0}, p^*_{r=0}) \to 0$.

The equilibrium Poisson mean number of bidders per listing is endogenous to the fee structure and in positive reserve auctions also depends on seller selection. Listings with no reserve price are structurally more attractive to bidders than those with a reserve price, increasing bidder entry into those auctions so $\lambda^*_{r>0}(f, v^*_0) > \lambda^*_{r=0}(f)$.

Proposition 2. *For any fee structure f, the entry equilibrium of the auction platform game subject to the large population approximation is characterized by the triple of* $(v^*_0(f), \lambda^*_{r>0}(f, v^*_0(f)), \lambda^*_{r=0}(f))$ *that uniquely solve zero profit conditions of potential bidders and the marginal seller.*

Lemma 8. *For $r \in \{r = 0, r > 0\}$, with with large N^B_r and small p^*_r, the number of bidders per listing has a probability mass function approximated by:*

$$f_{N_r}(k; \lambda_r) = \frac{\exp(-\lambda_r)\lambda_r^k}{k!}\ , \forall k \in \mathbb{Z}^+,\ \textit{with: } \lambda_r = \frac{N^B_r p^*_r}{T_r} \tag{13}$$

3 Wine auction data

What is commonly termed "fine, rare, and vintage wine" is sold at auction in secondary markets, run by online wine platforms as well as brick-and-mortar auction houses. Auction data for the empirical analysis in this paper comes from online auction platform: www.Bidforwine.co.uk (BW). It offers a marketplace for buyers and sellers to trade, akin to the eBay consumer-to-consumer format. The presence of outside platforms is captured in the model by the opportunity cost of trading on BW, and therefore the analysis is of a partial equilibrium nature where it is implicitly assumed that other platforms do not react to changes in the fee structure of BW.For successful sales, sellers receive payment from the winning bidder, ship the wine, and are invoiced for the amount of seller commission, listing fee and reserve price fee due. For these seller-managed lots and during the time period covered in the data, BW

Table 1: Fee structure wine auction data

	Notation	Amount / rate		Conditional on sale
Bidders:				
buyer premium	c_B	0		✓
Entry fee	e_B	£0		
Opportunity cost of time	$e^o_{B,r=0}$, $e^o_{B,r>0}$	estimated	*("listing inspection cost")*	
Sellers:			On part transaction price:	
Seller commission	c_S	0.102	$\leq$ £200	✓
		0.09	£200.01- £1500	✓
		0.0792	£1500.01- £2500	✓
		0.066	$\geq$ £2500.01	✓
Listing fee	e_S	£1.75		
Reserve price fees	e_R	£0.75		
Opportunity cost of time	e^o_S	estimated		

Incl. 20% VAT. Opportunity cost fall outside platform fee structure $f = \{c_B, e_B, c_S, e_S, e_R\}$.

Table 2: Descriptive statistics

	N	Mean	St. Dev.	Min	Median	Max
Transaction price	3,487	140.56	239.94	1.00	82.50	6,000.00
Is sold	3,487	0.64	0.48	0	1	1
Number bottles	3,487	3.70	4.22	1	2	72
Price per bottle if sold	2,230	74.84	124.52	0.50	35.00	2,200.00
Number of bidders	3,487	3.10	2.52	0	3	13
Has reserve price	3,487	0.67	0.47	0	1	1

charges no buyer premium and maintains a seller commission on a sliding scale between 8.5-5.5 percent of the sale price (see Table 1). Upfront charges to sellers are: a 1.75 pounds listing fee, a 0.50 pounds minimum bid fee (optional, if increased), and a 0.25 pounds reserve price fee (optional, if set).

Items are sold through an English auction mechanism with proxy bidding. [9] A soft closing rule extends the end time of the auction by two minutes whenever a bid is placed in the final two minutes of the auction. Therefore, there is no opportunity for a *bid sniping* strategy (bidding in the last few seconds, potentially aided by sniping

[9] Bidders submit a maximum bid and the algorithm places bids to keep the current price one increment above the second-highest bid. When the highest bid is less than one increment above the second highest bid, the transaction price remains the second highest bid. This is different from the rule at eBay, where the standing price in that case would increase to the highest bid. Engelberg and Williams (2009), Hickman (2010) and Hickman et al. (2017) assess implications of this alternative bidding rule.

software) on the BW platform.[10] The combination of proxy bidding with a soft closing rule suggests that the data is well approximated by the second-price sealed bid model.

I construct a dataset of wine auctions by web-scraping all open auctions on BW at 30-minute intervals between January 2017 and May 2018. At these intervals, I observe most of what bidders observe as well and this resulted in a wealth of data. Observed wine characteristics $\mathbf{Z}$ include the type of wine, grape, vintage, region of origin, delivery and payment information, returns, seller feedback, and the seller's description. Summary statistics are reported in Table 2. Only a quarter of listings is created by a seller with feedback, pointing to the consumer-to-consumer nature of the platform. Furthermore, in the 7% of auctions on which bidders left feedback their identities are observed and this data confirms the non-professional setting: 58 percent of winning bidders that left feedback has only won an auction (and left feedback on it) once or twice over the entire 15 months period. The sample includes $3,487$ auctions after excluding auctions that are consigned, sell spirits, or sell multiple lots at once. While there is a significant range in sale prices, 84 percent of all sales in the sample do not exceed the 200 pounds over which sellers pay a higher marginal seller commission. I focus on these auctions (the "main sample"), and estimate the model separately for "high-value" auctions with transaction prices between 200 and 1500 pounds to assess heterogeneity of fee impacts and the role of such high-end listings for the platform's profitability.

The repetitive recording of bids for ongoing auctions was necessary to approximate the reserve price distribution. When the seller sets a reserve price without making it public in the form of a minimum bid amount, the notifications "reserve not met" or "reserve almost met" accompany any standing price that does not exceed the reserve. I approximate the reserve price as the average between the highest standing price for which the reserve price is not met and the lowest for which it is met.[11] While only 26 percent of listings has an increased minimum bid amount, 44 percent has a (secret) reserve price, and 3 percent has both. The use of secret reserve prices in auction platforms remains a puzzle in the empirical auction literature and solving that puzzle

[10] See Ockenfels and Roth (2006) on strategic behaviour in auctions with these two types of closing rules and Hasker and Sickles (2010) and Bajari and Hortaçsu (2004) for an overview of various explanations for bid sniping evaluated in the literature.

[11] If all bids would be recorded in real time, this approximation would be accurate up to half a bidding increment due to the proxy bidding system. The appendix shows that also the 30-minute scraping interval results in a good approximation of the reserve price distribution.

is beyond the scope of this paper.[12] In the rest of this paper I group them together and refer to the "reserve price" as the maximum of: the minimum bid amount and the approximated secret reserve price. Of larger consequence is the choice made by a third of sellers to refrain from setting any form of reserve. This is observable to bidders by a "no reserve price" button - even before they enter the listing. This is captured in my model by allowing equilibrium number of bidder distributions to differ between these two types of listings.

3.1 Why listing inspection and seller selection matter

A key difference between my secondary market for vintage wines and retail wines is that the former is sold by individual collectors, who sometimes keep the bottles for decades either in temperature-controlled warehouses or in private cellars. Sellers arguably know how much the wine is worth to them and they have their own idiosyncratic value (taste) for it.[13] This is true for idiosyncratic goods more generally, and hence an idiosyncratic good auction platform needs to consider how changing the fee structure affects both the number and the type of sellers that enter. Moreover, my equilibrium results show how this feeds back on how attractive the platform is for potential bidders given that lower-value sellers set lower reserve prices.[14]

Listing inspection cost arise in this context because all offered wines are different. This has to do with why there is a flourishing secondary market in the first place. The paramount influence of weather and harvesting conditions results in some vintages outperforming others in terms of quality.[15] Older wines can be valuable as increased scarcity of these star vintages drives up prices, given that fewer of them remain uncorked over time. Moreover, certain high-tannin wines such as red Bordeaux age well and are thought to reach their full potential only after many years. But the commodities are also perishable so that humidity and temperature control are key to deliver this potential quality. As such, assessing the wine's idiosyncratic storage

[12] See e.g. Jehiel and Lamy (2015) and Hasker and Sickles (2010).

[13] The fact that sellers appear to value their items shows up in the data by the fact that they set binding reserve prices, with 54 percent of those not selling, and don't appear to relist unsold items (at least not without changing the listing title; Table 3).

[14] I believe Ellison et al. (2004) first hypothesize that seller selection was likely a main driver for why auction sites of Amazon and Yahoo! struggled in some countries: their zero listing fees attracted non-serious sellers with high reserve prices, shunning bidders.

[15] Ashenfelter et al. (1995) predict with surprising accuracy the value of high-end Bordeaux using weather data from their growing and harvesting seasons.

Table 3: Evidence for thin markets (percentiles)

	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
Times product is listed, per 4 weeks:	1	1	1	1	1	2	2	3	6	37
Times product is listed, total 15 months:	1	3	8	16	28	37	68	148	215	223
Times title occurs, total 15 months:	1	1	1	1	1	1	1	1	2	17

Product: (region x wine type x vintage decade), e.g. a red Bordeaux from the 1980s, corresponding to high-level filters.

Table 4: Evidence for non-selective bidder entry

	Product & market (PM) specification:						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Bidders / listing	10.010	10.724	10.715	10.639	10.676	10.054	8.803
	(0.666)	(0.612)	(0.618)	(0.614)	(0.627)	(0.691)	(0.718)
Bidders / PM	-0.014	0.031	0.008	0.049	0.011	-0.065	0.331
	(0.076)	(0.026)	(0.035)	(0.050)	(0.103)	(0.218)	(0.201)
Adj. R^2	0.362	0.237	0.291	0.267	0.315	0.362	0.344

Standard errors in parenthesis. All OLS regressions have 900 observations (main sample, no reserve) and include product fixed effects. PM specifications: (1) market = fixed 4 week intervals, product = region x type x decade (as in Table 3), markets in (2)-(7) rolling 2 day window around end-time listing, products in (2) all wine, (3) type (e.g. red), (4) region (e.g. Bordeaux), (5) region x type, (6) region x type x vintage, (7) subregion (e.g. Margaux) x type x vintage.

conditions, provenance, *ullage* and other indicators of wine quality, make it costly for bidders to bid in every auction they enter.[16] Moreover, listing pages contain too many descriptors to summarize in the usual landing page excerpts.[17] I next document four empirical patterns related to the idiosyncratic nature of the goods and inherent listing inspection, motivating the model in 2.1.

First, the data reveals a strikingly low number of comparable listings. Even with coarse product-market specifications, I find that for 50 percent of listings this is the only one of that product offered in that market and for another 20 percent there are only two of these products available (see Table 3).[18] Half of the products have been listed only 28 times during the full 15 months spanning my data, conditional on

[16] *Ullage* describes the unfilled space in a container; in wine auctions it refers to visible oxidation. A "Base of Neck" fill level is better than "Top Shoulder" in Bordeaux-style bottles. Burgundy-style bottles have a metric classification (see appendix).

[17] Idiosyncratic goods/services like second hand cars, freelance jobs, or bulky shipments likely involve costly listing inspection, in contrast (arguably) to auctions for Kindle e-readers, iPads, CD's, CPU's, and compact camera's featuring in previous auction platform studies.

[18] All listings are active for at most 31 days, and most of them for 5, 7 or 10, so I conservatively use a 4 week interval to define a market. The BW site has filters for high level characteristics. Correspondingly, let the three main high level filters i) region of origin, ii) vintage decade and iii) wine type define a product. A 1980s red Bordeaux and a non-vintage Champagne are distinct products by that definition.

having been offered at least once. An implication of the model with listing inspection cost is that the option value of bidding in a certain auction is zero so there are also no dynamic incentives. The almost non-existence of repeat listings reported in Table 3 supports this as well.

Second, I cannot reject that the data is generated by a process in which bidders learn their values after they enter the listing. In a selective bidder entry model, valuations are FOSD lower when additional bidders enter the platform, because the marginal bidder has a lower valuation.[19] The relevant comparison in my model is between markets with more and less *total listings* of a certain product. For example, with products defined as above, a month with more listings of non-vintage Champagne should attract more bidders for that type of wine. Reported patterns in Table 4 are consistent with non-selective bidder enter: while an extra bidder in an auction is associated with a transaction price that is about 9-11 pounds higher, having more total bidders / a larger market does not affect the winning bid.[20] Results control for product fixed effects and are estimated in no-reserve auctions in the main sample, and are consistent also for alternative product specifications and narrowing the market to all listings ending within two-days of each other.

Third, listings turn out to be independent of each other even when they have similar end times and products. The presence of more competing listings does not affect average i) number of bidders per listing, ii) number of bids per bidder, iii) transaction prices and iv) reserve prices. Results control for product fixed effects and are robust to a host of different product / market specifications (see footnote Table 5).The coefficient on competing listings is in 68 out of 72 regressions statistically insignificant even at the 10 percent level. Again, costly listing inspection disable a cross-bidding strategy and generate a zero option value. The fact that reserve prices are not affected by competing listings is intuitive since most of them are kept secret. As bidders cannot select on what they cannot observe, there is no motive for sellers to compete on that margin. Overall, the fact that transaction prices do not decrease with the number of competing listings points to the absence of a "business stealing" effect and is also consistent with bidders entering and bidding in one listing at a time. In other words: sellers retain their monopoly position. Again, this sets the

[19] Not observing the pool of potential bidders precludes me from testing selection on obsevables directly, as done in e.g. Roberts and Sweeting (2013).

[20] Regressions are informative for mean effects; results remain when comparing nonparametric Kernel-estimated price distributions of above- vs. below-median total bidders.

