ESTIMATING AN AUCTION PLATFORM GAME WITH TWO-SIDED ENTRY

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Draft: January 27, 2023

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.

JEL: D44, C57, L10

Keywords: Ascending auctions, Auctions with entry, Seller selection, Structural estimation of games

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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.[1]

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.[2] 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.[3] 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 Hortaçsu and Perrigne (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 in an auction platform expect lower (reservation) prices when sellers who value their goods less are

[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).

[2] See Hendricks and Porter (2007) on the close links between auction theory, empirical practice and public policy.

[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 Jullien, Pavan, and Rysman (2021). For example (taken from Jullien, 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.

attracted to the platform, so bidder entry depends on both the expected number of sellers who enter and their types.[4] Quantifying the buyer-seller interaction and how it affects entry is important, as many markets are designed to sell goods or services from heterogeneous sellers.[5] For example, the peer-to-peer lending market, which is expected to grow globally to over US$ 700 billion by 2030, is designed for individual lenders to invest in loans by heterogeneous borrowers.[6] Selection is a highly-relevant aspect of the business model; attracting more creditworthy borrowers makes a lending platform more valuable to potential investors. By the same reasoning, platforms in the gig economy –already employing one-third of the US workforce– will be more valuable to job posters when they have a larger pool of qualified freelancers.[7]

The analysis exploits a new dataset of vintage wine auctions from an online marketplace that exhibits the high-level characteristics of such peer-to-peer platforms. Most importantly, the reduced-form evidence suggests that heterogeneous 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 first need to understand the wine's many idiosyncrasies, such as its fill level (informative about the amount of oxidation), whether it is stored in a temperature-controlled bonded warehouse, its provenance, delivery costs, and more.

Building on these empirical facts, a suitable auction platform game with two-sided entry is specified. 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 (e.g., marginal costs) 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

[4] 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. 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] At a high level, many peer-to-peer platforms such as Prosper, Upwork, Uship, Vinted, ClassicCarAuctions, or Bondora fit the characterization.

[6] The market forecast is available at https://www.precedenceresearch.com/peer-to-peer-lending-market, last accessed January 16, 2023.

[7] See https://www.forbes.com/sites/forbesbusinesscouncil/2021/08/12/will-the-gig-economy-become-the-new-working-class-norm/?sh=55d299fdaee6, last accessed January 17, 2023.

side.[8]

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.[9]

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.

The result that most clearly underscores the role of seller selection in the two-sided platform setting is that the reduction in seller surplus after a unit increase of the listing fee is less than one. It is driven by the positive externality that the exclusion of higher-valuation (cost) sellers from the platform has on other sellers, as this exclusion increases the equilibrium number of bidders in all remaining listings.[10] Consequentially, it is estimated that a 1 British Pound Sterling (henceforth: pound) increase in the listing fee lowers the expected surplus for sellers who remain on the platform by only 65-87 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 pound 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.

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

[8]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 D). 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.

[9]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).

[10]This is referred to as a "lemons effect" (after Akerlof (1970)), to emphasize that it crucially relies on the presence of private information by users on one side of the market about something that users on the other side of the market care about. In the auction platform setting, the lemons effect arises because bidders enter based on the expected distribution of unobserved reserve prices. In peer-to-peer lending platforms it would apply when borrowers have private information about their creditworthiness, as lenders care about the repayment probability (conditional on borrower observables).

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)).

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 has been assumed previously (in e.g., McAfee (1993), Ashenfelter and Graddy (2005), and Marks (2009)) even winning bidders are affected. Their surplus decreases by 7.6 percent of the counterfactual hammer price when the seller commission is doubled. However, 64 percent of the incidence of the damages falls on sellers. These results are placed in the context of a high-profile 2001 Sotheby's and Christie's commission-fixing case, where a simple (and flawed) 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. Moreover, the intuition developed in this paper is not limited to auction settings alone; it also applies to posted-price markets with heterogeneous sellers where sales volumes and prices are endogenous to the number and type of users attracted to the platform.

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 Hortaçsu and Perrigne (2021), which also places the current paper in that literature.[11] 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, **?**, 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 (2021), and Coey, Larsen, and Platt (2020)).[12] 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.[13] In a recent 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 rest of the paper is organized as follows. Section 2 describes the data and provides empirical facts related to the two-sided entry environment. Section 3 presents an auction platform game fitting

[12] Backus and Lewis (2016) propose a dynamic model that also accounts for bidder substitution across heterogeneous goods and apply it in order to estimate demand for compact cameras on eBay. Hendricks and Sorensen (2018) study bidding behavior for iPads with a model of sequential, overlapping auctions. To estimate the demand for Kindle e-readers, Bodoh-Creed, Boehnke, and Hickman (2021) employ a dynamic search model with bidder entry. Coey, Larsen, and Platt (2020) model time-sensitive consumer search and also evaluate the impact of changing the listing fee with that model.

[13] In addition, Lee (2013) estimates a dynamic network formation game in which heterogeneous consumers select into competing platforms and Sokullu (2016) recovers nonlinear effects with a semiparametric estimator.

to this empirical setting and solves for the equilibrium strategies. Nonparametric identification and the estimation of model primitives is addressed in section 4. Structural estimates are presented in section 5 and counterfactual simulations in section 6. Section 7 concludes.

2. Online wine auctions: empirical facts

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.[14] 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.[15] 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.[16] A soft-closing rule extends the end time of the auction by two minutes whenever a bid is placed in the final two minutes of the auction. Therefore, there are no opportunities to use a *bid sniping* strategy (bidding in the last few seconds, potentially aided by sniping software) on the BW platform. The combination of proxy bidding with a soft closing rule suggests that the data are well approximated by the second-price sealed bid auction model.

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.[17] 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.[18] These details and many more can be found on the listing page. This is

[14]The others are Bacchus, Bonhams, Chiswick, Christies, Sotheby's, Sworders, and Tennants.

[15]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.

[16]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)).

[17]Management used the term "prosumers" to describe its user base; consumers with some specific knowledge of wine.

[18]To highlight the importance of weather conditions for wine quality, Ashenfelter (2008) predicts with surprising accuracy

Table 1—: Fee structure in wine auction data

Fee	Bidders / sellers	Only if sold	Notation	Amount / rate	For price range
Buyer premium	Bidders	✓	c_B	0	
Seller commission	Sellers	✓	c_S	0.102	≤ £200
				0.090	£200.01- £1500
Listing fee	Sellers		e_S	£2.1	

Notes. Fees include a 20 percent value-added tax. The platform also charges a reserve price fee that is made up of 0.50 pounds for raising the minimum bid and 0.25 pounds for adding a secret reserve price, but these are not part of the analysis, which focuses on fee structure $c = \{c_B, c_S, e_S\}$. Bidders and sellers furthermore face opportunity cost of time from entering the platform.

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 pounds on average, delivery costs are approximately 12-16 pounds, storage is costly, and anticipated future seller fees and opportunity cost of time reduce the gains from resale further.[19] 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 rich set of auction-level observables (described in section 5).[20]

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 pounds and 9 percent for marginal amounts between 200 and 1500 pounds. Regardless of whether the sale is successful, sellers are charged a listing fee of 2.1 pounds, a minimum bid fee (0.6 pounds, but only when increasing the minimum bid) and a reserve price fee (0.3 pounds, 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. Table 1 summarizes the fee structure.

the price of a sample of Bordeaux grand Cru's using weather data.

[19]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.

[20]Moreover, empirical analysis of a common values ascending auction model would be infeasible given the lack of positive identification results for such a model.

Table 2—: Auction-level descriptive statistics

	N	Mean	St. Dev.	Min	Median	Max
Hammer price	3,481	140.33	239.68	1.00	82.24	6,000
Number of bidders	3,481	3.10	2.52	0	3	13
Number bottles	3,481	3.70	4.23	1	2	72
Is sold	3,481	0.64	0.48	0	1	1
Price per bottle if sold	2,228	74.81	124.55	0.50	35.00	2,200
Sold in Bond	3,481	0.16	0.37	0	0	1
Seller has feedback	3,481	0.29	0.46	0	0	1
Seller has ratings	3,481	0.73	0.45	0	1	1
Has any reserve	3,481	0.67	0.47	0	1	1
Reserve price	2,333	136.62	264.31	1.00	75.00	6,000

Notes. The hammer price equals the standing price when the auction closes, irrespective of whether the item is sold. 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.

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 include the type of wine (red, white, rosé, 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 2. One-third of listings are created by a seller with feedback from previous transactions, indicating the consumer-to-consumer nature of the platform, and 27 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 264 out of 2,583 potential sellers created a listing during the sample period. If we consider all 13,179 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.[21] Moreover, in the structural analysis, bidders and sellers are treated as distinct groups of users, but this is an abstraction: the data show that 41 out of the 246 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 repetitive recording of bids for ongoing auctions was necessary to approximate the reserve price distribution. The number of bidders and the standing price are observed every time that auctions are scraped. Public reserve prices (e.g., raised minimum bid amounts) are recovered as the standing price when there are no bidders. When a seller sets a reserve price without making it public in the form of a minimum bid amount, the notifications "reserve not met" or "reserve almost met" also accompany any standing price that does not exceed the reserve. Secret reserve prices are approximated as the average of the highest standing price for which the reserve price is not met and the lowest one for which it is met.[22] Only 26 percent of listings have an increased minimum bid amount, while 44 percent have a (secret) reserve price, and 3 percent have both. It is interesting to note here that the use of secret reserve prices in auction platforms remains a puzzle in the empirical auction literature, although solving that puzzle is beyond the scope of this paper (for more details see, e.g., Jehiel and Lamy (2015) and Hasker and Sickles (2010)). 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.[23]

The sample includes $3,481$ 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 hammer prices, 80

[21] These statistics are provided for context; population sizes are not needed for the estimation of the model primitives.

[22] 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 Appendix G. Accuracy of the reserve price approximation is also established separately when taking out unsold lots, for which the secret reserve price can only be bounded from below. Treating the approximated reserve price as data in the remainder of the paper can be considered as a cautious approach, in the sense that seller heterogeneity and its impact on bidder entry will be underestimated when recognizing that higher-reserve listings are —all else equal— less likely to result in a sale.

[23] Treating no-reserve auctions separately from positive reserve auctions is also done for instructive reasons: zero reserve price auctions serve as a benchmark to evaluate the two-sidedness of positive reserve price auctions against, as explained in the discussion in section 3.C.

percent of auctions fall in the lowest seller commission bracket ($\leq$ 200 pounds) while also having a reserve price lower than 200 pounds. These auctions are the focus of this paper and are referred to as the "main sample". The empirical analysis controls for observable wine characteristics in order to estimate idiosyncratic residual value distributions for bidders and sellers. To still assess any heterogeneous impacts of fee changes in different product classes, especially for the counterfactual policy simulations in section 6.B, the model is estimated separately for "high-end" auctions with hammer prices between 200 and 800 pounds and with a reserve price of at most 800 pounds.

B. Seller side

Sellers on this platform can be thought of as individual collectors with private values (marginal costs) for each wine, which resonates with the way they are described by the platform's management (see footnote 17). While it is not surprising in our platform setting that sellers are heterogeneous in various ways, it is important to document here because it also implies that counterfactual fee structures affect the type of sellers that is attracted to the platform.

