ESTIMATING AN AUCTION PLATFORM GAME WITH TWO-SIDED ENTRY

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This paper develops and estimates a structural auction platform model with endogenous entry of buyers and sellers to study the theoretically ambiguous welfare impacts of fee changes. Estimates from a new wine auction dataset illustrate the striking feature of two-sided markets that some users can be made better off despite paying higher fees. Quantifying the damages from (anticompetitive) fee changes through a model that accounts for important user interactions enables antitrust policy to be applied to such markets. The results also underscore the importance of addressing seller selection when endogenizing (buyer) entry onto auction platforms.

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1. Introduction

How should an online platform allocate fees between buyers and sellers? What antitrust damages should be awarded when the platform raises fees anticompetitively? The theoretical literature on two-sided markets emphasizes that both the platform’s revenue-maximizing fee structure and the welfare impacts of those fees are theoretically ambiguous (Evans (2003), Rochet and Tirole (2006), Rysman (2009)). It is widely understood that both sides of the market are in theory affected by price changes on either side and that welfare impacts ultimately depend on the externalities that platform users impose on each other. However, only rough guidance regarding the relevant factors informing the incidence of harm or optimal pricing is provided by the theoretical literature on platform economics, and the empirical literature that estimates those externalities in practice is still underdeveloped. It is of immediate importance to make progress toward this end; the difficulty of quantifying user interactions is a bottleneck in the regulation of these increasingly popular platform markets.

This paper develops a structural auction platform model with endogenous entry of bidders and sellers in order to quantify network externalities in such a market. In line with the wider empirical auction literature, it exploits a relatively controlled auction environment where strategic interactions are accurately described by the equilibrium properties of an incomplete information game. Payoffs and equilibrium actions characterize precisely how the entry of an additional user onto the platform affects the surplus of other users, providing a microfoundation for the platform’s network externalities. With this novel approach, the identification of network externalities follows from the identification of primitives of the structural model. An added benefit is that this allows such externalities to be non-linear, depending on the shapes of the latent bidder and seller valuations and their entry costs.

The paper also presents the first structural auction model with selective seller entry (see Perrigne and Vuong (2021)), which is an important feature of many platform markets. Seller selection generates an interaction effect that is relevant for identifying how fee changes affect welfare. Bidders expect lower (reservation) prices when sellers who value their goods less are attracted to the platform.

\[^1\] For example, sellers claiming that eBay charged supracompetitive fees were denied a class action suit in 2010 due to the absence of a method for quantifying damages in the presence of network effects (Tracer (2011)). Moreover, the 2018 landmark Supreme Court decision in Ohio v. American Express Co. stipulated that plaintiffs must show harm on both sides of the market (see, e.g., [https://www.nytimes.com/2018/06/25/us/politics/supreme-court-american-express-fees.html last accessed December 23, 2021]), increasing the urgency of the need for empirical two-sided market studies. See also Bomse and Westrich (2005) and Evans and Schmalensee (2013).


\[^3\] Empirical two-sided market papers instead rely on exclusion restrictions to overcome the reflection problem noted by Manski (1993), as discussed by Rysman (2019) and Julien, Pavan and Rysman (2021). For example (taken from Julien, Pavan and Rysman (2021)), a direct network effect can be identified in a model where the technology adoption decision of an agent is a linear function of the number of other agents of the same type already adopting the technology and agent characteristics that affect their own utility from adoption but that are excluded from the utility of other agents.
form, so bidder entry depends on both the expected number of sellers who enter and their types. The importance of such an effect for auction platform profitability was first postulated in Ellison, Fudenberg and Mobius (2004), but to date, it has not been modeled or addressed empirically.

Values are assumed to be private and independent across bidders and sellers, conditional on auction observables, and entry is sequential. Sellers who enter pay the listing fee and the latent opportunity cost of time and set a secret reserve price. Bidders who enter face an entry cost that is associated with inspecting the listing, learn their valuation, and place a bid. It is shown that the relevant distribution of conditional seller valuations is identified in this model for any counterfactual fee policy that reduces expected seller surplus, resulting, for instance, from unilateral fee increases. Parametric assumptions are needed to extend identification beyond this point. Another key result is that the two-sided entry equilibrium is the unique solution to a fixed-point problem in seller valuation space with a nested zero-profit entry condition on the bidder side.

The two-sided entry setting with seller selection does complicate the estimation of the distribution of seller valuations. First, the support for the distribution of reserve prices depends on the parameters to be estimated. Second, a full solution method that computes the equilibrium for each set of candidate parameters is costly to implement —as with the Rust (1987) nested fixed-point algorithm. Both issues are addressed by an estimation algorithm that resembles the Aguirregabiria and Mira (2002) Nested Pseudo Likelihood estimator for single agent dynamic discrete choice games.

The game is estimated on a new dataset of vintage wine auctions from an online marketplace, which exhibits the high-level characteristics of peer-to-peer platforms where idiosyncratic goods or services are offered by heterogeneous users. Most importantly, the reduced-form evidence shows that sellers enter selectively, while bidders learn their valuations after entry. Both results are compelling in this context. Sellers own the wine before creating a listing on the platform and would know how much they value it. Bidders need to understand the wine’s many idiosyncrasies, such as its fill level (informative regarding the amount of oxidation), whether it is stored in a temperature-controlled bonded warehouse, its provenance, delivery costs, and more. Structural estimates indeed reveal a significant listing inspection cost of 5-9 percent of the transaction price.

4 The authors hypothesized that a major reason why Yahoo! and Amazon were unsuccessful as auction platforms was their zero listing fee policy, which attracted high reserve price sellers that in turn deterred bidders from joining the platforms.

5 It is furthermore shown that the same model with selective bidder entry, where bidders enter after knowing their valuation, also results in a unique entry equilibrium (Appendix B). Reduced form evidence confirms that the random entry model where bidders need to inspect a listing to learn their valuation is more suitable for the empirical setting.

6 Specifically, the initial estimates maximize a concentrated likelihood function derived from the first-order condition characterizing optimal reserve prices, given a consistent estimate of the equilibrium seller entry threshold. These results are used in the next step to compute the equilibrium seller entry threshold, and parameters are re-estimated by maximizing the likelihood function concentrated at that value. The algorithm is guaranteed to converge in this setting by the uniqueness property of the entry equilibrium, and therefore not subject to concerns about non-convergence expressed in Pesendorfer and Schmidt-Dengler (2010), Kasahara and Shimotsu (2012), and Egesdal, Lai and Su (2015).

7 To include as much information in the empirical analysis as possible, text mining techniques are applied to the seller’s
The estimated model primitives are used to perform three sets of counterfactual analyses, shedding light on the implications of seller selection for this market, the welfare effects of fee changes, and the effect of the fee structure on platform profits.

Perhaps the most telling finding is that the reduction in seller surplus after a unit fee increase is less than one. This counterintuitive result is driven by the negative externality that the selection of higher-valuation sellers has on other sellers, caused by making the platform less attractive for bidders. Specifically, a 1 GBP increase in listing fee lowers the expected surplus for sellers who remain on the platform by only 77-89 pence. The loss in surplus is less for sellers with lower values and for all inframarginal sellers when there is greater seller heterogeneity. Moreover, all users are better off when the 1 GBP higher listing fee is paired with a budget-neutral bidder entry subsidy, including the sellers, who pay more to create a listing. These results are especially interesting as they provide evidence for the special circumstance in two-sided markets that users can be better off despite paying higher fees. For brevity and because of the crucial role of the negative seller-side externality, this mechanism is (imperfectly) referred to as a “lemons effect” after Akerlof (1970).

The lemons effect arises here because bidders enter based on the expected distribution of reserve prices but generalizes to other platforms with listing heterogeneity and private information. For example, it applies to the selection in peer-to-peer lending platforms where borrowers have private information about their creditworthiness and where their expected surplus from requesting a loan increases in the number of lenders whom they are matched with. Moreover, many other important peer-to-peer platforms feature listings of idiosyncratic goods from heterogeneous users and could be studied with a version of the two-sided entry game presented here.

A second set of simulations analyzes the canonical two-sided market pricing problem of how to allocate fees to user groups. Results show that alternative fee structures can increase platform revenues by more than 40 percent. It is particularly striking that winning bidders should be given a discount on the transaction price when paired with a higher seller commission or listing fee. A negative buyer commission would certainly be innovative for auction platforms but would
resemble pricing in other two-sided markets, such as cash-back policies on credit cards or free drinks for early club-goers. Below-marginal cost pricing is in fact consistent with subsidizing users who generate larger indirect network effects (Rysman, 2009). The role of platform composition beyond heterogeneity in seller tastes is assessed with model estimates from a subsample of the data with more high-end wines.

Third, the model estimates facilitate the estimation of currently hard-to-measure antitrust damages from anticompetitive fee changes. The estimated damages from unilateral increases of commissions are larger than in simpler models without (seller) entry, and, unlike what follows from simple models without entry, even winning bidders are affected. Their surplus decreases by 7.5 percent of the counterfactual hammer price when the seller commission is doubled. This value is estimated to be only 1 percent when entry is shut down on both sides so that only equilibrium bids and reserve prices respond to the fee change, and 3.9 percent when only the set of sellers is held constant. However, approximately 60 percent of the loss in user surplus due to the increase in commission falls on the sellers, regardless of which side is targeted. These results are placed in the context of a high-profile 2001 Sotheby’s and Christie’s commission-fixing case, where a rule of thumb was used to award most of the $512 million settlement to winning bidders.

On the whole, the results underscore the importance of accounting for seller selection when evaluating mechanism design changes for auction platforms and provide guidance for making much needed progress in applying antitrust policy to specific two-sided markets.

Related literature. This paper builds on a large and influential literature on the nonparametric identification and estimation of auction models. A comprehensive review is provided in a forthcoming Handbook of Econometrics chapter by Perrigne and Vuong (2021), which also places the current paper in that literature. To summarize, the key methodological contribution of this paper is that it develops and estimates a structural auction model with endogenous entry of heterogeneous sellers and shows how the equilibrium entry decisions of bidders and sellers are interconnected in an auction platform setting.

Related to the paper are structural analyses accounting for endogenous bidder entry, including Kong (2020), Fang and Tang (2014), Li and Zheng (2012), Athey, Levin and Seira (2011), and Krasnokutskaya and Seim (2011). These papers use the commonly applied Levin and Smith (1994) entry model—also part of the baseline model in this paper—in which bidders learn their values after entering the auction. A model extension shows how the two-sided entry model functions in the case of selective bidder entry, as in Samuelson (1985) and Menezes and Monteiro (2000), and

11 The companion Handbook of Industrial Organization chapter on empirical auction papers, Hortaçsu and Perrigne (2021), also references the paper.
by extension that the presented equilibrium results go through in the intermediate case of the affiliated signal bidder entry model adopted by, e.g., Gentry and Li (2014), Roberts and Sweeting (2013), and Ye (2007). The latter applies to marketplaces where bidders already know part of their valuation before entry and requires an additional exclusion restriction for identification. While almost the entire empirical auction literature adopts the perspective of one seller or assumes seller homogeneity, Elyakime et al. (1994), Larsen and Zhang (2018), and Larsen (2020) are the few papers accounting for seller heterogeneity but not entry. Recently, others have estimated demand in large auction markets (e.g., Backus and Lewis (2016), Hendricks and Sorensen (2018), Bodoh-Creed, Boehnke and Hickman (2020), and Coey, Larsen and Platt (2019)). These papers generally focus on dynamic issues for relatively commoditized goods and rely on steady-state requirements for tractability. Here, the listing inspection cost associated with idiosyncratic goods is exploited to estimate a (static) two-sided auction platform model with seller heterogeneity.

Also relevant are studies on pricing and demand in two-sided markets (e.g., Lee (2013), Rysman (2007), Ackerberg and Gowrisankaran (2006), Fradkin (2017), and Cullen and Farronato (2020)), which build on an influential theoretical literature. A fundamental difference between the current paper and these papers is that the structural auction model is used to quantify the expected user surplus from entry as a function of the composition of buyers and sellers on the platform. Payoffs from the auction platform game therefore provide a microfoundation for the platform’s network externalities. These are simulated for counterfactual (fee) policies, resulting in a rich pattern of direct and indirect nonlinear network effects. Typically, the empirical two-sided market literature estimates linear effects by using instrumental variables or by relying on quasi-experimental variation. In a forthcoming Handbook of Industrial Organization chapter, Jullien, Pavan and Rysman (2021) provide a comprehensive review of both the theory of two-sided markets and the application of that theory. They additionally link the impact of seller selection found in this paper to an analysis of seller selection into an internet brokerage platform in Hendel, Nevo and Ortalo-Magné (2009). Finally, Athey and Ellison (2011) and Gomes (2014) are conceptually related papers that model the two-sidedness of position auctions.

The following Section describes the model. Section 4 addresses nonparametric identification and estimation of model primitives. The focus is then narrowed to an online wine auction platform,
providing reduced form evidence for the model assumptions in Section 4. Structural estimates are presented in Section 5 and counterfactual simulations in Section 6. Section 7 concludes.

2. An auction platform with two-sided entry

This Section develops an empirically tractable structural auction platform model with entry of buyers and sellers and solves for the game’s equilibrium strategies. It will be shown that the two-sided entry game generates positive indirect network effects but also results in constant returns to scale when holding the seller type distribution constant. These features are based on a parsimonious set of assumptions suitable for the empirical application, but also reflecting first-order aspects of peer-to-peer platforms with significant listing heterogeneity in general. Possible extensions to the model are commented on in the discussion following the derivation of the equilibrium. Conceptually, seller entry and how bidders respond to it are the novel elements of this game and the focus of the paper.

A. Model

A monopoly platform offers listing services to facilitate trade between buyers and sellers. The listings use second-price sealed bid auctions to allocate indivisible goods among bidders with unit demands. The platform’s fee structure $f = \{c_B, c_S, e_B, e_S, e_R\}$ contains respectively a buyer premium and seller commission (both are shares of the transaction price), a buyer entry fee, a listing fee, and a reserve price fee, any of which might be zero. Risk-neutral users face a deterministic opportunity cost of time spent on the platform, on top of any monetary fees charged. For bidders, these are referred to as “listing inspection cost” associated with each listing they enter. Sellers set non-negative secret reserve prices. For additional flexibility, the opportunity cost of time for potential bidders in auctions with no reserve price ($e_{B,r=0}^o$) is allowed to be different from this cost in auctions with a positive reserve price ($e_{B,r>0}^o$). The opportunity cost of time for sellers is denoted by $e_S^o$ and also referred to as “entry cost”.

Before entering, bidders observe whether reserve prices are zero or positive. One way to justify this is that the platform in the empirical application attaches a highly visible “no reserve price” button to such auctions, which bidders observe before selecting a listing. Another justification is that the distinction helps to clarify the source of the two-sidedness of auctions with positive secret reserve prices in the model by benchmarking the results against those for zero reserve auctions. In a more general sense, the secret reserve price represents an aspect of the seller side that is imperfectly observed by buyers while important for their expected surplus.
This setting is modeled as a two-stage game. In the first stage, potential sellers—owning a good and knowing their valuation for it—decide to create a listing or not, and potential bidders decide to enter or not after observing the number of listings on the platform. Listings are ex-ante identical up to the reserve price button, so conditional on this event bidders are sorted with some constant probability over listings\textsuperscript{14} Potential bidders are ex-ante identical up to their valuation draw. To simplify the exposition, the model contains two separate potential bidder populations that are distinct only by a preference for positive- or zero reserve auctions\textsuperscript{15} As such, \( N_{r=0}^B \), \( N_{r>0}^B \), and \( N^S \) respectively denote the number of potential bidders for no reserve auctions, the number of potential bidders for positive reserve auctions, and the number of potential sellers. \( N^B = N_{r=0}^B + N_{r>0}^B \) denotes the total number of potential bidders. \( N^B \) and \( N^S \) respectively denote the sets of potential bidders and sellers.

The auction stage is standard: sellers set a secret reserve price and bidders bid after learning their valuations. To show that the assumption that bidders learn their valuations after entering does not drive the equilibrium results, an extension with selective bidder entry is presented in Appendix B.

Random variables are denoted in upper case and their realizations in lower case. \( F_V \) and \( F_{V_0} \) respectively denote the valuation distributions for potential sellers and bidders. The empirical analysis controls for auction-level observables so \( V_i \) and \( V_i^0 \) should be interpreted as conditional valuations, and the model assumes no unobserved auction-level heterogeneity. \( V_i^0 \) is equivalently interpreted as a seller’s (marginal) cost of selling. The population valuations distributions are allowed to differ, and satisfy:

**Assumption 1 (Two-sided IPV).** All \( i = \{1, \ldots, N^B\} \) potential bidders independently draw values \( v_i \) from \( V \sim F_V \) and all \( k = \{1, \ldots, N^S\} \) potential sellers independently draw values \( v_{0k} \) from \( V_0 \sim F_{V_0} \) such that: \( v_i \perp v_{i'} \forall i \neq i' \in N^B \) and \( v_i \perp v_{0k} \forall i \in N^B \) and \( \forall k \in N^S \). Further, \( F_V \) and \( F_{V_0} \) satisfy regularity conditions: \( \text{supp}(V) = [v, \bar{v}] \), \( \text{supp}(V_0) = [v_0, \bar{v}_0] \), \( F_V \) is absolutely continuous, and \( \frac{f_V(x)}{1-F_V(x)} \) increases in \( x \) \( \forall x \in [v, \bar{v}] \) (Increasing Failure Rate).

Most importantly, this assumption states that conditional on the vector of observed product at-

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\textsuperscript{14}When bringing the model to data, listings can be grouped according to additional observables such as filters on the website.

\textsuperscript{15}The results would be identical with one pool of potential bidders who are in equilibrium indifferent between the two types of listings. Just as with two populations, as dictated by the zero profit entry conditions, potential bidders would enter into positive- and zero reserve auctions to the point of depleting all expected surplus. Besides this abstraction, it is a meaningful restriction that potential bidders draw their private values from the same distribution rather than being systematically different in that dimension. Data from the empirical application supports this assumption. Bidder identities are generally unobserved, but for 247 bidders their identities are known as they won an auction and left feedback to the seller. From the 133 feedback-leaving winning bidders that are observed multiple times, 70 percent has won in both zero- and positive reserve auctions, so at least in this small sample the majority of bidders randomize between the two types of listings over time.

\textsuperscript{16}The non-selective bidder entry assumption made in the baseline model reflects the idea that the model describes two-sided entry in a platform with significant listing heterogeneity and (associated) costly listing inspection. The reduced form evidence based on data from a wine auction platform presented in Section 4 supports this assumption.
tributes, variation in values across buyers and sellers is of a purely idiosyncratic —private values— nature. In addition, the idiosyncratic variation is independent. The valuation distributions, allocation mechanism, population sizes, platform fees, and entry costs are common knowledge.

B. Equilibrium strategies

Equilibrium strategies are solved for by backwards induction. Attention is restricted 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.

Auction stage

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

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

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

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.

Auctions without reserve price 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 (as in Jehiel and Lamy (2015)). In what follows, $v_0^R$ indicates the no-reserve screening value:
Lemma 2. A seller with valuation \( v_0 \geq v_R^0 \) sets a reserve price solving

\[
(2) \quad r^*(v_0, f) = \frac{v_0}{1-c_S} + \frac{1-F_V((1+c_B)r^*(v_0, f))}{(1+c_B)f_V((1+c_B)r^*(v_0, f))}
\]

Proof is provided in the appendix.