Table 5: Evidence for independent listings

Dependent var:	*bidders / listing*		*bids / bidder*		*hammer price*		*reserve price*	
	coef.	s.e.	coef.	s.e.	coef.	s.e.	coef.	s.e.
Product: any wine								
30 days	-0.001	(0.0004)	0.00002	(0.0001)	-0.0001	(0.019)	0.016	(0.029)
7 days	-0.001	(0.001)	-0.0002	(0.0003)	0.008	(0.056)	-0.067	(0.101)
2 days	-0.003	(0.001)	0.0003	(0.0004)	0.062	(0.086)	-0.156	(0.181)
Product: type (red)								
30 days	-0.004	(0.003)	0.001	(0.001)	0.155	(0.142)	0.265	(0.236)
7 days	-0.001	(0.006)	0.002	(0.002)	0.376	(0.357)	-0.336	(0.740)
2 days	-0.020	(0.009)	0.006	(0.003)	0.171	(0.496)	-0.525	(1.065)
Product: region (Bordeaux)								
30 days	-0.001	(0.001)	0.00004	(0.0002)	0.012	(0.043)	0.074	(0.072)
7 days	-0.0003	(0.002)	-0.0002	(0.001)	0.084	(0.131)	-0.060	(0.256)
2 days	-0.003	(0.003)	0.001	(0.001)	0.167	(0.195)	-0.375	(0.396)
Product: region x type								
30 days	-0.003	(0.004)	0.001	(0.001)	0.228	(0.206)	-0.024	(0.347)
7 days	0.011	(0.010)	0.004	(0.003)	1.134	(0.561)	-0.532	(1.096)
2 days	-0.019	(0.016)	0.007	(0.004)	0.905	(0.819)	-1.994	(1.501)
Product: region x type x vintage								
30 days	-0.012	(0.013)	0.001	(0.003)	-0.561	(0.627)	-0.938	(0.899)
7 days	-0.006	(0.034)	0.005	(0.007)	-0.465	(1.597)	-1.371	(2.198)
2 days	-0.061	(0.052)	0.004	(0.009)	-0.938	(2.113)	-0.669	(2.745)
Product: subregion (Margaux) x type x vintage								
30 days	-0.009	(0.008)	0.001	(0.002)	0.433	(0.372)	-0.303	(0.565)
7 days	0.003	(0.019)	0.003	(0.005)	1.914	(0.941)	-1.677	(1.658)
2 days	-0.034	(0.026)	0.007	(0.006)	0.775	(1.143)	-3.026	(1.908)
Observations	1,150		2,898		2,230		2,337	
Sample	0 reserve		all		sold lots		sold lots	

Results from 72 separate OLS regressions of how the number of competing listings affects the four outcome variables (columns). Competing listings defined as offering the same product in the same market, using 6 different product definitions (6 horizontal blocks) and a market being all listings ending within a 30 day, 7 day, or 2 day rolling window of the listing of interest.

idiosyncratic good auction platform apart from previously studied settings where the presence of a thick market for similar items result in strategies that generate different reduced form statistics.[21]

[21]See e.g. Peters and Severinov (1997) and Anwar et al. (2006) for the competing seller model, and Newberry (2015) for the thinning of bidders per listing.

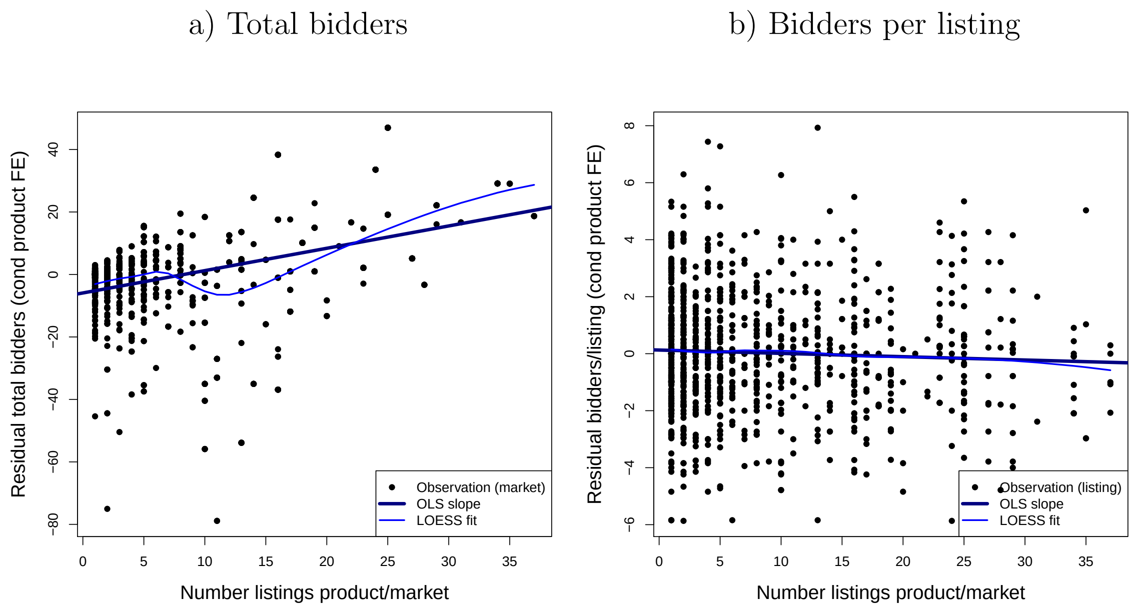

Figure 1: Feedback effects consistent with model predictions
Based on no-reserve auctions. A product is (region x type x vintage) and markets are 4 week intervals. Plotting the residual total bidders (a) and bidders per listing (b) after controlling for product fixed effects (FE).

3.2 Feedback effects are consistent with model predictions

This auction platform data can also be evaluated in terms of its indirect network effects.[22] Such effects arise mechanically in auction platforms from the mere fact that transaction prices are endogenous to the number of bidders per listing. As bidders sort over available listings, a platform with more listings is more attractive to potential bidders c.p., and vice versa. This generates a positive *feedback effect*, observed from the positive correlation between the number of total bidders and the availability of listings after controlling for product fixed effects in Figure 1 a. An equilibrium prediction from a model in which (reserve) prices are unaffected by the number of listings, as shown in the theory section, is that the mean number of bidders per listing is independent of the number of listings (Figure 1 b). Given that the fee structure is fixed in the data, additional listings are not associated with higher cost sellers populating the platform. Network effects are such that bidders enter to the point of keeping the mean number of bidders per listing constant (Table 5).

[22] Indirect network effects describe that a product is more valuable to a group of users when it is more widely adopted by another group, see Katz and Shapiro (1985) and Rochet and Tirole (2006).

4 Nonparametric identification

Model primitives are: the conditional valuation distributions $F_{V0|\mathbf{Z},v_{0,r=0}}$ (defined in (7)) and $F_{V|\mathbf{Z}}$, and opportunity costs (e^o_S, $e^o_{r>0}$, $e^o_{r=0}$). Endogenous observables are: the number of actual bidders (A), the second-highest bid (B), and the reserve price (R). Exogenous observables are denoted by X and include: f, $\mathbf{Z}$, N^S, $N^B_{r>0}$, and $N^B_{r=0}$.[23]

Proposition 3. *Given exogenous observables X and endogenous observables (A, B, R), the idiosyncratic-good auction platform model $\mathcal{M}$ in 2.1 identifies $[F_{V|\mathbf{Z}}, e^o_S, e^o_{B,r>0}, e^o_{B,r=0}]$ and identifies $F_{V0|\mathbf{Z},v_{0,r=0}}$ right-truncated at $v^*_0(f)$.*

Athey and Haile (2002, Theorem 1) prove identification of $F_{V|\mathbf{Z}}$ in an English auction model that places identical restrictions on this distribution up to the presence of binding reserve prices. Observing the empirical distribution F_B in auctions without a reserve price, an event that is known, completes the proof.

Given that $F_{V|\mathbf{Z}}$ is identified, the reserve price identifies the seller's valuation in that listing. Re-arranging the equilibrium reserve price strategy:

$$v_0 = (1 - c_S)\left(r - \frac{1 - F_{V|\mathbf{Z}}(r(1 + c_B))}{(1 + c_B)f_{V|\mathbf{Z}}(r(1 + c_B))}\right) \equiv \underline{r}, \tag{14}$$

The distribution of $\underline{r}$, $F_{\underline{R}}$, identifies the distribution of valuations *among sellers who enter* and set a positive reserve price, point-wise $\forall v \in [v_{0,r=0}, v^*_0(f)]$:[24]

$$F_{\underline{R}}(v) = \frac{F_{V0|\mathbf{Z},v_{0,r=0}}(v)}{F_{V0|\mathbf{Z},v_{0,r=0}}(v^*_0(f))} \tag{15}$$

Without identifying variation in $v^*_0(f)$ and unless $v^*_0(f) = \bar{v}_0$, the population distribution $F_{V0|\mathbf{Z},v_{0,r=0}}(v)$ is not identified on the part of its support exceeding $v^*_0(f)$. However, nonparametric identification of the right-truncated distribution of potential seller valuations is sufficient for any counterfactual that reduces expected seller

[23] These positive identification results go through with the large population assumption when ($N^B_{r>0}$, $N^B_{r=0}$, N^S) are unobserved. This is because: i) $f_{N,r=0}(;p^*_{r=0}(f))$ is identified from observables in auctions without a reserve price, ii) $f_{N,r>0}(;p^*_{r>0}(f, v^*_0), v^*_0(f))$ is identified from variation in the number of actual bidders in auctions with a positive reserve price (for any reserve price that delivers variation in A), iii) the expectations over values of $N_{r>0}$ in (9) and $N_{r=0}$ in (31) are then over an infinite support, and iv) the results don't rely on population sizes otherwise.

[24] Elyakime et al. (1994) also identify seller cost with a first order condition using the secret reserve price in first price auctions (in which case, $r^* = v_0$).

surplus. In my data this is the relevant part of the support because limiting entry of non-serious sellers attracts sufficient additional bidders to each listing to outweigh a reduction in sales from excluded listings.

Opportunity cost are identified from the three zero profit conditions ((10), (15), and (33) evaluated at equilibrium values). I show this in the appendix.

5 Estimation method

I parameterize the latent value distributions and estimate bidder (θ_b) and seller (θ_s) parameters, allowing me on the seller side to extrapolate beyond the support on which $F_{V_0|\mathbf{Z},v_{0,r=0}}$ is identified. However, the fact that the entry equilibrium depends on these structural parameters complicates estimation. A second issue stems from the equilibrium seller entry threshold being the solution to a fixed point problem that itself depends on a threshold-crossing problem on the bidder side, making full maximum likelihood estimation (computationally) infeasible. To address these issues, I adopt a multi-step estimation method:

1. Controlling for auction heterogeneity $\mathbf{Z}$ to obtain homogenized values.

2. Estimating θ_b by maximum likelihood using homogenized bids.

3. Estimating θ_s by maximum concentrated likelihood using homogenized reserves and a consistent estimate of the seller entry equilibrium.

4. Solving for the entry equilibrium given estimated parameters.[25]

5. Re-estimating seller parameters at the updated entry equilibrium.

My algorithm resembles solutions to solving parameters involving fixed point characterizations in the estimation of games. Indeed, the seller entry problem resembles the discrete choice programming problem central to that literature. The rest of this section provides further details including on the estimation of opportunity cost and the entry process.

[25] Steps 4 and 5 are taken because small sample estimation error from steps 1 and 2 affect the concentrated likelihood estimator of θ_s in step 3, which involves the sample *maximum* of noisy implied seller values.

Estimating bidder and seller values. Potential bidder and seller valuations are taken to satisfy the following log-linear single-index structure:

$$ln(V) = g(\mathbf{Z}) + U, \qquad ln(V_0) = g(\mathbf{Z}) + U_0 \tag{16}$$

with ln the natural logarithm and $(U, U_0, \mathbf{Z})$ mutually independent. The common $g(\mathbf{Z})$ term is interpreted as "quality", capturing the importance of provenance, ullage, the expected quality of wines from different vintages or regions, and delivery conditions.[26] On top of that, values are based on an idiosyncratic "taste" component and are non-negative. By additivity of the idiosyncratic taste component, for all bidders i: $V_i = g(\mathbf{Z}) + U_i$ so that also: $V_{(n-1:n)} = g(\mathbf{Z}) + U_{(n-1:n)}$. Quality is then estimated by regressing the transaction price on auction characteristics, using only data from auctions without a reserve price and with more than one bidder in which the transaction price equals the second-highest valuation.[27] Residuals from this regression (plus the intercept) are the homogenized second-highest bids, $\hat{U}_{n-1:n}$, used for estimation of θ_b in (17). U_0 is the basis for estimation of θ_s in (20).

Both U and U_0 in (16) are assumed to be normally distributed.[28] The mean and standard deviation of U, $(\mu_b, \sigma_b \in \theta_b)$, are estimated by maximum likelihood estimation in auctions with a zero reserve price, mapping tightly with the identifying equation.

Let $\mathcal{T}$, $\mathcal{T}_{r0}$ and $\mathcal{T}_{r>0}$ denote the set of listings, listings with a zero reserve price, and listings with a positive reserve. Let $h(b_t|n_t, \mathbf{z}_t, f; \theta_b)$ denote the density of transaction prices given the number of bidders n_t, $\mathbf{z}_t$ and f. For zero reserve auctions it is the probability that the homogenized second-highest bid b_t is the second-highest among n_t draws from $F_{V|\mathbf{Z}}$. Hence $\forall t \in \mathcal{T}_{r0}$:

$$h(b_t|n_t, \mathbf{z}_t, f; \theta_b) = n_t(n_t - 1)F_{V|\mathbf{Z}}(b_t; \theta_b)^{n_t-2}[1 - F_{V|\mathbf{Z}}(b_t; \theta_b)]f_{V|\mathbf{Z}}(b_t; \theta_b) \tag{17}$$

[26] It is for instance is commonly accepted that the 1961 Bordeaux vintage is better than most others due to favourable weather conditions.

[27] This homogenization step stems from Haile et al. (2003) and is used often in the analysis of ascending auctions, e.g. in Bajari and Hortaçsu (2003) and Freyberger and Larsen (2017).

[28] The lognormal distribution is commonly used to analyze bidding data (e.g. Paarsch (1992), Laffont et al. (1995), Haile (2001), Hong and Shum (2002)). Results go through with the loglogistic distribution, but its heavier tails deliver a worse fit.