First, there is substantial variation in where sellers live, which is observed for the 63 percent of sellers who indicate that the wine can be collected by the buyer. Sellers reside in all corners of the UK; in cities like London, Leeds, Liverpool, and Belfast, as well as in rural parts of Wales and in the picturesque villages of The Cotswolds. Sellers also differ in other observable ways, such as in the number of words they use to describe a wine. These textual descriptions vary from a sober "Original Wooden Case" to a 772-word history lesson about the origins of the "Les Bosquets des Papes" vineyard of Chateauneuf du Pape by a seller named *Roussillon* located in South London. Incidentally, Roussillon has been on the platform since March 2012 and is a stellar seller according to 12 feedback-leaving winning bidders.[24] The point of these remarks is mostly to highlight that it is reasonable to assume that sellers are heterogeneous, too, in their unobserved idiosyncratic values for a wine just as bidders have idiosyncratic tastes.[25]

Moreover, it is compelling that sellers know their idiosyncratic values before entering the platform considering that they own the wines they offer for sale and sometimes have owned them for decades. One way to explore the issue of selective seller entry in the data relies on information about potential sellers and how likely they are to enter based on observed characteristics. Recall that all registered users who have ever listed a wine for sale between January 2017 and May 2018 are labelled as

[24]To quote two of them: "Great service. Popped over and handed me the wine. Will deal with this gentleman again." "Wines delivered to my office near seller's house. Both were in top condition and enjoyed over the festive season."

[25]Location-based differences in living costs may also directly affect sellers idiosyncratic valuation. Information on the magnitude of such differences, based on the UK's Statistical Digest of Rural England, can be found here: https://assets.publishing.service.gov.uk/Expenditure_June_2021_final_with_cover_page.pdf, last accessed November 15, 2022.

Table 3—: Potential sellers: predicting entry

Dependent variable:	1(Entered market)			Number listings in market		
Regression model:	*Probit*	*OLS*	*OLS*	*Zero-inflated count data*	*OLS*	*Zero-inflated count data*
	(1)	(2)	(3)	(4)	(5)	(6)
Duration membership BW (years)	−0.090***	−0.001***	−0.004***	−0.110***	0.005	−0.012+
	(0.009)	(0.0003)	(0.0003)	(0.010)	(0.004)	(0.007)
Nr members joined same month (100s)	−0.268***	−0.003*	−0.012***	−0.099	0.042*	0.058
	(0.051)	(0.001)	(0.002)	(0.066)	(0.020)	(0.044)
Nr ratings received (100s)	0.205***	0.022***		0.102***	0.134***	
	(0.041)	(0.002)		(0.016)	(0.032)	
Nr ratings received (100s), squared	−0.008***	−0.001***		−0.003***	0.010***	
	(0.002)	(0.0001)		(0.001)	(0.002)	
Share ratings = negative	−0.482+	−0.008		1.051**	0.465***	
	(0.285)	(0.008)		(0.365)	(0.104)	
Share ratings = neutral	−0.235	−0.003		0.769+	0.039	
	(0.254)	(0.006)		(0.406)	(0.082)	
Has negative ratings	0.255**	0.004		−0.377***	−0.359***	
	(0.089)	(0.004)		(0.065)	(0.050)	
Nr $r = 0$ listings other sellers (100s)	0.129	0.003	0.010***	0.963***	0.139***	0.333***
	(0.081)	(0.002)	(0.002)	(0.067)	(0.033)	(0.051)
Nr $r > 0$ listings other sellers (100s)	0.197***	0.006***		−0.290***	−0.035+	
	(0.044)	(0.001)		(0.039)	(0.019)	
Share other markets entered	4.093***	0.755***		2.723***	7.752***	
	(0.146)	(0.010)		(0.078)	(0.128)	
Constant	−2.168***	0.001	0.048***	0.522***	−0.203***	1.262***
	(0.104)	(0.003)	(0.004)	(0.122)	(0.045)	(0.090)
Observations	30,972	30,972	30,972	30,972	30,972	30,972
Adjusted R^2		0.234	0.007		0.171	
Log Likelihood	−1,789.745			−4,054.471		−6,152.514

Notes. Standard errors in parenthesis, $^+$p<0.1; *p<0.05; **p<0.05; ***p<0.01. Based on the main sample only.

Table 4—: Sellers: suggestive evidence for selection

Dependent variable:	Reserve price		1(Reserve price>0)			
Regression model:	*OLS*	*Tobit*	*Probit*	*Probit*	*Probit*	*Probit*
	(1)	(2)	(3)	(4)	(5)	(6)
Predicted entry dummy (column 3 table 3)	1,200.592***	1,200.592***	10.699***		−2.702*	
	(125.327)	(125.243)	(0.821)		(1.121)	
Predicted entry count (column 6 table 3)				1.071***		−0.479***
				(0.107)		(0.124)
Observations	1,499	1,499	2,350	2,350	2,350	2,350
Adjusted R^2	0.057					
Log Likelihood		−8,071.505	−1,531.626	−1,564.178	−833.622	29.115

Notes. Standard errors in parenthesis, $^+$p<0.1; *p<0.05; **p<0.05; ***p<0.01. Based on the main sample only. Column 6 includes auction observables used for the homogenization of auctions in the structural analysis, listed in table C. 5.

potential sellers. The time dimension of the data must therefore be exploited to generate variation in the entry decision of potential sellers. For the sake of this descriptive analysis, define a market as a month, and consider the reduced form seller selection equation

$$y^s_{hm} = X^s_{hm}\beta^s - v_{hm}, \tag{1}$$

where the expected surplus from entering for seller h in market m (y^s_{hm}) is strictly decreasing in its unobserved idiosyncratic valuation v_{hm}, reducing gains from trade, and may also be a function of observed seller and market characteristics X^s_{hm}. Seller h enters market m iff $y^s_{hm} > 0$, a process that is formalised as the zero profit seller entry condition in the structural model (see lemma 3).

Similar to the analysis done in Roberts and Sweeting (2011) based on a Heckman regression model of selective bidder entry, the predicted entry probability $X^s_{hm}\hat{\beta}^s$ is used in a second stage to assess whether seller selection can be detected in the data. The reasoning goes as follows. It is well-known that reserve prices and the benefit of setting a positive reserve price are both increasing in v_{hm} (Riley and Samuelson (1981), Jehiel and Lamy (2015)). For sellers with a higher expected utility from entering based on observed characteristics ($X^s_{hm}\hat{\beta}^s$), higher values of v_{hm} will satisfy $y^s_{hm} > 0$. This will be picked up by a positive association between the (average) reserve price and $X^s_{hm}\hat{\beta}^s$ for all sellers that did enter. A key identifying assumption for interpreting this as seller selection is that X^s_{hm} is independent of v_{hm}, so that that conditional on entry, X^s_{hm} does not affect the reserve price.

Estimation results for the selection equation in (1) are reported in table 3 and reveal some interesting empirical facts. Seller-level variables in X^s_{sm} describe how many years they have been registered with the platform, the number of users that joined in the same month as they did, and how they have been rated. We also know the number of listings in the market offered by other sellers, which correlates positively with the decision to enter perhaps because the platform used marketing campaigns to engage users. Marketing campaigns or other outside factors boosting interest in the platform would also explain the negative effect of the number of members that joined in the same month. Having more listings in more other markets than m makes a seller more likely to enter into market m too, highlighting the fact that some sellers post listings on a regular basis. Columns 4-6 of table 3 repeat the analysis but with as dependent variable the number of listings that are created by a potential seller in a market. Here, the preferred specification is the zero-inflated Poisson count model that accounts for the abundance of seller-market observations with zero listings. As the exclusion restriction is more difficult to defend for seller ratings and for the share of other markets they enter, a smaller entry model including only the time when the seller joined the platform and the number of other zero reserve price listings offered by other sellers is used to predict $X^s_{hm}\hat{\beta}^s$ (columns 3 and 6 of table 3).[26] A downside of this approach is that the low predictive power of this more conservative entry model might mask the effect of seller selection in the second stage.

Estimation results from the second stage reported in table 4 support the conjecture that higher reserve prices are associated with a higher predicted entry probability, which is indicative of selective seller entry as explained above.[27] However, these results should be taken as suggestive only as the data does not contain strong entry shifters that are plausibly excluded from the seller's valuation, and the effect disappears when including the rich set of auction-level observables that is used in the structural analysis to homogenize auctions (see section 4.B). Nonetheless, it is considered reasonable to assume that potential sellers are heterogeneous and know their own idiosyncratic value draws, and to let the structural estimation determine how heterogeneous sellers are.

C. *Bidder side*

Selective seller entry has interesting ramifications for bidder entry into such platforms as well, as for instance outlined in Ellison, Fudenberg, and Mobius (2004).[28] For bidders, entry is the act of entering into a listing on the platform. Whether or not bidders know their idiosyncratic value for a wine before entering will affect how profitable it is to change the fee structure and to attract additional bidders. Unfortunately, bidder identities are not observed, so we have to rely on indirect empirical evidence towards this end.

First, OLS regression results are consistent with non-selective bidder entry: while an extra bidder in an auction is associated with a transaction price that is approximately 10 pounds higher, markets (months) that attract more *total* bidders for a product do not have significantly different prices.[29]

[26] Including the share of other markets entered could violate the exclusion restriction if regular entrants also are more professional and, say, are less attached to their wine or have higher opportunity cost of selling. The ratings variables might suffer from similar issues, and the positive coefficient on the number of ratings received can also result from reverse causality.

[27] While the estimation results go in the expected direction for five regression specifications, the effect is insignificant in one of those, and when including additional auction-level variables the coefficient swaps sign. Column 1 is based on an OLS regression of reserve prices on the entry probability. Column 2 presents results from a Tobit model with left-censoring of the reserve price at the lowest observed value. The dependent variable in columns 3-6 is an indicator for whether the seller has set a positive reserve price. Columns 4-6 furthermore use the alternative measure of $X^s_{hm}\hat{\beta}^s$ from the zero-inflated Poisson count model based on the number of listings that seller h created in market m.

[28] These authors make the following concluding remarks regarding the interaction of bidder and seller entry. *"We would like to develop a model that incorporates adverse selection in the market-participation decision. Our causal empiricism suggests that a major reason that the Amazon and Yahoo! auction sites have struggled is that they tried to compete by having zero listing fees. This led to their listings being filled up with products being offered by nonserious sellers with very high reserve prices. If we suppose that there is a cost to reading web pages, or to investigating the quality of a good and/or its seller, then buyers will prefer to frequent sites with a high percentage of good listings—listings by reputable sellers who have high-quality goods and are willing to sell them at a reasonable price.*

[29] The coefficient on the total number of bidders in the market is economically small and statistically insignificant (-0.013 with a standard error of 0.074 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. See table C. 2 in Appendix B.

Table 5—: Thin markets

— Percentiles:	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
Number of times product listed, 4 weeks:	1	1	1	1	1	2	2	3	6	37
Number of times product listed, 15 months:	1	1	1	1	2	3	4	8	16.2	222
Number of times same title occurs, 15 months:	1	1	1	1	1	1	1	1	2	17

Notes. The table reports 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.

By contrast, selective bidder entry would appear in the data as markets that have more listings of a certain product attracting more total bidders and having stochastically lower bids, given that bidders with higher valuations would enter first.[30]

Moreover, that the wines offered for sale are preowned by heterogeneous sellers is also important as it generates a listing inspection cost. Indeed, listing pages report much for bidders to inspect: the wine's storage conditions, provenance, 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" and "shoulders" have a metric classification in centimeters from the bottom of the capsule.