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 \( c_B \). In what follows, a buyer premium-adjusted optimal reserve price is denoted by \( \tilde{r} \):

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

The entry equilibrium relies on expected surpluses for bidders and sellers in the auction stage, which are defined next. Before knowing their valuation and conditional on entry, the expected surplus for bidders in a listing with \( n-1 \) competing bidders, fee structure \( f \), when the seller has a private value of \( v_0 \):

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

with the last term denoting the sale probability and the \( \max(. \) term the transaction price including buyer premium. Expected surplus for a seller in such a listing equals:

\[
(4) \quad \pi_s(n, f, v_0) \equiv (\mathbb{E}[\max(V_{n-1:n}, \tilde{r})|V_{n:n} \geq \tilde{r}] (1-c_S) - v_0) [1 - F_{V(n:n)}(\tilde{r})]
\]

\(^{17}\) \( v_R^0 \) is taken to be exogenous. Endogenizing it complicates the estimation of the game, while early analysis suggested little impact. Theoretically, endogenizing \( v_R^0 \) would strengthen the importance of the seller selection effect on bidder entry in \( r > 0 \) auctions. To see why, consider a policy that would make bidder entry into \( r > 0 \) auctions more attractive. As the number of bidders per \( r > 0 \) listing increases, \( v_R^0 \) would adjust downwards in addition to the seller (platform) entry threshold \( v_0^* \) shifting upwards as captured by the model, resulting in a stochastically lower reserve price distribution than when not endogenizing \( v_R^0 \) and hence encouraging additional bidders to enter into \( r > 0 \) auctions. Endogenizing \( v_R^0 \) would be especially interesting to evaluate changes in the height of the (flat) reserve price fee or the introduction of alternative policies such as a proportional fee. Evaluating such policies and a more detailed analysis of the reserve price choice is left for future research, and might provide additional insight into unresolved puzzles regarding the use of secret reserve prices in auctions (see e.g. Jehiel and Lamy (2015) and references in Hasker and Sickles (2010)).
For auctions without a reserve price, expected bidder and seller surplus simplify to:

\[
\pi_b(n, f, 0) \equiv \frac{1}{n} \mathbb{E}[V(n:n) - V(n-1:n)] \\
\pi_s(n, f, 0) \equiv \mathbb{E}\left[\frac{V(n-1:n)}{1 + cB}\right]
\]

permitting a slight abuse of notation as sellers do not necessarily have \( v_0 = 0 \) when setting no reserve price, and adopting the convention that \( \pi_b \) and \( \pi_s \) are zero when \( n = 0 \). The entry equilibrium relies on the following properties:

**Lemma 3.** Listing-level expected surplus for bidders, \( \pi_b(n, f, v_0) \), decreases in \( n \) and \( v_0 \), and listing-level expected surplus for sellers, \( \pi_s(n, f, v_0) \), increases (decreases) in \( n \) (\( v_0 \)).

**Proof is provided in the appendix.**

**ENTRY STAGE: OVERVIEW AND PROPOSITION**

Any entry equilibrium of the described game consists of two bidder entry probabilities, as potential bidders learn values after entering (as in Levin and Smith (1994)), and a seller entry threshold as sellers know their values before listing. Results are derived under a large population approximation, which guarantees empirical tractability of the game and does not require players to know the exact population sizes.\(^{18}\) When the population of potential bidders is large relative to the number of bidders on the platform, the distribution of the number of bidders per listing is approximately Poisson and fully characterized by its mean.

**Assumption 2.** For \( r \in \{r = 0, r > 0\} \), the number of bidders per listing has a probability mass function approximated by:

\[
f_{N_r}(k; \lambda_r) = \frac{\exp(-\lambda_r)\lambda_r^k}{k!}, \forall k \in \mathbb{Z}^+
\]

The equilibrium \( \lambda_r \) is endogenous to the fee structure and in positive reserve auctions also depends on seller selection. The following proposition describes the main theoretical result of the paper that characterizes the entry equilibrium.\(^{19}\)

\(^{18}\)Appendix A proves that the Poisson approximation applies in the auction platform model where the number of bidders who enter is a function of the number of listings. Proof that the approximation does not drive equilibrium existence and uniqueness is provided in the online Appendix where results for the original game with a finite population of potential bidders are presented. The large population approximation avoids the large combinatorial problem where expected seller surplus is computed for any realization of the number of bidders that enter given their equilibrium entry probability. It is good to note here that the empirical distribution of the number of bidders closely resembles a Poisson distribution in the empirical application (Figure 2 plot e). Also, in a platform setting it is natural to assume that the populations of potential bidders are large relative to the observed number of bidders, and the assumption is previously made in e.g. Engelbrecht-Wiggans (2001), Bajari and Hortacsu (2003), Jehiel and Lamy (2015), and Bodoh-Creed, Boehnke and Hickman (2020).

\(^{19}\)A no-trade equilibrium where no bidders and sellers enter is excluded from consideration.
Proposition. The entry equilibrium of the auction platform game exists and is unique. It is characterized by the set:

\[
\left\{ \begin{array}{ccc}
  v^*_0(f), & \lambda^*_r > 0(f, v^*_0(f)), & \lambda^*_r = 0(f) \\
  \text{Seller entry threshold} & \text{Mean bidders } r > 0 & \text{Mean bidders } r = 0
\end{array} \right.
\]

The values of \(v^*_0(f), \lambda^*_r > 0(f, v^*_0(f)), \text{ and } \lambda^*_r = 0(f)\) are defined respectively by equations (13), (10), and (11), and solve zero profit conditions of the marginal seller and potential bidders.

The equilibrium is derived in the next two pages. Section 2.C summarizes the economic intuition behind these results, and discusses model extensions and implications. Below, it is first documented that any candidate seller entry threshold \(\tilde{v}_0\) maps to an equilibrium mean number of bidders per listing \(\lambda^*_r > 0(f, \tilde{v}_0)\) in auctions with positive reserves (Lemma 4). That mapping is used to solve for \(v^*_0(f)\). It turns out that because \(\lambda^*_r > 0(f, \tilde{v}_0)\) is strictly decreasing in \(\tilde{v}_0\) (Lemma 5), sellers’ best-response entry thresholds satisfy a single-crossing property, so that the entry game has a unique equilibrium (Lemma 6). In addition, the mean number of bidders per listing in auctions with zero reserve price \(\lambda^*_r = 0(f)\) is independent of the seller entry threshold (Lemma 4).

**ENTRY STAGE: BIDDER ENTRY**

The bidder entry equilibrium is characterized by the \(\lambda^*_r > 0 (\lambda^*_r = 0)\) that solves potential bidders’ zero profit condition in positive (zero) reserve price auctions. In the case of \(r > 0\), \(\Pi_{b, r > 0}(f, \tilde{v}_0; \lambda^*_r > 0)\) denotes potential bidders’ expected surplus from entering the platform. Besides fees and the listing inspection cost, it includes listing-level surplus \(\pi_b(n, f, v_0)\) in expectation over: 1) seller-values \(V_0\) given candidate threshold \(\tilde{v}_0\), and 2) the Poisson-distributed number of competing bidders \(2^\circ\)

\[
\Pi_{b, r > 0}(f, \tilde{v}_0; \lambda^*_r > 0) = \int \mathbb{E}[\pi_b(n + 1, f, v_0)|V_0 \in [v_0^R, \tilde{v}_0]]f_{N_r > 0}(n; \lambda^*_r > 0)dn - e_B - e^0_{B, r > 0}
\]

In the zero reserve price case, \(\Pi_{b, r = 0}(f; \lambda^*_r = 0)\) does not depend on seller values:

\[
\Pi_{b, r = 0}(f; \lambda^*_r = 0) = \int \pi_b(n + 1, f, 0)f_{N_r = 0}(n; \lambda^*_r = 0)dn - e_B - e^0_{B, r = 0}
\]

\(^{20}\Pi_{b, r > 0}(f, \tilde{v}_0; \lambda^*_r > 0)\) is independent of the number of listings \(T_r > 0\), as conditional on the number of competing bidders in a listing, the number of other listings on the platform does not affect bidder surplus.
Lemma 4. For any candidate seller entry threshold $\tilde{v}_0$, a unique equilibrium $\lambda_{r>0}^*$ solves potential bidders’ zero profit condition in positive reserve auctions:

$$\lambda_{r>0}^*(f, \tilde{v}_0) \equiv \arg_{\lambda_r>0 \in \mathbb{R}^+} \{ \Pi_{b,r>0}(f, \tilde{v}_0; \lambda_{r>0}) = 0 \}$$

and a unique equilibrium $\lambda_{r=0}^*$ solves:

$$\lambda_{r=0}^*(f) \equiv \arg_{\lambda_{r=0} \in \mathbb{R}^+} \{ \Pi_{b,r=0}(f; \lambda_{r=0}) = 0 \}$$

Proof. Listing-level surpluses $\pi_b(n, f, v_0)$ and $\pi_b(n, f, 0)$ strictly decrease in $n$ (Lemma 3), and $f_{N_r>0}(n; \lambda)$ increases in a first-order stochastic dominance sense in $\lambda$.

Entry decisions are conditional on $\tilde{v}_0$ or independent of it so the result also follows from Levin and Smith (1994) and Ginsburgh, Legros and Sahuguet (2010). It holds for any realized number of listings with a positive reserve price ($T_{r>0}$) given $\tilde{v}$, and also for any number of listings with a zero reserve price ($T_{r=0}$).

Entry stage: seller entry

Central for the analysis of the two-sided entry equilibrium is the following result, describing how the equilibrium number of bidders per listing responds to the seller entry threshold.

Lemma 5. The equilibrium $f_{N_r>0}(n; \lambda_{r>0}^*(f, \tilde{v}_0))$ decreases in the first-order stochastic dominance sense in $\tilde{v}_0$.

Proof. Candidate seller entry threshold $\tilde{v}_0$ affects $\Pi_{b,r>0}(f, \tilde{v}_0; \lambda_{r>0})$ only through the distribution of reserve prices in those listings. A higher $\tilde{v}_0$ draws in sellers with higher values 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 $\lambda_{r>0}^*(f, \tilde{v}_0)$ strictly decreases in $\tilde{v}_0$.

Importantly, this result determines that sellers’ expected surplus decreases in the threshold that competing sellers adopt, as shown in the next lemma. The seller entry equilibrium is characterized by the $v_0^*$ that solves the zero profit entry condition for the marginal seller. Let $\Pi_s(f, v_0; \lambda_{r>0}^*(f, \tilde{v}_0), \tilde{v}_0)$ denote expected surplus for a seller with valuation $v_0 > v_0^R$ when $N_S - 1$ competing sellers enter the platform if and only if their valuation is less than threshold $\tilde{v}_0$. Besides fees and the opportunity cost of time, it involves: 1) their listing-level expected surplus, and 2) an expectation over $f_{N_r>0}(n; \lambda_{r>0}^*(f, \tilde{v}_0))$ avoids introducing additional notation to capture that sellers care about competing bidders +1. This is without loss: the two distributions are identical by the environmental equivalence property of the Poisson distribution (Myerson 1998).
the number of bidders per listing given \( \tilde{v}_0 \) and bidders’ equilibrium best-response to this threshold summarised in Lemma 5:

\[
(12) \quad \Pi_s(f, v_0; \lambda^*_{r>0}(f, \tilde{v}_0), \tilde{v}_0) = \int \pi_s(n, f, v_0) f_{N_{r>0}}(n; \lambda^*_{r>0}(f, \tilde{v}_0), \tilde{v}_0) dn - e_s - e^0_S
\]

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

\[
(13) \quad v^*_0(f) \equiv \arg_{\tilde{v}_0 \in [0,1]} \{ \Pi_s(f, \tilde{v}_0; \lambda^*_{r>0}(f, \tilde{v}_0), \tilde{v}_0) = 0 \}
\]

with \( \lambda^*_{r>0}(f, \tilde{v}_0) \equiv \arg_{\lambda_{r>0} \in \mathbb{R}^+} \{ \Pi_{b,r>0}(f, \tilde{v}_0; \lambda_{r>0}) = 0 \} \) as defined in (10).

**Proof.** The proof requires three parts. First, sellers have a unique best-response for any competing \( \tilde{v}_0 \), because \( \Pi_s(f, v_0; \lambda^*_{r>0}(f, \tilde{v}_0), \tilde{v}_0) \) strictly decreases in their own \( v_0 \). Second, given that 1) \( \lambda^*_{r>0}(f, \tilde{v}_0) \) is strictly decreasing in \( \tilde{v}_0 \) (Lemma 5), 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, \( v^*_0(f) \), which is the fixed point in seller value space solving (13) i.e., making the marginal seller indifferent between entering and staying out.

This completes the proof of Proposition 2.3.

**C. Discussion**

Figure 1 shows graphically why the entry equilibrium is unique in this model despite the presence of cross-side externalities that make the platform more attractive to bidders when there are more sellers and vice versa. The figure depicts the best-response entry threshold of seller \( i \) as a function of the threshold adopted by competing sellers (on the x-axis). The solid line shows what happens on the equilibrium path. As shown by Lemma 6, the best-response function \( \tilde{v}^i_{BR}(\tilde{v}_0, -i, \lambda^*_{r>0}(\tilde{v}_0, -i)) \) is downward-sloping: a higher competing seller entry threshold decreases expected seller surplus for any \( v_0 \), lowering the threshold \( v^i_{BR} \) for which seller \( i \) breaks-even. It can be explained by the the particular two-sidedness of this market: bidders expect a less attractive reserve price distribution when higher-value sellers populate the platform and respond by entering less numerously, which negatively affects expected surplus for all sellers including seller \( i \). The downward-sloping best-response function generates a single crossing property resulting in a unique symmetric seller entry threshold where the best-response function intersects the 45 degree line.
A specific challenge in two-sided markets is what happens off the equilibrium path. Simply put, multiple equilibria exist when, if one side adopts a non-equilibrium entry strategy, this strategy is sustainable due to the best-response of users on the other side. Consider the case where bidders enter more numerously than their equilibrium strategy \( \lambda > \lambda^*_r(v_0) \). The dashed line in Figure 1 represents seller \( i \)'s best-response threshold. It shifts up relative to the solid line as expected seller surplus is higher for any \( v_0 \) due to the increased number of bidders per listing. However, this cannot be an equilibrium in the two-sided entry game as it violates bidders zero-profit condition: with expected bidder surplus strictly decreasing in \( v_0 \) (detailed in Lemma 4), \( \lambda > \lambda^*_r(v_0) \) can only be sustained by some \( \tilde{v}_0 < v_0(\lambda^*_r) \). In turn, the latter leaves money on the table for sellers with values \( \in [\tilde{v}_0, v_0(\lambda^*_r)] \) and is therefore also excluded as an equilibrium. For the same reasons \( \lambda < \lambda^*_r(v_0) \) cannot be sustained in equilibrium as that would require expected seller surplus to decrease in the number of bidders.

For illustration purposes, consider the central role of Lemma 5 and how it would apply to other (auction) platform models. The Lemma implies that the expected surplus of sellers is decreasing in the seller entry threshold when taking the best-response of bidders to that threshold into account. An important model extension is one where bidders learn their valuation before entering (as in e.g., Samuelson (1985) and Menezes and Monteiro (2000)). Appendix B presents the equilibrium.
analysis for this fully selective bidder entry model. Even though excluding a bidder lowers the expected surplus of sellers less than in the random entry case, expected seller surplus still increases when additional bidders enter. As such, the best-response function remains downward-sloping — although at a shallower slope. By extension, an auction platform model where bidders decide to enter based on a somewhat informative signal of their valuation (as in e.g., Gentry and Li (2014) and Roberts and Sweeting (2013)) also results in a unique two-sided entry equilibrium.

The presented model with its unique entry equilibrium is useful as a starting point for structural analysis of other two-sided markets as well.

For example, Lemma 5 implies that a model extension with a match value, where the probability that a bidder finds a suitable item increases in the number of listings, results in a unique equilibrium as long as the seller selection effect dominates so that each additional listing generates a lower additional expected surplus for potential bidders.

The presence of other negative seller-side externalities as modeled by Belleflamme and Toulemonde (2009) or arising from price competition intensifying in the number of competing listings as in Karle, Peitz and Reisinger (2020) would also fit the framework, and would result in a more steeply downward-sloping best-response function than in the presented baseline model. It is useful to remark that the seller best-response function is not downward-sloping in two-sided markets with a strong positive scale effect, where additional listings increase the expected bidder surplus from each listing beyond the potential decrease in surplus from the selection of higher-valuation sellers.

The described two-sidedness also does not exist for bidder entry into zero reserve listings or when the fee structure is held fixed. For those cases, the model predicts that the average number of bidders per listing is independent of the number of listings. This model prediction is verified with data from the empirical application by means of a simple regression analysis. Regressing the total number of bidders for a product in a market on the number of listings of that product in that market reveals a positive association, simply justified by auction prices and sale probabilities being endogenous to the number of bidders per listing (columns 1 and 2 of Table 1). However, in the presence of a positive scale effect the mean number of bidders per listing would need to increase with the number of listings in equilibrium. By contrast, the number of bidders per listing does not vary with the total number of listings of that product (columns 3 and 4 of Table 1), supporting the...
Table 1—: Reduced form evidence predicted network effects

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>Number bidders for product in market</th>
<th>Number bidders per listing of product</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>Number listings of product in market</td>
<td>2.920</td>
<td>3.095</td>
</tr>
<tr>
<td>(0.073)</td>
<td>(0.138)</td>
<td>(0.008)</td>
</tr>
<tr>
<td>No-reserve auctions only</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>1,230</td>
<td>451</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.874</td>
<td>0.933</td>
</tr>
</tbody>
</table>

Standard errors in parenthesis. Data from the online wine auction platform in the empirical application. Results from OLS regressions including product fixed effects, where a product is defined as the combination of (region \(x\) wine type \(x\) vintage decade) corresponding to high-level filters on the website. All listings are active for at most 31 days, and most of them for 5, 7 or 10. A market is defined as the month when the auction ends.

The model’s suitability for analysing the data.

Network effects are nonlinear in this model and, following i.e. Katz and Shapiro (1985), are defined by how much expected surplus (\(\Pi_{b,r>0}, \Pi_{b,r=0}\), and \(\Pi_s\)) changes if an additional user on the other or own side enters exogenously. The presence of such effects creates a clear trade-off for the platform that will be explored further in counterfactual simulations. Lower fees increase the number of listings and boost the sales volume, but higher fees populate the platform with lower reserve price listings and more bidders per listing. Sunk entry cost to users make that the platform faces the classic two-sided market pricing problem of how to best allocate fees between the two sides. \(\Pi_{b,r>0}, \Pi_{b,r=0}\), and \(\Pi_s\) depend crucially on the two value distributions and on latent entry costs. If sellers are relatively homogeneous, for example, reflected by low dispersion in values drawn from \(F_{V_s}\), the seller selection channel is less important. In that case the benefit from adding additional listings might outweigh the cost of attracting sellers with higher values for the platform. A primary task for the remainder of the paper is therefore to recover the model primitives that pin down the magnitudes of the described network effects, which drive how changes in fees affect outcomes of interest.

Finally, it is worth highlighting that constant listing inspection cost associated with the idiosyncratic nature of the products also dissipate any continuation value of bidding in an auction. Fundamentally, any option value is depleted by bidders’ zero profit entry condition in this model. If bidder identities are observed, this can be tested by comparing the bid distributions from more and less experienced bidders or those of past winners to past losers. Such an exercise could highlight for instance whether bidders who have won previous auctions and whose storage space is running...
out bid lower than past losers, as per the constrained capacity mechanism driving intertemporal constraints in Jofre-Bonet and Pesendorfer (2003). Also the intra-auction dynamics modelled by Kong (2021) and Hickman, Hubbard and Paarsch (2017) do not arise when expected surplus of bidding in another listing is depleted by paying the constant listing inspection cost as in the presented model.

3. Empirical strategies to recover model primitives

The equilibrium analysis highlights that seller selection and its impact on bidder entry in positive reserve auctions is of central importance for the empirical results, and that for any fee structure we can solve for a unique equilibrium characterized by \( (v^*_0, \lambda^*_{r>0}, \lambda^*_r) \) given model primitives. Treating the no-reserve screening value \( v^*_0 \) as structural avoids having to solve for another equilibrium threshold value. It also implies that the part of the support of \( V_0 < v^*_0 \) is irrelevant in counterfactuals that restrict attention to the case where at least one seller would find it profitable to set a positive reserve price. The screening value is recovered as the lowest seller valuation in positive reserve price auctions implied by the first order optimality condition on \( r^* \) defined in (2).