Bidder parameters are estimated by maximizing the log likelihood function:

$$\mathcal{L}(\theta_b; \{n_t, \mathbf{z}_t, b_t, r_t\}_{t\in\mathcal{T}_{r0}}, f) = \sum_{t\in\mathcal{T}_{r0}} ln((h(b_t|n_t, \mathbf{z}_t, f; \theta_b))) \tag{18}$$
$$\hat{\theta}_b = \arg\max \mathcal{L}(\theta_b; \{n_t, \mathbf{z}_t, b_t, r_t\}_{t\in\mathcal{T}_{r0}}, f)$$

The equilibrium mapping of reserves to values exploited for identification (14) is the basis for recovering a sample of implied seller values, $\forall t \in \mathcal{T}_{r>0}$:

$$\hat{u}_{0,t} = ln\left((1-c_S)\left(r_t - \frac{1-F_{V|\mathbf{Z}}(ln(\tilde{r}_t) - \hat{g(\mathbf{z}_t)}; \hat{\theta}_b)}{(1+c_B)f_{V|\mathbf{Z}}(ln(\tilde{r}_t) - \hat{g(\mathbf{z}_t)}; \hat{\theta}_b)}\right)\right) - \hat{g(\mathbf{z}_t)}, \tag{19}$$

with $\tilde{r}_t = r_t(1+c_B)$ denoting the buyer premium-adjusted reserve price and $\hat{u}_{0,t}$ the homogenized idiosyncratic part of the implied seller value in auction t. The sample maximum of implied residual seller valuations, $\hat{v_T} = \max(\{\hat{u}_{0,t}\}_{t\in\mathcal{T}_{r>0}})$, is a consistent estimator of the seller entry threshold. Intuitively, sellers with higher residual value draws than $v_0^*(f)$ will never list so $\hat{v_T} - v_0^*(f, \theta_b, \theta_s)$ is always negative (at population values of θ_b, θ_s, and $g(\mathbf{Z})$) and the more sellers that do list the larger the probability that the marginal seller has a valuation equal to the threshold.[29]

Let $h(r_t|\mathbf{z}_t, f, v_0^*(f, \theta_b, \theta_s), \hat{\theta}_b; \theta_s)$ denote the density of r_t given the true seller equilibrium threshold, which follows from equation (15):

$$h(r_t|\mathbf{z}_t, f, v_0^*(f, \theta_s, \theta_b), \hat{\theta}_b; \theta_s) = \frac{f_{V0|\mathbf{Z},v_{0,r=0}}(\hat{u}_{0,t}; \theta_s)}{F_{V0|\mathbf{Z},v_{0,r=0}}(v_0^*(f, \theta_s, \theta_b); \theta_s)}, \tag{20}$$

for $r_t \in [r^*(v_{0,r=0}, f), r^*(v_0^*(f, \theta_s, \theta_b), f)]$, and 0 otherwise. A complication is that the support of reserve prices (and implied $\hat{u}_{0,t}$) observed in the data depends on θ_s through its effect on $v_0^*(f, \theta_s, \theta_b)$, so that standard regularity conditions demonstrating consistency and asymptotic normality of the maximum likelihood estimate of θ_s don't apply. I therefore estimate initial seller parameters by maximizing a concentrated

[29] A more precise statement, with continuous $F_{V_0|\mathbf{Z}}$, is that the probability increases that the marginal seller has a valuation within a fixed small interval around the threshold.

likelihood with $\hat{v_T}$ in place of $v_0^*(f, \theta_s, \theta_b)$:[30]

$$\mathcal{L}(\theta_s; \{\hat{u}_{0,t}, \mathbf{z}_t\}_{t \in \mathcal{T}_{r>0}}, f, \hat{v_T}, \hat{\theta}_b) = \sum_{t \in \mathcal{T}_{r>0}} ln(h(r_t | \mathbf{z}_t, f, \hat{v_T}, \hat{\theta}_b; \theta_s)) \tag{21}$$

$$\hat{\theta}_s^{\,0} = \arg\max \mathcal{L}(\theta_s; \{\hat{u}_{0,t}, \mathbf{z}_t\}_{t \in \mathcal{T}_{r>0}}, f, \hat{v_T}, \hat{\theta}_b) \tag{22}$$

This addresses the support problem as the first order condition of the concentrated likelihood with respect to $(\mu_s, \sigma_s \in \theta_s)$ does not depend on $\hat{v_T}$. However, the fact that $\hat{u}_{0,t}$ depends on estimated $\hat{\theta}_b$ and $g(\hat{\mathbf{Z}})$ makes it likely that in finite samples $\hat{v_T}$ is biased. In particular, because it is the maximum of a noisily estimated sample of homogenized idiosyncratic seller valuations it likely an overestimate of the true $v_0^*(f)$. Relatedly, it introduces the possibility that the largest values of $\hat{u}_{0,t}$ incorporate the highest bias.[31]

In steps 4 and 5, I therefore solving the entry game and re-estimate seller parameters with the new threshold, $v_0^*(f, \hat{\theta}_s^{\,0}, \hat{\theta}_b)$, incorporated in (22).[32]The appendix provides computational details, including about numerical approximation of the entry equilibrium, and provides Monte Carlo results that one update is sufficient to correct for the noisy first stage. The final estimated seller parameters are denoted by $\hat{\theta}_s$.

Estimating entry parameters. The mean number of bidders in no reserve auctions is a consistent estimate of $\lambda^*_{r=0}$:

$$\hat{\lambda}^*_{r=0} = \frac{1}{|\mathcal{T}_{r=0}|} \sum_{t \in \mathcal{T}_{r=0}} n_t \tag{23}$$

A consistent estimate of $\lambda^*_{r>0}$ maximizes the likelihood of transaction prices (b_t) and number of actual bidders (a_t), in positive reserve auctions and given estimated bidder values. The joint density of b_t, a_t *if the number of potential bidders per listing* (n_t) *would be known*, $\forall t \in \mathcal{T}_{r>0}$:

[30]Donald and Paarsch (1993, Footnote 4) suggest this for a support problem in first-price auctions.

[31]Monte Carlo simulations confirm that the initial standard devation σ_b overestimates the truth as the sample of implied seller values appears more disperse.

[32]Iterating on steps 3-5 until convergence would be in line with the NPL estimator in Aguirregabiria and Mira (2002). Roberts and Sweeting (2010) are the first to apply this algorithm to the auction literature to study auctions with selective bidder entry. Pesendorfer and Schmidt-Dengler (2010), Kasahara and Shimotsu (2012) and Egesdal et al. (2015) provide conditions under which NPL does (not) converge to the true equilibrium. A best-response stable equilibrium is a sufficient condition for the algorithm to converge and this is certainly guaranteed by my game reducing to a single agent discrete choice problem with unique equilibrium (Proposition 1).

$$
\begin{aligned}
h(b_t, a_t|n_t, r_t, \mathbf{z}_t, f, \hat{\theta}_b) &= \{F_{V|\mathbf{Z}}(\tilde{r}_t; \hat{\theta}_b)^{n_t}\}\mathbb{I}\{a_t = 0\} \\
&\{n_t F_{V|\mathbf{Z}}(\tilde{r}_t; \hat{\theta}_b)^{n_t-1}[1 - F_{V|\mathbf{Z}}(\tilde{r}_t; \hat{\theta}_b)]\}\mathbb{I}\{a_t = 1\} \\
&\{\binom{n_t}{n_t - a_t} F_{V|\mathbf{Z}}(\tilde{r}_t; \hat{\theta}_b)^{n_t-a_t}[1 - F_{V|\mathbf{Z}}(\tilde{r}_t; \hat{\theta}_b)]^{a_t} \\
&a_t(a_t - 1)F_{V|\mathbf{Z}}(\tilde{b}_t; \hat{\theta}_b)^{a_t-2}[1 - F_{V|\mathbf{Z}}(\tilde{b}_t; \hat{\theta}_b)]f_{V|\mathbf{Z}}(\tilde{b}_t; \hat{\theta}_b)\}\mathbb{I}\{a_t \geq 2\}
\end{aligned} \tag{24}
$$

The first line covers the probability that all n_t bidders draw a value below the reserve price, the second line the probability that one out of n_t draw a value exceeding $\tilde{r}$ while the others don't (in which case $b_t = r_t$ with certainty), and the final two lines capture the probability that a_t out of n_t draw a valuation exceeding the reserve and that the second-highest out of them draws a valuation equal to $\tilde{b}_t = b_t(1 + c_B)$. Without observing n_t, a feasible specification takes the expectation over realizations of random variable $N \sim Pois(\lambda^*_{r>0})$. This is the basis of the likelihood function that $\hat{\lambda}^*_{r>0}$ maximizes, $\forall t \in \mathcal{T}_{r0}$:

$$
g(b_t, a_t|r_t, \mathbf{z}_t, f, \hat{\theta}_b; \lambda^*_{r>0}) = \sum_{n_t=a_t}^{\infty} h(b_t, a_t|k, r_t, \mathbf{z}_t, f, \hat{\theta}_b) f_{N|N\geq A}(k; \lambda^*_{r>0}) \tag{25}
$$

$$
\mathcal{L}(\lambda^*_{r>0}; \{b_t, a_t, r_t\mathbf{z}_t\}_{t\in\mathcal{T}_{r>0}}, f, \hat{\theta}_b) = \sum_{t\in\mathcal{T}_{r>0}} ln(g(b_t, a_t|r_t, \mathbf{z}_t, f, \hat{\theta}_b; \lambda^*_{r>0})) \tag{26}
$$

$$
\hat{\lambda}^*_{r>0} = \arg\max \mathcal{L}(\lambda^*_{r>0}; \{b_t, a_t, r_t, \mathbf{z}_t\}_{t\in\mathcal{T}_{r>0}}, f, \hat{\theta}_b) \tag{27}
$$

Bidder opportunity cost $\hat{e}^o_{B,r>0}$ and $\hat{e}^o_{B,r=0}$ are estimated as the values that equal expected surplus from entering, estimated by computing the values in equations (9) and (31) at the estimated ($\hat{\theta}_b$, $\hat{\theta}_s$, $\hat{\lambda}^*_{r>0}$, $\hat{\lambda}^*_{r=0}$). As the seller opportunity cost are identified off only one data point (the expected surplus of the marginal seller) I instead estimate $\hat{e}^o_S$ as the average between $\hat{e}^o_{B,r>0}$ and $\hat{e}^o_{B,r=0}$. The equilibrium seller entry threshold is calculated as the value that makes the marginal seller indifferent, i.e. by solving equation (12) at the estimated parameters.

6 Estimation results

Estimates from the homogenization step show that the (sign of) coefficients for various key variables are as expected. Prices are higher for bottles sold in a case of 6 or 12, and conditional on this case effect the price is lower the more bottles are included in the lot. Bottles stored in specialized temperature-controlled warehouses and special format bottles (e.g. magnums) are more attractive. All fill levels that are not the best deliver (weakly) lower prices. The full set of coefficients is provided in the appendix, and are insightful about the relative attractiveness of a host of regions, grapes, shipping options, etc.

It is important to point out that the rich set of auction observables obtained through web scraping explains a remarkably large share of total price variation: the adjusted R-squared is 0.530 for the main sample and 0.855 for the smaller high-value sample. This compares favorably even with how much price variation can be explained by observables in auction data with more homogeneous goods.[33] It is especially encouraging given the notorious difficulty to address unobserved heterogeneity in English auctions (Hernández et al. (2019)).[34]

The estimated population distribution of seller valuations is more dispersed than that of bidders but the distribution of bidder values (at least) second-order stochastically dominates the distribution of values among sellers on the platform who set a positive reserve price (see Table 6).[35] Auction characteristics explain the majority of price variation in the sample, but there is significant variation in the idiosyncratic tastes for the fine wine offered on the platform. For example, at the median estimated quality (-0.33) the mean bidder value is estimated to be 26 pounds and the

[33] Bodoh-Creed et al. (2019) explain 42% of price variation for Amazon Kindles with a more elaborate set of controls obtained with machine learning techniques (Hernández et al. (2019)). Bodoh-Creed et al. (2019) state that the 0-15% of variation with simple OLS regressions is representative of low predictive power in the literature, and they manage to increase the fit to on average 48% with random forest estimation and machine learning techniques.

[34] Hernández et al. (2019) require exogenous variation in bidder participation, as do Aradillas-López et al. (2013) to obtain narrow bounds on expected surpluses. In Roberts (2013), homogeneous sellers and bidders observe the characteristic unobserved to the econometrician, which is recovered from variation in reserve prices. Freyberger and Larsen (2017) have heterogeneous sellers but require two bid order statistics to apply a deconvolution.

[35] Estimation of θ_s excludes the 4.17 (0.22 in high-value sample) percent of sellers for which $\hat{u}_{0,t}$ is estimated to be negative. This could be driven by: i) a portion of sellers setting reserve prices below optimal, ii) small-sample estimation bias stemming from first-stage estimates, or potentially iii) approximation error in the reserve price.

Table 6: Estimation results

Idiosyncratic values		main	high-value	**Entry equilibrium**		main	high-value
Bidders (θ_b)	μ_b	3.1736 (0.029)	5.376 (0.034)	Bidders per listing	$\lambda^*_{r>0}$	3.835 (0.007)	4.651 (0.033)
	σ_b	0.903 (0.001)	0.564 (0.022)		$\lambda^*_{r=0}$	5.238 (0.004)	7.271 (0.011)
Sellers (θ_s)	μ_s	4.175 (0.084)	5.957 (0.093)	Seller entry probability		0.811 (0.002)	0.828 (0.003)
	σ_s	1.491 (0.165)	0.741 (0.022)	Opportunity cost	e^o_S	4.991 (0.165)	13.848 (0.642)
					$e^o_{B,r>0}$	4.782 (0.159)	13.285 (0.641)
					$e^o_{B,r=0}$	5.200 (0.171)	14.412 (0.661)

Standard errors are obtained with 250 bootstrap repetitions (including homogenization stage).

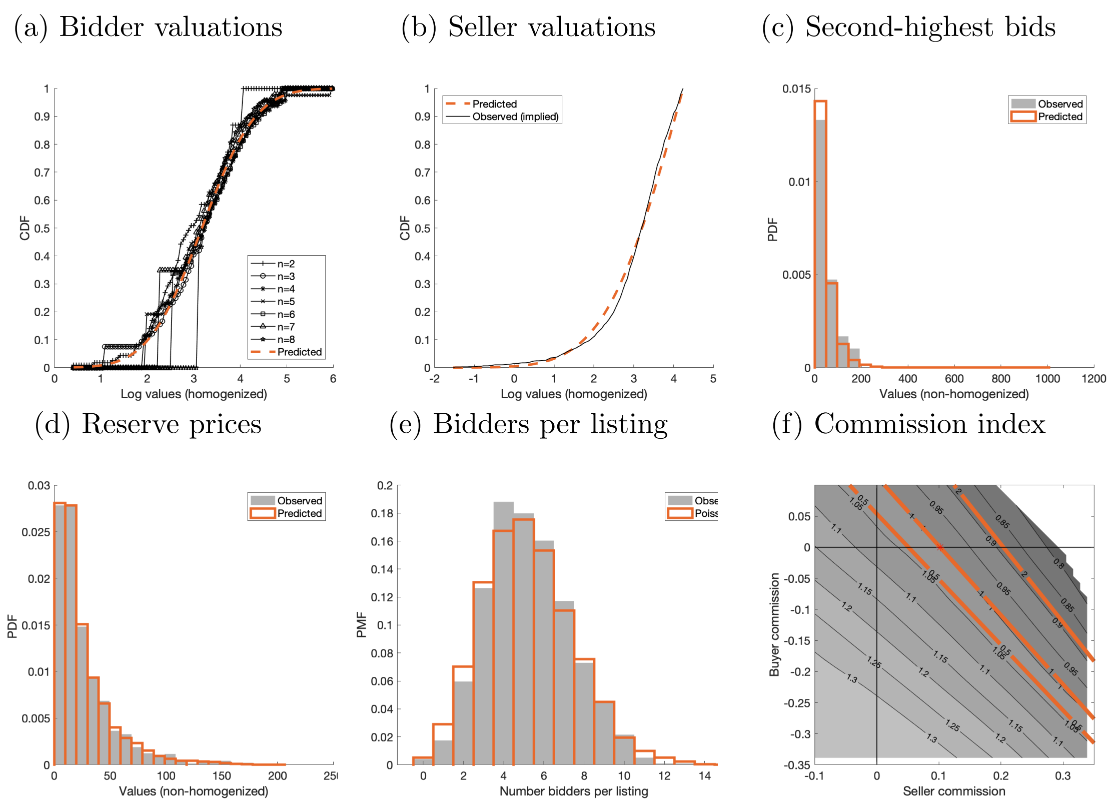

Figure 2: Model fit / validation

Plotting: (a) $F_{V|\mathbf{Z}}(;\hat{\theta_b})$ vs empirical CDFm $n = 2, \ldots, 8$ bidders (no reserve), (b) $F_{V_0|\mathbf{Z},v_{0,r=0}}(;\hat{\theta_b})$ vs empirical CDF (positive reserve), (c) second-highest bid, predicted (incl. estimated quality) and observed, (d) reserve price, predicted (inc. estimated quality) and observed, (e) PMF bidders per listing, predicted (given Poisson $\hat{\lambda}^*_{r=0}$, no reserve), and (f) contour plot of counterfactual v_0^* (grey tones) and commission indices (thick orange lines), shares of baseline values.

interquartile range 9-32 pounds. Sellers are estimated to have an average value of 20 pounds for that item, with an interquartile range of 9-31 pounds. Real gains from trade come from some bidders drawing a much higher value, with the 95th percentile of estimated bidder values at 75 pounds and the same statistic for sellers at 45 pounds. Estimated taste distributions have a higher mean but lower dispersion in high-value listings.