Nonselective bidder entry is also plausible when listing inspection cost are important simply because bidders learn their valuations after inspecting the auction characteristics. The data can speak to the presence of a constant cost of inspecting a listing, as this would imply 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 further in section 3.C, the listing inspection cost depletes all expected surplus from entering in another auction after having entered the current one. Indeed, in the data the presence of more competing listings does not systematically affect the average number of bidders per listing, the transaction price, or the reserve price.[31]

[30] In second-price sealed-bid auctions it is optimal to bid one's valuation independent of the number of competing bidders.

[31] These results are consistent across 18 different definitions of what constitutes a competing listing (see table C. 1 in Appendix B). 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.

D. Conclusions from empirical facts

The presented empirical patterns underscore that the auction platform under consideration 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.[32] One distinguishing feature of an auction platform with heterogeneous goods is that at each point in time, the platform contains a low number of highly similar listings. This is certainly true for the BW 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 30 percentage points, only three such products are available (see table 5). The next section presents a parsimonious model suitable to study auction platforms with two-sided entry, selection of heterogeneous sellers, and a listing inspection cost.

3. A model of an auction platform with two-sided entry

This section develops an empirically tractable structural auction platform model with two-sided entry and solves for the game's equilibrium strategies.

A. Setting and model assumptions

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 $c = \{c_B, c_S, e_S\}$ contains respectively a buyer premium, a seller commission (both are shares of the transaction price), and a listing 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" e_B^o associated with each listing they enter.[33] Sellers set non-negative secret reserve prices.[34] The opportunity cost of time for sellers is denoted by e_S^o and also referred to as "entry cost".

This setting is modelled 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

[32]Structural auction (platform) models have been applied to the study of compact cameras (Backus and Lewis (2016)), Kindle e-readers (Bodoh-Creed, Boehnke, and Hickman (2021)), iPads (Hendricks and Sorensen (2018)), pop music CDs (Nekipelov (2007)), CPUs (Anwar, McMillan, and Zheng (2006)), and iPods (Adachi (2016)).

[33]Listing inspection cost are not expected to be different for auctions with or without a reserve price. The model therefore restricts the two to be the same, and this restriction is then tested empirically. A second remark to make here is that any option value for bidding in an auction is depleted by bidders' zero profit entry condition given the assumption that each listing incurs its own e_B^o. Hence, intra-auction dynamics captured in Kong (2021) and Hickman, Hubbard, and Paarsch (2017) do not arise in this model. The (related) absence of a scale effect is discussed in section 3.C.

[34]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.

to enter or not after observing the number of listings on the platform and whether they have a reserve price.[35] Listings are ex-ante identical up to having a reserve price, so conditional on this bidders are sorted with some constant probability over listings.[36]

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.[37] As such, $N^B_{r=0}$, $N^B_{r>0}$, 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. $N^B = N^B_{r=0} + N^B_{r>0}$ denotes the total number of potential bidders. $\mathcal{N}^B$ and $\mathcal{N}^S$ respectively denote the sets of potential bidders and sellers.

The entry stage is followed by a standard auction stage: 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 D.[38] F_{V_0} and F_V respectively denote the valuation distributions for potential sellers and bidders. The empirical analysis controls for auction-level observables so V_0 and V should be interpreted as conditional valuations, and the model assumes no unobserved auction-level heterogeneity. V_0 is equivalently interpreted as a seller's (marginal) cost of selling.

The following assumptions on the valuation distributions are maintained when solving for the game's equilibrium strategies:

Assumption (Two-sided IPV). *All $i = \{1, ..., N^B\}$ potential bidders independently draw values v_i from $V \sim F_V$ and all $k = \{1, ..., N^S\}$ potential sellers independently draw values v_{0k} from $V_0 \sim F_{V_0}$ such that:*

i) $v_i \perp v_{i'}$ $\forall i \neq i' \in \mathcal{N}^B$, and

ii) $v_i \perp v_{0k}$ $\forall i \in \mathcal{N}^B$ and $\forall k \in \mathcal{N}^S$.

F_V and F_{V_0} satisfy regularity conditions: $supp(V) = [\underline{v}, \bar{v}]$, $supp(V_0) = [\underline{v_0}, \bar{v}_0]$, F_V is absolutely continuous, and $\frac{f_V(x)}{1-F_V(x)}$ increases in x $\forall x \in [\underline{v}, \bar{v}]$ (Increasing Failure Rate or IFR).

[35]One way to justify this assumption is that the platform in the empirical application attaches a highly visible "no reserve price" button to auctions without a reserve price, which bidders observe before selecting a listing. The distinction also 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.

[36]When bringing the model to data, listings can be grouped according to additional observables such as filters on the website.

[37]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.

[38]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 2 supports this assumption.

Most importantly, these assumptions guarantee that conditional on the vector of observed product attributes, variation in values across buyers and sellers is of a purely idiosyncratic —private values— nature. In addition, the idiosyncratic variation is independent. Note that the two valuation distributions, as well as their supports, are allowed but not restricted to differ for populations on the two sides of the market (potential sellers and bidders).

The valuation distributions, allocation mechanism, platform fees, and entry costs are assumed to be common knowledge. Finally, the entry equilibrium 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. Specifically, it is maintained that

Assumption (Poisson game). *The populations* $N^B_{r=0}$ *and* $N^B_{r>0}$ *are large, so that the number of bidders per listing has a probability mass function approximated by*

$$f_{N_r}(k;\lambda_r) = \frac{\exp(-\lambda_r)\lambda_r^k}{k!}\ ,\ \forall k \in \mathbb{Z}^+, \tag{2}$$

for $r \in \{r = 0, r > 0\}$*, denoting respectively zero and positive reserve price auctions.*

Intuitively, the population of potential bidders considering whether or not to enter the platform is large relative to the number of bidders in a listing, so that the distribution of the number of bidders per listing is approximately Poisson and fully characterized by its mean.[39] A particular benefit of this assumption is that, when bringing the model to data, it avoids the large combinatorial problem where expected seller surplus needs to be computed for any realization of the number of bidders that enter given their equilibrium entry probability.[40] Proof that the approximation does not drive equilibrium existence and uniqueness is provided in Appendix C where results for the game with a finite population of potential bidders are presented.

B. Equilibrium strategies

Equilibrium strategies are solved for by backwards induction, and all results are subject to the assumptions made in the previous section. 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.

[39] 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 f). Further, 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 Hortaçsu (2003), Jehiel and Lamy (2015), and Bodoh-Creed, Boehnke, and Hickman (2021).

[40] Appendix A proves that the relevant decomposition property of the Binomial distribution exploited also in Myerson (1998) applies to the presented model where the total number of bidders who enter is a function of the number of listings.

Auction stage

Conditional on entry decisions and the sorting of bidders over listings, the heterogeneous-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. In particular, A bidder with valuation v bids

$$b^*(v, c) \equiv \frac{v}{1 + c_B}. \tag{3}$$

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 a 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)). Let v_0^R denote the no-reserve screening value.[41]

Following the standard reserve price derivation, it can be shown that a seller with valuation $v_0 \geq v_0^R$ sets a reserve price that solves

$$r^*(v_0, c) = \frac{v_0}{1 - c_S} + \frac{1 - F_V((1 + c_B)r^*(v_0, c))}{(1 + c_B)f_V((1 + c_B)r^*(v_0, c))}. \tag{4}$$

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 $r^*(v_0, c)$ is secret, it does not affect the number of bidders in the seller's listing. The optimal reserve price is increasing in c_S and (given IFR) decreasing in c_B. In what follows, let $\tilde{r}$ denote the buyer premium-adjusted

[41] The decision to set a positive reserve price is optimal in the sense that only higher-valuation sellers do so, but the threshold value v_0^R is taken to be exogenous as endogenizing v_0^R complicates the estimation of the game further. Four points should be made in this regard. Conceptually, endogenizing v_0^R 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_0^R 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_0^R and hence encouraging additional bidders to enter into $r > 0$ auctions. Second, endogenizing v_0^R could in theory lead to multiple equilibria of the two-sided entry game. For example, if for some policy change $r > 0$ listings become more attractive relative both to the outside option *and* to $r = 0$ auctions, so that v_0^R decreases while v_0^* increases, and given the ambiguous effect that this has on bidders in $r > 0$ auctions, multiple combinations of v_0^R and v_0^* could be sustained. Numerical simulations based on the estimated model primitives confirm that changes in c_S and c_L both would have a negligible effect on v_0^R compared to the effect that they have on v_0^*, and that there is no ambiguity as v_0^R moves in the same direction as v_0^*. Also, endogenizing v_0^R would (therefore) be especially interesting when studying (counterfactual) reserve price policies. This, 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)). Finally, the analysis considers only fee structures for which $v_0^* \in (\underline{v_0}, \bar{v_0}]$ and lets $v_0^R \in (\underline{v_0}, v_0^*)$, restricting attention to the case where at least some sellers find it optimal to create listings with and without a reserve price on the platform.

optimal reserve price

$$\tilde{r} = (1 + c_B) r^*(v_0, c)$$

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 c, when the seller has a private value of v_0 equals

$$\pi_b(n, c, v_0) \equiv \frac{1}{n}\mathbb{E}[V_{(n:n)} - \max(V_{(n-1:n)}, \tilde{r}) | V_{(n:n)} \geq \tilde{r}][1 - F_{V_{(n:n)}}(\tilde{r})], \tag{5}$$

with the last term denoting the sale probability and the max(.) term the transaction price including buyer premium.[42] Expected surplus for a seller in such a listing equals

$$\pi_s(n, c, v_0) \equiv \left(\mathbb{E}[\max(V_{n-1:n}, \tilde{r}) | V_{n:n} \geq \tilde{r}](1 - c_S) - v_0\right) [1 - F_{V_{(n:n)}}(\tilde{r})]. \tag{6}$$

For auctions without a reserve price, expected bidder and seller surplus simplify to

$$\pi_b(n, c, 0) \equiv \frac{1}{n}\mathbb{E}[V_{(n:n)} - V_{(n-1:n)}] \tag{7}$$

$$\pi_s(n, c, 0) \equiv \mathbb{E}[\frac{V_{(n-1:n)}}{1 + c_B}], \tag{8}$$

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 π_b and π_s are zero when $n = 0$. The entry equilibrium relies on the following properties from the auction stage. Listing-level expected surplus for bidders, $\pi_b(n, c, v_0)$, decreases in the number of (competing) bidders in the listing n.[43] $\pi_b(n, c, v_0)$ decreases in the seller's valuation v_0, as higher-v_0 sellers set weakly higher reserve prices, unless they have a low enough v_0 to set no reserve price in which case there is no effect on expected listing-level bidder surplus. Further, listing-level expected seller surplus $\pi_s(n, c, v_0)$ decreases in sellers own v_0, e.g. by reducing gains from trade, and it increases in the number of bidders by driving up expected transaction prices and as r^* in (4) is independent of n.

[42] $X_{(i:n)}$ is order statistics notation to refer to the $(n-i+1)^{\text{th}}$ highest out of a sample of n draws from random variable X.