The rest of this section discusses how \( F_V, F_{V_0|v_0 \geq v^*_0} = \frac{F_{V_0}(v_0) - F_{V_0}(v^*_0)}{F_{V_0}(v^*_0)} \), and latent entry costs \( (e^0_S, e^0_{r>0}, e^0_{r=0}) \) are identified and estimated. Key endogenous variables to do so are the number of actual bidders \( A \), the second-highest bid \( B \), and the reserve price \( R \). Random variable \( A \) departs from the allocated number of bidders \( N \) in auctions with a positive reserve price, to allow for (secret) reserve prices to censor bidders. Exogenous observables are denoted by \( X = \{f, Z\} \), with \( Z \) the rich set of auction-level observables that account for auction-level heterogeneity.

A. Nonparametric identification

Athey and Haile (2002, Theorem 1) prove identification of \( F_V \) in an ascending auction model that places identical restrictions on this distribution up to the presence of binding reserve prices. Identification of \( F_V \) therefore follows in the current setting from observing \( N \) and the empirical distribution \( F_B \) in auctions without a reserve price. It relies on the equilibrium bidding strategy, and inverting the function mapping the resulting distribution of the second-highest value to its parent distribution. Specific assumptions underlying the result are the absence of unobserved heterogeneity (conditional on \( X \)) and that all interested bidders have the opportunity to place a

---

26One would expect that a positive option value, regardless of its exact source, would cause winning bids to decrease in the number of (comparable) listings. Reduced form regressions towards that end discussed in Section confirm the absence of such a pattern in the data.
bid.\footnote{The abstraction from unobserved heterogeneity is in line with the literature standard regarding analysis of ascending auction data. Conditional on sufficient data availability, new identification methods for a bidding model with unobserved heterogeneity can be applied. These methods rely for instance on exogenous shifters in bidder participation (Hernández, Quint and Turansick 2020) or the observation of multiple bid order statistics (e.g. Freyberger and Larsen 2017, Luo and Xiao 2020). These more stringent data requirements are not met in the empirical application presented in this paper. Moreover, it is shown that the rich set of auction observables furthermore explain a remarkably large share of the variation in second-highest bids, minimizing the potential impact of unobserved heterogeneity. Also relevant to mention in this context is that Roberts (2013) uses variation in reserve prices to control for unobserved heterogeneity but require sellers to be homogeneous.}

Given identification of $F_V$, each reserve price maps to that seller’s value by re-arranging the equilibrium reserve price strategy in (2):

\begin{equation}
\begin{align*}
v_0(r) &= (1 - c_S) \left( r - \frac{1 - F_V(r(1 + c_B))}{(1 + c_B)f_V(r(1 + c_B))} \right)
\end{align*}
\end{equation}

where $v_0(r)$ denotes the seller valuation implied by reserve price $r$ assuming equilibrium play.\footnote{Note that it is not strictly necessary that sellers play the optimal Riley and Samuelson (1981) reserve price strategy: the identification result applies to any known strategy. For uniqueness of the two-sided entry equilibrium it is only strictly required that $v_0(r)$ is monotonically increasing in $r$.}

The distribution of $v_0(r)$ is equal to the distribution of seller values conditional on entering and setting a positive reserve price, so that $\forall v \in \left[ v^R_0, v^*_0 \right]$:

\begin{equation}
F_{v_0(r)}(v) = \frac{F_{v^R_0 \geq v}(v)}{F_{v^R_0 \geq v^*_0}(v^*_0)}
\end{equation}

Without identifying variation in $v^*_0$ and unless $v^*_0 = v_0$ and all potential sellers enter, the population distribution $F_{v^R_0 \geq v^*_0}$ is not nonparametrically identified on the part of its support exceeding $v^*_0$. However, the right-truncated distribution of potential seller values is the foundation for any counterfactual that reduces expected seller surplus, including unilateral fee increases. The counterfactuals show that this is the relevant part of the support in the empirical context.

The three entry cost amounts are identified from the three zero profit conditions, as $\Pi_{b,r>0}$, $\Pi_{b,r=0}$, and $\Pi_a$ given equilibrium play are revealed in the data up to and strictly decreasing in entry costs. This does rely on knowing the equilibrium entry strategies, which are recovered as follows. $v^*_0$ is revealed as the maximum of seller values implied by (14), $\lambda^*_r=0$ is equal to the mean $A$ in zero reserve auctions, and $\lambda^*_{r>0}$ as the value that maximizes the likelihood of the observed $B$ and $A$ given $F_V$ and the Poisson distribution of the number of potential bidders per listing.

To summarize, the identification results are based on the premise that the data is generated by equilibrium strategies of one iteration of the two-sided entry game. The distribution of bidder valuations is identified from variation in second-highest bids. The distribution of seller valuations is identified on the relevant part of its support by variation in reserve prices, but parametric restrictions are needed to extend identification to higher values. The seller entry cost is recovered

$\varepsilon$
as the amount that makes the marginal seller indifferent between entering and staying out, and
bidder entry cost are identified as the amounts that, given bidder and seller values, justify the
observed levels of participation.

B. Estimation method

The strategies to estimate the model primitives closely follow their respective nonparametric
identification arguments. To extrapolate beyond the support on which \( F_{v_0} \geq v_0 \) is identified, and to
estimate \( F_V \) independent of the number of bidders, the latent value distributions are parameterized.
The goal is to estimate their finite-dimensional parameters. To account for auction-level hetero-
geneity, potential bidder and seller values are taken to satisfy the following single-index structure:
\[
\ln(\tilde{V}) = g(Z) + V, \quad \text{and} \quad \ln(\tilde{V}_0 | V_0 \geq v_0) = g(Z) + V_0, \quad \text{with} \quad (V, V_0, Z) \text{ mutually independent.}
\]
In the empirical application, the \( g(Z) \) term can be interpreted as the wine’s quality, and \( V \) and \( V_0 \) as the
idiosyncratic taste components of bidders and sellers.

Estimation of the bidder parameters by MLE is straightforward and in line with previous analysis
of ascending auction data. To estimate the value distribution across auctions, the second-highest
bid is first homogenized (as in Haile, Hong and Shum (2003)). For all bidders \( i \): \( \ln(\tilde{V}_i) = g(Z) + V_i \),
so that: \( \ln(\tilde{V}_{(n-1:n)}) = g(Z) + V_{(n-1:n)} \). With \( c_B = 0 \) in the data and given equilibrium play,
quality \( \hat{g}(Z) \) is estimated by regressing the log of the second-highest bid on auction characteristics in
auctions with \( r = 0 \) and with more than one bidder. The residual plus intercept deliver homogenized
values \( V_{(n-1:n)} \), forming the basis of the likelihood function.\(^{29}\)

Next, a suitable distribution function needs to be chosen depending on the empirical application.
Because the empirical CDF’s of \( V \) (for different number of bidders) and \( V_0 \) (on the observed part of
the support) show departures from symmetry in the data, taste distributions are parameterized as:
\[
V \sim \mathcal{GGD}(\mu_b, \sigma_b^2, \kappa_b) \quad \text{and} \quad V_0 \sim \mathcal{GGD}(\mu_s, \sigma_s^2, \kappa_s), \quad \text{with} \quad \mathcal{GGD} \text{ the Generalized Gaussian Distribution.}^{30}\]

\(^{29}\)Specifically, let \( \mathcal{T}_{r_0} \) denote the set of listings with a zero reserve price and \( h(.|n_t, z_t; \theta_h) \) the density of homogenized
transaction prices given the number of bidders \( n_t \). For all auctions with a zero reserve price, and with \( c_B = 0 \) in the data, it
is simply the probability that the homogenized second-highest bid \( b_t \) is the second-highest among \( n_t \) draws from \( F_V \). Hence
forall \( t \in \mathcal{T}_{r_0} \):

\[
\begin{align*}
\ln(h(b_t|n_t, z_t; \theta_h)) &= n_t(n_t - 1)F_V(b_t; \theta_h)^{n_t-2}(1 - F_V(b_t; \theta_h))F_V(b_t; \theta_h) \\
\end{align*}
\]

The log likelihood of bidder parameters given data is specified as:

\[
\mathcal{L}(\theta_h; \{n_t, z_t, b_t\}_{t \in \mathcal{T}_{r_0}}) = \sum_{t \in \mathcal{T}_{r_0}} \ln(h(b_t|n_t, z_t; \theta_h))
\]

\(^{30}\)The \( \mathcal{GGD}(\mu, \sigma^2, \kappa) \) has PDF:

\[
\begin{align*}
f(x; \mu, \sigma^2, \kappa) &= \frac{\phi(y)}{\sigma^2 - \kappa(x - \mu)} \phi(\cdot), \text{with} \ \phi(\cdot) \ \text{the standard normal PDF and} \\
y &= \frac{x - \mu}{\sigma^2} \mathbb{1}(\kappa = 0) - \frac{1}{\kappa} \ln(1 + \frac{\kappa(x - \mu)}{\sigma^2}) \mathbb{1}(\kappa \neq 0)
\end{align*}
\]
This allows for additional flexibility relative to the Normal distribution, with values of $\kappa > 0$ ($\kappa < 0$) introducing skewness to the left (right).

Recovering the parameters of the seller taste distribution $\theta_s = (\mu_s, \sigma_s^2, \kappa_s)$ is more complex as they depend on $v^*_s$ that itself is a function of $\theta_s$. A second issue stems from $v^*_0$ being the solution to a fixed point problem with a nested threshold-crossing problem (equation [13]), making full maximum likelihood estimation (computationally) infeasible. To address this, an initial estimate $\hat{\theta}^0_s$ is obtained by maximum concentrated likelihood estimation, after which the entry equilibrium is solved given $\hat{\theta}^0_s$ and $\hat{\theta}_b$, and finally seller parameters re-estimated using the resulting seller entry threshold.

Specifically, the following mapping of equilibrium reserve prices to homogenized seller values is exploited (equation [14]):

\[
\hat{v}_{0t} = \ln \left( (1 - c_S) \left( r_t - \frac{1 - F_V(\ln(\tilde{r}_t)) - g(\tilde{z}_t); \hat{\theta}_b)}{(1 + c_B) F_V(\ln(\tilde{r}_t)) - g(\tilde{z}_t); \hat{\theta}_b)} \right) \right) - \hat{g}(\tilde{z}_t),
\]

with $\tilde{r}_t = r_t(1 + c_B)$ denoting the buyer premium-adjusted reserve price and $\hat{v}_{0t}$ the implied conditional seller values in auction $t$. The density of implied seller values given entry threshold $v^*_0$, $r_t$, and $z_t$ ($h(\hat{v}_{0t}|v^*_0, r_t, z_t; \theta_s)$) equals $\forall t \in T_{r>0}$:

\[
h(\hat{v}_{0t}|v^*_0, r_t, z_t; \theta_s) = \frac{F_{V_{0 \ge v^*_0}}(\hat{v}_{0t}; \theta_s)}{F_{V_{0 \ge v^*_0}}(v^*_0; \theta_s)}
\]

As mentioned before, the no-reserve screening value is simply estimated as $\hat{v}^R_0 = \min(\{\hat{v}_{0t}\}_{t \in T_{r>0}})$. The initial $\hat{\theta}^0_s$ maximize the resulting likelihood function concentrated at $\hat{v}_{T_{r>0}} = \max(\{\hat{v}_{0t}\}_{t \in T_{r>0}})$ [31]

\[
\ell(\theta_s; \{\hat{v}_{0t}, r_t, z_t\}_{t \in T_{r>0}}, \hat{v}_{T_{r>0}}) = \sum_{t \in T_{r>0}} \ln(h(\hat{v}_{0t}|v^*_0 = \hat{v}_{T_{r>0}}, r_t, z_t; \theta_s))
\]

\[
\hat{\theta}^0_s = \arg \max \ell(\theta_s; \{\hat{v}_{0t}, r_t, z_t\}_{t \in T_{r>0}}, \hat{v}_{T_{r>0}})
\]

The next steps are to compute the entry equilibrium to recover $v^*_0$ given $(\hat{\theta}_b, \hat{\theta}^0_s)$ and re-estimate $\hat{\theta}_s$ accordingly. The described estimation algorithm resembles the Aguirregabiria and Mira (2002) nested pseudo likelihood (NPL) estimator, albeit with a nested concentrated likelihood estimator derived from the optimal reserve price strategy to recover structural parameters. NPL is more widely used as a solution to solving parameters involving fixed point characterizations in the estimation algorithm.

\[31\] $\hat{v}_{T_{r>0}}$ is a consistent estimate of $v^*_0$ with $\hat{v}_{T_{r>0}} \to v^*_0$ as $T_{r>0} \to \infty$ at the true population parameters, by the law of large numbers, asymptotically over multiple iterations of the game.
tion of (dynamic) discrete choice entry games.  

Entry cost $\hat{e}_{B,r>0}^o$, $\hat{e}_{B,r=0}^o$, and $\hat{e}_S$ are estimated as the values that equal expected surplus from entering at the estimated $(\hat{\theta}_b, \hat{\theta}_s)$ and given the computed entry equilibrium at estimated parameters. As such, estimated entry costs equal numerical approximations of the expected user surpluses defined in equations (8) and (9) for potential bidders and (12) for the marginal seller. Finally, to account for potential unexplained variation in the entry process, an additional share $(p_{0,r>0} \geq 0)$ of listings is allowed to attract no bidders. It is estimated by maximimizing the likelihood of the observed joint distribution of number of actual bidders ($A$) and the second-highest bid, given a (generalized) Poisson distribution of the number of bidders per listing ($N$). The empirical distribution of $N$ in zero reserve auctions show that no such flexibility is needed there. The online Appendix provides additional details about the computation of the entry equilibrium and estimation of the three entry cost values.

4. Online wine auctions

Auction data for the empirical analysis in this paper come from the online auction platform www.BidforWine.co.uk (BW). This platform offers a peer-to-peer marketplace for buyers and sellers to trade their wine and caters (currently) to over 20,000 users. BW is one of 8 UK wine auctioneers recognized by The Wine Society. Importantly, none of the other 7 intermediaries provide a peer-to-peer format but instead work on consignment to trade on behalf of sellers. This comes with additional shipping costs and value assessments by the intermediary, which is worthwhile only for higher-end wine. This naturally positions BW at the lower end of the market. BW is therefore taken to be a monopolist in the UK secondary market for lower-end fine wine, as its sellers cannot readily switch to Bonhams or Sotheby’s when BW raises fees. To the extent that there are local marketplaces for these products, their presence is captured by the opportunity cost of trading on BW.

Items are sold through an English (ascending) auction mechanism with proxy bidding. A soft-closing rule extends the end time of the auction by two minutes whenever a bid is placed in the

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32 Roberts and Sweeting (2010) previously applied NPL to an auction setting. Importantly, Pesendorfer and Schmidt-Dengler (2010), Kasahara and Shimotsu (2012) and Egesdal, Lai and Su (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 the game reducing to a single agent (marginal seller) discrete choice problem with a unique equilibrium. As any number of iterations results in a consistent estimator $\hat{\theta}_s$, the equilibrium is computed only once.

33 The others are Bacchus, Bonhams, Chiswick, Christies, Sotheby’s, Sworders, and Tennants.

34 Seller-managed listings are the focus of this paper. BW also offers consignment services for sales of large collections exceeding five cases or for exclusive wines.

35 Bidders submit a maximum bid, and the algorithm places their bids so that the current price is kept 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 differs from the pricing rule at eBay (see Hickman, Hubbard and Paarsch (2017)).
Table 2—: Fee structure in wine auction data

<table>
<thead>
<tr>
<th>Bidders:</th>
<th>Notation</th>
<th>Amount / rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Buyer premium</td>
<td>$c_B$</td>
<td>0</td>
</tr>
<tr>
<td>Entry fee</td>
<td>$e_B$</td>
<td>£0</td>
</tr>
<tr>
<td>Listing inspection cost</td>
<td>$c_{B,r=0}$, $c_{B,r&gt;0}$</td>
<td>estimated</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Sellers:</th>
<th>Notation</th>
<th>Amount / rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Seller commission</td>
<td>$c_S$</td>
<td>0.085</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.075</td>
</tr>
<tr>
<td>Listing fee</td>
<td>$e_S$</td>
<td>£1.75</td>
</tr>
<tr>
<td>Reserve price fees</td>
<td>$e_R$</td>
<td>£0.75</td>
</tr>
<tr>
<td>Opportunity cost of time</td>
<td>$e_{S}$</td>
<td>estimated</td>
</tr>
</tbody>
</table>

Displayed fees include a 20 percent VAT. Opportunity cost $e_{B,r=0}$, $e_{B,r>0}$, and $e_{S}$ are added for reference but fall outside the platform fee structure $f = \{c_B, e_B, c_S, e_S, e_R\}$. The reserve price fee is made up of 0.50 GBP for raising the minimum bid and 0.25 GBP for adding a secret reserve price.

As in most empirical auction settings, bidder valuations are likely made up of both common value and private value components. A few remarks regarding the suitability of the private values assumption are warranted. First, conversations with the platform’s management suggest that users who buy and sell wine on BW are reasonably informed about the factors that influence the quality of a bottle of wine. For example, it is widely known that 1961 is a great Bordeaux vintage due to favourable weather conditions, and that low fill levels (ullage) for the age of the wine point to potential oxidation. These details and many more can be found on the listing page. This is important to point out because a common values model is appropriate when bidders expect that other bidders possess additional information that would affect their own value of the wine, as in the typical example of OCS oil and gas auctions. Another justification for a common values model would be a resale motive, where bidders plan to sell the wine in the future at a higher price. Despite any associations with luxury that readers might have—investment in luxury items such as art and fine wine is increasingly common—the scope for profitable resale is limited in the context of the lower-end fine wines in the sample. A bottle of wine in the main sample sells for 45 GBP on average, delivery costs are approximately 12-16 GBP, storage is costly, and anticipated future seller fees and

---

36 Management used the term “prosumers” to describe its user base; consumers with some specific knowledge of wine.
37 To highlight the importance of weather conditions for wine quality, Ashenfelter (2008) predicts with surprising accuracy the price of a sample of Bordeaux grand Cru’s using weather data.
Table 3—: Auction-level descriptive statistics

<table>
<thead>
<tr>
<th></th>
<th>N</th>
<th>Mean</th>
<th>St. Dev.</th>
<th>Min</th>
<th>Pctl(25)</th>
<th>Median</th>
<th>Pctl(75)</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Highest bid</td>
<td>3,500</td>
<td>148.10</td>
<td>302.45</td>
<td>0</td>
<td>40</td>
<td>82.1</td>
<td>170</td>
<td>6,400</td>
</tr>
<tr>
<td>Number of bidders</td>
<td>3,500</td>
<td>3.10</td>
<td>2.51</td>
<td>0</td>
<td>1</td>
<td>3</td>
<td>5</td>
<td>13</td>
</tr>
<tr>
<td>Number bottles</td>
<td>3,500</td>
<td>3.71</td>
<td>4.23</td>
<td>1</td>
<td>1</td>
<td>2</td>
<td>6</td>
<td>72</td>
</tr>
<tr>
<td>Is sold</td>
<td>3,500</td>
<td>0.64</td>
<td>0.48</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Price per bottle if sold</td>
<td>2,235</td>
<td>76.40</td>
<td>129.52</td>
<td>0.33</td>
<td>17.12</td>
<td>35.00</td>
<td>83.33</td>
<td>2,200.00</td>
</tr>
<tr>
<td>Sold “in bond”</td>
<td>3,500</td>
<td>0.16</td>
<td>0.37</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Has reserve price</td>
<td>3,500</td>
<td>0.67</td>
<td>0.47</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Seller received feedback</td>
<td>3,500</td>
<td>0.29</td>
<td>0.46</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Seller is rated</td>
<td>3,500</td>
<td>0.86</td>
<td>0.35</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>

Displaying summary statistics for selected auction-level observables. Sold “in bond” indicates that the wine has been stored in a bonded warehouse since arriving in the UK. Winning bidders can provide textual feedback describing the interaction with the seller, and can also rate the interaction as “positive”, “neutral”, or “negative”. Whether the listing has a reserve price includes both secret reserve prices and increased minimum bid amounts.

Overall, while it cannot be ruled out that some of the bidders on some of the wines will update their valuation after seeing other bids come in, it is considered reasonable that most of the variation in bidder valuations is due to variation in bidders’ idiosyncratic tastes for the wine conditional on the information contained in $g(Z)$.