Setting no reserve price attracts on average 1.6 additional bidders into a listing. It also makes intuitive sense that this participation differential is larger in the high-value sample; the probability of being the sole entrant and winning the more expensive bottle for the 1 pound opening bid contributes more to expected surplus. Estimated opportunity cost are also significantly different; roughly three times as high in the high-value sample. But relative to the second-highest bid, estimated opportunity cost are higher in the main sample: 6 - 7 percent, versus 4 percent in the high-value sample. Estimates do in both cases correspond to the idea that listing inspection cost are significant in this idiosyncratic goods environment.

Fit and validation. The model fits the data well, also when looking at cuts of the data not targeted in estimation. Figure 2 illustrates. Plot (a) and (b) show how nonparametric idiosincratic value distributions of bidders and sellers relate to the estimated parametric distributions. Plots (c) and (d) include draws of estimated quality and number of bidders to simulate second-highest bids and reserve prices. Both are in expectation over the number of bidders per listing, and plot (d) includes out-of-sample predictions of quality that is estimated in auctions without a reserve. As another measure of model fit I compute the mean absolute deviation between observed and predicted second-highest bids separately for $n = \{2, 3, .., 10\}$ bidders: mean absolute deviations are between 0.042-0.997 and there is no clear pattern by number of bidders. A two-sample Kolmogorov-Smirnov test cannot reject the null that observed and predicted reserve prices are drawn from the same population distribution (p-value 0.448).

Plot (e) displays the remarkable fit of the assumed Poisson distribution with the estimated $\lambda^*_{r=0}$ to the observed Binomial number of bidder distribution. A chi-square goodness of fit test fails to reject that N is generated by a Poisson distribution (p-value 0.146). It is of particular interest that the data does not reveal any overdispersion relative to the Poisson distribution.[36]

[36] That would point to an entry process in which bidders enter significantly more numerously into auctions with certain characteristics - conditional on the reserve price button. Preferences for high-level characteristics (filters) may vary across the population of potential bidders, but a model with uniform sorting over listings captures the first order effects of entry behavior in the BW data.

Plot (f) confirms centrality of the commission index. In theory, outcomes are independent of the allocation of total commissions to buyers and sellers as long as commission index $\frac{c_B+c_S}{1+c_B}$ remains constant (Ginsburgh et al. (2010)). In other words, only the commission index and flat fees should matter for the platform revenue-maximization problem. The plot shows how computed counterfactual equilibrium v_0^* levels line up perfectly with the commission-index level lines in orange.[37] Reducing the commission index by half increases the seller entry threshold by about 5 percent and doubling the commission index leads approximately to a 10 percent reduction in the threshold.

Another source of model validation comes from comparing $\hat{e}^o_{B,r=0}$ with $\hat{e}^o_{B,r>0}$. While they are allowed to be different, there is no reason to suspect that it is significantly more time-intensive to inspect listings with or without a reserve price *if the reserve price does itself not reveal any information about the quality of the item*. Indeed, the 95 percent confidence intervals of $\hat{e}^o_{B,r=0}$ and $\hat{e}^o_{B,r>0}$ overlap, in both the main and high-value sample. Recall that $\hat{e}^o_{B,r=0}$ and $\hat{e}^o_{B,r>0}$ are computed in two different cuts of the data as the values that justify $N_{r=0} \sim$Pois$(\hat{\lambda}_{r=0})$ and $N_{r>0} \sim$Pois$(\hat{\lambda}_{r>0})$ using two very different estimation methods. Hence the fact that they are statistically insignificant as they should be confirms that the parsimonious model provides a plausible description of bidder behavior and payoffs on this platform.

Robustness analysis. Table 7 shows that results are robust to alternative empirical choices. The table presents the fit of the homogenization step, equilibrium parameters and opportunity cost with standard errors from 250 bootstrap replications. Only the estimated opportunity cost turn out slightly higher in the fourth robustness check.

In (1), I test robustness to the parametric specification by assuming that (U, U_0) are logistically distributed. Although entry results are similar, the heavier-tailed logistic distribution has a worse fit and it can even be rejected at the 5% level that the resulting simulated reserve price distribution is identical to the observed one.

In (2), I use text mining techniques to control for additional listing information in the homogenization step. Specifically, I load all textual descriptions (generated by the seller), create a corpus, remove punctuation, stopwords, and numbers, and adopt

[37] First, equilibrium values of v_0^* are computed at a grid of all 30 commission combinations from $c_B = \{-0.2, -0.1, 0, 0.1, 0.2\}$ and $c_S = \{-0.2, 0.1, 0, 0.1, 0.2, 0.4\}$ and interpolated on a finer grid of 41x41. Displayed values are normalised by baseline values, and are estimated in the main sample.

Table 7: Robustness analysis

	(1)		(2)		(3)		(4)	
Adj. R^2	0.530	(0.001)	0.550	(0.001)	0.542	(0.001)	0.530	(0.001)
$\lambda^*_{r>0}$	3.791	(0.007)	3.837	(0.007)	3.771	(0.006)	4.288	(0.007)
$\lambda^*_{r=0}$	5.260	(0.004)	5.260	(0.004)	5.452	(0.004)	5.260	(0.004)
$F_{V_0\|\mathbf{Z}}(v_0^*)$	0.872	(0.002)	0.834	(0.002)	0.808	(0.002)	0.835	(0.002)
e^o_S	6.341	(0.149)	5.979	(0.157)	5.251	(0.132)	7.042	(0.125)
$e^o_{B,r>0}$	6.183	(0.145)	5.814	(0.153)	5.160	(0.128)	6.462	(0.115)
$e^o_{B,r=0}$	6.499	(0.153)	6.145	(0.161)	5.341	(0.136)	7.621	(0.136)

Results from four robustness exercises described in main text. Standard errors from 250 bootstrap repetitions in parenthesis. Estimated using data from the main sample.

stemming. I then generate dummy variables for the presence of words associated with four important types of descriptors related to provenance, storage conditions, delivery conditions, and expert opinion. I also add the total number of words in the description, and the number of words squared. Furthermore, I add feedback data: whether the seller has received feedback from previous transactions, whether he has any ratings, the number of ratings, the share of the ratings being neutral, and the share being positive. This text mining exercise only marginally improves the adj. R^2 from 0.53 to 0.55, underlining the richness of the original set of controls.

In (3), I estimate the model for auctions with red wine only, representing 65 percent of all auctions in the main sample. Results show that latent value distributions and entry processes are not very different from other types of wine, and therefore that the model is not misspecified along this dimension.

In (4), I adopt a different reserve price approximation that imputes unobserved secret reserve prices in unsold auctions with a linear combination of its two nearest neighbour values, after first ranking listings based on their estimated quality. I also replace approximated reserve prices for which the highest bid exceeds the 95th percentile.

7 Counterfactuals

I next use model estimates to address two key indeterminacy's of two-sided markets. First, how should the platform allocate fees between different platform users? Second, how do increases in fees affect users on both sides? I first highlight the added value

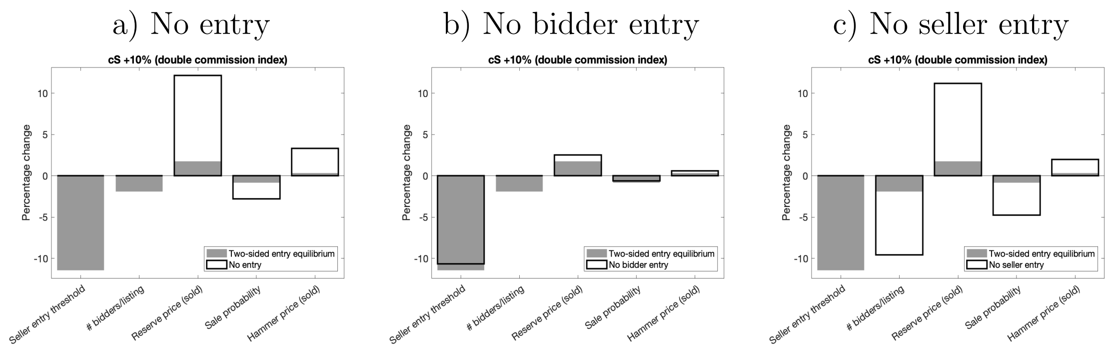

Figure 3: Ignoring seller entry significantly biases results

of modelling endogenous seller entry.

Addressing seller entry. Accounting for endogenous seller entry is new to the structural auction literature, and Figure 3 confirms its importance empirically. I simulate a 10 percentage point increase in the seller commission. Impacts are theoretically ambiguous: reserve prices are driven up for sellers already on the platform, but the higher-commission platform will be populated with lower-value sellers setting lower reserves. Because only the former direct price effect is present when shutting off entry altogether (panel a), one would severely overpredict the increase in reserve prices, as shown. Panel b illustrates a second take-away: seller entry reduces by less when not letting bidder entry adjust optimally. It turns out that reserve prices increase so that in the full equilibrium the number of bidders per listing decreases. This would make the platform even less attractive to sellers: a feedback effect that explains the additional decrease in seller entry. Finally, a model that ignores only seller entry (panel c) would fail to capture the counterbalancing effect of attracting more serious sellers. The omission exaggerates by more than 300% the reduction in the number of bidders and the sale probability.

Increasing platform profitability. All fee changes generate a crucial trade-off between the volume of sales and platform revenue. Higher listing fees, for example, make it less attractive for sellers to enter and the lower number of listings depresses the sales volume. I therefore consider the problem of maximizing current volume-constrained fee revenues.[38] Figure 4 displays contour plots of estimated counterfactual

[38]In any scenario where the volume of sales affects future revenues, through word of mouth or brand awareness, a forward-looking platform will include this outcome in their objective function. Such scenario's are consistent with a model of network growth with myopic users who can terminate their participation at no cost, as in Evans and Schmalensee (2010).

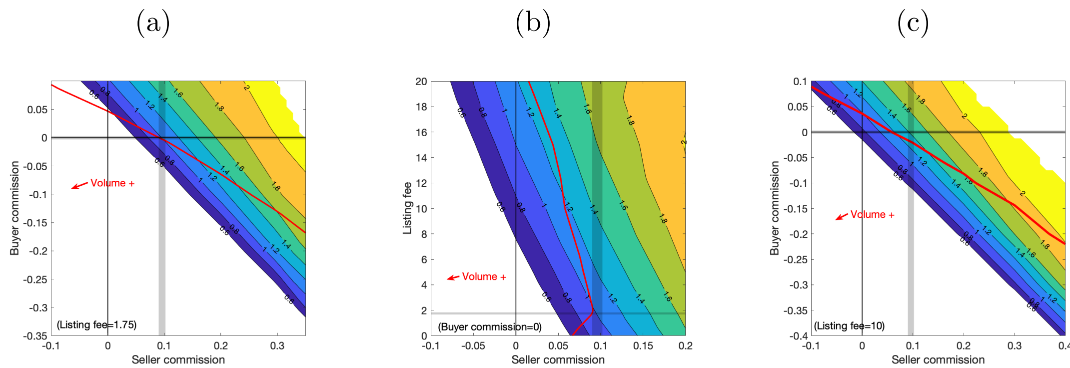

Figure 4: Platform revenue at counterfactual fees

Contour plots of revenue relative to baseline platform revenue. The red line indicates current sales volume; fee combinations to the south west increase volume. Grey bars indicate baseline fee levels.

platform revenues.[39] When altering just the commission levels, the platform cannot increase its revenues without reducing volume unless it is willing to charge a negative buyer commission (plot a).It is striking that the platform can increase its revenues by more than 60 percent without reducing the sales volume by charging a negative buyer commission and finance that by increasing the seller commission. Plot b shows that platform demand is relatively inelastic with respect to the listing fee.[40] Platform revenues can increase by more than 20 percent when pairing a higher listing fee with a lower seller commission. Simulations in plot c combine these results for a range of counterfactual buyer commissions.

Table 8 provides further insight into profit strategies. Simulated fee structures increase volume by 2-3% and increase revenues by 13-35%. In the first column, platform profitability increases primarily through increasing the commission index. Transaction prices increase despite the selection of more serious sellers, and the platform keeps a larger share of it. In the second column switching from seller commission to listing fee boosts profitability, improving the share of (higher-return) high-value listings. This is especially attractive for a platform that wants to position itself on the high-end of the market. The last column combines a modest bidder discount and

[39] The game is estimated for all fee combinations on coarse grids ($c_L = \{0, 1.75, 5, 10, 15\}$ and (c_B, c_S) $= \{-0.2, -0.1, 0, 0.1, 0.2\}$) and interpolated on finer grids. Results are expressed as changes with respect to baseline levels and are computed in homogenized value space, including both the main and high-value samples.

[40] The average transaction price in the data is about 140 pounds so increasing the listing fee from 1.75 to 10 pounds should deliver effects in the same order of magnitude of changing the seller commission from about 0.01 to 0.07.

Table 8: Effects of specific fee changes

Counterfactual (c_B, c_S, c_L)	$(-0.1, 0.22, 1.75)$	$(0, 0.05, 10)$	$(-0.03, 0.08, 6.75)$
Commission index $\frac{c_B+c_S}{1+c_B}$	0.136	0.05	0.052
	(percentage change w.r.t. baseline:)		
Platform revenue	34.914	13.986	12.901
Volume	3.072	2.912	2.440
Transaction price (avg)	4.254	-8.710	-5.614
Share high value listings	-1.983	14.617	6.014
Share high value revenues	-28.455	4.007	-7.574
Seller entry prob (main)	-4.637	-18.296	-10.362
Number bidders (high)	-1.756	11.565	6.613

Baseline fee values: ($c_B = 0, c_S = \{0.102$ (main),0.09 (high)$\}$, $c_L = 1.75$), commission index = $\{0.102$ (main),0.09 (high)$\}$.

Table 9: Antitrust damages

	$c_S + 5\%$, main	$c_S + 5\%$, high	$c_B + 5\%$, main	$c_B + 5\%$, high
	(percentage change w.r.t. baseline:)			
Total seller surplus	-16.863	-11.764	-16.456	-9.487
Total winning bidder surplus	-6.215	-7.087	-5.927	-5.890
Surplus per seller	-12.602	-13.683	-10.996	-13.069
Surplus per winning bidder	-1.209	-0.762	-0.475	-0.956
Heterogeneous impacts on sellers:				
Q25 seller on platform (at baseline)	-4.352	-12.072	-2.805	-9.997
Median seller on platform (at baseline)	-8.405	-18.003	-6.103	-15.358
Q75 seller on platform (at baseline)	-14.082	-29.747	-11.892	-24.545
Marginal seller counterfactual	-36.650	-73.922	-34.151	-74.166

small seller commission decrease with a small listing fee increase. The seller entry probability decreases less than in column 2. This dampens the feedback effect on bidder entry and lowers the share of profits from high-value listings by 8%.