[43] To be precise, the result that listing-level expected bidder surplus decreases in the number of competing bidders relies on the Increasing Failure Rate (IFR) property of F_V. Li (2005) proves that a monotonically nondecreasing failure rate implies decreasing spacings so that $\mathbb{E}[V_{(n+1:n+1)} - V_{(n:n+1)}] - \mathbb{E}[V_{(n:n)} - V_{(n-1:n)}] \leq 0$. The inequality is strict if the failure rate is strictly increasing and holds in the case with or without a reserve price as it is independent of n.

Entry stage

Typically, an entry equilibrium of the auction platform 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. Under the large population approximation it can on the bidder side be captured by the equilibrium mean number of bidders per listing. This equilibrium λ_r (for $r \in \{r = 0, r > 0\}$) is endogenous to the fee structure and in positive reserve auctions also depends on seller selection.

The equilibrium results are derived in the next 2.5 pages. It is first documented that any candidate seller entry threshold ($\tilde{v_0}$) maps to an equilibrium mean number of bidders per listing $\lambda^*_{r>0}(c, \tilde{v_0})$ in auctions with positive reserve prices. That mapping is used to solve for the equilibrium seller entry threshold $v_0^*(c)$. It turns out that because the mean number of bidders in positive reserve price auctions is strictly decreasing in $\tilde{v_0}$, sellers' best-response entry thresholds satisfy a single-crossing property, so that the entry game has a unique equilibrium despite its two-sidedness.[44] In addition, the mean number of bidders per listing in auctions with zero reserve price ($\lambda^*_{r=0}(c)$) is independent of the seller entry threshold. Section 3.C summarizes the economic intuition behind these results, and discusses model extensions and implications.

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 $r > 0$, let $\Pi_{b,r>0}(c, \tilde{v_0}; \lambda_{r>0})$ denote potential bidders' expected surplus from entering the platform. Besides fees and the listing inspection cost, it includes listing-level surplus $\pi_b(n, c, v_0)$ in expectation over: 1) seller-values V_0 given candidate threshold $\tilde{v_0}$, and 2) the Poisson-distributed number of competing bidders, and can be written as

$$\Pi_{b,r>0}(c, \tilde{v_0}; \lambda_{r>0}) = \int \mathbb{E}[\pi_b(n+1, c, v_0) | V_0 \in [v_0^R, \tilde{v_0}]] f_{N_{r>0}}(n; \lambda_{r>0}) dn - e_B^o. \tag{9}$$

It is crucial to note here that $\Pi_{b,r>0}(c, \tilde{v_0}; \lambda_{r>0})$ 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. In the zero reserve price case, $\Pi_{b,r=0}(c; \lambda_{r=0})$ does not

[44] A no-trade equilibrium where no bidders and sellers enter is excluded from consideration.

depend on seller values and equals

$$\Pi_{b,r=0}(c;\lambda_{r=0}) = \int \pi_b(n+1,c,0) f_{N,r=0}(n;\lambda_{r=0})dn - e_B^o. \tag{10}$$

The following Lemma describes the equilibrium entry decisions on the bidder side.

Lemma 1. *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*

$$\lambda^*_{r>0}(c,\tilde{v_0}) \equiv \arg_{\lambda_{r>0}\in\mathbb{R}^+}\{\Pi_{b,r>0}(c,\tilde{v_0};\lambda_{r>0}) = 0\}, \tag{11}$$

and a unique equilibrium $\lambda^*_{r=0}$ solves

$$\lambda^*_{r=0}(c) \equiv \arg_{\lambda_{r=0}\in\mathbb{R}^+}\{\Pi_{b,r=0}(c;\lambda_{r=0}) = 0)\}. \tag{12}$$

These results follow from listing-level surpluses $\pi_b(n,c,v_0)$ and $\pi_b(n,c,0)$ strictly decreasing in n, and $f_{N_{r>0}}(n;\lambda)$ increasing in a first-order stochastic dominance sense in λ. 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 2. *The equilibrium $f_{N_{r>0}}(n;\lambda^*_{r>0}(c,\tilde{v_0}))$ decreases in a first-order stochastic dominance sense in $\tilde{v_0}$.*

It follows because any candidate seller entry threshold $\tilde{v_0}$ affects $\Pi_{b,r>0}(c,\tilde{v_0};\lambda_{r>0})$ 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, resulting in lower $\pi_b(n,c,v_0)$. The zero profit condition in (11) therefore dictates that $\lambda^*_{r>0}(c,\tilde{v_0})$ strictly decreases in $\tilde{v_0}$. This property is central to the equilibrium uniqueness result as is shown after introducing more notation.

Let $\Pi_s(c,v_0;\lambda^*_{r>0}(c,\tilde{v_0}),\tilde{v_0})$ denote expected surplus for a seller with valuation $v_0 > v_0^R$ when competing sellers enter the platform if and only if their valuation is less than threshold $\tilde{v_0}$.[45]

[45] Using $f_{N_{r>0}}(n;\lambda^*_{r>0}(c,\tilde{v_0}))$ 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)).

Besides fees and the opportunity cost of time, it involves: 1) their listing-level expected surplus, and 2) an expectation over the number of bidders per listing given $\tilde{v_0}$ and bidders' equilibrium best-response to this threshold summarised in Lemma 2, and equals

$$\Pi_s(c, v_0; \lambda^*_{r>0}(c, \tilde{v_0}), \tilde{v_0}) = \int \pi_s(n, c, v_0) f_{N_{r>0}}(n; \lambda^*_{r>0}(c, \tilde{v_0}), \tilde{v_0}) dn - e_S - e^o_S. \tag{13}$$

The seller entry equilibrium is characterized by the v_0^* that solves the zero profit entry condition for the marginal seller. Importantly, Lemma 2 implies that sellers' expected surplus decreases in the threshold that *competing sellers* adopt, through the impact that this threshold has on the number of bidders they expect in their own listing. This results in a unique seller entry threshold as formalised in the next Lemma.

Lemma 3. *A unique equilibrium seller entry threshold solves the marginal seller's zero profit condition*

$$v_0^*(c) \equiv \arg_{\tilde{v_0} s.t. F_{V_0}(\tilde{v_0}) \in [0,1]} \{\Pi_s(c, \tilde{v_0}; \lambda^*_{r>0}(c, \tilde{v_0}), \tilde{v_0}) = 0\}, \tag{14}$$

with $\lambda^*_{r>0}(c, \tilde{v_0}) \equiv \arg_{\lambda_{r>0} \in \mathbb{R}^+} \{\Pi_{b,r>0}(c, \tilde{v_0}; \lambda_{r>0}) = 0\}$ *as defined in* (11).

The proof requires three parts. First, sellers have a unique best-response for any competing $\tilde{v_0}$, because $\Pi_s(c, v_0; \lambda^*_{r>0}(c, \tilde{v_0}), \tilde{v_0})$ strictly decreases in their own v_0. Second, given that 1) $\lambda^*_{r>0}(c, \tilde{v_0})$ is strictly decreasing in $\tilde{v_0}$ (Lemma 2), 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, $v_0^*(c)$, which is the fixed point in seller value space solving (14) i.e., making the marginal seller indifferent between entering and staying out. The results from this section, as proven with Lemma's 1-3, can be summarized as follows.

Corollary. *The entry equilibrium of the auction platform game presented in section 3.A exists and is unique. It is characterized by the set:*

$$\left\{ \begin{array}{ccc} v_0^*(c), & \lambda^*_{r>0}(c, v_0^*(c)), & \lambda^*_{r=0}(c) \\ \textit{Seller entry threshold} & \textit{Mean bidders } r > 0 & \textit{Mean bidders } r = 0 \end{array} \right\}$$

The values of $v_0^*(c)$, $\lambda^*_{r>0}(c, v_0^*(c))$, *and* $\lambda^*_{r=0}(c)$ *solve zero profit conditions of the marginal seller and potential bidders as defined respectively in equations* (14), (11), *and* (12).

C. Discussion

Two-sided market and equilibrium uniqueness

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 3, the best-response function $\bar{v_0}_i^{BR}(\bar{v_0}_{-i}, \lambda^*_{r>0}(\bar{v_0}_{-i}))$ is downward-sloping: a higher competing seller entry threshold decreases expected seller surplus for any v_0, lowering the threshold v_{0i}^{BR} for which seller i breaks-even. It can be explained by 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 the 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 ($\lambda > \lambda^*_{r>0}(\bar{v_0}_{-i})$). 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 $\tilde{v_0}$ (detailed in Lemma 1), $\lambda > \lambda^*_{r>0}$ can only be sustained by some $\tilde{v_0} < v_0^*(\lambda^*_{r>0})$. In turn, the latter leaves money on the table for sellers with values $\in [\tilde{v_0}, v_0^*(\lambda_{r>0})]$ and is therefore also excluded as an equilibrium. For the same reasons $\lambda < \lambda^*_{r>0}$ cannot be sustained in equilibrium as that would require expected seller surplus to decrease in the number of bidders.

Network effects

Network effects are nonlinear in this model and, following i.e. Katz and Shapiro (1985), are defined by how much expected surplus from entering the platform changes if an additional user on the other or own side enters exogenously. The case with positive reserve prices is the most interesting as it can be used to illustrate the role of seller selection and the resulting effect on

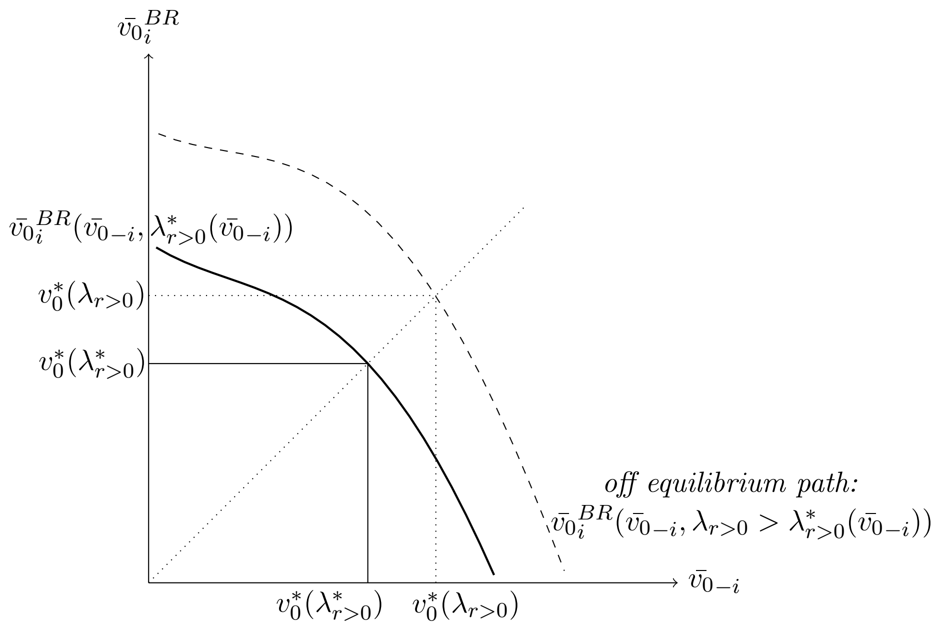

Figure 1. : Graphic representation of unique entry equilibrium result

Notes. The solid black line represents the equilibrium entry threshold of seller i as best-response to competing sellers adopting threshold $\bar{v}_{0-i}$ and potential bidders best responding with $\lambda^*_{r>0}(\bar{v}_{0-i})$, i.e. the seller best-response function $\bar{v_0}_i^{BR}(\bar{v}_{0-i}, \lambda^*_{r>0}(\bar{v}_{0-i}))$. Details are provided in section 3.C.

bidder entry.[46] The main model predictions are summarized in table 6.