During the time period under study, BW did not charge a buyer premium but did maintain a seller commission of 10.2 percent for sale amounts below 200 GBP and 9 percent for marginal amounts between 200 and 1500 GBP. Regardless of whether the sale is successful, sellers are charged a listing fee of 2.1 GBP, a minimum bid fee (0.6 GBP, but only when increasing the minimum bid) and a reserve price fee (0.3 GBP, but only when setting a secret reserve). These fees include a 20% VAT. The buyer premium and seller commission are charged as a percentage of the transaction price. For completeness, the analysis also includes a buyer entry fee that is currently set to 0. Table 2 summarizes the fees in the sample.

A. Data description

The dataset of wine auctions was constructed by web-scraping all open auctions on BW at 30-minute intervals between January 2017 and May 2018. During these intervals, most of what bidders observe is recorded. Observed wine characteristics ($Z$) include the type of wine (red, white, rosé, opportunity cost of time reduce the gains from resale further. Overall, while it cannot be ruled out that some of the bidders on some of the wines will update their valuation after seeing other bids come in, it is considered reasonable that most of the variation in bidder valuations is due to variation in bidders’ idiosyncratic tastes for the wine conditional on the information contained in $g(Z)$.

Indeed, the fact that winning bidders can use the BW platform to sell wine does not by itself call for an auction model with resale—they must still expect to gain a profit by going through the process of buying and re-selling the wine. On the investment prospects of luxury items such as art and high-end find wine, see, e.g., https://www.ft.com/content/aca193f8-5850-11e4-a31b-00144feab7de, last accessed December 23, 2021.

Moreover, empirical analysis of a common values ascending auction model would be infeasible given the lack of positive identification results for such a model.
sparkling, or fortified), grapes, vintage, region of origin, delivery and payment information, storage conditions, returns and insurance, seller ratings and feedback, fill level of the bottle, and the seller’s textual description. Summary statistics are reported in table 3. One-third of listings are created by a seller with feedback from previous transactions, indicating the consumer-to-consumer nature of the platform, and 14 percent of sellers have not been rated at all. Seller identities are observable, but bidder identities are unobservable except for those bidders who have left feedback after winning an auction. Sixteen percent of the listings offer wine sold “in bond”, which means that they have been stored in bonded warehouses approved by HM Customs & Excise since being imported into the UK. The alcohol duty due upon taking the wine out of storage depends on the alcohol content and whether the wine is still or sparkling, and the duty amount is scraped from the relevant listing pages.

The profile pages of all users ever registered were examined as well. When defining a potential seller as a member who has listed a wine for sale at least once, only 279 out of 2,591 potential sellers created a listing during the sample period. If we consider all 13,176 remaining users as potential bidders, this simple accounting exercise indicates entry on the bidder side as well. Even under the extreme assumption that all auctions are populated by different bidders, only 10,856 actual bidders would be counted. Moreover, in the structural analysis, bidders and sellers are treated as distinct groups of users, but this is an abstraction: the data show that 44 out of the 248 feedback-leaving winning bidders have also listed a wine for sale. While the share of bidders who also sell is probably lower in the full sample if it is important for aspiring sellers to leave a positive footprint, one can consider a user as belonging to the bidder or seller group merely for the duration of a potential transaction. In the model, idiosyncratic conditional value distributions for buyers and sellers on the platform are allowed (but not required) to be different.

The sample includes 3,500 auctions after excluding auctions that were consigned, include spirits, or involve the sale of multiple lots at once. While there is a significant range of sale prices, 81 percent of auctions fall in the lowest seller commission bracket (≤ 200 GBP). These auctions are the focus of this paper (the “main sample”), and the model is estimated separately for “high-end” auctions with prices between 200 and 1500 GBP. The empirical analysis controls for observable wine characteristics in order to estimate idiosyncratic residual value distributions, so the two sets of model estimates are used to assess the heterogeneous effects of fee changes in these two classes.

The repetitive recording of bids for ongoing auctions was necessary to approximate the reserve price distribution. When a seller sets a reserve price without making it public in the form of a

40These statistics are provided for context; population sizes are not needed for the estimation of the model primitives.
minimum bid amount, the notifications “reserve not met” or “reserve almost met” accompany any standing price that does not exceed the reserve. Reserve prices are approximated as the average of the highest standing price for which the reserve price is not met and the lowest for which it is met.\footnote{\textsuperscript{31}} Only 26 percent of listings have an increased minimum bid amount, while 45 percent have a (secret) reserve price, and 4 percent have both.\footnote{\textsuperscript{32}} In the rest of this paper, the “reserve price” refers to the maximum of the minimum bid amount and the approximated secret reserve price. Of greater consequence is the choice made by one-third of sellers to refrain from setting any form of reserve. This is observable to bidders by the presence of a “no reserve price” button—even before they enter the listing. Correspondingly, the model is constructed to result in a different distribution of the equilibrium number of bidders for these two listing types.

\textit{B. Selection and entry}

Sellers on this peer-to-peer platform can be thought of as individual collectors with private values (marginal costs) for each wine, and a subset of these sellers set a (secret) reserve price for the wine that they list for sale. For sellers, entry is the act of creating a listing on the platform. The estimation results from a Heckman two-stage selection model suggest that potential sellers with lower valuations for their wine are indeed more likely to enter the platform and that those who enter are more likely to have a value draw that is low enough to set a zero reserve price. Specifically, with the reserve price increasing in a seller’s valuation (Lemma\textsuperscript{2}), in the second stage, the reserve price is regressed on the estimated inverse Mills ratio from a first-stage Probit regression of the decision to enter. The exclusion restriction central to this test is that the number of potential sellers might influence sellers’ entry decisions in a given market (month), but conditional on entry, it should not affect their valuations nor therefore the reserve price that they set.\footnote{\textsuperscript{33}} A confounding factor in this analysis is that conditional on entry, seller valuations are left-censored if sellers optimally sort themselves into setting a zero reserve price (as in, e.g., Jehiel and Lamy (2015)). Two solutions are proposed. In columns 1 and 2 of Table\textsuperscript{4}, the dependent variable is the residual reserve price after conditioning on auction observables, imputed to be the lowest estimated value for all sellers who set a zero reserve.\footnote{\textsuperscript{34}} In columns 3 and 4, the dependent variable is a dummy variable that

\begin{footnotesize}
\textsuperscript{31}If all bids were recorded in real time, this approximation would be accurate up to half a bidding increment due to the proxy bidding system. Additionally, the 30-minute scraping interval results in a good approximation of the reserve price distribution obtained in a smaller sample where bids are recorded at 30-second intervals, as documented in the online Appendix.

\textsuperscript{32}The use of secret reserve prices in auction platforms remains a puzzle in the empirical auction literature, and solving that puzzle is beyond the scope of this paper (see Jehiel and Lamy (2015) and the comments in footnote\textsuperscript{17}).

\textsuperscript{33}This is the seller equivalent of the exclusion restriction in Roberts and Sweeting (2013) that was used to test for bidder selection into USFS timber auctions. Other variables included in the first-stage entry decision that are plausibly excluded from sellers’ valuations conditional on entry are the share of markets that the potential seller entered, the number of listings that he or she has in other markets, the date he or she created an account on the platform, and the number of other users who created an account in the same month. Estimation results from the first-stage entry model are reported in Appendix\textsuperscript{E}.

\textsuperscript{34}The residual is obtained from a linear regression of the reserve price on the auction observables.
\end{footnotesize}
Table 4—: Heckman seller selection model: second-stage results

<table>
<thead>
<tr>
<th>Estimated residual reserve</th>
<th>Setting a zero reserve</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
</tr>
<tr>
<td>Inverse Mills ratio</td>
<td>−64.646</td>
</tr>
<tr>
<td></td>
<td>(14.027)</td>
</tr>
<tr>
<td>First stage entry model</td>
<td>basic</td>
</tr>
<tr>
<td>Observations</td>
<td>3,500</td>
</tr>
</tbody>
</table>

Standard errors are reported in parenthesis. An observation in the first stage is a potential seller-month combination, including all potential sellers who listed at least once during the sample period. The first stage dependent variable $\text{List} = 1$ if the potential seller has at least one listing in the month. Two models are estimated, with more or less potential seller-level explanatory variables alongside the number of potential sellers in the market. The complete set of estimation results from the first stage are reported in Appendix C.

indicates whether the seller set a zero reserve price. Estimates in columns 2 and 4 are based on a more elaborate first-stage entry model, detailed in the appendix. All four regression models suggest that sellers enter BW selectively.

An important institutional detail is that the wines offered for sale are preowned by the sellers and therefore idiosyncratic in the sense used by Einav et al. (2018), explaining the presence of listing inspection cost in this market. Indeed, listing pages report the wine’s storage conditions, provenance, in bond status, estimated alcohol duty, and other relevant characteristics that are not provided in the brief landing page excerpts. The wine’s ullage classification (fill level) is also given as a measure of the degree of oxidation. For instance, the classification “Base of Neck” is better than “Top Shoulder” in Bordeaux-style bottles, and Burgundy-style bottles without a pronounced “neck” or pronounced “shoulders” have a metric classification.

For bidders, entry is the act of entering into a listing on the platform. Nonselective bidder entry can be motivated by the above-mentioned listing inspection cost: bidders learn their valuations after inspecting the auction characteristics. OLS regression results are indeed consistent with such a model: while an extra bidder in an auction is associated with a transaction price that is approximately 10 GBP higher, markets (months) that attract more total bidders for a product do not have significantly different prices. By contrast, selective bidder entry would appear in the

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45 In the context under study in which sellers own the wine that they are selling (sometimes for decades), less pertinent than for bidder selection is the question of how selective seller entry is.

46 The coefficient on the total number of bidders in the market is economically small and statistically insignificant ($-0.061$ with a standard error of 0.072 for zero reserve auctions in the main sample, a finding which is robust to numerous specifications). For the purpose of this reduced-form analysis, a market is defined as a month, and a product is defined through a combination of the high-level filters used on the platform: type of wine, region of origin, and vintage decade. Red Bordeaux from the 1960s and nonvintage Champagne are, for instance, classified as different products in the regressions. The appendix reports the complete estimation results.
Table 5—: Thin markets

<table>
<thead>
<tr>
<th>Variables:</th>
<th>— Percentiles:</th>
<th>10%</th>
<th>20%</th>
<th>30%</th>
<th>40%</th>
<th>50%</th>
<th>60%</th>
<th>70%</th>
<th>80%</th>
<th>90%</th>
<th>100%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Times product listed, 4 weeks:</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>2</td>
<td>2</td>
<td>3</td>
<td>6</td>
<td>37</td>
<td></td>
</tr>
<tr>
<td>Times product listed, 15 months:</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>8</td>
<td>16</td>
<td>230</td>
<td></td>
</tr>
<tr>
<td>Times same title occurs, 15 months:</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>2</td>
<td>17</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Reporting deciles of distributions of the number of times a product or listing title is observed in the sample. In the first row, an observation is a product in each 4 week non-overlapping interval. Conservative product definitions are used (region x wine type x vintage decade), corresponding to high-level filters on the website, and products that do not occur in a month are not counted to avoid the large mass at 0. In the second row an observation is a product and in the third row it is the title of the listing, in both cases counting how often they occur within the full 15 months of the sample.

Data as markets that have more listings of a certain product attracting more total bidders and having stochastically lower bids as bidders with higher valuations enter first. As bidder identities are not observed, selection cannot be tested for directly as done on the seller side (and for bidder entry in Roberts and Sweeting (2013)).

A constant cost of inspecting each listing furthermore implies that listings are independent of each other, even when they are similar in product characteristics or end in close proximity to each other. In other words, as explained in Section 2.C, the listing inspection cost depletes all expected surplus from entering in another auction. A regression analysis empirically supports this prediction. The presence of more competing listings does not systematically affect the average i) number of bidders per listing, ii) number of bids per bidder, iii) transaction price, and iv) reserve price.

As a result, this setting is notably distinct from those studied previously. Auction platform models with dynamic or static search elements and without seller selection (or entry) have fittingly been estimated for more commodity-like products. One distinguishing feature of an auction platform with idiosyncratic goods is that at each point in time, the platform contains a low number of highly similar listings. This is certainly true for the wine auction platform. Even with the coarse product definitions derived from the high-level filters discussed above, for 50 percent of listings on BW, there is only one such product offered during the same month, and for another 20 percent, only three such products are available (see Table 5).

---

47 Recall that in the second-price sealed-bid auction model the optimal bidding strategy is to bid one’s valuation independent of the number of competing bidders.

48 These results are consistent across 18 different definitions of what constitutes a competing listing. Specifically, a competing listing is defined as a listing whose auction ends within a rolling window of i) 30 days, ii) 7 days, or iii) 2 days of the listing in question and that offers the same product, with product definitions ranging from any wine to one of five combinations of the high-level filters. Appendix C reports the complete estimation results.

49 Structural auction (platform) models have been applied to the study of compact cameras (Backus and Lewis (2016)), Kindle e-readers (Bedoh-Creed, Boehke and Hickman (2020)), iPads (Hendricks and Sorensen (2018)), pop music CDs (Nekipelov (2007)), CPUs (Anwar, McMillan and Zheng (2006)), and iPods (Adachi (2016)).
Table 6—: Estimated structural parameters

<table>
<thead>
<tr>
<th>Taste parameters</th>
<th>$\hat{\mu}_b$</th>
<th>$\hat{\sigma}_b^2$</th>
<th>$\hat{\kappa}_b$</th>
<th>$\hat{\mu}_s$</th>
<th>$\hat{\sigma}_s^2$</th>
<th>$\hat{\kappa}_s$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Main sample</td>
<td>3.389</td>
<td>1.020</td>
<td>0.084</td>
<td>3.453</td>
<td>0.851</td>
<td>0.260</td>
</tr>
<tr>
<td></td>
<td>(0.033)</td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.037)</td>
<td>(0.006)</td>
<td>(0.007)</td>
</tr>
<tr>
<td>High-end sample</td>
<td>5.303</td>
<td>0.313</td>
<td>-0.615</td>
<td>5.570</td>
<td>0.477</td>
<td>-0.477</td>
</tr>
<tr>
<td></td>
<td>(0.041)</td>
<td>(0.004)</td>
<td>(0.011)</td>
<td>(0.042)</td>
<td>(0.011)</td>
<td>(0.020)</td>
</tr>
<tr>
<td>Entry parameters</td>
<td>$\hat{e}_{B,r&gt;0}$</td>
<td>$\hat{e}_{B,r=0}$</td>
<td>$\hat{e}_S^0$</td>
<td>$\hat{p}_{0,r&gt;0}$</td>
<td>$\hat{v}_{R0}$</td>
<td></td>
</tr>
<tr>
<td>Main sample</td>
<td>6.562</td>
<td>6.865</td>
<td>11.081</td>
<td>0.045</td>
<td>0.165</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.172)</td>
<td>(0.186)</td>
<td>(0.288)</td>
<td>(0.001)</td>
<td>(0.043)</td>
<td></td>
</tr>
<tr>
<td>High-end sample</td>
<td>16.954</td>
<td>17.984</td>
<td>14.764</td>
<td>0.152</td>
<td>4.860</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.733)</td>
<td>(0.795)</td>
<td>(0.978)</td>
<td>(0.006)</td>
<td>(0.045)</td>
<td></td>
</tr>
</tbody>
</table>

The structural estimates are based on 2770 observations in the main sample and 598 observations in the high-end sample. Standard errors based on 100 nonparametric bootstrap repetitions are reported in parenthesis.

5. Estimation results

A. Parameter estimates and model validation

The data contain information on observables related to the type of wine, the region of origin, the number and type of bottles, the auction month, storage in a temperature-controlled warehouse, delivery cost/conditions, returns and insurance, payment options, seller ratings, ullage, in-bond lot status, and more. The extent to which auction characteristics explain the variation in prices is explored to assess the degree to which abstracting from unobserved heterogeneity might be problematic. Obtaining the data by scraping the content of the listing pages results in an unusually rich dataset that contains at least the majority of what bidders also observe. To fully exploit this information, text mining techniques are applied to the description of the wine provided by the seller. Words that relate to each of the following three categories are identified. First, the category expert opinion includes listings for which the description refers to tasting notes or points from well-known wine critics Robert Parker or Janice Robinson. The second category includes listings whose descriptions include words indicating that the wine was bought en primeur (French for “in advance” or “first”), which refers to the sale of a portion of Bordeaux wines based on young barrel samples taken after the latest harvest but before the wine has been bottled and matured.

While the first classification provides the bidder with information about the wine’s taste, the second classification relates to its provenance and the professionalism of the seller. The third category includes listings with words related to the delivery or shipment of the wine. Whether

50For example, words related to expert opinion include “advocate”, “points”, “color”, and “tannin”; words related to en primeur status include “temperature”, “member”, “facility”, and “society”; and words related to delivery and storage include
A regression of the log of the transaction price in zero reserve auctions with at least two bidders on these characteristics, done to homogenize the auctions and allow the data from heterogeneous auctions to be pooled together, shows that the observables explain a strikingly large share of the price variation. In the main sample, the $R^2$ is 0.49, and in the high-end sample, the $R^2$ is 0.92. These results compare favorably to the amount of price variation that can typically be explained in auction studies, including in studies of more homogeneous goods and in those that use innovative methods to recover information otherwise unobservable to the econometrician (see, e.g., Bodoh-Creed, Boehnke and Hickman (2017) and Kong (2020)). It is impossible to capture literally everything that might affect bidder valuations in the data, but unobserved heterogeneity likely plays a minor role in the current context.
The full set of estimation results is reported in the appendix. Estimates for the impact of key variables are generally as expected. Prices are higher for bottles sold by the case, and conditional on this case effect, the price is lower when more bottles are included in the lot. Specialized temperature-controlled warehouses and special format bottles (e.g., magnums) are sold with a premium. All fill levels that are not the best earn (weakly) lower prices. Table 6 reports the remaining estimated structural parameters. Estimation of $\theta_s$ excludes the 9.2 (5.1 in the high-end sample) percent of sellers for which $\hat{v}_{0t}$ is estimated to be negative. Moreover, both $\hat{u}_{0t}$ and $\hat{g}(Z)$ are trimmed at their 1st and 99th percentiles to minimize the impact of outliers. The model fits the data well, as illustrated by the various plots in Figure 2.

Plots (b) and (d) of Figure 2 include draws of estimated quality to simulate second-highest bids and reserve prices, which are out-of-sample predictions for the reserve price sample. The second-highest bid, moreover, is simulated in expectation over the number of bidders per listing. As another measure of model fit, the mean absolute deviation between the observed and predicted second-highest bids is computed separately for $n = \{2, 3, \ldots, 10\}$ bidders: the mean absolute deviations are small, between 0.016-0.742 GBP, and there is no clear pattern by number of bidders. Furthermore, two-sample Kolmogorov–Smirnov tests cannot reject the null hypothesis that the observed and predicted reserve prices are drawn from the same population distribution (p value 0.2).

Plot (e) displays the goodness of fit of the assumed Poisson distribution with the estimated $\hat{\lambda}^*_r=0$ relative to the empirical distribution. Notably, the data do not reveal any overdispersion relative to the Poisson distribution. This indicates that while preferences for high-level characteristics (filters) might vary across the population of potential bidders, the uniform sorting over listings—conditional only on the reserve price button—assumed in the estimation captures the first-order effects of entry behavior in the BW data. A chi-squared goodness-of-fit test fails to formally reject the hypothesis that $N$ is generated by a Poisson distribution (p value 0.2). The high-end sample does contain some underdispersion, and the test barely fails to reject the null (p value 0.06).

The estimated listing inspection cost is significantly higher in the high-end sample. However, relative to the second-highest bid, the estimated cost is higher in the main sample: 9 percent versus 5 percent in the high-end sample. Estimates in both cases do correspond to the idea that the cost of inspecting a listing to prepare for bidding is significant in this idiosyncratic goods environment.

At the estimated parameters, setting no reserve price attracts on average 1.2 additional bidders.