Antitrust damages and heterogeneous impacts. In Table 9 I compute hypothetical antitrust damages (not tripled) from increasing either buyer or seller commission by 5 percentage points. Results debunk two paradigms previously applied to assess the impacts of commissions, both in relation to the Sotheby's and Christie's commission fixing case that resulted in a settlement of 512 million dollars that mostly went to winning bidders. Its litigation makes clear that damages are awarded pro-rata, which would in the table correspond to a 5% damage to sellers in columns 1 and 2 and a 5% damage to buyers in columns 3 and 4. Estimated damages instead fall mostly on sellers in both instances, and decrease by more than twice these amounts.[41] The fact that also winning bidders are affected breaks with the so-called one-sided market perspective on this issue: the idea that in a world without entry and fully inelastic sellers, winning bidders should not be affected.[42] Instead, expected surplus of winning bidders as a group drops by 6 (7) percent after the buyer (seller) commission increase. Also the surplus per winning bidder decreases because the additional bidders per listing reduce the spacing between the highest two order statistics; an effect that would clearly be overlooked when ignoring the two-sidedness of the platform.

The highly non-linear damages to sellers also stand out. The seller who is marginal in the higher commission counterfactual must have a lower surplus than at baseline, because he is inframarginal there. By the same reasoning, the seller who was marginal at baseline is not affected because he was indifferent between entering and staying out. In general the most serious, lowest-value sellers are affected the least but those that were almost marginal at baseline experience an enormous 34 (37) percent reduction in their expected surplus from the five percent increase in buyer (seller) commission. The inter-quartile range of seller damages is in the main sample between 4-14 percent (seller commission increase) and 3-12 percent (buyer commission increase). Per-seller damages are about two to three times as large in the more high-end listings.

8 Conclusions and discussion

The main contribution of this paper is to merge two important literatures with the goal to provide a tight quantitative assessment of the impacts of auction platform fees. I have presented, solved, and estimated the first structural auction model that accounts for seller selection. I have also shown that the model's parsimonious set of assumptions combined with basic English auction data renders its model primitives point identified. For the distribution of potential seller valuations this holds on the support of values for sellers on the platform and therefore for relevant counterfactuals that make seller entry less attractive. In this type of platform, restricting entry of less serious sellers is beneficial as it makes the platform more attractive to bidders. It is precisely this sort of network effect generated through bidder-seller interactions

[41] The court ruling can be found here on Casetext. It states that "[an expert witness] admits that there is no supply and demand elasticity evidence from which any conclusion might be drawn about where the ultimate economic incidence of the alleged conspiracy fell."

[42] See Ashenfelter and Graddy (2005), Marks (2009), McAfee (1993)

that complicate the analysis of fee impacts. Hence, besides bringing a two-sided market perspective to the empirical auction literature I also show how to trace fees through the auction game to justify the network effects central to the two-sided market literature.

I have described several testable implications of the model. For data to be consistent with it, it needs to be generated from an environment with significant listing inspection cost, such as in other auctions with idiosyncratic goods. The resulting independence of listings is key to solve the two-sided entry equilibrium: it means that the equilibrium mean number of bidders per listing is only affected by the type and not the number of listings. As such, the independent listing property and a large population assumption bring the tractability to my model that stationarity restrictions bring to dynamic (auction) models. It would clearly be interesting to extend my framework in future work to add a (dynamic) search dimension (as in Backus and Lewis (2019) and Bodoh-Creed et al. (forthcoming)), to include the overlapping open nature of listings in which bidders choose where to bid (as in Hendricks and Sorensen (2018)), and to consider seller competition (as in Anwar et al. (2006)) for markets where this is relevant.

Network effects in this market can be harnessed to improve platform profitability. I estimate that platform revenues can increase by 60 percent when combining a bidder discount with higher seller fees or by 20 percent when combining a lower seller commission with a higher listing fee.[43] Antitrust damages from increasing commissions fall mostly on sellers, are more than twice as large as in a simple model without network effects, and heterogeneous. Competition authorities and courts recognize the importance of network effects in two-sided markets, but the difficulty to quantify user interactions has been a practical bottleneck.[44] My auction platform model with two-sided entry provides sufficient structure to allow such a case to be evaluated.

[43] A negative commission is consistent with the idea that businesses in two-sided markets should subsidize the side that contributes most to profits, even charging below marginal cost. See e.g., Rochet and Tirole (2003, 2006), Wright (2004), Armstrong (2006), Rysman (2007), Evans and Schmalensee (2013) Rysman and Wright (2002). I am not aware of any auction platform with negative fees, but eBay uses temporary discount coupons.

[44] See e.g. Bomse and Westrich (2005), Tracer (2011), Evans and Schmalensee (2013). In (this eBay case, discussed here), sellers were denied a class action suit due to the absence of a method to quantify damages in the presence of network effects. A decisive move towards the need for structural platform models came with the landmark 2018 *Ohio vs Amex* Supreme Court decision, which requires plaintiffs (merchants) to provide evidence that anti-steering rules negatively impact consumers as well. The decision can be found here.

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References to (1) - (27) are to equations in the main text of the article.

Supplement: Omitted proofs

Optimal reserve price

Proof Lemma 2. For brevity I omit conditioning on characteristics $\mathbf{Z}$, and define hat and check notation as: $\hat{x} = x(1 + c_B)$ and $\check{x} = \frac{x}{1+c_B}$. Let R denote expected revenue for a seller with valuation v_0 when setting reserve price r in an auction with n bidders:

$$R = v_0 F_V(\hat{r})^n + (1 - c_S) rn F_V(\hat{r})^{n-1}[1 - F_V(\hat{r})] + \\ T(1 - c_S) \int_{\hat{r}}^{\bar{v}} \check{x} n(n-1) F_V(x)^{n-2}[1 - F_V(x)] f_V(x) dx \tag{28}$$

The three terms in the above equation for R cover three cases: i) no sale takes place, ii) a sale takes place but the second-highest bid is less than the reserve price and iii) the sale takes place and the second-highest bid exceeds the reserve. Maximizing R with respect to r:

$$\begin{aligned} \frac{\partial R}{\partial r} = v_0 n F_V(\hat{r})^{n-1} f_V(\hat{r})(1 + c_B) + (1 - c_S) n F_V(\hat{r})^{n-1}[1 - F_V(\hat{r})] \\ +(1 - c_S) rn(n-1) F_V(\hat{r})^{n-2} f_V(\hat{r})(1 + c_B)[1 - F_V(\hat{r})] \\ -(1 - c_S) rn F_V(\hat{r})^{n-1} f_V(\hat{r})(1 + c_B) \\ -(1 - c_S) rn(n-1) F_V(\hat{r})^{n-2}[1 - F_V(\hat{r})] f_V(\hat{r})(1 + c_B) \end{aligned} \tag{29}$$

The second and last line cancel out. Re-arranging delivers the optimal reserve price $r^*(v_0, f)$ which solves:

$$r^*(v_0, f) \equiv \{r = \frac{v_0}{1 - c_S} + \frac{1 - F_V(r(1 + c_B))}{(1 + c_B) f_V(r(1 + c_B))}\} \tag{30}$$

$r^*(v_0, f)$ is unique $\forall (v_0, f)$ given the IFR property of F_V, increasing in v_0, and independent of n. $\square$

Listing-level properties

Proof Lemma 3. $\frac{\partial \pi_b(n,f,v_0)}{\partial n} < 0$ because $F_{V|\mathbf{Z}}$ satisfies the increasing failure rate (IFR) property. Li (2005) prove that a monotonically nondecreasing failure rate implies decreasing spacings so that $\mathbb{E}[V_{(n+1:n+1)} - V_{(n:n+1)}] - \mathbb{E}[V_{(n:n)} - V_{(n-1:n)}] \leq 0$. This holds without a reserve price or fees and since both are independent of n, and the inequality is strict in the IFR case. For $v_0 \leq v_{0,r=0}$ sellers set a zero reserve price so $\pi_b(n,f,v_0) = \pi_b(n,f,0)$ is independent of v_0, and otherwise $\frac{\pi_b(n,f,v_0)}{v_0} \leq 0$ since the optimal reserve increases in v_0 (Lemma 2). On the seller side, $\frac{\partial \pi_s(n,f,v_0)}{\partial n} > 0$ as $r^*(v_0, f)$ is independent of n (Lemma 2) and $F_{V_{(n:n)}}$ is stochastically increasing in n. It is clear from (4) that $\frac{\partial \pi_s(n,f,v_0)}{\partial v_0} \leq 0$ and intuitively: higher seller values reduce gains from trade. □

Bidder entry equilibrium in auctions with zero reserve price

Proof Lemma 7. $N^B_{r=0}$ potential bidders only form an expectation over the number of competing bidders in their listing if all enter with probability p, using its compound Binomial distribution, $f_{N,r=0}(n;p)$. From the perspective of a bidder who enters the platform, $f_{N,r=0}(n;p)$ combines uncertainty about: 1) the stochastic number of listings T (with realization t) given screening value $v_{0,r=0}$, and 2) how many of $N^B_{r=0}-1$ competing bidders end up in his listing when they enter the platform with probability p and sort uniformly over available listings with zero reserve. Combined with entry and opportunity cost, $\Pi_{b,r=0}(f;p)$ denotes the expected surplus from entering the platform for these potential bidders:

$$\Pi_{b,r=0}(f;p) = \sum_{n=0}^{N^B_{r=0}-1} \pi_b(n,f,0) f_{N_{r=0}}(n;p) - e_B - e^o_{B,r=0} \tag{31}$$

$$f_{N,r=0}(n;p) = \sum_{t=0}^{N^S} \binom{N^B_{r=0}-1}{n} (\frac{p}{t})^n (1-\frac{p}{t})^{N^B_{r=0}-1-n} \times \tag{32}$$

$$\binom{N^S}{t} F_{V_0|\mathbf{Z}}(v_{0,r=0})^t (1 - F_{V_0|\mathbf{Z}}(v_{0,r=0}))^{N^S-t}$$

In equilibrium, $N^B_{r=0}$ potential bidders are indifferent between staying out and entering the platform:

$$p^*_{r=0}(f) \equiv p \in (0,1)\{\Pi_{b,r=0}(f;p) = 0\} \tag{33}$$

Uniqueness follows from $\Pi_{b,r=0}(f;p)$ strictly decreasing in p for any fee structure that induces non-trivial entry ($p \in (0,1)$). $\square$

Poisson decomposition property for number of bidders per listing

Proof Lemma 8. The proof concerns the statement that when N^B potential bidders enter a platform with T listings with probability p, the distribution of the number of bidders per listing is approximately Poisson with mean $\frac{N^B p}{T}$. Let M denote the total number of bidders on the platform, distributed Binomial$(N^B p, N^B p(1-p))$. The limiting distribution of M when the population of potential bidders $N^B \to \infty$ and associated $p \to 0$ s.t. $N^B p$ remains constant is Poisson$(\lambda = N^B p)$. Bidders on the platform get uniformly allocated over T listings, entering each listing with probability $q = \frac{1}{T}$. Due to the stochastic number of bidders on the platform, the probability that m bidders get allocated in listing t and n enter into other listings also includes the probability that $m+n$ bidders enter the platform.

$$f_{N_t,N_{-t}}(m,n) = \frac{\exp(-\lambda)\lambda^{(m+n)}}{(m+n)!}\frac{(m+n)!}{m!n!}(q)^m(1-q)^{(n)} \tag{34}$$

This joint distribution function can be manipulated to conclude that:

$$f_{N_t}(m) = \sum_{n=0}^{\infty} \frac{\exp(-\lambda q)(\lambda q)^m}{m!}\frac{\exp(-\lambda(1-q))(\lambda(1-q))^n}{n!} = \frac{\exp(-\lambda q)(\lambda q)^m}{m!}$$

This is referred to as the *decomposition property* of the Poisson distribution, e.g. in Myerson (1998), and novel here is that it does not require M to be independent of T. The t subscript is dropped from f_{N_t} as the distribution is identical for all listings $t = \{1,..,T\}$.

Binomial decomposition property. Alternatively, we can show that $N \sim Binom(N^B \frac{p}{T}, N^B \frac{p}{T}(1-\frac{p}{T}))$ and apply the large sample approximation afterwards. Including the expectation over the number of bidders on the platform, M, the probability mass function of the number of bidders per listing, $\forall n \in \mathbf{Z}^{\geq}$:

$$P[N=n] = \underbrace{\sum_{m=0}^{N^B} P[N=n|m]P[M=m]}_{\mathbb{E}_M[P[N=n|m]]} = \tag{35}$$
$$\sum_{m=0}^{N^B} \binom{N^B}{m} p^m (1-p)^{N^B-m} \binom{m}{n} \frac{1}{T}^n (1-\frac{1}{T})^{m-n}$$

and 0 otherwise. I use the law of iterated expectations ($\mathbb{E}[N] = \mathbb{E}_M[\mathbb{E}[N|m]]$) and iterated variance ($Var(N) = \mathbb{E}_M[Var(N|M=m) + Var(\mathbb{E}_M[N|M=m]))$:

$$\begin{aligned} \mathbb{E}_M[Var(N|M=m)] = \mathbb{E}_M[m\frac{1}{T}(1-\frac{1}{T})] &= (N^B)p\frac{1}{T}(1-\frac{1}{T}) \\ &= N^B p\frac{1}{T} - (N^B)p(\frac{1}{T})^2 \end{aligned} \tag{36}$$

$$\begin{aligned} Var(\mathbb{E}_M[N|M=m]) = Var(\frac{M}{T}) = (\frac{1}{T})^2 Var(M) &= (\frac{1}{T})^2 N^B p(1-p) \\ &= -(\frac{1}{T})^2 N^B p^2 + (\frac{1}{T})^2 N^B p \end{aligned} \tag{37}$$

Re-arranging shows that the mean and variance of N are:

$$\mathbb{E}[N] = \mathbb{E}_M[\frac{m}{T}] = \frac{\mathbb{E}[M]}{T} = \frac{N^B p}{T} \tag{38}$$
$$Var(N) = N^B \frac{p}{T}(1-\frac{p}{T}) \tag{39}$$

This proves that the large population assumption, and success probability of *entering in listing* t (for any $t \in \{1, .., T\}$) equal to $\frac{p}{T}$, means that f_N is approximately Poisson with mean $\frac{N^B p}{T}$. $\square$