Consider an exogenous increase in the seller entry threshold so that more and higher v_0 sellers enter, setting higher reserve prices. This lowers the expected surplus for all sellers (who were already on the platform) because it results in stochastically fewer bidders per listing, and hence the model generates a negative seller-side direct network effect. It is precisely this feature of bidders being uncertain about the height of the reserve price that they will face upon entering, and the fact that excluding high reserve price setting sellers ("lemons") results in a more favorable reserve price distribution on the platform, that justifies the labeling of the negative seller-side direct network effect as a *lemons effect* after Akerlof (1970). As discussed above, it is also precisely this feature of the model that generates a unique equilibrium despite the two-sidedness of the market.

The lemons effect does not exist in the zero reserve price benchmark. The same holds for positive reserve price auctions as long as the seller type distribution (i.e., the reserve price distribution) is held fixed, which occurs in the model when the platform's fee structure does not change so that $v_0^*(c)$ remains constant. For those cases, the model predicts that the average number of bidders per listing is independent of the number of listings. Bidders will enter to the point of depleting

[46]Indeed, the case without reserve prices primarily functions as a benchmark to explain what happens in platforms where sellers have no private information about something that buyers also care about.

Table 6—: Summary of network effects generated by the model

	$r > 0$ and seller selection	$r = 0$ benchmark (or: no seller selection) (or: $v_0^*(c)$ constant)
Direct network effect seller-side	- ("lemons effect")	0
Indirect network effect sellers on bidders	?	+
Direct network effect bidder-side	?	0
Indirect network effect bidders on sellers	+	+

Notes. An indirect network effect considers how the entry of an additional user affects users on the other side, before any equilibrium adjustments. A direct network effects also takes the equilibrium response of those users on the other side into account, but not the equilibrium adjustment of users on the own side. In addition to the explanations provided in the text, the indirect network effect of sellers on bidders is ambiguous in the case of $r > 0$ as the benefit of more listings is at least partially offset by the expectation of less favorable reserve prices. The direct bidder-side network effect is ambiguous because the entry of additional bidders attracts more but higher-reserve setting sellers, although in equilibrium bidders are all equally well off given their zero profit entry condition.

the additional surplus generated by the additional listings, and as there is no change in the reserve price distribution the resulting distribution of the number of bidders per listing will remain the same. As such, this is a property that can be referred to as *constant returns to scale when holding the seller type distribution constant.*

The model prediction of constant returns to scale conditional on the seller type distribution can be verified with data from the empirical application, where the fee structure is held fixed over the period under consideration. By contrast, 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 even when holding $v_0^*(c)$ constant or when looking at auctions without a reserve price. This is most cleanly assessed in the sample with $r = 0$ where the number of bidders per listing is directly observed. The regression results reported in table C. 3 in the appendix show that the mean number of bidders per listing does not vary with the total number of listings of that product, supporting the absence of a scale effect in the data. It reflects that, in the context of unvetted listings of vintage wines, bidders need to inspect each listing's many product idiosyncracies before knowing how much to value the wine.[47] Of course it remains true that more listings attract more bidders, and 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 correlation.

The described (indirect) network effects create 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

[47]The absence of positive scale effects is consistent with quasi-experimental empirical evidence in other peer-to-peer platforms (see, for instance, Cullen and Farronato (2020) and Li and Netessine (2020)).

and more bidders per listing. Moreover, the platform faces the classic two-sided market pricing problem of how to best allocate fees between the two sides. The magnitudes of the network effects are important here and depend crucially on the latent value distributions and entry costs. If sellers are relatively homogeneous, for example, reflected by low dispersion in values drawn from F_{V_0}, 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.

Generalizability

The presented model with its unique entry equilibrium is useful as a starting point for structural analysis of other two-sided markets as well, especially those where the selection of users on one side creates the negative own-side network effect that is described above. One example is credit markets such as Prosper.com, studied in e.g. Kawai, Onishi, and Uetake (2022), Liu, Wei, and Xiao (2020), and Freedman and Jin (2017). To expand on this, the market is expected to generate positive indirect network effects as funding probabilities and interest rates are endogenous to the number of lenders per listing. Borrowers can be considered to have private information about their creditworthiness beyond their observable characteristics and do not internalize the impact of their entry decisions on other platform users. Similar to the wine auction setting, the selection of borrowers with lower creditworthiness is then expected to decrease the equilibrium lender/borrower ratio as the market grows. The model can also describe interaction effects in markets with intermediaries more generally, and the impact of fee changes on equilibrium outcomes. Consider for instance the market for realtor services, when relatively patient sellers offer their house for sale through a direct channel such as a For-Sale-By-Owner platform (as in Hendel, Nevo, and Ortalo-Magné (2009)). The fact that realtors charge high commissions could be explained by the benefit of excluding the most patient sellers from their pool of listings, in order to keep the buyer-to-seller ratio and the resulting transaction prices high.

Moreover, Lemma 2 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, still 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.[48] The presence of other negative seller-

[48]In a theoretical auction model with endogenous entry of buyers and sellers, no seller selection, heterogeneous entry cost, and a match value, Deltas and Jeitschko (2007) show that the entry equilibrium is unstable and the platform profit function

side externalities, such 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, as they would result in a more steeply downward-sloping best-response function ($\bar{v_0}_i^{BR}(\bar{v_0}_{-i}, \lambda^*_{r>0}(\bar{v_0}_{-i}))$) than in the model presented in section 3.A. Moreover, when bidders lean their valuation before entering (as in e.g., Samuelson (1985) and Menezes and Monteiro (2000)), the seller best-response function remains downward-sloping —although at a shallower slope.[49] 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.

On the other hand, the seller best-response function will not be 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.[50]

4. Empirical strategies to recover model primitives

This section discusses identification and estimation of model primitives (most importantly: valuation distributions and latent entry costs) given the assumptions of the model outlined in section 3 and given observables, which include the number of bidders, the hammer price, the reserve price, and the platform's fee structure. Specifically, the model restricts that the actual number of bidders observed in zero reserve price auctions is equal to the number of bidders that entered into the listing ($N_{r=0}$ with realization n). In positive reserve price auctions, the number of bidders that entered ($N_{r>0}$) is allowed to be larger than the number of actual bidders that are observed ($A_{r>0}$), motivated by some unspecified degree of censoring associated with information revealed when the standing price is below the reserve price (the "reserve not met" and "reserve almost met" messages). The hammer price equals the second-highest bid ($B_{n-1:n}$) in auctions without a reserve price when $n \geq 2$.[51]

discontinuous in the listing fee. One implication of Lemma 2 is that an empirically tractable model can still be estimated for settings where seller heterogeneity has a relatively strong effect on expected bidder surplus relative to the match value.

[49] A full analysis of the case with selective bidder entry is provided in Appendix D.

[50] Many two-sided markets feature positive scale effects, see Jullien, Pavan, and Rysman (2021).

[51] A complete characterization of the hammer price H in this model where the reserve price r is secret, with $r \geq 0$, as a function of the number of bidders allocated to the auction (n) and their bids and values, when the opening bid is set at 1 is given below. The model implications regarding the observed actual number of bidders, a, given the conditions on r and n, is given in the final column.

$$H = \begin{cases} 1 & r = 0 & n \leq 1 & & a = n \\ B_{n-1:n} = V_{n-1:n} & r = 0 & n \geq 2 & & a = n \\ 1 & r > 0 & n = 0 & & a = 0 \\ B_{n:n} = V_{n:n} & r > 0 & n \geq 1 & V_{n:n} < r \text{ (unsold)} & a \leq n \\ r & r > 0 & n = 1 & V_{n:n} \geq r \text{ (sold)} & a \leq 1 \\ \max(B_{n-1:n} = V_{n-1:n}, r) & r > 0 & n \geq 2 & V_{n:n} \geq r \text{ (sold)} & a \leq n \end{cases}$$

A. Nonparametric identification

The distribution of bidder valuations F_V is identified from the second-highest bid and the number of bidders in auctions with $r = 0$ and $n \geq 2$, which follows directly from Athey and Haile (2002, Theorem 1). The second-highest (equilibrium) bid relates to the second-highest value according to (3), so that in the wine auction setting where $c_B = 0$ the two are identical. This gives the distribution of the second-highest valuation. Then, F_V is obtained by inverting the known relationship between this distribution, e.g. the distribution of the second-highest out of n i.i.d. draws from F_V, and F_V itself, where n denotes a realization of the random variable $N_{r=0}$. Specifically, the distribution of the second-highest valuation ($F_{V_{n-1:n}}$) satisfies $\forall v \in [\underline{v}, \bar{v}]$ and $n \geq 2$

$$F_{V_{n-1:n}}(v) = n(n-1)\int_{\underline{v}}^{v} F_V(u)^{n-2}[1 - F_V(u)]du, \tag{15}$$

so that inverting this relationship separately for each n identifies F_V. This is the standard identification argument based on order statistics that is applicable to symmetric IPV ascending auctions.[52]

Next consider identification of the distribution of seller values. We focus on identifying

$$F_{V_0|v_0 \geq v_0^R} = \frac{F_{V_0}(v_0) - F_{V_0}(v_0^R)}{1 - F_{V_0}(v_0^R)} \tag{16}$$

because, under the restriction that v_0^R is structural, the part of the support of $V_0 < v_0^R$ is irrelevant in counterfactuals where at least one seller finds it profitable to enter and set a positive reserve price. Assuming that sellers play the equilibrium reserve price strategy, each reserve price maps to that seller's value as can be seen by rearranging (4) to

$$v_0(r) = (1 - c_S)\left(r - \frac{1 - F_V(r(1 + c_B))}{(1 + c_B)f_V(r(1 + c_B))}\right). \tag{17}$$

Here, $v_0(r)$ denotes the seller valuation implied by reserve price r, which is known as F_V (and hence f_V) is identified and the other elements on the right-hand side of (17) are observed.[53] As such, the distribution of implied seller values, $F_{v_0(r)}$, is equal to the distribution of seller values conditional

[52] Hence, in line with the literature standard regarding analysis of ascending auction data, the identification proof relies on the absence of unobserved heterogeneity conditional on the set of observed auction-level characteristics. New identification methods for a bidding model with unobserved heterogeneity could be applied to settings where additional data is available to the econometrician. 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 (2022), 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 explains 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.

[53] 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.

on entering and setting a positive reserve price. In particular, $\forall v \in [v_0^R, v_0^*]$ it equals

$$F_{v_0(r)}(v) = \frac{F_{V_0 \geq v_0^R}(v)}{F_{V_0 \geq v_0^R}(v_0^*)}. \tag{18}$$

Equation 18 shows that without identifying variation in v_0^* and unless $v_0^* = \bar{v}_0$ and all potential sellers enter, the population distribution $F_{V_0 \geq v_0^R}$ is not nonparametrically identified on the part of its support exceeding v_0^*. However, the (identified) right-truncated distribution of potential seller values in (18) 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 our empirical context, where the lemons effect described in section 3.C appears important enough to justify modifying the fee structure to exclude some high-v_0 sellers on the platform.