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51 This could be explained by (some) bidders entering auctions with a lower standing price rather than entering randomly. The counterfactual simulations abstract from such behavior insofar as there are departures from the uniform matching assumption in the high-end sample.
Table 7—: Estimated indirect network effects

<table>
<thead>
<tr>
<th>Exogenous change number sellers (T):</th>
<th>-100</th>
<th>-40</th>
<th>-20</th>
<th>-10</th>
<th>+10</th>
<th>+20</th>
<th>+40</th>
<th>+100</th>
</tr>
</thead>
<tbody>
<tr>
<td>Effect on Π_b</td>
<td>-0.11</td>
<td>-0.056</td>
<td>-0.028</td>
<td>-0.014</td>
<td>0.013</td>
<td>0.025</td>
<td>0.045</td>
<td>0.080</td>
</tr>
<tr>
<td>Exogenous change number bidders (M):</td>
<td>-100</td>
<td>-40</td>
<td>-20</td>
<td>-10</td>
<td>+10</td>
<td>+20</td>
<td>+40</td>
<td>+100</td>
</tr>
<tr>
<td>Effect on Π_s (marginal seller)</td>
<td>-0.206</td>
<td>-0.082</td>
<td>-0.041</td>
<td>-0.021</td>
<td>0.021</td>
<td>0.041</td>
<td>0.082</td>
<td>0.205</td>
</tr>
<tr>
<td>Effect on Π_s (median seller)</td>
<td>-0.377</td>
<td>-0.151</td>
<td>-0.075</td>
<td>-0.038</td>
<td>0.038</td>
<td>0.075</td>
<td>0.150</td>
<td>0.376</td>
</tr>
</tbody>
</table>

Simulations based on \( r > 0 \) homogenized auctions in the main sample, where \( M + 100 \) corresponds to \( M + 1.25\% \) bidders and \( T + 100 \) corresponds to \( T + 5.34\% \) sellers.

It makes intuitive sense that this participation differential is larger in the high-end sample (1.9), as the probability of being the sole entrant and winning the more expensive wine for the 1 GBP opening bid is more valuable.

Another source of model validation is the comparison of \( \hat{e}_{B,r=0} \) with \( \hat{e}_{B,r>0} \). While these parameters are allowed to be different, there is no reason to suspect that the presence of a reserve price significantly changes how time intensive it is to inspect listings if the presence of a reserve price does not itself reveal any information about the quality of the item. Indeed, \( \hat{e}_{B,r=0} \) and \( \hat{e}_{B,r>0} \) are statistically indistinguishable in both the main and high-end samples. Recall that \( \hat{e}_{B,r=0} \) and \( \hat{e}_{B,r>0} \) are computed from two different subsets of the data as the values that justify the observed participation levels (e.g., that set \( \Pi_{b,r=0}(.) = 0 \) and \( \Pi_{r>0}(.) = 0 \), respectively) based on \( \hat{\lambda}_{r=0} \) and \( \hat{\lambda}_{r>0} \), which are estimated with different methods.

Taken together, these results suggest that the parsimonious model provides a plausible description of behavior and payoffs on this platform.

B. Seller selection and indirect network effects

The impact of fee changes depends on the entry elasticities of potential bidders and sellers and hence on the network effects generated by user interactions on the platform. This Section estimates their magnitudes on the BW platform according to the following procedure. First, homogenized auctions are simulated by applying equilibrium strategies to the estimated parameters while altering either the number of bidders (\( M \)) or sellers (\( T \), incorporating selection) on the platform. Then, the expected bidder and seller surplus is estimated. The results are reported in Table 7 for various values of \( M \) and \( T \) and are all based on the main sample with \( r > 0 \) for illustration.

Indirect network effects, by its usual definition as in i.e. [Katz and Shapiro (1985)], have the following magnitude: adding one additional bidder to the platform increases the expected surplus of the marginal seller by 0.0022 GBP, and this effect is twice as large as the effect of adding one
The game is estimated on a grid of: \( c_B \times c_S \) \((c_B = \{-0.3, -0.2, -0.1, 0, 0.1\}, c_S = \{-0.1, 0.1, 0.2, 0.3\})\) and interpolated linearly. Values are normalised by baseline levels and are based on parameter estimates from the main sample.

additional seller on the expected surplus of bidders. One benefit of the structural analysis is that it relaxes the assumption that these network effects are constant. In fact, the results show significant heterogeneity. Sellers with lower valuations for the item on sale benefit more: the indirect network effect is 50 percent larger for the median potential seller than the marginal seller (at the 85th percentile). Increasing the number of sellers also has a weaker effect on bidders than does reducing that number.

These results are driven by the estimated bidder and seller taste parameters, which impact the importance of the seller selection channel. For example, a lower level of dispersion in seller tastes/reserve prices would increase the indirect network effect of attracting additional sellers. The estimates indicate that taste distributions are such that seller selection plays a significant role on the BW platform. Relative to an environment where sellers are homogeneous, adding 100 listings reduces the positive indirect network effect on bidders by 62 percent because sellers in these listings set relatively high reserve prices. Similarly, the reduction in bidder surplus is 47 percent smaller when 100 listings are removed relative to the reduction in the no-selection benchmark.

C. Commission index and revenue-volume trade-off

It is also useful to use model estimates to illustrate two features of the market. The first is the role of what is called a “commission index”, defined as: \( \alpha = \frac{c_B + c_S}{1 + c_B} \). Ginsburgh, Legros and Sahuguet
show that expected platform revenue (and bidder and seller surplus) are independent of
\((c_B, c_S)\) as long as \(\alpha\) remains constant. They do not model seller entry or heterogeneity, but their
result applies here, too, since the marginal seller’s expected surplus (and hence \(v^*_0\)) remains con-
stant unless \(\alpha\) changes. Hence, only the commission index and the flat fees matter for the platform
revenue-maximization problem. Plot a of Figure 3 confirms that the simulated counterfactual plat-
form revenue levels line up perfectly with the theoretical commission-index level lines (in orange).
However, theory can tell us no more than the combinations of \(c_B\) and \(c_S\) that keep platform revenue
and user surplus constant, motivating the empirical analysis in this paper.

Secondly, the platform faces a trade-off between maximizing revenues and maximizing the volume
of sales. Intuitively, increasing fees lowers the sales volume but increases the share of that volume
paid to the platform. In the case of commissions, it is important to note that this holds even when
the commission index is held constant. For example, increasing \(c_B\) and decreasing \(c_S\) such that \(\alpha\) is
unchanged would lower the volume because bidders scale down their bids (Lemma 1), while at the
same time, the reserve price and sale probability are unaffected (as shown by Ginsburgh, Legros and
Sahuguet (2010)).\(^{52}\) Plot b of Figure 3 illustrates this point: the simulated volume levels decrease
when moving up (when \(c_B\) becomes higher) along the commission index level lines. Similarly,
increasing the listing fee generates more revenue but depresses the sales volume by reducing the
number of listings on the platform. This is especially relevant as fee structures that increase
platform revenue at the expense of reducing volume (by a large amount) are generally considered
unattractive.\(^{53}\) To account for the volume impact without placing restrictions on the platform
growth dynamics, in what follows a nonparametric volume constraint is reported alongside the
platform revenues.

6. Counterfactuals

In this Section the model estimates are used to address the two key indeterminacies of two-sided
markets: 1) how do fee changes affect user welfare, and 2) what fee structures improve platform
profitability? Each simulated variation in the fee structure requires solving the auction platform
game for a new entry equilibrium and new auction outcomes.

\(^{52}\)Note that platform revenue = volume \((c_B + c_S) + \text{income from } (e_S, e_B, e_R)\). Even when entry is held constant, and hence
\(c_B + c_S\), the sales volume decreases in \(c_B\).

\(^{53}\)The trade-off is crucial in any scenario in which the volume of sales affects future revenues, for instance, through word of
mouth or brand awareness. See also Evans and Schmalensee (2010), who explain why startups focus on network growth in their
early years using a platform model with myopic users, no switching costs, and significant indirect network effects.
A. Welfare impacts

Being able to quantify the welfare effects of fee changes in a two-sided market is of immediate policy relevance. While it is widely understood that both sides of the market are affected by price changes on either side, the difficulty of quantifying network effects has been a bottleneck in the application of antitrust policy to two-sided markets.\footnote{See, e.g., Bomse and Westrich (2005), Tracer (2011), Evans and Schmalensee (2013). For example, in one eBay case sellers claiming that eBay charged supracompetitive fees were denied a class action suit due to the absence of a method for quantifying damages in the presence of network effects (https://casetext.com/case/in-re-ebay-seller-antitrust-litigation-7, last accessed December 23, 2021). Furthermore, the landmark 2018 Ohio v. American Express Co. Supreme Court decision required plaintiffs (merchants) to provide evidence that anti-steering rules negatively impact consumers as well (https://www.supremecourt.gov/opinions/17pdf/16-1454a26.pdf, last accessed December 23, 2021).}

To illustrate a key aspect of two-sided markets with seller (listing) heterogeneity, the first simulation focuses on the effect on sellers when the listing fee is increased by 1 GBP. In a model that ignores entry, the expected surplus for all sellers on the platform would decrease by 1 GBP, and no other user groups would be affected. Instead, when the equilibrium is recomputed with two-sided entry, the expected surplus for sellers who remain on the platform decreases by less than 1 GBP. The higher listing fee excludes some of the highest-valuation sellers from the platform, increasing the expected surplus for potential bidders and driving up the number of bidders per listing. For brevity and because of the crucial role of the negative seller-side externality, this mechanism is (imperfectly) referred to as a “lemons effect” after Akerlof (1970).\footnote{The term is meant to reflect a mechanism where entry of higher-cost sellers makes the platform less attractive to other sellers because of the way potential bidders react to it. However, the term should be interpreted with care. The well-known lemons mechanism in Akerlof (1970) refers to the expected quality of the item. In this paper, the conditional valuations of bidders and sellers are assumed to reflect their independent idiosyncratic tastes, so seller entry does not affect the value that bidders place on the items on offer.}

Figure 4 shows that the magnitude of the lemons effect is inversely related to the inframarginal seller’s value draw. Increasing the listing fee by 1 GBP reduces expected seller surplus by 11-23 percentage points less than when the two-sided entry is not taken into account. The effect increases with the degree of seller heterogeneity in the market. To illustrate, the figure includes results simulated after increasing the variance in the distribution of seller values ($\sigma^2_s$) by 10 percent (“additional seller heterogeneity”). Fully accounting for the welfare impacts on sellers, those who set no reserve price simply experience the full 1 GBP loss in surplus, while the expected surplus of the 2 percent of sellers who are pushed out of the market but would otherwise set a positive reserve price must be lower in the counterfactual scenario.

Furthermore, plot b of Figure 4 demonstrates that the network effects in BW can be exploited to make all sellers (weakly) better off despite paying a 1 GBP higher listing fee by using the proceeds to subsidize bidder entry. The budget-neutral size of the bidder entry subsidy is computed to deplete all additional revenue raised through the higher listing fee. This makes the marginal entrant with...
(a) Only increasing listing fee  
(b) Adding bidder entry subsidy

![Graphical representation of effects](image)

Figure 4. Lemons effect: heterogeneous change in expected seller surplus when increasing listing fee by one pound.

Estimated effects plotted by decile of $F_{V_0}\mid V_0 \geq v_0$, for sellers who are inframarginal (with $v_0 \in [\tilde{v}_0, v^*_0]$) both at baseline and in the counterfactual. Simulations based on $r > 0$ homogenized auctions in the main sample.

$V_0 = v^*_0$ indifferent, as $v^*_0$ remains roughly the same at the estimated magnitudes. Inframarginal sellers with $V_0 \in [\tilde{v}_0^R, v^*_0]$ are better off: in the main sample, their expected surplus increases by up to 1.2 GBP. Even sellers who set a zero reserve price are better off. At the estimated values of the model primitives, the benefits of the subsidy-induced entry of additional bidders into auctions with $r = 0$ outweigh the cost of the higher listing fee. These results are especially interesting in that they provide evidence for the special circumstance in two-sided markets that (some) users could be better off when paying higher fees.

Due to the zero-profit entry condition, bidders are unaffected in expectation, and as the number of listings remains constant, the total surplus for bidders as a group also remains unaffected. No intervention by a social planner is needed to bring about these benefits: the fee change is estimated to increase platform profits by 1 percent and sales volume by 4 percent, driven by a higher sale probability and higher transaction prices.

B. Platform revenues

In two-sided markets, it is profitable to subsidize the entry of users on the side that generates stronger positive externalities for the other side, as those users can then be charged a higher price.

In terms of practical implementation, the platform could invest in lowering listing inspection cost by increasing the standardization of listings or by introducing an estimated quality index. A negative bidder entry fee is infeasible (if it costs users less to enter the platform and collect it), but a voucher to reduce the transaction price for winning bidders would also stimulate entry. In a similar vein, the next section discusses a negative buyer commission to encourage bidder entry.
As documented above, bidders generate stronger indirect network effects than sellers, which is partly driven by the fact that any additional sellers attracted to the platform set higher reserve prices. This is not lost on platform management, who, up to a nonnegativity constraint, have set the lowest optimal buyer commission \( c_B = 0 \) and bidder entry fee \( e_B = 0 \). The previous section discussed the benefits of subsidizing bidder entry by, for instance, lowering the cost of inspecting a listing or by giving cash back to winning bidders. Here, a negative buyer commission is considered, which is merely a discount on successful sales. While charging negative commissions would certainly be innovative in the auction platform world, it is similar to the (temporary) discount vouchers periodically offered on eBay or the cash-back policies of certain credit cards.

To study the impact of fee changes on the composition of listings on the platform, in addition to those related to seller heterogeneity, the results in this Section include homogenized auctions based on parameter estimates from the high-end sample. Figure 5, plot (a), illustrates that also in this richer setting a self-imposed nonnegativity constraint on the buyer commission is binding. The plot shows that platform revenues cannot increase by changing the allocation of commissions to buyers and sellers unless buyers are subsidized through a winning bidder discount. When doing so, the estimates reveal that volume-constrained revenues can increase by over 40 percent when combining a negative \( c_B \) with a larger increase in \( c_S \). The latter is needed to finance the winning bidder discount. Such a change results in a higher commission index and generates benefits through the selection of sellers with lower valuations.

In the unit–percentage seller fee space, when \( c_B = 0 \), the volume- and revenue index levels are parallel to each other in both the main and the high-end sample. Hence, any global improvement requires a buyer discount to relax the volume constraint and/or relies on compositional changes from changing the share of high-end listings on the platform. To illustrate, with a 10 percent buyer discount, the platform achieves a 30 percent revenue increase (without reducing volume) either by increasing \( c_S \) to 0.23 or by increasing the listing fee to approximately 19 GBP (Figure 5, plot b). The latter policy is especially attractive for a platform interested in establishing itself in the higher-end market, as the share of high-end listings increases by 20 percent. However, given that the buyer discount costs more for high-end listings at the estimated parameter values, the share of profits from high-end listings decreases by 52 percent in the high-unit fee scenario, while the high-end profit share increases by 8.5 percent in the high-percentage fee case.

The model relies on the monopoly position of the platform, which is motivated by the fact that BW is the only large UK wine auction platform that uses an unvetted seller-managed listing format.
(a) \((c_B,c_S)\) at baseline \(e_S\)

(b) \((e_S,c_S)\) at \(c_B = -0.1\)

Figure 5. : Platform revenue at alternative fee structures

Contour plots of simulated platform revenues, normalised by baseline revenues. Grey vertical bar corresponds to \(c_S \in [0.9\ (\text{high-end}), 0.102\ (\text{main sample})]\), horizontal bars indicate baseline \(c_B = 0, e_S = 2.1\), i.e. their baseline levels including 20% VAT. For plot a the game is estimated on a grid of: \(c_B \times c_S\ (c_B = \{-0.3, -0.2, -0.1, 0, 0.1\}, c_S = \{-0.1, 0, 0.1, 0.2, 0.3\})\) and for plot b on a grid of \(e_L \times c_S\ (e_L = \{0.1, 1.75, 5, 10, 15, 20\}, c_S = \{-0.1, 0, 0.1, 0.2, 0.3\})\), and in both cases interpolated linearly. Results are based on parameter estimates from both main and high-end samples.

An interesting direction for further research would be to model the competition in fee structures between (auction) platforms. While such an analysis is beyond the scope of this paper, we can consider briefly two non-differentiated platforms competing only with one fee. If a competing platform best-responds to a fee increase on BW by also increasing its fee, this would appear as a higher entry (opportunity) cost for the targeted users. In that case, users’ true entry elasticity with respect to an increase in the fee on BW would be lower than simulated, and the estimated revenue impacts of an increase in the fees on BW would be conservative.

C. Antitrust damages

The incidence of a (potentially anticompetitive) change in fees depends crucially on the assumptions made about entry and whether sellers set a reserve price. For instance, the idea that winning bidders are unaffected by changes in either the buyer or seller commission (as argued in, e.g., McAfee (1993), Ashenfelter and Graddy (2005), and Marks (2009)) is correct only in a market without entry and with fully elastic sellers. A different paradigm was adopted in the 2001 Sotheby’s and Christie’s commission fixing case: in the absence of a method for evaluating the incidence of

\[^{57}\text{As a starting point for further analysis, Karle, Peitz and Reisinger (2020) provide a competing platform model with a negative seller-side externality. E-commerce platforms compete in the listing fee in a model where the competition among homogeneous-cost sellers intensifies in the number of competing sellers that post a listing in the same product category.}\]
commission increases, pro-rata damages were deemed appropriate and most of the $512 million settlement went to the winning bidders.\(^{58}\) With this rule of thumb, damages to buyers (sellers) are equal to the overcharge in buyer (seller) commissions as a share of the realized hammer price. An advantage of the structural approach advocated for in this paper is that it allows for the estimation of the welfare impacts of any fee change without having to rely on such rules of thumb.\(^{59}\)

This is demonstrated by simulating the effects of a doubling of the commission index by increasing the seller commission from 0.102 to 0.204. The results are reported in Table 8 and further illustrate the bias present in simpler models without (seller) entry.\(^{60}\) One take-away from the table is that while in the two referenced benchmark paradigms the incidence of the seller commission increase falls for 100 percent on sellers, this number is substantially lower when accounting for entry. At the estimated values of the model primitives, the incidence on sellers drops to 91 percent when accounting only for whether they set reserve prices (see the “no entry” row in Table 8). When bidder entry is also endogenized, but the set of listings is held constant (the “no seller entry” row), the incidence on sellers drops further to 76 percent. Fewer bidders enter because reserve prices are higher so the additional loss in seller surplus is driven by the exclusion of some bidders who would have become the highest bidders. In the full two-sided entry equilibrium also the number of listings also decreases, although the entry of additional bidders attracted by the more favorable reserve price distribution on the platform undoes part of the reduction in seller surplus. In this case, the incidence on sellers is only 60 percent.

Moreover, instead of suffering no welfare loss at all as in the two benchmarks, buyers are estimated to experience substantial damages of 7.5 percent of the average hammer price. The estimated loss in buyer surplus in the full two-sided entry model is larger than when shutting down the entry response on both sides (1 percent) or when only allowing bidders to enter endogenously (3.9 percent).

7. Conclusions

This paper studies an auction platform with two-sided entry. A structural model is presented that captures user interactions on such a platform in order to study the welfare and revenue impacts of the platform’s fee structure. A computationally feasible estimation algorithm is provided, and


\(^{59}\) Of course, the structural approach also facilitates the simulation of the welfare impacts of multiple simultaneous fee changes and allows for more detailed breakdowns by user subgroups, if desired.