Identification of opportunity cost

Proof. In auctions with a zero reserve price the number of bidders is not truncated; observables from those auctions render the equilibrium distribution $f_{N_{r=0}}(;p^*_{r=0}(f, v^*_0), v^*_0(f))$ identified. $\Pi_{b,r>0}(f, v^*_0(f); p^*_{r>0}(f, v^*_0(f)))$ is strictly decreasing in the last remaining unobservable, opportunity cost $e^o_{B,r>0}$, which is identified as the value that solves (10). Similarly, the surplus for a marginal seller must by equilibrium play and the zero profit condition in (12) correspond to opportunity cost e^o_S. With $v_0^*(f)$ identified as the largest observed (14) and $\Pi_s(f, v_0^*; p^*(f, v_0^*(f)), v_0^*(f))$ is strictly decreasing in e^o_S, e^o_S is identified as the value that solves (15). Finally, $e^o_{B,r=0}$ is identified as the value that solves (33), with $\Pi_{b,r=0}(f; p^*_{r=0}(f))$ strictly decreasing in $e^o_{B,r=0}$. $\square$

Supplement: Additional tables and figures

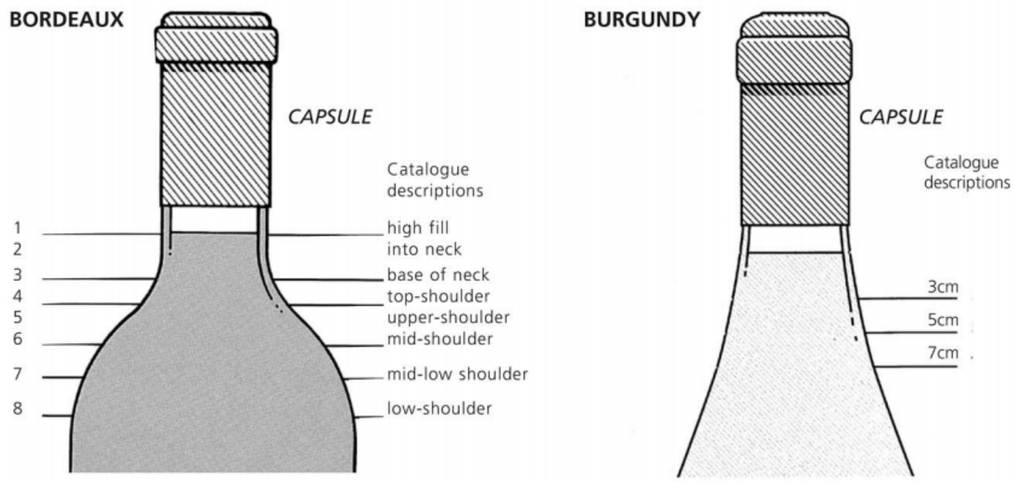
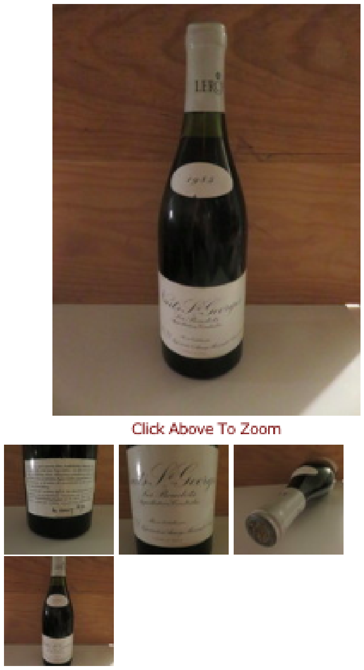


Figure 5: Ullage classification and interpretation

Source: Christie's. Numbers refer to auction house *Christie's* interpretation of the fill levels, which are for Bordeaux-style bottles: 1) Into Neck: level of young wines. Exceptionally good in wines over 10 years old. 2) Bottom Neck: perfectly good for any age of wine. Outstandingly good for a wine of 20 years in bottle, or longer. 3) Very Top-Shoulder. 4) Top-Shoulder. Normal for any claret 15 years or older. 5) Upper-Shoulder: slight natural reduction through the easing of the cork and evaporation through the cork and capsule. Usually no problem. Acceptable for any wine over 20 years old. Exceptional for pre-1950 wines. 6) Mid-Shoulder: probably some weakening of the cork and some risk. Not abnormal for wines 30/40 years of age. 7) Mid-Low-Shoulder: some risk. 8) Low-Shoulder: risky and usually only accepted for sale if wine or label exceptionally rare or interesting. For Burgundy-style bottles where the slope of the shoulder is impractical to describe such levels, whenever appropriate [due to the age of the wine] the level is measured in centimetres. The condition and drinkability of Burgundy is less affected by ullage than Bordeaux. For example, a 5 to 7 cm. ullage in a 30 year old Burgundy can be considered normal or good for its age.



Click Above To Zoom

Nuits St George Les Boudots Domaine Leroy

Sold by **waitsmusic** (13 ratings, 76% positive, 0% neutral.)

- Email the seller
- Show my bids on this auction
- Add this auction to my watch list

BID NOW

(Your bid is for 1 bottle of 750 ml.)

Your **maximum** bid:

(At least £52.00)

£

Place Bid Now

1	1	£50.00	2d 19h
		Reserve not met	Remaining time
Bids placed	No. of Bidders	Current price	closes 18/12/2018, 12:37 PM

Lot size:	1 bottle of 750 ml each	**Wine type:**	Red, 1985 vintage
Tax status:	Duty Paid	**Origin:**	Burgundy, France
Fill level:	Into Neck (IN)	**Grape variety:**	

An incredibly rare bottle of the sublime Nuits St George Les Boudots from Domaine Leroy from the exceptional 1985 vintage. In great order, this legend of a wine has lain in the same Berlin cellar or decades.
The last time this was on WineSearcher - 2016 - it was listed at £2,200, the reserve on this is a faction of that.

PayPal preferred but will charge 4% for fees.

Other details

Aux Boudots' thin soils consist of gravel, crumbly limestone marl and a small amount of clay. This fragmented soil, along with the natural slope of the vineyard, gives good drainage, making sure that vines do not receive excessive water. Instead, vines have to grow deep into the ground in search of hydration, a process which lessens vigor and reduces grape yields. This ultimately leads to the production of small, concentrated berries which make excellent wines.

Payment methods:	PayPal
Returns policy:	No returns
Shipping Method:	Courier delivery.
Shipping paid by:	buyer
Cost of delivery:	Will quote
Delivers to UK and Singapore	
Other countries delivered to:	Worldwide
Insurance options:	TBC

Figure 6: Listing page example: Nuits St George Les Boudouts, Domaine Leroy

Table 10: Results of homogenization (main sample)

Dep. var: log transaction price	Estimate	Std. error
Intercept	3.6489	0.19609
Number bottles	-0.21539	0.017116
Case of 6	0.27556	0.095747
Case of 12	1.4731	0.19992
Stored in warehouse	0.50618	0.21052
Special format bottle	0.22868	0.068221
Duty estimate	-0.025728	0.0089444
VAT estimate	0.0084091	0.0061728
Fill level:		
Low Shoulder (LS) or worse	-0.36428	0.19026
Mid Shoulder (HS)	-0.42731	0.15924
High Shoulder (HS)	-0.39359	0.1475
Missing	0.011749	0.054735
Top Shoulder (TS)	-0.40094	0.13587
Very Top Shoulder (VTS)	-0.13936	0.11603
Base of Neck (BN)	-0.21467	0.068404
Delivery, payment, insurance:		
Delivers to UK	0.066067	0.04426
Returns accepted	-0.14013	0.15147
Can collect	0.027191	0.043785
Can ONLY collect	-0.23677	0.11006
Payment by bank	0.33601	0.089092
Payment by paypal	-0.032981	0.0447
Payment by cheque	-0.13909	0.046535
Payment in cash	-0.087927	0.11286
Ships with Royal Mail	0.024636	0.049909
Ships with Parcelforce	-0.15524	0.046403
Ships fast	0.44448	0.065755
Insurance included	0.098217	0.040632
Lowest shipping cost quote	0.0068978	0.0040808
Percentage range quotes	-0.92277	0.094298
Percentage range quotes, squared	0.36073	0.047906
Type:		
Red	0.24706	0.078636
Sparkling	0.42272	0.12286
Assorted	0.25613	0.097468
Fortified	0.086496	0.14033
Rose	0.060914	0.33319
Grape:		
Bordeaux Blend	0.15323	0.065532
Sangiovese	0.34799	0.10675
Corvina	-0.026913	0.23762
Other	-0.088319	0.09856
Riesling	-0.0080086	0.19827
Chardonnay	0.20738	0.11688
Nebbiolo	0.2534	0.1455
Cabernet Sauvignon	0.16329	0.16683
Malbec	-0.18969	0.38099
Tempranillo	0.33364	0.20931
Pinot Noir	-0.0099559	0.10682
Syrah	0.21314	0.15054
Syrah/Shiraz	0.24614	0.10732
Port Blend	0.74413	0.24307
Rhone Blend	0.033721	0.12254
Semillon-Sauvignon Blanc Blend	0.63091	0.25825
Merlot	-0.33742	0.19263
Champagne Blend	0.67258	0.22837
Barbera	-0.36743	0.30878
Region:		
Bordeaux	-0.044787	0.08825
Tuscany	-0.22131	0.11748
Rhone	0.093169	0.10645
Champagne	0.31475	0.14194
Provence	-0.27554	0.2493
Veneto	-0.20353	0.18023
Alsace	-0.036888	0.1951
Rioja	-0.18305	0.18384
France	0.15407	0.095296
Other	-0.0013572	0.11399
Piedmont/Lombardy	-0.24297	0.13518
South Australia	-0.19426	0.1239
Douro	-0.1946	0.20116
Mendoza	-0.28441	0.34971
Bekaa Valley	0.25667	0.36982
Scotland	0.38223	0.26569
Oporto	-0.062656	0.20725
Assorted	0.25194	0.10205
Australia	-0.22322	0.12596

Region (continued):		
United States	0.050704	0.20414
Cognac	0.82644	0.30492
Spain	-0.26405	0.27147
California	0.15564	0.1613
Portugal	0.26479	0.20461
Loire	-0.60529	0.27191
Cuba	0.039369	0.3486
Italy	-0.17386	0.15408
Oregon	-0.54988	0.26392
South Africa	-0.43236	0.34435
Ribera del Duero	-0.2138	0.34008
Islay	0.83556	0.47675
South West France	0.32013	0.48487
Vintage:		
1964	0.35223	0.19983
2013	-0.59117	0.13696
2009	-0.27027	0.10769
2011	-0.19276	0.13778
2014	-0.70132	0.12713
2012	-0.34879	0.12422
1999	-0.19369	0.13045
1998	-0.20165	0.12028
2001	-0.15094	0.1287
1995	0.046022	0.11528
2006	-0.35597	0.12054
1983	-0.21256	0.14926
1963	0.73722	0.2395
2010	-0.30494	0.10972
2007	-0.17486	0.12049
1982	0.26524	0.18063
2008	-0.39046	0.1245
2005	-0.12856	0.11457
2004	-0.30579	0.1197
2003	-0.37819	0.12416
2015	-0.63448	0.13769
1996	-0.22807	0.12462
1961	0.15099	0.23279
1975	-0.29674	0.18456
1973	-0.87209	0.228
1991	-0.0085375	0.21126
1980	-0.20726	0.27126
1989	-0.11813	0.18799
1990	0.12206	0.1759
2002	-0.12586	0.13153
1966	0.43358	0.20951
1997	-0.013324	0.14033
1977	0.17451	0.23742
1988	-0.042258	0.18272
1970	0.12446	0.16848
1979	0.26572	0.23932
1994	-0.35023	0.1688
1986	0.067719	0.16992
1985	0.23406	0.15225
1969	0.13819	0.21797
1981	0.21658	0.1784
1993	0.084064	0.20527
1978	0.19208	0.23107
1976	-1.0092	0.2703
1992	0.37019	0.30722
2016	-0.57635	0.27587
Vintage missing	-0.47621	0.098779
Other popular vintage	0.34867	0.1283
Month:		
Market 2	-0.054348	0.087349
Market 3	-0.16098	0.085564
Market 4	-0.17332	0.086001
Market 5	-0.039102	0.087946
Market 6	-0.18727	0.11413
Market 7	-0.12831	0.092929
Market 8	-0.22309	0.088613
Market 9	-0.15772	0.098956
Market 10	-0.015821	0.088427
Market 11	-0.20739	0.088167
Observations	2007	
Adj. R^2	0.52954	

Regressions of log per-bottle transaction price on variables in main sample, using only auctions with at least two bids.

Table 11: Results of homogenization (high value sample)

Dep. var: log transaction price	Estimate	Std. error
Intercept	5.7925	0.34162
Number bottles	-0.12083	0.01139
Case of 6	-0.88077	0.10499
case of 12	-0.51377	0.13094
Stored in warehouse	-0.70492	0.24753
Special format bottle	0.39337	0.14462
Duty estimate	0.022627	0.0097216
VAT estimate	-0.0027369	0.0036909
Fill level:		
Into Neck (IN)	0.08217	0.089802
Base of Neck (BN)	0.1123	0.15042
Mid Shoulder (HS)	0.18239	0.23427
Top Shoulder (TS)	0.34727	0.35965
Very Top Shoulder (VTS)	0.042979	0.17697
High Shoulder (HS)	0.25889	0.26226
Low Shoulder (LS) or worse	-0.048324	0.3404
Delivery, payment, insurance:		
Delivers to UK	-0.29311	0.095925
Returns accepted	0.0015449	0.16383
Can collect	0.036081	0.086119
Can ONLY collect	-0.54616	0.19581
Payment by bank	-0.14579	0.21141
Payment by paypal	-0.091967	0.083221
Payment by cheque	-0.091064	0.077945
Payment in cash	0.014711	0.22493
Ships with Royal Mail	-0.051519	0.099403
Ships with Parcelforce	-0.21799	0.1203
Ships fast	0.12408	0.12868
Insurance included	-0.13281	0.075941
Lowest shipping cost quote	0.0054736	0.0038868
Percentage range quotes	-0.19224	0.32051
Percentage range quotes, squared	0.063746	0.15017
Type:		
White	-0.039941	0.21617
Red	0.1905	0.13473
Assorted	0.33678	0.1343
Fortified	0.56809	0.28406
Grape:		
Bordeaux Blend	0.010528	0.11638
Syrah/Shiraz	-0.123	0.18673
Cabernet Sauvignon	0.32178	0.30605
Sangiovese	-0.22487	0.27601
Syrah	-0.032936	0.31557
Chardonnay	0.21846	0.27169
Tempranillo	-0.41538	0.65032
Nebbiolo	0.40275	0.5309
Other	-0.59911	0.36187
Pinot Noir	0.39317	0.19672
Port Blend	0.29561	0.66451
Merlot	-0.093398	0.26387
Rhone Blend	0.3362	0.33175
Semillon-Sauvignon Blanc Blend	-0.11619	0.35124
Champagne Blend	0.1699	0.24306
Riesling	-0.21634	0.56662
Region:		
Rhone	-0.1459	0.25233
Bordeaux	-0.14137	0.13464
France	0.0054448	0.12934
Champagne	0.10748	0.16731
Other	-0.13379	0.23745
South Australia	-0.0069858	0.22838
United States	-1.4027	0.4864
Tuscany	-0.40708	0.24436
Spain	-0.77954	0.47496
Scotland	-0.061112	0.52083
Burgundy	-0.35163	0.20952
Ribera del Duero	-0.34928	0.48916
California	-0.46525	0.25565
Piedmont/Lombardy	-0.76687	0.4857
Portugal	-0.23714	0.26529
Douro	-0.53114	0.47793
Australia	-0.24895	0.31107
Italy	-0.67266	0.45919
Veneto	-0.43384	0.491
Region (continued):		
Alsace	0.25049	0.65342
Islay	-0.65913	0.53229
Cognac	-1.3445	0.53178
Oporto	-0.35557	0.59298
Vintage:		
2009	-0.059636	0.19672
1999	0.30734	0.20153
1996	-0.041475	0.20991
1986	0.097436	0.23419
2005	0.1363	0.19871
1976	-0.028595	0.25309
1982	0.46675	0.23726
2002	0.011413	0.25866
1981	0.31165	0.30081
1985	0.24947	0.22771
1998	0.15312	0.19379
1995	0.31252	0.21454
2001	0.19748	0.30892
2010	0.13697	0.20042
2007	-0.24049	0.30297
1975	-0.20677	0.26616
2000	0.65534	0.2074
1989	0.3476	0.22377
2012	0.23304	0.24246
2011	0.37465	0.24834
1983	-0.036473	0.31617
1990	0.64865	0.22429
2014	-0.033155	0.2426
1997	0.12923	0.28177
2015	-0.1195	0.27636
2008	0.31954	0.24658
1977	0.33872	0.31823
2004	0.12084	0.22781
1966	0.15243	0.25341
1994	-0.10505	0.3257
1963	-0.87918	0.49647
1991	0.48368	0.35426
1969	-0.76683	0.55347
1992	-0.16277	0.26588
2003	0.1359	0.24603
1973	-0.48898	0.39621
1988	0.20438	0.23558
1978	0.23451	0.49574
2013	0.14936	0.31352
1993	-0.20021	0.3537
2016	-0.049026	0.51039
1970	0.14985	0.38704
1979	0.17072	0.37018
1980	-0.092695	0.47559
1964	-0.45269	0.47773
1961	0.22537	0.52924
Vintage missing	-0.017064	0.20925
Other popular vintage	0.14334	0.21091
Market 3	-0.07077	0.097536
Market 4	-0.00067518	0.1131
Market 5	0.21096	0.11463
Market 1	0.016734	0.14292
Market 6	-0.12201	0.17249
Market 7	-0.044597	0.12882
Market 8	0.13271	0.10568
Market 9	0.026294	0.15164
Market 10	0.027939	0.11969
Market 11	-0.17592	0.13437
Observations	390	
Adj. R^2	0.85545	