Given the identification of F_V and observing all platform fees in c, the entry cost amounts e_S^o and e_B^o are identified from the zero profit conditions that govern platform users' entry decisions (e.g., (11), (12), and (14)). This follows from $\Pi_{b,r>0}$, $\Pi_{b,r=0}$, and Π_s being revealed in the data at equilibrium up to —and strictly decreasing in— the entry costs. In particular, e_S^o is identified as the value that sets

$$\Pi_s(c, v_0^*; \lambda_{r>0}^*(c, v_0^*), v_0^*) = 0. \tag{19}$$

The bidder listing inspection cost e_B^o is the value that either sets

$$\Pi_{b,r=0}(c; \lambda_{r=0}^*) = 0 \tag{20}$$

or that sets

$$\Pi_{b,r>0}(c, v_0^*; \lambda_{r>0}^*) = 0 \tag{21}$$

so that, clearly, e_B^o is overidentified.[54] It is also easy to see that the expected bidder surplus in zero reserve auctions in (20) is knowable directly from the data. The number of bidders (equal to $N_{r=0}$) is observed and F_V is identified, so we can simply take the sample average of expected listing-level surplus in (7). But as (potential) bidders might be censored in auctions with $r > 0$, the zero profit conditions in (19) and (21) rely on the entry equilibrium that is recovered as follows. v_0^* is revealed as the maximum of seller values implied by (17). $\lambda_{r>0}^*$ is recovered as the value that

[54]Recall that e_B^o is assumed to be the same in auctions with and without a reserve price as the cost of inspecting a listing is not expected to differ between these two listing types. The fact that e_B^o can be identified using either subset exploits a degree of freedom in the data and allows for testing this restriction empirically.

maximizes the likelihood of the sample of observed second-highest bids and the number of bidders in auctions with $r > 0$, given F_V. This likelihood will in practice also depend on an additional parameter, $p_{0,r>0} \geq 0$, introduced below to allow for any unexplained variation in the entry process causing relatively many $r > 0$ listings to have no bidders. The value of $p_{0,r>0}$ is identified given the parametric restrictions of the generalized Poisson distribution, as best fitting the observed variation in the number of actual bidders into a lower-dimensional (two, together with the $\lambda^*_{r>0}$ played in the data) parameter space. The last structural parameter that still requires attention is v_0^R, which is identified as the minimum seller value in $r > 0$ listings implied by (17).

B. *Estimation method*

The strategies to estimate the model primitives closely follow their respective nonparametric identification arguments. However, to extrapolate beyond the support on which $F_{V_0 \geq v_0^R}$ is identified, and to estimate F_V independent of the number of bidders, the latent value distributions are parameterized.[55] The demeaning approach introduced in Haile, Hong, and Shum (2003) is applied to account for auction heterogeneity.

Overview and estimation of bidder taste parameters

Let $\mathbf{Z}$ denote the rich set of auction covariates, including the number of bottles, type of wine, its fill level, storage conditions, and information about how the wine is regarded by experts. Potential bidder and seller values are taken to satisfy the following single-index structure:

$$\ln(\tilde{V}) = g(\mathbf{Z}) + V \tag{22}$$

$$\ln(\tilde{V_0} | \tilde{V_0} \geq v_0^R) = g(\mathbf{Z}) + V_0, \tag{23}$$

assuming furthermore that $(V, V_0, \mathbf{Z})$ are mutually independent, and using tilde notation to indicate unconditional values. In our setting, $g(\mathbf{Z})$ can be interpreted as the quality of a wine with characteristics $\mathbf{Z}$, and V and V_0 as the idiosyncratic taste components of bidders and sellers. Furthermore, parametric restrictions are based on an initial assessment of the empirical CDF of V, which can be estimated nonparametrically for each number of bidders $n \geq 2$, and the empirical CDF of V_0, which can be estimated nonparametrically on the observed part of its support. Details of the demeaning approach and how to obtain the relevant estimation samples are provided below. What is important to note here is that both for bidders and for sellers these nonparametrically estimated idiosyncratic value distributions are unimodal and continuous but not symmetric. The

[55]To be exact, nonparametric estimation of F_V requires conditioning on each realization n of $N_{r=0}$ because the relationship between the second-highest bid, conditional on auction observables, and F_V is nonlinear in n (see (15)).

Generalized Gaussian Distribution ($\mathcal{GGD}$) appears suitable (see plots a and b in figure 2), and the estimation results are therefore based on:[56]

$$V \sim \mathcal{GGD}(\mu_b, \sigma_b^2, \kappa_b) \tag{24}$$

$$V_0 \sim \mathcal{GGD}(\mu_s, \sigma_s^2, \kappa_s). \tag{25}$$

A particular benefit of this distribution is that it allows for additional flexibility relative to the often-imposed Normal distribution, with values of $\kappa > 0$ ($\kappa < 0$) introducing skewness to the left (right).

Estimating the parameters of the bidder taste distribution ($\theta_b = (\mu_b, \sigma_b^2, \kappa_b)$) is done by maximum likelihood estimation in line with previous analysis of ascending auction data, so a brief description suffices. First, the demeaning (or homogenization) approach is applied to be able to estimate F_V across auctions with different covariates. Specifically, with $c_B = 0$ in the data and following the identification arguments from section 4.A, the quality term is estimated by regressing the log of the second-highest bid on auction characteristics in auctions with more than one bidder. The residual plus intercept of this regression deliver (the log of) homogenized second-highest values $V_{n-1:n}$ for all auctions in this sample with $r = 0$, forming the basis of the likelihood function.[57]

Estimating the parameters of the seller taste distribution ($\theta_s = (\mu_s, \sigma_s^2, \kappa_s)$) is more complex as they depend on v_0^* that itself is a function of θ_s. A second issue stems from v_0^* being the solution to a fixed point problem with a nested threshold-crossing problem ((14)), making full maximum likelihood estimation (computationally) infeasible. The following solution is proposed. First, an initial estimate $\hat{\theta}_s^0$ is obtained by maximum concentrated likelihood estimation using the mapping of equilibrium reserve prices to homogenized seller values and a consistent estimate of v_0^*. Then, the entry equilibrium is solved given $\hat{\theta}_s^0$ and $\hat{\theta}_b$. Finally, seller parameters are re-estimated using

[56]The $\mathcal{GGD}(\mu, \sigma^2, \kappa)$ has PDF:

$$f(x; \mu, \sigma^2, \kappa) = \frac{\phi(y)}{\sigma^2 - \kappa(x-\mu)} \text{ ,with } \phi(.) \text{ the standard normal PDF and}$$
$$y = \frac{x-\mu}{\sigma^2}\mathbb{I}\{\kappa = 0\} + -\frac{1}{\kappa}\ln(1 - \frac{\kappa(x-\mu)}{\sigma^2})\mathbb{I}\{\kappa \neq 0\},$$

[57]$\mathcal{T}_{r0}$ denotes the set of listings with a zero reserve price and $h(.|n_t, \mathbf{z}_t; \theta_b)$ the density of homogenized hammer prices given the number of bidders n_t and auction covariates $\mathbf{z}_t$ in auction t, as a function of bidder parameters θ_b. For all auctions with a zero reserve price, and with $c_B = 0$ in the data, it equals the probability that the homogenized second-highest bid b_t is the second-highest among n_t draws from F_V. Hence $\forall t \in \mathcal{T}_{r0}$:

$$h(b_t|n_t, \mathbf{z}_t; \theta_b) = n_t(n_t - 1)F_V(b_t; \theta_b)^{n_t - 2}[1 - F_V(b_t; \theta_b)]F_V(b_t; \theta_b) \tag{26}$$

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

$$\mathcal{L}(\theta_b; \{n_t, \mathbf{z}_t, b_t\}_{t \in \mathcal{T}_{r0}}) = \sum_{t \in \mathcal{T}_{r0}} ln((h(b_t|n_t, \mathbf{z}_t; \theta_b))) \tag{27}$$

the resulting equilibrium v_0^*. The steps are explained in more detail below.

Estimation of seller taste parameters

Let $\mathcal{T}_{r>0}$ denote the set of auctions with $r > 0$. Based on equations 17 and 25, and with $c_B = 0$ we know that $\forall t \in \mathcal{T}_{r>0}$

$$\hat{v}_{0t} = \ln\left((1-c_S)\left(r_t - \frac{1-F_V(ln(r_t) - \hat{g}(\mathbf{z}_t);\hat{\theta}_b)}{f_V(ln(r_t) - \hat{g}(\mathbf{z}_t);\hat{\theta}_b)}\right)\right) - \hat{g}(\mathbf{z}_t), \tag{28}$$

with r_t the reserve price, $\mathbf{z}_t$ auction covariates, and $\hat{v}_{0t}$ the implied conditional seller value in auction t, and $\hat{g}(\mathbf{z}_t)$ and $\hat{\theta}_b$ respectively the estimated quality term in auction t and the estimated bidder taste parameters. The density of implied seller values given entry threshold v_0^*, r_t, and $\mathbf{z_t}$ ($h(\hat{v}_{0_t}|v_0^*, r_t, \mathbf{z}_t;\theta_s)$) equals $\forall t \in \mathcal{T}_{r>0}$[58]

$$h(\hat{v}_{0t}|v_0^*, r_t, \mathbf{z}_t;\theta_s) = \frac{f_{V_0 \geq v_0^R}(\hat{v}_{0t};\theta_s)}{F_{V_0 \geq v_0^R}(v_0^*;\theta_s)}. \tag{29}$$

Using this density, we get an initial estimate of the seller taste parameters ($\hat{\theta}_s^0$), by maximizing the resulting likelihood function concentrated at a consistent estimate of the seller entry threshold $\hat{v}_{T_{r>0}} = \max(\{\hat{v}_{0,t}\}_{t\in\mathcal{T}_{r>0}})$:[59]

$$\mathcal{L}(\theta_s;\{\hat{v}_{0,t}, r_t, \mathbf{z}_t\}_{t\in\mathcal{T}_{r>0}}, \hat{v}_{T_{r>0}}) = \sum_{t\in\mathcal{T}_{r>0}} ln(h(\hat{v}_{0t}|v_0^* = \hat{v}_{T_{r>0}}, r_t, \mathbf{z}_t;\theta_s)) \tag{30}$$

$$\hat{\theta}_s^0 = \arg\max \mathcal{L}(\theta_s;\{\hat{v}_{0,t}, r_t, \mathbf{z}_t\}_{t\in\mathcal{T}_{r>0}}, \hat{v}_{T_{r>0}}) \tag{31}$$

The next step is to compute the entry equilibrium to recover v_0^* by solving (14), using the estimated taste parameters ($\hat{\theta}_b$, $\hat{\theta}_s^0$) to determine the value of V_0 at which a seller is indifferent between entering and staying out of the platform.[60] Finally, $\hat{\theta}_s$ is obtained by plugging the resulting equilibrium threshold (denoted by $v_0^*(\hat{\theta}_s^0)$) and solving

$$\hat{\theta}_s = \arg\max \mathcal{L}(\theta_s;\{\hat{v}_{0,t}, r_t, \mathbf{z}_t\}_{t\in\mathcal{T}_{r>0}}, v_0^*(\hat{\theta}_s^0)). \tag{32}$$

The described estimation algorithm resembles the Aguirregabiria and Mira (2002) nested pseudo likelihood (NPL) estimator, albeit with a nested concentrated likelihood estimator derived from

[58] The no-reserve screening value that determines the lower bound on the support is simply $\hat{v}_0^R = \min(\{\hat{v}_{0,t}\}_{t\in\mathcal{T}_{r>0}})$.