\(^{60}\) Damages are computed as the reduction in expected surplus resulting from the increase in commission for groups of (expected) buyers and sellers on the platform and per-user as a percentage of the expected counterfactual hammer price. For an equivalent increase in the commission index brought about by increasing the buyer commission to 0.1281, the total damages and the incidence on sellers are the same, but because the hammer price decreases by more, the estimated percentage damages are larger. These results are provided in Appendix C.
Table 8—: Antitrust damages of doubling the commission index \( (c_S + 0.102) \)

<table>
<thead>
<tr>
<th></th>
<th>Total damage (1000s GBP)</th>
<th>Incidence on sellers (%)</th>
<th>Hammer price (% change)</th>
<th>Buyer damage (% post-hammer)</th>
<th>Seller damage (% post-hammer)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Benchmark elastic seller</td>
<td>100.0</td>
<td>0.0</td>
<td>0.0</td>
<td>10.2</td>
<td>10.2</td>
</tr>
<tr>
<td>Benchmark pro-rata</td>
<td>100.0</td>
<td>0.0</td>
<td>0.0</td>
<td>10.2</td>
<td>10.2</td>
</tr>
<tr>
<td>Simulated impacts:</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No entry</td>
<td>13.4</td>
<td>91.1</td>
<td>-4.1</td>
<td>1.0</td>
<td>10.5</td>
</tr>
<tr>
<td>No seller entry</td>
<td>16.8</td>
<td>76.3</td>
<td>-6.0</td>
<td>3.9</td>
<td>12.5</td>
</tr>
<tr>
<td>Full two-sided entry</td>
<td>17.1</td>
<td>60.7</td>
<td>-0.9</td>
<td>7.5</td>
<td>11.6</td>
</tr>
</tbody>
</table>

Simulations are based on homogenized auctions with \( r > 0 \) in the main sample. To stay close to antitrust applications, damages are computed as a share of the counterfactual expected hammer price (expected sale probability multiplied by the expected transaction price conditional on a sale). Buyer and seller damages are computed in expectation for groups of buyers and sellers, with a buyer being the in expectation winning bidder, including in unsold listings. In the pro-rata benchmark, the damage to buyers (sellers) equals the amount of overcharge of the buyer (seller) commission. In the elastic seller benchmark, the damage to buyers is none while the damage to sellers is the amount of overcharge of either buyer or seller commission.

it is shown that the relevant model primitives are nonparametrically identified with basic auction data. The model is estimated with data from a wine auction platform —after presenting reduced form evidence supporting the model assumptions— and is shown to fit the data well.

Counterfactual simulations highlight that the network effects generated by entry and by user interactions are nonlinear, the selection of sellers with higher valuations depletes much of the indirect network effect on bidders, and the benefit of additional bidder entry is lower for higher-valuation sellers. What is termed a “lemons effect” clearly illustrates the role of seller selection in this two-sided market. The reduction in surplus due to an increase in the unit listing fee by one GBP is, for sellers who remain on the platform, less than one as it causes some higher-valuation sellers (“lemons”) to choose not to enter. As such, the platform becomes more attractive to potential bidders, which drives up transaction prices for the remaining sellers. This effect increases with the degree of seller heterogeneity in the market. Furthermore, pairing the listing fee increase with a budget-neutral bidder entry subsidy (weakly) increases the expected surplus for all users on the platform, including for sellers, despite paying more to create a listing on the platform.

Platform revenues can increase significantly when a bidder discount (negative buyer commission) is combined with higher seller fees. The results furthermore account for compositional effects beyond those on the distribution of seller valuations through the use of model estimates from a sample of higher-end wines. Increasing the unit listing fee rather than the percentage seller commission results in a platform with relatively more higher-end listings but a lower profit share from those listings.

The results highlight that the economic principles underlying regulations in traditional markets do not necessarily apply to two-sided markets and that both sides should be evaluated in tandem.
A competitive auction platform could combine high fees on one side of the market with below-marginal cost prices on the other side. Both practices could be considered predatory when evaluated in isolation, but they prove to be socially optimal in the two-sided market in this paper. In recent years, competition authorities and courts have also recognized that the regulation of platform markets requires new empirical models, but the perceived difficulty of quantifying user interactions has been a bottleneck for the practical application of these ideas. While the empirical results presented here are based on a specific platform, this paper provides the tools necessary to make much needed progress in applying antitrust policy to two-sided markets.
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REFERENCES


A. Omitted proofs

**Proof Lemma 2: Optimal reserve price.** This Section derives the optimal reserve price for sellers with \( V_0 = v_0 \). Hat and check notation is defined 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:

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

The three terms in the above equation 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 \( r \):

\[
\frac{\partial R}{\partial r} = v_0 n F_V(\hat{r})^{n-1} f_V(\hat{r})(1 + c_B) + (1 - c_S) n F_V(\hat{r})^{n-1} [1 - F_V(\hat{r})] +
\]
\[
+ (1 - c_S) r n (n - 1) F_V(\hat{r})^{n-2} f_V(\hat{r})(1 + c_B)[1 - F_V(\hat{r})] - (1 - c_S) r n F_V(\hat{r})^{n-1} f_V(\hat{r})(1 + c_B)
\]
\[
- (1 - c_S) r n (n - 1) F_V(\hat{r})^{n-2} [1 - F_V(\hat{r})] f_V(\hat{r})(1 + c_B)
\]

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

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

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

**Proof Lemma 3: Listing-level properties.** \( \frac{\partial \pi_b(n,f,v_0)}{\partial n} < 0 \) (defined in [3]) because \( F_V \) satisfies the increasing failure rate (IFR) property. [L][2005] prove that a monotonically nondecreasing failure rate implies decreasing spacings so that \( E[V_{(n+1):n+1}] - E[V_{(n):n}] - E[V_{(n):n+1}] - E[V_{(n-1):n}] \leq 0 \). 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 \( v_0 \leq v_0^R \) sellers set no reserve price so in that case \( \pi_b(n,f,0) \) 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, \( \frac{\partial \pi_s(n,f,v_0)}{\partial n} > 0 \) (defined in [4]) 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 this is because higher seller values reduce gains from trade.

Proof Lemma 4: Poisson decomposition property for number of bidders per listing. 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 sort 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.

\[
(A.4) \quad f_{N_t,N_{-t}}(m, n) = \exp(-\lambda)\lambda^{m+n} \frac{(m+n)!}{m!n!} (q)^m (1-q)^n
\]

This joint distribution function can be manipulated to conclude that:

\[
f_{N_{i}}(m) = \sum_{n=0}^{\infty} \frac{\exp(-\lambda q)(\lambda q)^m}{m!} \frac{\exp(-\lambda (1-q))(\lambda (1-q))^n}{n!} = \frac{\exp(-\lambda q)(\lambda q)^m}{m!}
\]

The above is referred to as the decomposition property of the Poisson distribution in Myerson (1998). Novel here is the stochastic nature of \( M \); the above shows that \( M \) does not need to be independent of \( T \). The \( t \) subscript can be dropped from \( f_{N_{i}} \) as the distribution is identical for all listings \( t = \{1, .., T\} \).
B. Two-sided entry model: Extension to selective entry

This Section extends the model to one where bidders enter after knowing their valuation as in the models of Samuelson (1985) and Menezes and Monteiro (2000). Results are presented for the case with positive reserve prices, which generates the two-sidedness that is of main interest in this paper. By standard reasoning, the selective entry model results in an equilibrium where bidders enter if and only if their valuation exceeds the equilibrium threshold $v^*$. The distribution of valuations for bidders on the platform is denoted by $\forall v \in [v^*, \bar{v}]$:

$$F_{V|V \geq v^*}(v) = \frac{F_V(v)}{1 - F_Y(v^*)}$$

The auction stage equilibria remain the same as in the random entry model presented in the main text, as actions are taken after bidders learn their valuation in both cases. Listing-level expected surpluses are different from those in equations (3)-(6). The listing-level expected surplus for a bidder with valuation $v_i$ in a listing with $n - 1$ competing bidders, fee structure $f$, when the seller has a private value of $v_0$, and conditional on $v_i \geq \tilde{r}$:

$$\pi_b(v_i, n, f, v_0, v^*) = F_{V|V \geq v^*}(v_i)^{n-1}E^{v^*}[v_i - \max(V_{n-1}, \tilde{r})|V_{n-1} \leq v_i, v_i \geq \tilde{r}]$$

$\pi_b(v_i, n, f, v_0, v^*)$ conditions on $v_i \geq \tilde{r}$ because it takes the seller value $v_0$ as known at this point. The first part indicates the probability that $n-1$ competing bidders in the listing draw a lower value than $v_i$ —the probability of winning— and the second part consists of the expected surplus conditional on winning. The latter is computed with the distribution of valuations among bidders who enter the platform, indicated with the $v^*$ superscript on the expectation. The expected listing-level surplus for sellers is the same as in the random entry model, except that the expected transaction price is computed using $F_{V|V \geq v^*}(v)$:

$$\pi_s(n, f, v_0, v^*) \equiv \left(E^{v^*}[\max(V_{n-1}, \tilde{r})|V_{n} \geq \tilde{r}](1 - c_S) - v_0 \right) [1 - F_{V^*(n,n)}(\tilde{r})]$$

where $F_{V^*(n,n)}$ denotes the distribution of the highest out of $n$ values drawn from $F_{V|V \geq v^*}$. It is straightforward to see that, as in the random entry model, $\pi_b(v_i, n, f, v_0, v^*)$ decreases in $n$ and in $v_0$ and $\pi_s(n, f, v_0, v^*)$ increases in $n$ and decreases in $v_0$.

The next steps are to show how the equilibrium bidder entry threshold is best-responds to a candidate seller entry threshold $\tilde{v}_0$ and how the seller entry threshold is set in equilibrium. The bidder entry equilibrium is characterized as the threshold value that solves the marginal bidder’s zero profit
condition when other bidders also enter if and only if their valuation exceeds that threshold. Let \( \tilde{v} \) denote a candidate bidder entry threshold. Moreover, \( \Pi_{b,r>0}(v_i, f, \tilde{v}_0; \tilde{v}) \) denotes potential bidders’ expected surplus from entering the platform if they have valuation \( v_i \) and competing bidders adopt threshold \( \tilde{v} \). As in the random entry model, it builds on the listing-level expected bidder surplus and takes expectations over: 1) seller valuations \( V_0 \) given \( \tilde{v}_0 \), and 2) the number of competing bidders:

\[
\Pi_{b,r>0}(v_i, f, \tilde{v}_0; \tilde{v}) = \mathbb{E}[\pi_b(v_i, n + 1, f, v_0, \tilde{v}) | V_0 \in [v_0, \tilde{v}_0]] f_{N_{r>0},T_{r>0}}(n; \tilde{v}) dn - e_B - e_{B,r>0}
\]

Without imposing a large population approximation, \( f_{N_{r>0},T_{r>0}}(n; \tilde{v}) \) is Binomial, and it also depends on the total number of potential bidders in the population \( N_{r>0} \) and the observed number of listings \( T_{r>0} \):

\[
f_{N_{r>0},T_{r>0}}(n; \tilde{v}) = \binom{N_{r>0} - 1}{n} \left( \frac{1}{T_{r>0} (1 - F_V(\tilde{v}))} \right)^n \left( \frac{1}{T_{r>0} F_V(\tilde{v})} \right)^{N_{r>0} - 1 - n}
\]

where \( \frac{1}{T_{r>0} (1 - F_V(\tilde{v}))} \) is equal to the probability that a potential bidder enters (i.e., draws a valuation above \( \tilde{v} \)) the platform and is sorted to the same listing as bidder \( i \) (with uniform sorting, this happens with probability \( \frac{1}{T_{r>0}} \)). The following Lemma describes the bidder entry equilibrium.

**Lemma 7.** A unique entry equilibrium bidder entry threshold solves the marginal bidder’s zero profit condition:

\[
v^*(f, \tilde{v}_0) \equiv \arg\max_{\tilde{v} \in [v_0, \bar{v}]} \{ \Pi_{b,r>0}(\tilde{v}, f, \tilde{v}_0; \tilde{v}) = 0 \}
\]

**Proof.** The result relies on the facts that: 1) bidders have a unique best-response for any \( \tilde{v} \) because \( \Pi_{b,r>0}(v_i, f, \tilde{v}_0; \tilde{v}) \) is strictly increasing in their own \( v_i \), and 2) \( \Pi_{b,r>0}(v_i, f, \tilde{v}_0; \tilde{v}) \) is strictly increasing in \( \tilde{v} \) because the number of competing bidders is stochastically decreasing in \( \tilde{v} \), so the best-response function \( v^*(\tilde{v}) \) is downward-sloping in \( \tilde{v} \) and satisfies a single-crossing property. As such there is a unique symmetric equilibrium threshold \( v^* \), which is a fixed point as defined in (B.6) that makes the marginal bidder indifferent between entering and staying out.

The result holds for any realization of \( T_{r>0} \) given \( \tilde{v}_0 \). As in the baseline model, whether also a unique seller entry equilibrium exists depends on how the expected surplus of sellers is affected by \( v^*(f, \tilde{v}) \). We know that \( v^* \) decreases in \( \tilde{v} \) as it generates stochastically higher reserve prices on
the platform, and Menezes and Monteiro (2000) show that the expected seller revenue decreases in $v^*$. Expected seller surplus therefore decreases in competing sellers entry threshold, which is—as explained in the discussion of the equilibrium results in the main text—in the baseline model guaranteed by Lemma 5. In what follows, $f_{N^S>0,T_r>0}(n;v^*(\tilde{v}_0))$ describes the equilibrium distribution of the number of bidders per listing when sellers adopt entry threshold $\tilde{v}_0$.

The seller entry equilibrium is characterized by the $v^*_0$ that solves the zero profit entry condition for the marginal seller. Let $\Pi_s(f,v_0;\lambda^*_r>0(f,\tilde{v}_0),\tilde{v}_0)$ denote expected surplus for a seller with valuation $v_0 > v_0^R$ when $N^S - 1$ competing sellers enter the platform if and only if their valuation is less than threshold $\tilde{v}_0$. It involves: 1) their listing-level expected surplus, 2) an expectation over the number of bidders per listing given $\tilde{v}_0$ and bidders’ equilibrium best-response to this threshold captured with the equilibrium distribution of the number of bidders per listing, and 3) an expectation over the realized number of listings $T_r>0$ when $N^S$ potential sellers adopt entry threshold $\tilde{v}_0$:

(B.7) \[ \Pi_s(f, v_0; f_{N^S>0,T_r>0}(n;v^*(\tilde{v}_0)), \tilde{v}_0) = \sum_{T_r>0=1}^{N^S} \sum_{n=0}^{N^B} \pi_s(n,f,v_0,v^*(\tilde{v}_0)) f_{N^S>0,T_r>0}(n;v^*(\tilde{v}_0)) - e_S - e_S^0 \]

Lemma 8. A unique equilibrium seller entry threshold solves the marginal seller’s zero profit condition:

(B.8) \[ v^*_0(f) \equiv \arg_{v_0 \in (0,1)} \Pi_s(f, \tilde{v}_0; f_{N^S>0,T_r>0}(n;v^*(\tilde{v}_0)), \tilde{v}_0) = 0 \]

Proof. The proof requires three parts. First, sellers have a unique best-response for any competing $\tilde{v}_0$, because $\Pi_s(f, \tilde{v}_0; f_{N^S>0,T_r>0}(n;v^*(\tilde{v}_0)), \tilde{v}_0)$ strictly decreases in their own $v_0$. Second, given that 1) $\Pi_s(f, \tilde{v}_0; f_{N^S>0,T_r>0}(n;v^*(\tilde{v}_0)), \tilde{v}_0)$ strictly decreases in competing sellers’ $\tilde{v}_0$ because $v^*(\tilde{v}_0)$ decreases in $\tilde{v}_0$ and $\pi_s(n,f,v_0,v^*(\tilde{v}_0))$ decreases in $v^*$ (see e.g. Menezes and Monteiro (2000)), and 2) because 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, $v^*_0(f)$, which is the fixed point in seller value space solving (B.8) i.e., making the marginal seller indifferent between entering and staying out.

Compared to the random entry model presented in the main text, the seller best-response function $v^*_0(\tilde{v}_0)$ is less steep as the least attractive bidders refrain from entering when $\tilde{v}_0$ increases.
C. Omitted tables and figures

Table C. 1—Independent listings: regression analysis

<table>
<thead>
<tr>
<th>Dependent var:</th>
<th>bidders / listing</th>
<th>bids / bidder</th>
<th>transaction price</th>
<th>reserve price</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>coef.</td>
<td>s.e.</td>
<td>coef.</td>
<td>s.e.</td>
</tr>
<tr>
<td>Product: any wine</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>30 days</td>
<td>0.0002</td>
<td>(0.0002)</td>
<td>0.0002</td>
<td>(0.0002)</td>
</tr>
<tr>
<td>7 days</td>
<td>0.001</td>
<td>(0.001)</td>
<td>0.0003</td>
<td>(0.001)</td>
</tr>
<tr>
<td>2 days</td>
<td>0.001</td>
<td>(0.001)</td>
<td>0.001</td>
<td>(0.001)</td>
</tr>
<tr>
<td>Product: type (red)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>30 days</td>
<td>0.002</td>
<td>(0.002)</td>
<td>0.001</td>
<td>(0.001)</td>
</tr>
<tr>
<td>7 days</td>
<td>0.016</td>
<td>(0.005)</td>
<td>0.005</td>
<td>(0.004)</td>
</tr>
<tr>
<td>2 days</td>
<td>0.009</td>
<td>(0.006)</td>
<td>0.004</td>
<td>(0.005)</td>
</tr>
<tr>
<td>Product: region (Bordeaux)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>30 days</td>
<td>0.001</td>
<td>(0.001)</td>
<td>0.0002</td>
<td>(0.0004)</td>
</tr>
<tr>
<td>7 days</td>
<td>0.004</td>
<td>(0.002)</td>
<td>0.0003</td>
<td>(0.001)</td>
</tr>
<tr>
<td>2 days</td>
<td>0.004</td>
<td>(0.002)</td>
<td>0.001</td>
<td>(0.002)</td>
</tr>
<tr>
<td>Product: region x type</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>30 days</td>
<td>0.002</td>
<td>(0.002)</td>
<td>0.00001</td>
<td>(0.002)</td>
</tr>
<tr>
<td>7 days</td>
<td>0.015</td>
<td>(0.007)</td>
<td>0.004</td>
<td>(0.006)</td>
</tr>
<tr>
<td>2 days</td>
<td>-0.004</td>
<td>(0.010)</td>
<td>-0.002</td>
<td>(0.008)</td>
</tr>
<tr>
<td>Product: region x type x vintage</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>30 days</td>
<td>-0.010</td>
<td>(0.007)</td>
<td>-0.008</td>
<td>(0.006)</td>
</tr>
<tr>
<td>7 days</td>
<td>-0.026</td>
<td>(0.017)</td>
<td>-0.011</td>
<td>(0.015)</td>
</tr>
<tr>
<td>2 days</td>
<td>-0.049</td>
<td>(0.021)</td>
<td>-0.013</td>
<td>(0.018)</td>
</tr>
<tr>
<td>Product: subregion (Margaux) x type x vintage</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>30 days</td>
<td>-0.005</td>
<td>(0.004)</td>
<td>0.0002</td>
<td>(0.004)</td>
</tr>
<tr>
<td>7 days</td>
<td>0.004</td>
<td>(0.012)</td>
<td>-0.001</td>
<td>(0.010)</td>
</tr>
<tr>
<td>2 days</td>
<td>-0.010</td>
<td>(0.014)</td>
<td>0.003</td>
<td>(0.012)</td>
</tr>
<tr>
<td>Observations</td>
<td>3,500</td>
<td></td>
<td>3,500</td>
<td></td>
</tr>
<tr>
<td>Sample</td>
<td>all</td>
<td></td>
<td>all</td>
<td></td>
</tr>
</tbody>
</table>

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 and a market being all listings ending within a 30 day, 7 day, or 2 day rolling window of the listing. Regressions condition on product fixed effects.
Table C. 2—- Heckman selection model estimates suggestive of seller selection