Regressions of log per-bottle transaction price on variables in high value sample, using only auctions with at least two bids.

Supplement: Reserve price approximation

Reserve prices are approximated as the average between the highest standing price for which the reserve price is not met and the lowest for which it is met. If all bids would be recorded in real time, this approximation would be accurate up to half a bidding increment due to the proxy bidding system. But to relieve traffic pressure on the site I only track bids on 30-minute intervals. The reserve price approximation could be more than half a bidding increment off if the bids are not placed at regular intervals. As a compromise with constant high website traffic a separate dataset is collected that accesses open listings at 30-second intervals for the duration of two weeks, to test the reserve price approximation in the main sample.

My estimation method requires that the estimated distribution of reserve prices is consistent for its population counterpart. Equality of the distribution of approximated reserve prices in the main sample and the distribution of (approximated) reserve prices in the smaller high frequency sample is tested with a two sample non-parametric Kolmogorov-Smirnov test. To account for different listing compositions the empirical reserve price distributions are right-truncated at the 90th percentile of the high frequency reserve price sample. The null hypothesis is that the two right truncated reserve price distributions are the same. In particular, letting F_R^H and F_R^M respectively denote the empirical distribution of right truncated approximated reserve prices in the high frequency (H) and main (M) sample, the Kolmogorov-Smirnov test statistic is defined as:

$$D_{h,m} = \sup_x |F_R^H(x) - F_R^M(x)|, \tag{40}$$

with $\sup_x$ the supremum function over x values and h and m respectively denoting the relevant number of observations in the high frequency and main samples, which are 330 and 596 (only for sold lots). With $D_{h,m} = 0.059$, the null cannot be rejected at the 5 pervent level ($D_{h,m} > 1.36\sqrt{(\frac{h+m}{hm}})$, the p-value $= 0.4406$). The two empirical distributions are plotted in Figure 7.

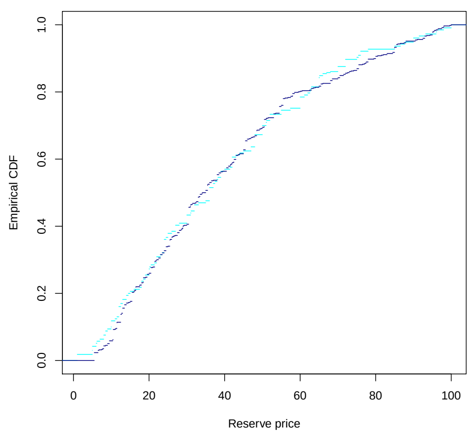


Figure 7: Testing equality of reserve price distribution and approximation

Supplement: Entry equilibrium

This supplementary material provides further intuition behind the entry equilibrium. Different from the main text, I consider the bidder entry equilibrium in positive reserve price auctions if the number of listings $T_{r>0}$ would be known. Key is that the equilibrium distribution of the number of bidders per listing is independent of the number of listings. Hence also in expectation, for the simultaneous entry equilibrium presented in the main text, the equilibrium distribution $f_{N_{r>0}}(;f, p^*_{r>0}(f, v^*_0))$ is independent of the number of listings conditional on selection of sellers.

In what follows, $\tilde{r}$ denotes the optimal reserve price increased with buyer premium, $\tilde{r} = (1 + c_B)r^*(v_0, f)$. Before knowing their valuation, the expected bidder surplus in a listing with n bidders equals:

$$\pi_b(n, f, r) \equiv \frac{1}{n}\mathbb{E}[V_{(n:n)} - \max(V_{(n-1:n)}, \tilde{r})|V_{(n:n)} \geq \tilde{r}][1 - F_{V_{(n:n)}}(\tilde{r})], \tag{41}$$

with the last term denoting the sale probability and the max(.) term the transaction price including buyer premium. Expected surplus for a seller with valuation v_0 in a listing with n bidders:

$$\pi_s(n, f, v_0) \equiv \left(\mathbb{E}[\max(V_{n-1:n}, \tilde{r})|V_{n:n} \geq \tilde{r}](1 - c_S) - v_0\right)[1 - F_{V_{(n:n)}}(\tilde{r})] \tag{42}$$

Consider a model in which the number of listings $T_{r>0}$ would be known to potential bidders. Let $\bar{v}_0$ denote a candidate seller entry threshold and $\Pi^{T_{r>0}}_{b,r>0}(f, \bar{v}_0; p)$ potential bidders' expected surplus from entering the platform as a function of their entry probability p, if they knew the number of listings $T_{r>0}$:

$$\Pi^{T,r>0}_{b,r>0}(f, \bar{v}_0; p) = \sum_{n=0}^{N^{B,r>0}-1} \mathbb{E}[\pi_b(n+1, f, v_0)|V_0 \in [v_{0,r=0}, \bar{v}_0]f^{T,r>0}_{N,r>0}(n; p) - e^o_{B,r>0}, \tag{43}$$

It takes the expectation of $\pi_b(n, f, v_0)$ (equation 41 with optimal r as in equation 2) over: i) possible seller values given sellers' entry threshold and ii) the number of competing bidders given their entry probability. $T^{r>0}$ superscripts in $\Pi^{T,r>0}_{b,r>0}(f, \bar{v}_0; p)$ and $f^{T,r>0}_{N,r>0}(n; p)$ emphasize that they relate to the thought exercise in which $T_{r>0}$ is known, while the true game's simultaneous entry requires taking the expectation over $T_{r>0}$ given candidate entry threshold $\bar{v}_0$ and N^S. I present this alternative model here to show more clearly that, in equilibrium, $f^{T,r>0}_{N_{r>0}}$ is independent of the realization of $T_{r>0}$ which implies that it must also be independent of the expectation over $T_{r>0}$.

Bidding in one listing at a time, the entry problem for potential bidders is then equivalent to one in which they consider entry into a listing (also given that opportunity cost (listing inspection) $e^{o}_{B,r>0}$ are associated with each listing). Components of equation (43) are:

$$\begin{aligned} &\mathbb{E}[\pi_b(n+1,f,v_0)|V_0 \in [v_{0,r=0},\bar{v_0}] = \\ &\int_{v_{0,r=0}}^{\bar{v_0}} \pi_b(n+1,f,v_0) f_{V_0|V_0\in[v_{0,r=0},\bar{v_0}]}(v_0)dv_0 \end{aligned} \tag{44}$$

$$f^{T,r>0}_{N,r>0}(n;p) = \binom{N^{B,r>0}-1}{n}(\frac{p}{T})^n(1-\frac{p}{T})^{N^{B,r>0}-1-n} \tag{45}$$

where $f^{T,r>0}_{N,r>0}(n;p)$ denotes the Binomial probability that n out of $N^{B,r>0}-1$ competing potential bidders arrive in the same listing as the potential bidder who considers entering the platform. Unpacking further, the seller's v_0 matter through its impact on the reserve price that bidders face, in expectation over all v_0's such that the seller enters and sets a positive reserve price:

$$f_{V_0|V_0\in[v_{0,r=0},\bar{v_0}]}(v_0) = \frac{f_{V_0\geq v_{0,r=0}}(v_0)}{F_{V_0\geq v_{0,r=0}}(\bar{v_0})} \tag{46}$$

Only right-truncation at entry threshold $\bar{v_0}$ is made explicit as the screening value $v_{0,r=0}$ is taken as given.

$\pi_b(n+1,f,v_0)$ is strictly decreasing in n (Lemma 3). So the bidder entry problem is equivalent to the Levin and Smith (1994) entry model, which assumes that expected bidder surplus decreases in n. The equilibrium bidder entry probability $p^{*T,r>0}$ solves zero profit condition:[45]

$$p^{*T,r>0}(T_{r>0},f,\bar{v_0}) \equiv \arg_{p\in(0,1)} \Pi^{T,r>0}_b(f,\bar{v_0};p) = 0 \tag{47}$$

In this equilibrium the number of (competing) bidders per listing follows a Bino-

[45] $p^{*T,r>0}$ is used to distinguish the entry probability from the central one pertaining to the central case where the number of listings is not known. A no-trade entry equilibrium at $p=0$ that trivially solves (47) always exists and excluding it requires the profit-maximizing platform to set fees such that entry is profitable for players on both sides and for players not to believe that the other side enters with zero probability.

mial distribution with mean $(N^{B,r>0}-1)\frac{p^{*T,r>0}}{T_{r>0}}$ and variance $(N^{B,r>0}-1)\frac{p^{*T,r>0}}{T_{r>0}}(1-\frac{p^{*T,r>0}}{T_{r>0}})$.[46]

A key property is that $\frac{p^{*T,r>0}}{T_{r>0}}$ is independent of $T_{r>0}$: bidders only derive positive surplus from the listing that they are matched to. $T_{r>0}$ does not affect $\mathbb{E}[\pi_b(n+1,f,v_0)|V_0 \in [v_{0,r=0},\bar{v_0}]$. The zero profit condition guarantees that in equilibrium a change in $T_{r>0}$ causes $p^{*T,r>0}$ to adjust to keep $f^{T,r>0}_{N_{r>0}}$ constant. The same reasoning applies when $T_{r>0}$ is the stochastic outcome of the simultaneously occuring seller entry process: the seller entry threshold only affects the equilibrium mean number of bidders per listing through $\mathbb{E}[\pi_b(n+1,f,v_0)|V_0 \in [v_{0,r=0},\bar{v_0}]$ and not through its effect on the distribution of $T_{r>0}$. This is defined more formally in the main text that describes the simultaneous-move entry equilibrium.

46 See the "Omitted proofs" section of this appendix. The variance of $N_{r>0}$ would be larger when also taking the expectation over $T_{r>0}$ given N^S and $\bar{v}_0$.

Supplement: Numerical approximation

The entry equilibrium is a function of listing-level bidder and seller surplus, which involve hard to compute (triple) integrals. This section details the numerical approximations relied on for computational feasibility. $\mathbf{Z}$ is omitted, estimated bidder and seller parameters are implicit, and $\tilde{r} = (1 + c_B)r^*(v_0, f)$. On the bidder side, one needs to compute $\pi_b(n + 1, f, v_0)$ and $\pi_s(n, f, v_0)$ defined in (3)-(4) for every considered v_0 and n. Given a candidate $\bar{v_0}$ and number of bidders n, the expected bidder surplus includes an expectation over realizations of $V_0 \in [v_{0,r=0}, \bar{v_0}]$, introducing a third integral. The final expectation sums over realizations of the number of bidders per listing governed by a Poisson distribution $f_{N,r>0}(;\lambda)$, with $\max(n)$ the largest value considered:

$$\Pi_b(f, \bar{v_0}; \lambda) = \sum_{n=0}^{\max(n)-1} \left[\int_{v_{0,r=0}}^{\bar{v_0}} \pi_b(n + 1, f, v_0) \frac{f_{V_0|V_0 \geq v_{0,r=0}}(v_0)}{F_{V_0|V_0 \geq v_{0,r=0}}(\bar{v_0})} dv_0 \right] \times f_{N,r>0}(n; \lambda) - e_B - e^o_{B,r>0} \tag{48}$$

Based on the estimated $\lambda^*_{r=0}$ I use $\max(n) = 15$. These computations are then sufficient to compute the equilibrium bidder entry probability in positive reserve price auctions given candidate $\bar{v_0}$, as:

$$\lambda^*_{r>0}(\bar{v_0}) \equiv \arg_\lambda \{\Pi_b(f, \bar{v_0}; \lambda) = 0\} \tag{49}$$

This feeds back into the seller's expected surplus at candidate $\bar{v_0}$, which also requires the computation of his listing-level surplus and the expectation over realizations of the number of bidders:

$$\begin{aligned} \pi_s(n, f, v_0) &= \left(\mathbb{E}[\max(\frac{V_{(n-1:n)}}{1 + c_B}, r) | V_{(n:n)} \geq \tilde{r}](1 - c_S) - v_0 \right) [1 - F_{V_{(n:n)}}(\tilde{r})] \\ &= \left[\max(r, \frac{1}{1 + c_B} \int_{\underline{v}}^{\bar{v}} v_{n-1} dF_{V_{n-1:n}|V_{n:n} \geq \tilde{r}}(v_{n-1}))(1 - c_S) - v_0 \right] [1 - F_{V_{(n:n)}}(\tilde{r})] \end{aligned} \tag{50}$$

$$\Pi_s(f, v_0; \lambda^*(\bar{v_0})) = \sum_{n=0}^{N^B_{r>0}} \pi_s(n, f, v_0) f_{N,r>0}(n, \lambda^*(\bar{v_0})) - e_S - e^o_S \tag{51}$$

And to compute the complete entry equilibrium, everything above needs to be repeated for many candidate $\bar{v_0}$'s:

$$v_0^* \equiv \arg_{\bar{v_0}} \{\Pi_s(f, \bar{v_0}; \lambda^*(\bar{v_0})) = 0\} \tag{52}$$

Equations (48)-(49) also need to be implemented for auctions with $r = 0$. As bidder surplus in those auctions is independent of v_0, the computation of $\lambda^*_{r=0}$ involves (only) the double integral of the listing-level surplus calculations that need to be repeated for $n = \{0, 1, .., \max(n)\}$.