[59] $\hat{v}_{T_{r>0}}$ 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.

[60] Expected seller surplus is also based on the maximum likelihood estimate of the distribution of $N_{r>0}$, described in the last paragraph of this section.

the optimal reserve price strategy to recover structural parameters.[61]

Estimation of entry parameters

Estimation of the entry costs requires solving for the values that satisfy the zero profit conditions in (19), (20), and (21) given the estimated taste parameters and the computed entry equilibrium, following the steps outlined in the identification section. The bidder listing inspection cost is estimated separately from the subsets of auctions with and without a reserve price (resulting in $\hat{e}^o_{B,r>0}$ and $\hat{e}^o_{B,r=0}$) to test the model restriction that the two are equal. As anticipated, an additional share ($p_{0,r>0} \geq 0$) of listings in $r > 0$ auctions is allowed to attract no bidders, and this share is estimated to maximize the joint likelihood of the observed number of actual bidders and the second-highest bid given the generalized Poisson distribution of $N_{r>0}$.[62] The empirical distribution of the number of bidders in zero reserve auctions, which can be estimated nonparametrically, shows that no such flexibility is needed there (see plot f in figure 2). Further details about the computation of the entry equilibrium and estimation of these parameters are provided in online appendices E-F.

5. Estimation results

This section describes the estimation results that are reported in table 7. Unless otherwise specified, the discussion in this section refers to the estimates from the main estimation sample that are of primary interest. Estimates from the high-end sample are used only to introduce a relevant dimension of heterogeneity when simulating platform revenues in counterfactual 6.B.

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

[61]The entry equilibrium is computed only once because this is the slowest part of the estimation algorithm and as any number of iterations results in a consistent estimator (Aguirregabiria and Mira (2002)). Practically, updating once also achieves the highest likelihood across iterations, when iterating until convergence. More details on the estimation algorithm are provided in Appendix E. NPL is more widely used as a solution to solving parameters involving fixed point characterizations in the estimation of (dynamic) discrete choice entry games, and Roberts and Sweeting (2010) previously applied NPL to an auction setting with bidder entry. Pesendorfer and Schmidt-Dengler (2010), Kasahara and Shimotsu (2012) and Egesdal, Lai, and Su (2015) provide conditions under which NPL may (not) converge to the true equilibrium. A best-response stable equilibrium is a sufficient condition for the algorithm to converge to the truth and this is guaranteed by the entry game reducing to a single agent (marginal seller) discrete choice problem with a unique equilibrium (see section 3.C).

[62]The generalized (or zero-inflated) Poisson distribution has PDF:

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

which reduces to a standard Poisson distribution for $p_{0,r>0} = 0$.

Table 7—: Estimated structural parameters

Conditional valuation (taste) parameters	$\hat{\mu}_b$	$\hat{\sigma}^2_b$	$\hat{\kappa}_b$	$\hat{\mu}_s$	$\hat{\sigma}^2_s$	$\hat{\kappa}_s$
Main sample	2.409	0.880	0.015	2.532	0.727	0.306
	(0.022)	(0.002)	(0.002)	(0.024)	(0.005)	(0.005)
High-end sample	5.315	0.449	-0.484	5.562	0.449	-0.348
	(0.025)	(0.002)	(0.008)	(0.025)	(0.014)	(0.015)
Entry parameters	$\hat{e}^o_{B,r>0}$	$\hat{e}^o_{B,r=0}$	$\hat{e}^o_S$	$\hat{p}_{0,r>0}$	$\hat{v}^R_0$	
Main sample	1.809	2.236	1.250	0.049	-0.462	
	(0.126)	(0.134)	(0.128)	(0.0004)	(0.030)	
High-end sample	14.152	15.036	14.811	0.116	4.821	
	(0.393)	(0.423)	(0.403)	(0.0004)	(0.027)	

Notes. The structural estimates are based on 2731 observations in the main sample and 592 observations in the high-end sample. Standard errors based on 250 nonparametric bootstrap repetitions are reported in parenthesis.

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.[63] Whether the description contains words in each of these categories and the number of words in the description are included in the set of auction covariates.

A regression of the log of the hammer price per bottle 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.[64] In the main sample the R^2 is 0.51 and 0.57 when including dummies

[63] For 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 "insurance", "arrange", "quote", "wales", and "invoice".

[64] Tables C. 5-C. 6 in the appendix report estimation results from these regressions, and also provide a comparison with variations that are based on the level of the hammer price rather than the logarithm, that include dummies for the number of bidders, or that are estimated only on the sample where $r = 0$.

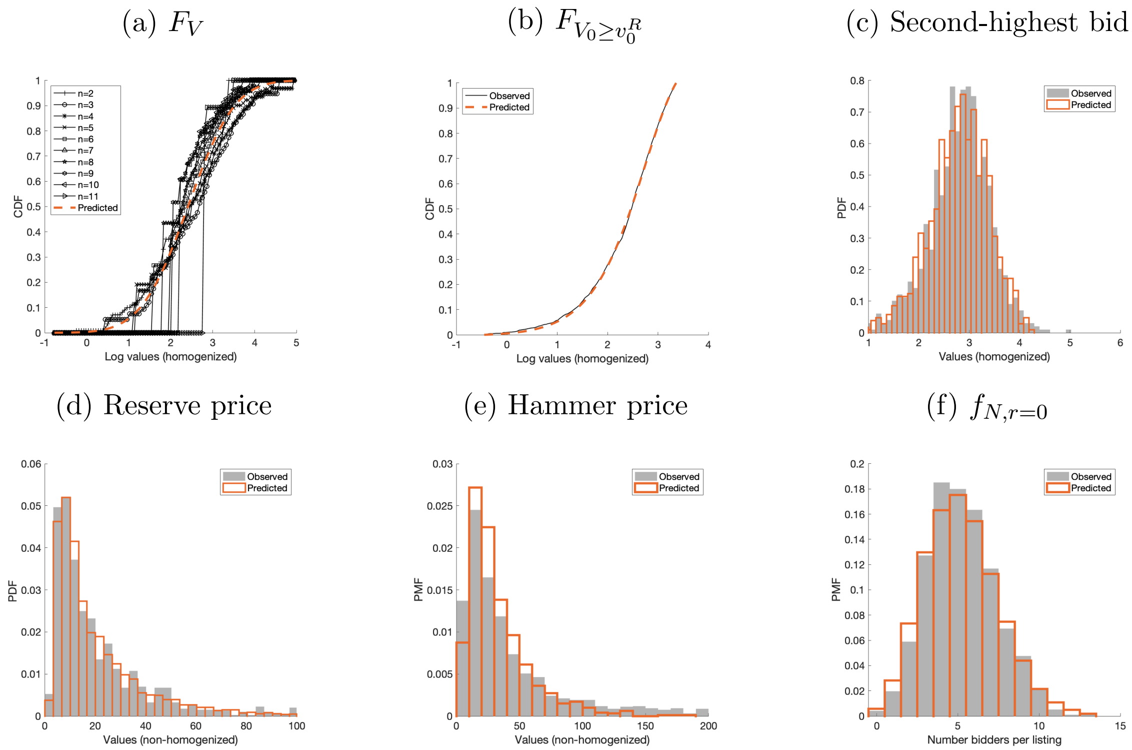

Figure 2. : Model fit: main sample

Notes. Model predictions and observed values of (a) F_V, and empirical CDF for $n = 2, ..., 11$ bidders ($r = 0$ auctions), (b) F_{V_0}, and empirical CDF ($r > 0$ auctions), (c) Second-highest bid ($r = 0$ auctions), (d) Reserve price (prediction includes estimated quality, $r > 0$ auctions), (e) Hammer price ($r > 0$ auctions), and (f) Number of bidders per listing ($r = 0$ auctions). Simulations of bidder values based on 1000 draws for each bidder and simulations of seller values based on 5000 draws. Observed values are based on the estimation sample. The same plots for the high-end sample are provided in the appendix (figure C.3).

for the number of bidders, and in the high-end sample the R^2 is 0.94. 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 impact of key variables is 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. All fill levels that are not the best earn (weakly) lower prices. Having words related to expert opinion or *En primeur* in the textual description, or having a longer description, is favorable for the price, as is fast shipping.

Table 7 reports the remaining estimated structural parameters.[65] The estimated taste distribution parameters imply that, on average, tastes in the populations of potential bidders and sellers (for $r > 0$ auctions) are virtually the same for lower-end bottles; in levels, the mean idiosyncratic value is about 11 pounds in the main sample. The sunk opportunity cost of time and the platform listing fee work to keep sellers with the highest values (marginal costs of selling) away from the platform. The average idiosyncratic value for sellers on the platform reduces to 10 pounds. Additional gains from trading on the platform are generated from the fact that only the highest-value bidder in the listing trades with the seller when bidding more than the reserve price. The estimation results also show that, even in the population of sellers with values exceeding $\hat{v}_0^R$, the distribution of their idiosyncratic tastes is more left-skewed than that of bidders. The opposite is true in the high-end sample where there is a long upper tail with some bidders having particularly high values.

The listing inspection costs are estimated to be substantial at 2-15 pounds. While the estimated inspection cost is in absolute terms seven times as large in the high-end sample, it is more informative to compare them in relation to the hammer price. Also in relative terms is the estimated inspection cost higher in the main sample (about 5 percent of the per-bottle equivalent average hammer price of 41 pounds) than in the high-end sample (about 10 percent of the per-bottle equivalent average hammer price of 155 pounds). Estimates do in both cases correspond to the idea that the cost of inspecting a listing to prepare for bidding is significant, justified by the heterogeneous nature of the goods and by a platform setting of unvetted listings generated by individual sellers.[66]

A key source of model validation is the comparison of $\hat{e}^o_{B,r=0}$ with $\hat{e}^o_{B,r>0}$. The model restricts these costs to be identical as there is no reason to suspect that the presence of a reserve price affects how time intensive it is to inspect listings if the presence of a reserve price does not reveal any information about the quality of the item. Indeed, the estimated listing inspection cost are highly similar in both the main and high-end samples. Recalling that these values are estimated from two different subsets of the data as the values that satisfy the zero profit conditions of potential bidders in zero- and positive reserve price auctions (which are, as explained, estimated using different methods), these results are encouraging.

The model also fits the data well on the usual dimensions, as illustrated by the various plots in figure 2.[67] It is particularly convincing that predicted hammer prices in $r > 0$ auctions match the observed values closely —given that the distribution of bidder values is estimated from the

[65]Estimation of θ_s excludes the 8.3 (2.3 in the high-end sample) percent of sellers for which $\hat{v}_{0t}$ is estimated to be negative. Moreover, both $\hat{u}_{0,t}$ and $\hat{g}(\mathbf{Z})$ are trimmed at their 1st and 99th percentiles to minimize the impact of outliers.

[66]By comparison, entry cost averages 2 percent of the winning bid in USFS timber auctions (Roberts and Sweeting (2013)).