<table>
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<th>First stage results</th>
<th>List=1</th>
<th></th>
<th></th>
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<tbody>
<tr>
<td></td>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>basic</td>
<td>elaborate</td>
</tr>
<tr>
<td>Market variables:</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td># Potential sellers, x1000</td>
<td>-3.248</td>
<td>-3.252</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(1.288)</td>
<td>(1.330)</td>
</tr>
<tr>
<td># Potential sellers r &gt; 0, x1000</td>
<td>0.071</td>
<td>-0.395</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(1.841)</td>
<td>(1.900)</td>
</tr>
<tr>
<td>Potential seller variables:</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Share of markets entered</td>
<td>4.314</td>
<td>4.267</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.282)</td>
<td>(0.302)</td>
</tr>
<tr>
<td># Listings other markets, x100</td>
<td>-1.427</td>
<td>-1.624</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.333)</td>
<td>(0.376)</td>
</tr>
<tr>
<td>(# Listings other markets, x100)^2</td>
<td>0.335</td>
<td>0.372</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.079)</td>
<td>(0.087)</td>
</tr>
<tr>
<td>Month account created (lower=older)</td>
<td>-0.033</td>
<td>0.016</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.011)</td>
<td>(0.014)</td>
</tr>
<tr>
<td># New members when joined</td>
<td>-0.001</td>
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<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.001)</td>
<td></td>
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<tr>
<td># New potential sellers when joined</td>
<td>0.022</td>
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<td></td>
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<tr>
<td></td>
<td></td>
<td>(0.005)</td>
<td></td>
</tr>
<tr>
<td># Ratings, x10.000</td>
<td>4.977</td>
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<td></td>
</tr>
<tr>
<td></td>
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<td>(3.464)</td>
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<tr>
<td>(# Ratings, x10.000)^2</td>
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<td></td>
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<td>(11.79)</td>
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<tr>
<td>Has negative ratings</td>
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<td>Share of ratings positive</td>
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<td>Share of ratings neutral</td>
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<td></td>
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<td>(21.510)</td>
<td>(28.918)</td>
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<table>
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<tr>
<th>Second stage results</th>
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<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>Inverse Mills ratio</td>
<td>-64.646</td>
<td>-57.205</td>
<td>0.083</td>
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<tr>
<td></td>
<td>(14.027)</td>
<td>(14.046)</td>
<td>(0.019)</td>
</tr>
<tr>
<td>First stage entry model</td>
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<td>elaborate</td>
<td>basic</td>
</tr>
<tr>
<td>Observations</td>
<td>3.500</td>
<td>3.500</td>
<td>3.500</td>
</tr>
<tr>
<td>Includes Z (auction descriptors)</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
</tr>
</tbody>
</table>

In the first stage, an observation is a potential seller-month combination, including all potential sellers who listed at least once during the sample period. The dependent variable in the first stage is a dummy equal to one if seller has at least one listing in the month (“List=1”). In the second stage, dependent variable r = 0 is a dummy equal to one if the seller has at least one listing with a zero reserve price, and dependent variable resid equals the estimated residual reserve price from a linear regression of the approximated reserve price on auction observables.
Table C. 3—: Suggestive evidence against bidder selection

**Panel A**

Dependent variable: sale price (conditional on sale), various samples and controls

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Number bidders in auction (standard error)</td>
<td>(1.146)</td>
<td>(1.170)</td>
<td>(1.170)</td>
<td>(0.432)</td>
<td>(0.427)</td>
<td>(0.428)</td>
<td>(0.618)</td>
<td>(0.642)</td>
<td>(0.643)</td>
</tr>
<tr>
<td>Product FE:</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Time trend:</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Sample</td>
<td>Full</td>
<td>Full</td>
<td>Full</td>
<td>Main</td>
<td>Main</td>
<td>Main</td>
<td>r = 0</td>
<td>r = 0</td>
<td>r = 0</td>
</tr>
<tr>
<td>Observations</td>
<td>2,235</td>
<td>2,235</td>
<td>2,235</td>
<td>1,874</td>
<td>1,874</td>
<td>1,874</td>
<td>985</td>
<td>985</td>
<td>985</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.078</td>
<td>0.274</td>
<td>0.274</td>
<td>0.117</td>
<td>0.350</td>
<td>0.349</td>
<td>0.179</td>
<td>0.330</td>
<td>0.332</td>
</tr>
</tbody>
</table>

**Panel B**

Dependent variable: hammer price (unconditional on sale), various product/market definitions

<table>
<thead>
<tr>
<th></th>
<th>(B1)</th>
<th>(B2)</th>
<th>(B3)</th>
<th>(B4)</th>
<th>(B5)</th>
<th>(B6)</th>
<th>(B7)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number bidders in auction</td>
<td>10.130</td>
<td>10.742</td>
<td>10.710</td>
<td>10.659</td>
<td>10.666</td>
<td>10.172</td>
<td>8.804</td>
</tr>
<tr>
<td>Number bidders in auction (standard error)</td>
<td>(0.664)</td>
<td>(0.611)</td>
<td>(0.618)</td>
<td>(0.613)</td>
<td>(0.628)</td>
<td>(0.690)</td>
<td>(0.714)</td>
</tr>
<tr>
<td>Product FE:</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Time trend:</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Sample</td>
<td>r = 0</td>
<td>r = 0</td>
<td>r = 0</td>
<td>r = 0</td>
<td>r = 0</td>
<td>r = 0</td>
<td>r = 0</td>
</tr>
<tr>
<td>Observations</td>
<td>989</td>
<td>989</td>
<td>989</td>
<td>989</td>
<td>989</td>
<td>989</td>
<td>989</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.365</td>
<td>0.239</td>
<td>0.294</td>
<td>0.269</td>
<td>0.317</td>
<td>0.365</td>
<td>0.346</td>
</tr>
</tbody>
</table>

Product/market specifications in Panel A: All columns: type×vintage×region, 4 weeks. Product/market specifications in Panel B: (B1): type×vintage×region, 4 weeks, (B2)-(B7) market: 2 day rolling window, (B2) any wine, (B3) type, (B4) region, (B5) region×type, (B6) region×type×vintage, (B7) subregion×type×vintage. “Product FE” stands for Product fixed effects. Results from column (B1) are reported in the main text.
Table C.4—: Auction covariates and price: results from homogenization step

<table>
<thead>
<tr>
<th></th>
<th>Main sample</th>
<th></th>
<th>High-end sample</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Point estimate</td>
<td>Std.error</td>
<td>Point estimate</td>
<td>Std.error</td>
</tr>
<tr>
<td>Number bottles</td>
<td>-0.3386</td>
<td>0.0552</td>
<td>-0.2278</td>
<td>0.0277</td>
</tr>
<tr>
<td>Number bottles(^2)</td>
<td>0.0142</td>
<td>0.0035</td>
<td>0.0048</td>
<td>0.0010</td>
</tr>
<tr>
<td>Contains more than one bottle</td>
<td>-0.2344</td>
<td>0.0801</td>
<td>0.5018</td>
<td>0.0848</td>
</tr>
<tr>
<td>Case of 6</td>
<td>0.4517</td>
<td>0.1244</td>
<td>-0.1969</td>
<td>0.0904</td>
</tr>
<tr>
<td>Case of 12</td>
<td>0.6933</td>
<td>0.2299</td>
<td>0.0915</td>
<td>0.1407</td>
</tr>
<tr>
<td>Special format bottle</td>
<td>0.1228</td>
<td>0.0685</td>
<td>0.1438</td>
<td>0.0932</td>
</tr>
<tr>
<td>Stored in bonded warehouse</td>
<td>0.3102</td>
<td>0.2072</td>
<td>-0.1647</td>
<td>0.1845</td>
</tr>
<tr>
<td>Month auction ends</td>
<td>-0.0136</td>
<td>0.004</td>
<td>-0.0039</td>
<td>0.0061</td>
</tr>
<tr>
<td><strong>Seller’s description of item:</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Textual description related to “en Primeur”</td>
<td>0.1765</td>
<td>0.0472</td>
<td>0.0358</td>
<td>0.0496</td>
</tr>
<tr>
<td>Textual description related to delivery / shipping</td>
<td>-0.0086</td>
<td>0.0387</td>
<td>-0.0017</td>
<td>0.0476</td>
</tr>
<tr>
<td>Textual description related to expert opinion</td>
<td>0.1766</td>
<td>0.0417</td>
<td>-0.0475</td>
<td>0.0581</td>
</tr>
<tr>
<td>Number words in textual description</td>
<td>0.0011</td>
<td>0.0002</td>
<td>0.00018</td>
<td>0.0003</td>
</tr>
<tr>
<td><strong>Delivery and payment options:</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Duty estimate</td>
<td>-0.0171</td>
<td>0.0096</td>
<td>-0.0027</td>
<td>0.0070</td>
</tr>
<tr>
<td>VAT estimate</td>
<td>0.0066</td>
<td>0.0154</td>
<td>0.0005</td>
<td>0.0038</td>
</tr>
<tr>
<td>Delivers to UK</td>
<td>0.0234</td>
<td>0.0489</td>
<td>-0.0828</td>
<td>0.0611</td>
</tr>
<tr>
<td>Returns accepted</td>
<td>-0.2120</td>
<td>0.1445</td>
<td>-0.0999</td>
<td>0.1074</td>
</tr>
<tr>
<td>Payment by bank</td>
<td>0.3009</td>
<td>0.0866</td>
<td>0.0166</td>
<td>0.1192</td>
</tr>
<tr>
<td>Payment by Paypal</td>
<td>-0.1221</td>
<td>0.0457</td>
<td>-0.1554</td>
<td>0.0587</td>
</tr>
<tr>
<td>Payment by cheque</td>
<td>0.0589</td>
<td>0.0515</td>
<td>-0.0279</td>
<td>0.0616</td>
</tr>
<tr>
<td>Payment in cash</td>
<td>0.0545</td>
<td>0.1115</td>
<td>0.2319</td>
<td>0.1365</td>
</tr>
<tr>
<td>Ships with Royal Mail</td>
<td>0.0494</td>
<td>0.0503</td>
<td>-0.1972</td>
<td>0.0873</td>
</tr>
<tr>
<td>Ships with Parcel Force</td>
<td>-0.1776</td>
<td>0.0493</td>
<td>-0.1972</td>
<td>0.0873</td>
</tr>
<tr>
<td>Ships fast</td>
<td>0.3437</td>
<td>0.0684</td>
<td>-0.1491</td>
<td>0.1062</td>
</tr>
<tr>
<td>Insurance included</td>
<td>0.1274</td>
<td>0.0433</td>
<td>0.0009</td>
<td>0.0507</td>
</tr>
<tr>
<td>Can be collected in person</td>
<td>0.0833</td>
<td>0.0446</td>
<td>-0.0525</td>
<td>0.0556</td>
</tr>
<tr>
<td>Can only be collected in person</td>
<td>-0.0183</td>
<td>0.1056</td>
<td>-0.1262</td>
<td>0.1224</td>
</tr>
<tr>
<td>Lowest shipping cost quote</td>
<td>0.0094</td>
<td>0.0039</td>
<td>0.0033</td>
<td>0.0028</td>
</tr>
<tr>
<td><strong>Seller ratings:</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Seller has ratings</td>
<td>-0.1591</td>
<td>0.0540</td>
<td>-0.0004</td>
<td>0.0003</td>
</tr>
<tr>
<td>Number seller ratings</td>
<td>-0.0008</td>
<td>0.0002</td>
<td>-0.0806</td>
<td>0.0536</td>
</tr>
<tr>
<td>Number seller ratings(^2)</td>
<td>3.6e-07</td>
<td>6.9e-08</td>
<td>2.0e-07</td>
<td>1.3e-07</td>
</tr>
<tr>
<td><strong>Fill level:</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mid Shoulder (HS)</td>
<td>-0.3737</td>
<td>0.2259</td>
<td>-0.0988</td>
<td>0.1425</td>
</tr>
<tr>
<td>Into Neck (IN)</td>
<td>-0.1298</td>
<td>0.1813</td>
<td>0.0400</td>
<td>0.0609</td>
</tr>
<tr>
<td>High Shoulder (HS)</td>
<td>-0.0365</td>
<td>0.1730</td>
<td>-0.0365</td>
<td>0.1730</td>
</tr>
<tr>
<td>Missing</td>
<td>-0.0567</td>
<td>0.1863</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Top Shoulder (TS)</td>
<td>-0.4374</td>
<td>0.2189</td>
<td>0.2645</td>
<td>0.2474</td>
</tr>
<tr>
<td>Very Top Shoulder (VTS)</td>
<td>-0.0797</td>
<td>0.1106</td>
<td>-0.0797</td>
<td>0.1106</td>
</tr>
<tr>
<td>Base of Neck (BN)</td>
<td>-0.2162</td>
<td>0.1883</td>
<td>0.0087</td>
<td>0.0971</td>
</tr>
<tr>
<td>Constant</td>
<td>3.8629</td>
<td>0.2203</td>
<td>5.6440</td>
<td>0.2127</td>
</tr>
</tbody>
</table>

Results from OLS regressions based on auctions with no reserve price and with at least two bidders, where the observed transaction price is interpreted as the second-highest bid. The dependent variable is the log of the transaction price normalized by the number of bottles in the auction. The main sample has auction transaction prices ≤ 200 GBP, and the high-end sample has transaction prices between 200-1500 GBP.
### Table C. 5—: Antitrust damages of doubling commission index \((c_B + 0.1281)\)

<table>
<thead>
<tr>
<th>Simulated impacts</th>
<th>Total damage (1000s GBP)</th>
<th>Incidence on sellers (%)</th>
<th>Hammer price (% change)</th>
<th>Buyer damage (% post-hammer)</th>
<th>Seller damage (% post-hammer)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Benchmark pro-rata</td>
<td>0.0</td>
<td>0.0</td>
<td>12.81</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>Benchmark elastic sellers</td>
<td>100.0</td>
<td>-11.36</td>
<td>0.0</td>
<td>12.81</td>
<td>0.0</td>
</tr>
<tr>
<td>Simulated impacts:</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No entry</td>
<td>13.5</td>
<td>90.5</td>
<td>-15.0</td>
<td>1.2</td>
<td>11.8</td>
</tr>
<tr>
<td>No seller entry</td>
<td>16.5</td>
<td>76.9</td>
<td>-16.5</td>
<td>4.2</td>
<td>14.0</td>
</tr>
<tr>
<td>Full two-sided entry</td>
<td>17.0</td>
<td>61.0</td>
<td>-12.1</td>
<td>8.3</td>
<td>13.0</td>
</tr>
</tbody>
</table>

Simulations based on homogenized auctions with \(r > 0\) in the main sample. To stay close to antitrust applications, damages are computed as a share of the counterfactual expected hammer price (expected sale probability multiplied by the expected hammer (transaction) price conditional on a sale). Buyer and seller damages are computed in expectations for groups of buyers and sellers, with a buyer being the in expectation winning bidder, including in unsold listings. Increasing the buyer commission from 0 to 0.1281 brings about the doubling of the commission index, just as increasing the seller commission from 0.102 to 0.204 as done in Table 8 in the main text.
Figure C.1: Ullage classification and interpretation

Source: [https://www.christies.com/Wine/Ullages_2013.pdf](https://www.christies.com/Wine/Ullages_2013.pdf), last accessed December 23, 2021. 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.
Nuits St George Les Boudots Domaine Leroy

Sold by: **winesnake** (13 ratings, 79% positive, 0% neutral)

- [Email the seller](#)
- [Show my bids on this auction](#)
- [Add this auction to my watch list](#)

**BID NOW**

(At least £52.00)

<table>
<thead>
<tr>
<th>Your maximum bid: 8</th>
<th>£</th>
</tr>
</thead>
<tbody>
<tr>
<td>Place Bid Now</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>1</th>
<th>1</th>
<th>£50.00</th>
<th>2d 19h</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bid placed</td>
<td>No. of Bidders</td>
<td>Current price</td>
<td>Remaining time</td>
</tr>
</tbody>
</table>

Lot size: 1 bottle of 750 ml each  
Wine type: Red, 1985 vintage  
Origin: Burgundy, France  
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 fraction 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 C.2. : Listing page example
SUPPLEMENTARY MATERIAL FOR ONLINE APPENDIX

Additional details entry equilibrium and results without large population approximation

This supplementary material provides further intuition behind the entry equilibrium. It also shows that the large population approximation is merely adopted for computational feasibility and does not drive the results. For brevity, attention is limited to auctions with \( r > 0 \) as they provide the more interesting case with two-sided entry. As before, \( \tilde{r} \) denotes the optimal reserve price increased with buyer premium, \( \tilde{r} = (1 + c_B) r^\ast (v_0, f) \), and the number of listings \( T_{r>0} \) is known to potential bidders before entering, and bidders are sorted with equal probability over available listings. Also, \( \tilde{v}_0 \) denotes a candidate seller entry threshold and \( \Pi_{b,r>0}(f, \tilde{v}_0; p) \) potential bidders’ expected surplus from entering the platform as a function of their entry probability \( p \):

\[
\text{(OA.1)} \quad \Pi_{b,r>0}(f, \tilde{v}_0; p) = \sum_{n=0}^{N_{B,r>0} - 1} \mathbb{E}[\pi_b(n + 1, f, v_0)|V_0 \in [v_0^R, \tilde{v}_0]f_{N_{r>0},T_{r>0}}(n; p) - e_B - e_{B,r>0}]
\]

It takes the expectation of \( \pi_b(n, f, v_0) \) (equation 3 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. 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, as entry cost \( e_{B,r>0} \) are associated with each listing. Components of equation (OA.1) are:

\[
\text{(OA.2)} \quad \mathbb{E}[\pi_b(n + 1, f, v_0)|V_0 \in [v_0^R, \tilde{v}_0]] = \int_{v_0^R}^{\tilde{v}_0} \pi_b(n + 1, f, v_0)f_{V_0|V_0 \in [v_0^R, \tilde{v}_0]}(v_0)dv_0
\]

\[
\text{(OA.3)} \quad f_{N_{r>0},T_{r>0}}(n; p) = \binom{N_{B,r>0} - 1}{n} (\frac{p}{T_{r>0}})^n (1 - \frac{p}{T_{r>0}})^{N_{B,r>0} - 1 - n}
\]

where \( f_{N_{r>0},T_{r>0}}(n; p) \) 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.

\( \pi_b(n+1, f, v_0) \) is strictly decreasing in \( n \) (Lemma 3). Hence, 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 solves zero profit condition:

\[
\text{(OA.4)} \quad p^\ast_{T_{r>0}}(T_{r>0}, f, \tilde{v}_0) \equiv \arg_{p \in (0,1)} \Pi_{b}^{T_{r>0}}(f, \tilde{v}_0; p) = 0
\]

In this equilibrium the number of (competing) bidders per listing follows a Binomial distribution
with mean \((N_{B,r>0} - 1)\frac{\hat{p}^*_{r>0}}{Tr_{r>0}}\) and variance \((N_{B,r>0} - 1)\frac{1 - \hat{p}^*_{r>0}}{Tr_{r>0}}\). Furthermore, a no-trade entry equilibrium at \(p = 0\) that trivially solves (OA.4) always exists, and it is excluded from the analysis based on the empirical observation that bidders currently play the positive trade equilibrium.

A key property is that \(\hat{p}^*_{r>0}T_{r>0}\) is independent of \(T_{r>0}\) conditional on \(\tilde{v}_0\). Bidders only derive positive surplus from the listing that they are matched to, and in the presented auction platform model \(T_{r>0}\) itself does not affect \(E[\pi_b(n + 1, f, v_0)|V_0 \in [v_0^R, \tilde{v}_0]]\). The zero profit condition therefore guarantees that in equilibrium a change in \(T_{r>0}\) causes \(\hat{p}^*_{r>0}T_{r>0}\) to adjust to keep \(f_{N_{r>0},T_{r>0}}(\cdot)\) constant.

**Additional details estimation algorithm**

This section provides details about the estimation of structural parameters not included in the main text. This regards \(\hat{e}^0_{B,r>0}, \hat{e}^0_{B,r=0}, \hat{e}^0_S,\) and \(\hat{p}_{0,r>0}\).

The estimated entry cost (opportunity cost of time) solve the relevant zero profit conditions, given estimated parameters \((\hat{\theta}_b, \hat{\theta}_s, \hat{v}_0^R, \hat{p}_{0,r>0})\) and given the entry equilibrium at those parameters. As estimating \(\hat{\theta}_s\) itself requires one iteration of solving for the entry equilibrium given initial parameters \(\hat{\theta}_s^0\), the estimation algorithm proceeds as follows. First, based on \(\hat{v}_0^R\) and \(\hat{v}_{T_{r>0}}\), estimate \(\hat{\theta}_s^0\) by maximum concentrated likelihood as described in the main text. Then, solve for initial entry cost estimates \((\hat{e}^0_{B,r>0}, \hat{e}^0_{B,r=0}, \hat{e}^0_S)\) as detailed below. Given these initial estimates solve for \(v_0^*(f; \hat{\theta}_s^0, \hat{\theta}_b)\) and update seller parameters to \(\hat{\theta}_s\) as described. Finally, use these values to re-estimate the entry cost.