Computing the entry equilibrium is clearly infeasible without relying on numerical approximation. I implement the following pseudo-code to compute the entry equilibrium, including actual object names to facilitate easy replication with my code.

- Initiating probability vectors for the simulation of bidder and seller values with importance sampling. Simulate 250 values from $Unif(0, 1)$ and collect in vector **v_probs** (making sure that $1e^{-4}$ and $1 - 1e^{-4}$ are lower bounds on extremum probabilities). Initiate a finer grid **v_probs_fine** by sampling 25000 values from $Unif(0, 1)$ with identical minimum extremum values. Simulate 500 values from $Unif(0, 1)$ and collect in vector **v0_probs_fine** (making sure that $1e^{-4}$ and $1 - 1e^{-4}$ are lower bounds on extremum probabilities). Sample a coarser grid for seller values by drawing without replacement 48 values from $v0\_probs\_fine$ and add the extremum values, call this vector **v0_probs**. Set $\max(n) = 15$. Never change these values.

- Importance sampling of $V_{n:n}$ and $V_{n-1:n}|V_{n:n}$. Set $\bar{v} = F_V^{-}1(1 - 1e^{-9}; \hat{\theta}_b)$ and $\underline{v} = 0$. Code the distributions in (5) and (6). For each $n = 1, .., 15$, simulate 250 values from the two distributions. For the highest valuation, solve for $F^{-1}_{V_n:n}(\textbf{v\_probs}; \hat{\theta}_b)$, separately for each n, resulting in matrix **h_mat** of dimension $[250 \times 15]$. For the second-highest valuation, solve for $F^{-1}_{V_n-1:n|V_n:n=v_n}(\textbf{v\_probs}; \hat{\theta}_b)$, where for each entry j in **v_probs** v_n equals the jth entry in **h_mat** from the relevant n column. Doing this separately for each $n > 1$ results in matrix **sh_mat** of dimension $[250 \times 15]$ with the first column made up of zeros.

- Linear interpolation of **h_mat** and **sh_mat** on finer grid using **v_probs_fine**, separately for each n column. This results in two matrices of dimension $[25000 \times 15]$, **h_mat_fine** and **sh_mat_fine**.

- Calculating optimal reserve price for grid of v_0's. Importance sampling of V_0: solve for $F_{V_0}^{-1}(\textbf{v0\_probs}; \hat{\theta}_s)$ and store in vector **v0_vec** of dimension $[50 \times 1]$. Given also $\hat{\theta}_b$, compute optimal $r^*(\textbf{v0\_vec})$ and store in vector **r_vec**.

- Compute listing-level bidder and seller surplus for v_0-n combinations. Initiate matrices of
v0_mat, **n_mat**, and **r_mat** with values of v_0 in the first dimension and n in the second dimension (so **n_mat** and **r_mat** are constant in the first dimension and **v0_mat** is constant in the second dimension). These three matrices are of dimension $[50 \times 15]$. For each entry, use the pre-calculated matrices **h_mat_fine** and **sh_mat_fine** to approximate listing-level surplus with monte carlo simulations, separately for bidders in auctions with positive and no reserve prices (the latter being a vector) and for sellers in auctions with a positive and with no reserve prices (both being matrices). For example, consider a $(v_0, 2)$ combination with $v0idx$ being the index of v_0 in the 2nd column of **v0_mat**. $\pi_b(2, f, v_0)$ is approximated as the mean of the second column of **h_mat_fine** including only all values exceeding $\textbf{r\_mat}(v0idx, 2) \times (1 + c_B)$, minus the mean of the same entries in **sh_mat_fine** or minus $\textbf{r\_mat}(v0idx, 2) \times (1+c_B)$ if that is higher, and multiplied by the sale probability $(1 - F_V(\log((1 + c_B)\textbf{r\_mat}(v0idx, 2)); \hat{\theta}_b)^2)$, all divided by two.

- Linear interpolation of listing-level surplus on **v0_probs_fine**. This results in listing-level surplus matrices of dimensions $[25000 \times 15]$ for bidders in positive reserve price auctions (**pib_posr_mat**), for sellers in positive reserve price auctions (**pis_posr_mat**), and for sellers in no reserve price auctions (**pis_nor_mat**). For bidders in auctions with no reserve price (**pib_nor_vec**) we obtain a vector of dimension $[1 \times 15]$ as their listing-level surplus is independent of the seller's value. Also pre-calculate a vector of probabilities that $V_0 = v_0$ using $F^{-1}_{V_0|V_0 \geq v_{0,r=0}}(\textbf{v0\_probs})$ and interpolate on the finer v_0 grid, resulting in **pdf_v0_mat**.

- Repeat the five previous steps only once for each new $\hat{\theta}_s$ or fee structure.
With the pre calculated listing-level surplus matrices as functions of v_0 and n,

the computation of v_0^* as a fixed point problem with a nested threshold-crossing problem to find λ^* for each candidate $\bar{v_0}$ is fast and straightforward.

- Coding equation (51) with nested in it equation (49). Make sure that for every candidate $\bar{v_0}$, the entries of **pdf_v0_mat** that function as weights of the listing-level bidder surplus (the $\frac{f_{V_0|V_0\geq v_{0,r=0}}(v_0)}{F_{V_0|V_0\geq v_{0,r=0}}(\bar{v_0})}$ in (48)) sum to one. The $\lambda^*(\bar{v_0})$ in (49) is obtained as the root of $(\Pi_b(f, \bar{v_0}; \lambda))^2$. I use MATLAB's fzero function with tolerance levels for the function and parameter of $1e^-6$. Then I pass (51) to a non-linear solver to find the fixed point, again using fzero root finding with the same tolerance levels.

Contraction mapping. Relevant for the NPL-like estimation method, the following argumentation shows that v_0^* is characterized by a contraction mapping. Let $\Pi_s(v_0^j, v_0^{-j})$ denote the expected surplus for seller with valuation v_0^j when entering the platform and setting a reserve price, with competing sellers' entry threshold only affecting Π_s through its effect on the the equilibrium mean number of bidders $\lambda^*(v_0^{-j})$. The fee structure and other exogenous inputs are omitted from notation. Let $v_0'(v_0^{-j})$ denote the seller's best response to threshold v_0^{-j}; to enter $i.f.f$ $v_0 \leq v_0'(v_0^{-j})$. A necessary and sufficient condition for v_0^* being characterized by a contraction mapping is that there are no other values of $v_0^{-j} \neq v_0^*$ that deliver zero surplus for the marginal seller so that $v_0'(v_0^{-j}) = v_0^{-j}$. We need to consider three cases:

- Case of $v_0^{-j} > v_0^*$: $\lambda^*(v_0^{-j}) < \lambda^*(v_0^*)$ which means that $\Pi_s(v_0^*, v_0^{-j}) < 0$. Since Π_s is decreasing in the seller's v_0^j, the resulting $v_0'(v_0^{-j}) < v_0^{-j} < v_0^*$. We conclude that $\Pi_s(v_0^{-j}, v_0^{-j})$ is not an equilibrium.

- Case of $v_0^{-j} < v_0^*$: $\lambda^*(v_0^{-j}) > \lambda^*(v_0^*)$ which means that $\Pi_s(v_0^*, v_0^{-j}) > 0$. With Π_s decreasing in the seller's v_0^j, the resulting $v_0'(v_0^{-j}) > v_0^{-j} > v_0^*$. Also in this case, $\Pi_s(v_0^{-j}, v_0^{-j})$ is not an equilibrium.

- The final case is the unique fixed point in seller value space, where $v_0^{-j} = v_0^*$. *By definition of* v_0^*, $\Pi_s(v_0^*, v_0^{-j}) = 0$ so that $v_0'(v_0^{-j}) = v_0^{-j} = v_0^*$.

This proves that Equation 12 is a contraction mapping.

Supplement: Monte Carlo simulations

Monte Carlo simulations illustrate that the estimation algorithm recovers the structural parameters of interest. Auctions are simulated according to the idiosyncratic-good auction platform model with:

Input parameters:	**Equilibrium values:**
$g(\mathbf{Z}) = 0.5Z, Z \sim \mathcal{N}(0,1)$	$F_{V\|Z,v_{0,r=0}}(v_0^*) = 0.659$
$U_0 \sim \mathcal{N}(5,2), U \sim \mathcal{N}(4,1)$	$\lambda^*_{r>0} = 5.541$
$e^o_{B,r>0} = e^o_{B,r=0} = 10, e^o_S = 5$	$\lambda^*_{r=0} = 8.686$
$f = \{e_S = 5, e_B = 0, c_B = 0, c_S = 0.1, e_R = 1\}$	
$p_{r0} = 0.10, N^S = 6000$	

Given selected input parameters, 66 percent of the 6000 potential sellers enter the platform. The marginal seller, or any seller who sets a positive reserve price receives on average 5.5 bidders in his listing but the mean number of bidders in auctions with no reserve price is significantly larger at 8.7.

Two elements warrant special attention in this Monte Carlo simulation exercise. The first is the number of iterations or convergence criteria for the estimation of seller parameters. This concerns steps 4) and 5) outlined on page 22 in the main text. The auction platform entry game delivers a best-response stable equilibrium as it reduces to a single-agent problem, with a unique entry equilibrium. Aguirregabiria and Mira (2002) show that any number of iterations delivers consistent and asymptotically normal estimates. But the initial estimate of θ_s is likely sensitive to small sample bias as the initial estimate of the seller entry equilibrium is the *maximum* of the implied seller valuations. From this perspective, $\hat{\theta}_s$ may improve when it relies on a better estimate of v_0^*. On the other hand, it is costly to compute the entry equilibrium. To evaluate this trade-off, I present estimated $\hat{\theta}_s^j$ for iterations $j = 0$ (given initial sample estimate of v_0^*), $j = 1$, $j = 2$ (with one and two iterations of solving for v_0^*), and $j = J$. The latter is the estimate at convergence, with the criteria that the maximum of differences in estimated means and variances of U_0 is less than $1e^{-2}$ *or* the number of iterations exceeds 25. These are quite loose tolerance levels and the resulting mean number of iterations is about 3. Tolerance levels for the equilibrium computations are as presented in Section 8.

The three columns of Table 12 titled "Precise Z" correspond to the above specifications. The three columns titled "Noisy Z" specifically account for small-sample noise from first stage regressions by adding draws from $Unif(-1,1)$ to observables Z *after simulating values and bids*. Results are as expected. The estimation algorithm performs worse before updating the entry equilibrium on the seller side and more so in the simulations with additional noise, although all estimates are consistent. The average point estimate $\hat{\mu_s}$ before updating so at $j = 0$ is 4.832 (true $\mu_s = 5$), while the point estimate in the simulations without added noise is 4.950. Updating the equilibrium once and re-estimating θ_s delivers the desired improvement in the point estimate. They are now respectively 4.992 and 5.006. A similar improvement is obtained for the estimated $\hat{\sigma_s}$. The largest improvement indeed results from the first update and I consider this to be worth the additional computation time associated with computing the equilibrium once.

The second element to pause at is the fact that seller opportunity cost e^o_S are identified off the expected surplus of the marginal seller. Estimating e^o_S off only one observation would be problematic. But the level of opportunity cost is only important to pin down the seller entry probability. It is irrelevant, e.g. a true normalization, for θ_s that are identified from the observed distribution of reserve prices. This is supported by the results in Table 12. Instead of estimating e^o_s, in both sets of simulations I adopt the completely arbitrary assumption that e^o_s is equal to the average between estimated $e^o_{B,r=0}$ and $\hat{e}^o_{B,r>0}$. True seller opportunity cost in the simulated auctions are only half of the true bidder opportunity cost so this assumption is not only arbitrary it is also erroraneous. Results show that this does not get in the way of obtaining correct parameter estimates.

Overall, the simulations show that the estimation algorithm with one iteration performs well in recovering the true parameters of interest. The gray colored rows in Table 12 correspond to the single recursion solution adopted in the main text.

Table 12: Monte Carlo simulations

	Iteration j	Truth	Precise Z Avg.	Precise Z St.d.	Precise Z M.a.d.	Noisy Z Avg.	Noisy Z St.d.	Noisy Z M.a.d.
Homogenization:								
α		0.5	0.495	0.012	0.008	0.495	0.012	0.009
adj. R^2			0.406	0.016		0.405	0.015	
Bidder side:								
μ_b		4	4.007	0.038	0.026	4.006	0.039	0.025
σ_b		1	1.001	0.035	0.023	1.005	0.035	0.024
$e^o_{B,r>0}$		10	10.811	0.742	0.787	10.939	0.695	0.933
$e^o_{B,r=0}$		10	10.142	0.666	0.45	10.092	0.637	0.441
$\lambda^*_{r>0}$		5.541	5.488	0.162	0.130	5.475	0.169	0.122
$\lambda^*_{r=0}$		8.686	8.690	0.148	0.102	8.855	0.146	0.089
Seller side:								
μ_s	0	5	4.950	0.222	0.194	4.832	0.185	0.180
	1	5	5.006	0.260	0.213	4.992	0.244	0.198
	2	5	5.016	0.272	0.228	5.000	0.257	0.211
	J	5	5.067	0.272	0.207	5.060	0.261	0.213
σ_s	0	2	1.951	0.141	0.113	1.899	0.129	0.093
	1	2	1.973	0.155	0.124	1.965	0.149	0.115
	2	2	1.980	0.158	0.119	1.968	0.154	0.116
	J	2	2.008	0.153	0.114	2.003	0.150	0.115
$F_{V_0\|Z}(v^*_0)$	0	0.659	0.676	0.053	0.044	0.708	0.046	0.046
	1	0.659	0.644	0.057	0.046	0.672	0.051	0.039
	2	0.659	0.622	0.066	0.057	0.628	0.064	0.053
	J	0.659	0.605	0.067	0.069	0.609	0.067	0.062
Nr. iterations J			2.992	1.232		3.072	1.023	

Statistics summarizing two sets of 250 MC simulations, displaying the average (Avg.) parameter estimate, its standard deviation (Std.) and the median absolute deviation with the true parameter (M.a.d.). In all simulations the seller opportunity cost of time e^o_S are assumed arbitrarily (and erroraneously) to be the average between the estimated $e^o_{B,r>0}$ and $e^o_{B,r=0}$ while the true seller opportunity cost are half of that. Gray rows correspond to the estimation algorithm adopted in the main text, which on the seller side solves for the entry equilibrium once given initial parameter estimates.