For \(\hat{e}^0_{B,r>0}\) and \(\hat{e}^0_{B,r=0}\), the initial estimator is the same as the final estimator although the latter is based on the updated \(\hat{\theta}_s\). They are estimated as the value of the entry cost that sets respectively the numerically approximated values of \(\Pi_{b,r>0}(\cdot)\) and \(\Pi_{b,r=0}(\cdot)\) equal to 0 as dictated by the zero profit entry condition. This clearly depends on the relevant distribution of the number of bidders per listing, and hence \(\hat{\lambda}^*_r\), \(\hat{p}_{0,r=0}\), and \(\hat{\lambda}^*_r\). In auctions with no reserve price, the mean observed \(N\) is a consistent estimator of \(\lambda^*_r=0\):

\[
(OA.5) \quad \hat{\lambda}^*_r = 0 = \frac{1}{|T_{r=0}|} \sum_{t \in T_{r=0}} n_t
\]

Note that \(\hat{\lambda}^*_r\) and \(\hat{\lambda}^*_r=0\) are only obtained to estimate entry cost and they are not treated as structural parameters. We now turn to the estimation of \(\hat{\lambda}^*_r\).

In positive reserve prices a difficulty is that only the actual number of bidders \(A\) is observed, which might be less than the number of bidders in the listing \(N\). In the BW data the reserve price...
is secret, but the platform provides some information about it (“reserve not met”, “reserve almost met”, or “” if the standing price exceeds the reserve). If the reserve price were observed (and the only reason for bidders not submitting a bid), a consistent estimate of \( \lambda_{r>0}^* \) equals the value that maximizes the likelihood of the homogenized second-highest bids \( b_t \) and number of actual bidders \( a_t \) in positive reserve auctions given estimated bidder valuation parameters and homogenized reserve prices \( r_t \). In particular, the joint density of \((b_t, a_t)\) if the number of potential bidders \( n_t \) would be known, with \( \tilde{r}_t = r_t(1 + c_B) \), \( \forall t \in T_{r>0} \):

\[
\text{(OA.6)} \quad h(b_t, a_t|n_t, r_t, \tilde{r}_t; \tilde{\theta}_b) = \{F_{\tilde{V}}(\tilde{r}_t; \tilde{\theta}_b)^{n_t}\} I\{a_t = 0\} \\
\{n_t F_{\tilde{V}}(\tilde{r}_t; \tilde{\theta}_b)^{n_t-1}[1 - F_{\tilde{V}}(\tilde{r}_t; \tilde{\theta}_b)]\} I\{a_t = 1\} \\
\{\binom{n_t}{a_t} F_{\tilde{V}}(\tilde{r}_t; \tilde{\theta}_b)^{n_t-a_t[1 - F_{\tilde{V}}(\tilde{r}_t; \tilde{\theta}_b)]^{a_t}} a_t(a_t-1)F_{\tilde{V}}(\tilde{b}_t; \tilde{\theta}_b)^{a_t-2}[1 - F_{\tilde{V}}(\tilde{b}_t; \tilde{\theta}_b)] F_{\tilde{V}}(\tilde{b}_t; \tilde{\theta}_b)\} I\{a_t \geq 2\}
\]

Note that \( h(b_t, a_t|n_t, r_t, \tilde{\theta}_b) = 0 \) when \( n_t = 0 \). The first line covers the probability that all \( n_t \) bidders draw a valuation below the reserve price, the second line the probability that one out of \( n_t \) draws a valuation exceeding \( \tilde{r} \) while the others don’t, 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 conditional value 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 \( N \sim \text{Pois}(\lambda_{r>0}^*, p_{0,r>0}) \).\(^{61}\)

Using the more flexible two-parameter Poisson distribution allows for an unspecified reason for observing no bids, in addition to all bids falling below the reserve price. This is the basis of the likelihood function that \((\lambda_{r>0}^*, \tilde{\theta}_0, p_{0,r>0})\) maximizes:

\[
\text{(OA.7)} \quad g(b_t, a_t|r_t, \tilde{r}_t; \tilde{\theta}_b; \lambda_{r>0}^*, p_{0,r>0}) = \\
\sum_{k=a_t}^{\infty} h(b_t, a_t|n_t = k, r_t, \tilde{r}_t; \tilde{\theta}_b)f_{N_{r>0}|N_{r>0} \geq a}(k; \lambda_{r>0}^*, p_{0,r>0})
\]

\[
\text{(OA.8)} \quad \mathcal{L}((\lambda_{r>0}^*, p_{0,r>0}); \{b_t, a_t, r_t, \tilde{r}_t\}_{t \in T_{r>0}}) = \sum_{t \in T_{r>0}} \ln(g(b_t, a_t|r_t, \tilde{r}_t; \tilde{\theta}_b; \lambda_{r>0}^*, p_{0,r>0}))
\]

\(^{61}\)The generalized Poisson distribution has PDF:

\[
f_{N_{r>0}}(k; \lambda_{r>0}^*, p_{0,r>0}) = (1 - p_{0,r>0}) \frac{\exp(-\lambda_{r>0}^*)\lambda_{r>0}^*}{k!} + p_{0,r>0}I\{k = 0\}
\]

which reduces to a standard Poisson distribution for \( p_{0,r>0} = 0 \).
\[(\hat{\lambda}_{r>0}, \hat{p}_{0,r>0}) = \arg \max \mathcal{L}(\lambda_{r>0}^*, p_{0,r>0}; \{b_t, a_{t}, r_t, z_t\}_{t \in T_{r>0}})\]

The estimator does not require interpretation of losing bids. While the resulting estimator does capture the censoring of bidders to some extent, is not a full treatment of intra-auction dynamics.\footnote{Hickman, Hubbard and Paarsch (2017) (for the case of non-binding reserve prices) and Bodoh-Creed, Boehnke and Hickman (2020) (for binding reserve prices) provide more comprehensive models to account for intra-auction dynamics in ascending auctions. My empirical setting is in between these cases, with the platform revealing some information about the secret reserve price, and the algorithm proposed by Platt (2017) based on a Poisson arrival process would apply if \(p_{0,r>0} = 0\).}

Also the estimated \(\hat{\theta}_b\) are based on the assumption that the second-highest bid equates to the second-highest out of \(N = A\) values in no-reserve auctions. It is worth emphasizing that the effect of this abstraction is limited in my model with endogenous two-sided entry. To see why, consider the case where the true \(\lambda_{r>0}^*\) is larger than estimated due to some bidders entering after the standing bid exceeds their valuation. This implies that the true \(F_V\) would be stochastically dominated by the estimated distribution, as the transaction price is really the second-highest out of more draws from \(F_V\). The true \(\hat{e}_{B,r>0}\) would also have to be lower than estimated, as the per-bidder expected surplus from entering the platform is lower. Combined, counterfactual simulations based on these alternative primitives would deliver similar results. Without changing the fee structure, simulating entry decisions of lower-value potential bidders facing lower entry cost results in the exact same outcomes. As such, the abstraction from intra-auction dynamics is internally consistent although due to nonlinearities in the system the direction of the effect of the abstraction when changing fees cannot be signed ex-ante.

The above describes how initial values \(\hat{e}_{B,r=0}^{o,0}\) and \(\hat{e}_{B,r>0}^{o,0}\) are estimated. The initial value \(\hat{e}_S^{o,0}\) needs to be estimated differently, as pinning it down as the value that sets the surplus for a marginal seller with \(v_0 = \hat{v}_{T,r>0}\) equal to 0 guarantees that the updated \(v_0^*\) will always equal \(\hat{v}_{T,r>0}\). Instead, as \(\hat{v}_{T,r>0}\) is the sample maximum of a noisy first stage estimator and therefore likely overestimates the true \(v_0^*\), the initial \(\hat{e}_S^{o,0}\) is set to max(\(\hat{e}_{B,r>0}^{o,0}, \hat{e}_{B,r=0}^{o,0}\)). After simulating the entry equilibrium (described in the next section) at initial estimates, and re-estimating \(\hat{\theta}_S, \hat{e}_{B,r>0}^{o,0}, \hat{e}_{B,r=0}^{o,0}\), and \(\hat{e}_S^{o}\) are updated as the values that solve zero profit conditions at the equilibrium solution. Note that \(\hat{\theta}_h, \hat{v}_0^R, p_{0,r>0}, \lambda_{r>0}^*, \lambda_{r=0}^*\) are never updated in the estimation algorithm.

**Numerical approximation of the entry equilibrium**

Solving for the entry equilibrium involves hard to compute (triple) integrals. This section details the numerical approximations relied on for computational feasibility. The equilibrium is computed for homogenized auctions based on conditional value distributions. The notation also does not make explicit that these distributions are in fact the estimated conditional value distributions.
notation \( \tilde{r} = (1 + c_B)r^*(v_0, f) \) is used and sample size \( n \) is omitted from order statistics. The goal is to approximate for a given fee structure and set of parameter estimates the entry equilibrium \( \{ \lambda^*_{r>0}(f, v_0^*), \lambda^*_{r=0}(f), v_0^*(f) \} \) as respectively defined in (10), (11), and (13) in the main text. This requires computing the expected surplus from entering the platform for bidders and sellers as a function of \( \lambda \) and \( \tilde{v}_0 \), and then solving for the equilibrium values that satisfy the zero profit entry conditions.

To compute \( \Pi_{b,r>0}(f, \tilde{v}_0; \lambda_{r>0}) \) we need to obtain \( \pi_b(n, f, v_0) \) defined in (3) in expectation over \( v_0 \) and \( n \), minus entry cost:

\[
\Pi_{b,r>0,T_{r>0}}(f, \tilde{v}_0; \lambda) = \max(n-1) \sum_{n=0}^{\tilde{v}_0} \left[ \int_{v_0}^{\tilde{v}_0} \pi_b(n+1, f, v_0) \frac{f_{V_0\mid V_0 \geq v^R_0}(v_0)}{F_{V_0\mid V_0 \geq v^R_0}(v_0)} dv_0 \right] \times \\
\bar{f}_{N_{r>0}}(n; \lambda_{r>0}) - e_B - e^B_{B,r>0}
\]

\[
\pi_b(n, f, v_0) = \frac{1}{n} \int_{\tilde{r}}^{v_0} v_n - \max(\tilde{r}, \int_{v_n}^{v_0} v_{n-1}dF_{V_{n-1}\mid V_n = v_n(n-1)})dF_{V_n}(v_n)
\]

\[
F_{V_n}(v_n) = \int_{v_n}^{\bar{v}} nF_V(x)^{n-1}f_V(x)dx
\]

\[
F_{V_{n-1}\mid V_n = v_n(n-1)} = \int_{v_n}^{\bar{v}} \frac{(n-1)F_V(y)^{n-2}f_V(y)}{F_V(v_n)^{n-1}} dy
\]

and \( f_{N_{r>0}}(n; \lambda_{r>0}) \) defined in (7). This is then sufficient to compute \( \lambda^*_{r>0} \) for any value of \( \tilde{v}_0 \):

\[
\lambda^*_{r>0}(\tilde{v}_0) \equiv \arg\max \{ \Pi_{b,r>0}(f, \tilde{v}_0; \lambda) = 0 \}
\]

As \( \Pi_{b,r>0}(f, \tilde{v}_0; \lambda) \) strictly decreases in \( \lambda \), \( \lambda^*_{r>0} \) solves a threshold-crossing condition that is nested in the fixed point problem that defines \( v_0^*(f) \). Moreover, the triple integral makes \( \Pi_b(.) \) costly to compute for any candidate \( \tilde{v}_0 \). For auctions with a zero reserve price, \( \lambda^*_{r=0} \) is similarly computed as a threshold-crossing problem based on \( \Pi_{b,r=0} \):

\[
\Pi_{b,r=0}(f, \lambda_{r=0}) = \max(n-1) \sum_{n=0}^{\tilde{v}_0} \pi_b(n+1, f, 0) f_{N_{r=0}}(n; \lambda_{r=0}) - e_B - e^B_{B,r=0}
\]
with \( \pi_b(n+1, f, 0) \) defined in (6).

Computing \( \Pi_s(f, \tilde{v}_0; \lambda_{r>0}) \) relies on \( \pi_s(n, f, v_0) \) defined in (4) in expectation over the number of bidders, minus entry cost:

\[
\Pi_s(f, v_0; \lambda_{r>0}) = \sum_{n=0}^{N_{r>0}} \pi_s(n, f, v_0) f_{N_{r>0}}(n, \lambda_{r>0}^s(\tilde{v}_0)) - e_S - e_0^S
\]  

This is then sufficient to compute \( v_0^*(f) \) for any fee structure and given potential bidders’ best-response characterized by \( \lambda_{r>0}^s(f, \tilde{v}_0) \):

\[
v_0^* \equiv \arg \tilde{v}_0 \{ \Pi_s(f, \tilde{v}_0; \lambda_{r>0}^s(\tilde{v}_0)) = 0 \}
\]

Given high computational cost of implementing these functions literally, estimates relies on numerical approximations. The following pseudo-code is implemented to compute the entry equilibrium, where object names in bold facilitate easy replication with access to the computer 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 \( v_{\text{probs}} \) (making sure that \( 1 - e^{-4} \) and \( 1 - 1e^{-4} \) are lower bounds on extremum probabilities). Initiate a finer grid \( v_{\text{probs \_ fine}} \) by sampling 25000 values from Unif\((0, 1)\) with identical minimum extremum values. Simulate 500 values from Unif\((0, 1)\) and collect in vector \( v_0 \_probs \_ fine \) (making sure that \( 1 - e^{-4} \) and \( 1 - 1e^{-4} \) are lower bounds on extremum probabilities). Sample a coarser grid for seller values by drawing without replacement 48 values from \( v_0 \_probs \_ fine \) and add the extremum values, call this vector \( v_0 \_probs \). Set max\((n) = 15 \) (pick a sensible number based on estimated \( \lambda \)'s). Never change these values.

- **Importance sampling** of \( V_n \_n \) and \( V_{n-1:n}|V_n:n \). Set \( \tilde{v} = F_{n-1}^{-1}(1 - 1e^{-9}, \hat{\theta}_b) \) and \( v = 0 \). Code the distributions in (OA.12) and (OA.13). For each \( n = 1, ..., 15 \), simulate 250 values from the two distributions. For the highest valuation, solve for \( F_{n:n}^{-1}(v_{\text{probs}}; \hat{\theta}_b) \), separately for each \( n \), resulting in matrix \( h_{\text{mat}} \) of dimension \([250 \times 15]\). For the second-highest valuation, solve for \( F_{n-1:n|V_n:n=v_n}(v_{\text{probs}}; \hat{\theta}_b) \), where for each entry \( j \) in \( v_{\text{probs}} \) \( v_n \) equals the \( j \)th
entry in $h_{\text{mat}}$ from the relevant $n$ column. Doing this separately for each $n > 1$ results in matrix $sh_{\text{mat}}$ of dimension $[250 \times 15]$ with the first column made up of zeros.

- Linear interpolation of $h_{\text{mat}}$ and $sh_{\text{mat}}$ on finer grid using $v_{\text{probs}}_{\text{fine}}$, separately for each $n$ column. This results in two matrices of dimension $[25000 \times 15]$, $h_{\text{mat}}_{\text{fine}}$ and $sh_{\text{mat}}_{\text{fine}}$.

- Calculating optimal reserve price for grid of $v_0$’s. Importance sampling of $V_0$: solve for $F_{V_0}^{-1}(v_{0}\text{probs}; \hat{\theta}_s)$ and store in vector $v_{0}\text{vec}$ of dimension $[50 \times 1]$. Given also $\hat{\theta}_b$, compute optimal $r^*(v_{0}\text{vec})$ and store in vector $r_{\text{vec}}$.

- Compute listing-level bidder and seller surplus for $v_0$-$n$ combinations. Initiate matrices of $v_{0}\text{mat}$, $n_{\text{mat}}$, and $r_{\text{mat}}$ with values of $v_0$ in the first dimension and $n$ in the second dimension (so $n_{\text{mat}}$ and $r_{\text{mat}}$ are constant in the first dimension and $v_{0}\text{mat}$ is constant in the second dimension). These three matrices are of dimension $[50 \times 15]$. For each entry, use the pre-calculated matrices $h_{\text{mat}}_{\text{fine}}$ and $sh_{\text{mat}}_{\text{fine}}$ 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 $v0\text{idx}$ being the index of $v_0$ in the 2nd column of $v_{0}\text{mat}$. $\pi_0(2, f, v_0)$ is approximated as the mean of the second column of $h_{\text{mat}}_{\text{fine}}$ including only all values exceeding $r_{\text{mat}}(v0\text{idx}, 2) \times (1 + c_B)$, minus the mean of the same entries in $sh_{\text{mat}}_{\text{fine}}$ or minus $r_{\text{mat}}(v0\text{idx}, 2) \times (1 + c_B)$ if that is higher, and multiplied by the sale probability $(1 - F_V(\log((1 + c_B)r_{\text{mat}}(v0\text{idx}, 2)); \hat{\theta}_b)^2)$, all divided by two.

- Linear interpolation of listing-level surplus on $v_{0}\text{probs}_{\text{fine}}$. This results in listing-level surplus matrices of dimensions $[25000 \times 15]$ for bidders in positive reserve price auctions ($pib_{\text{posr}}_{\text{mat}}$), for sellers in positive reserve price auctions ($pis_{\text{posr}}_{\text{mat}}$), and for sellers in no reserve price auctions ($pis_{\text{nor}}_{\text{mat}}$). For bidders in auctions with no reserve price ($pib_{\text{nor}}_{\text{vec}}$) 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 $F_{V_0|V_0\geq v_0^0}^{-1}(v_{0}\text{probs})$ and interpolate on the finer $v_0$ grid, resulting in $pdf_{\text{v0}\text{mat}}$.

- 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 $\lambda_{r^*>0}^*$ for each candidate $\tilde{v}_0$ is fast and straightforward.
• Coding equation (OA.16) with nested in it equation (OA.14). Make sure that for every candidate \( \tilde{v}_0 \), the entries of pdf_\( \tilde{v}_0 \) mat that function as weights of the listing-level bidder surplus (the \( \int_{v_0 \mid \tilde{v}_0 \geq \tilde{v}_0} f(v_0) \) in (OA.10)) sum to one. The \( \lambda^*(\tilde{v}_0) \) in (OA.14) is obtained as the root of (\( \Pi_{\lambda}(f, \tilde{v}_0; \lambda) \)). MATLAB’s fzero function is used with tolerance levels for the function and parameter of 1e-6, which delivers stable results. Then (OA.16) is passed to a nonlinear 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 \( \Pi_s \) through its effect on the the equilibrium mean number of bidders \( \lambda_{r>0}^*(v_0^{-j}) \). 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 \( v_0^{-j} > v_0^* \): \( \lambda^*(v_0^{-j}) < \lambda_{r>0}^*(v_0^*) \) which means that \( \Pi_s(v_0^*, v_0^{-j}) < 0 \). Since \( \Pi_s \) 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 \( v_0^{-j} < v_0^* \): \( \lambda^*(v_0^{-j}) > \lambda_{r>0}^*(v_0^*) \) which means that \( \Pi_s(v_0^*, v_0^{-j}) > 0 \). With \( \Pi_s \) 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 cost 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 OA.19 is a contraction mapping.

**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. To relieve traffic pressure on the site bids are tracked 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.

The presented 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 nonparametric 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 $F^H_R$ and $F^M_R$ 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:

\[
D_{h,m} = \sup_x |F^H_R(x) - F^M_R(x)|,
\]

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 percent level ($D_{h,m} > 1.36\sqrt{\frac{h+m}{hm}}$), the p-value = 0.4406).