[67]Plots d and e include draws of estimated quality to simulate second-highest bids and reserve prices, which are out-of-sample predictions for the reserve price sample, and the second-highest bid is simulated in expectation over the number of bidders per listing.

disjoint subset of auctions with no reserve price. This finding lends further support to the idea that bidders in positive and zero reserve auctions can be treated as identical up to their preference for bidding in either auction type. As another measure of model fit, the mean absolute deviation between the observed and predicted second-highest bids in $r = 0$ auctions is computed separately for $n = \{2, 3.., 10\}$ bidders: the mean absolute deviations are small, between 0.04-1.4 pounds, and there is no clear pattern by the 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 0.39).

Plot f of figure 2 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 0.14).[68]

Finally, at the estimated parameters, setting no reserve price attracts about the same number of bidders. It makes intuitive sense that this participation differential is larger in the high-end sample (2.5), as the probability of being the sole entrant and winning the more expensive wine for the 1 pound opening bid is more valuable.

Taken together, these results suggest that the parsimonious model presented in section 3 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. The signs of these network effects are given in table 6, and why they arise in this setting is discussed in section 3.C. 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 are estimated. The results are reported in table 8 for various values of M and T, based on homogenized auctions with $r > 0$, and

[68]The high-end sample does contain some underdispersion, and the test barely fails to reject the null (p value 0.06). 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 8—: Estimated indirect network effects

	Main sample				High-end sample			
Exogenous change number of sellers (T):	-50	-10	+10	+50	-50	-10	+10	+50
Effect on Π_b	-0.013	-0.002	0.002	0.013	-0.333	-0.071	0.075	0.431
Effect on Π_b (no selection)	-0.030	-0.006	0.006	0.029	-0.727	-0.141	0.139	0.677
	Main sample				High-end sample			
Exogenous change number of bidders (M):	-50	-10	+10	+50	-50	-10	+10	+50
Effect on Π_s (marginal seller)	-0.025	-0.005	0.005	0.025	-0.434	-0.087	0.087	0.434
Effect on Π_s (median seller)	-0.053	-0.011	0.011	0.053	-1.249	-0.249	0.249	1.243

Notes. Simulations are based on $r > 0$ homogenized auctions in the two samples.

separately for the high-end sample for illustration purposes.

Indirect network effects, by its usual definition as in i.e. Katz and Shapiro (1985), have the following magnitude: adding 10 additional bidders to the platform increases the expected surplus of the marginal seller by 0.5 pence, and this effect is about twice as large as the effect of adding 10 additional sellers 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 display heterogeneity. Sellers with lower valuations for the item on sale benefit more: the indirect network effect is about twice as large for the median potential seller than the marginal seller (at the 90th percentile). Increasing the number of sellers also has a weaker effect on bidders than reducing that number, which is more pronounced in the high-end sample.

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, the gain from adding 50 listings (the positive indirect network effect on bidders) is dampened by 55 percent because sellers in these listings set relatively high reserve prices. These patterns are similar in the high-end sample but the effects are an order of magnitude larger.

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 (2010) show that expected platform revenue (and bidder and seller surplus) are independent of (c_B, c_S) as long as α remains constant. They do not model seller entry or heterogeneity, but their

(a) Platform revenue (b) Sales volume

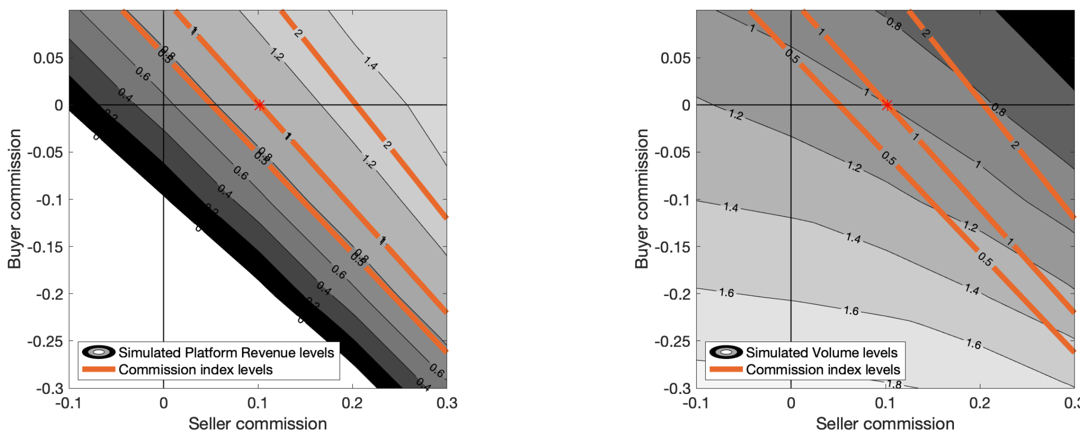

Figure 3. : Illustrating the commission index and revenue-volume trade-off

Notes. 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 interpolated linearly. Values are normalised by baseline levels and are based on parameter estimates from the main sample.

result applies here, too, since the marginal seller's expected surplus (and hence v_0^*) remains constant unless α changes. Hence, only the commission index and the flat fees matter for the platform revenue-maximization problem. Figure 3 plot (a) confirms that the simulated counterfactual platform 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 α is unchanged would lower the volume because bidders scale down their bids, while at the same time, the reserve price and sale probability are unaffected (as shown by Ginsburgh, Legros, and Sahuguet (2010)).[69] 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

[69]Note that platform revenue = volume$\times(c_B + c_S)$ + income from (e_S, e_B, e_R). Even when entry is held constant, and hence $\frac{c_B+c_S}{1+c_B}$, the sales volume decreases in c_B.

at the expense of reducing volume (by a large amount) are generally considered unattractive.[70] 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.

A. Welfare impacts and lemons effect

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.[71]

To illustrate what is termed in section 3.C as the "lemons effect" 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 pound. In a model that ignores entry, the expected surplus for all sellers on the platform would decrease by 1 pound, 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 pound. 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.

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 pound reduces expected seller surplus by 13-35 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 (σ_s^2) by 10 percent ("additional seller heterogeneity"). Fully accounting for the welfare impacts on sellers, those who

[70]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.

[71]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/16-1454$_5h26.pdf$ last accessed December 23, 2021).

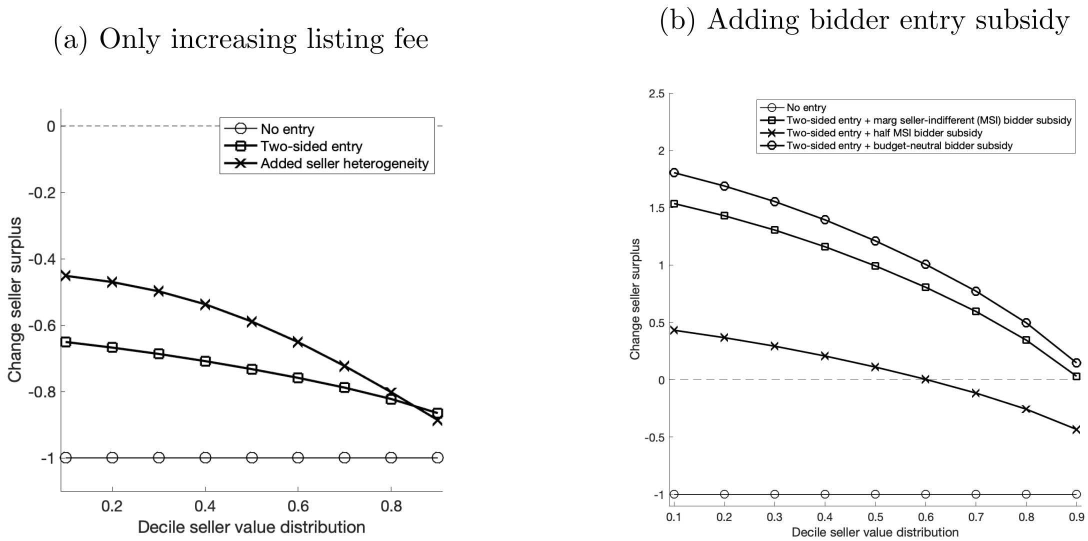

Figure 4. : Lemons effect: heterogeneous change in expected seller surplus when increasing the listing fee by one pound.

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

set no reserve price simply experience the full 1 pound loss in surplus, while the expected surplus of the 5 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 pound 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 $V_0 = v_0^*$ slightly better off. Inframarginal sellers with $V_0 \in [v_0^R, v_0^*)$ are also better off: their expected surplus increases by up to 1.8 pounds. 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.[72] No intervention by a social planner is needed to bring about these benefits: the fee change is estimated to increase both the sales volume and platform profits, driven by a higher sale probability and higher transaction prices.[73]

[72]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. 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.

[73]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, in which case the bidder subsidy does not need to be paid out of pocket. 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.

B. Platform revenues and listing heterogeneity

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 (Rochet and Tirole (2006)). 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 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 about 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. A platform wanting to establish itself in the higher-end market should tilt the fee structure on the seller side towards flat rather than proportional fees, which increases the share of high-end listings.

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. 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

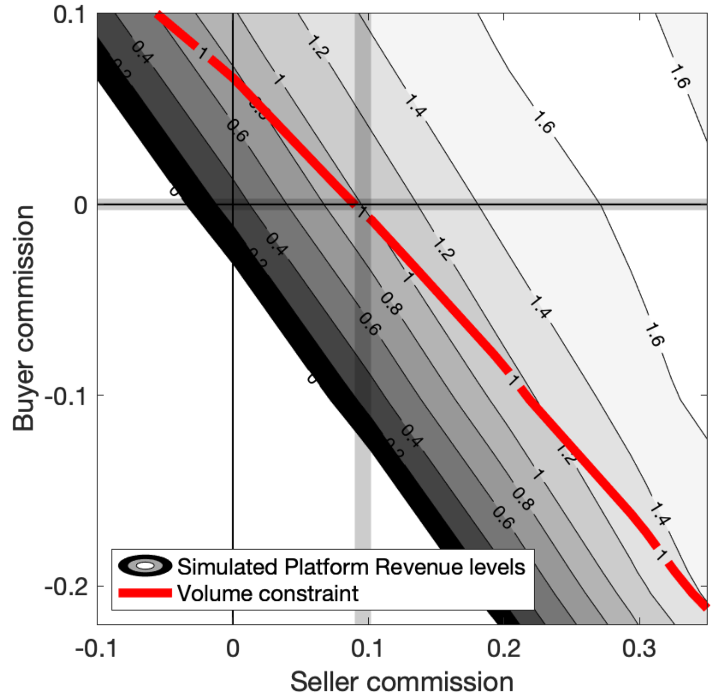

Figure 5. : Platform revenue at alternative fee structures

Notes. Figure displaying contour plots of simulated platform revenues, normalised by baseline revenues. The grey vertical bar corresponds to $c_S \in [0.9$ (high-end), 0.102 (main sample)], the horizontal bar indicates the baseline $c_B = 0$, and e_S is held at its baseline level of 2.1. 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 values are interpolated linearly. Results are based on parameter estimates from both main and high-end samples.

consider briefly two non-differentiated platforms competing only with one fee.[74] 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

[74]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.

without entry and with fully elastic sellers, as bidders simply scale down their bid by the amount of c_B (as in (3)) and sellers accept any price. 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 commission increases, pro-rata damages were deemed appropriate and most of the $512 million settlement went to the winning bidders.[75] 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.[76]

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 9 and further illustrate the bias present in simpler models without (seller) entry.[77] 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 or for the adjustment of reserve prices.[78] Moreover, the total welfare loss for sellers is 34 percent higher than when abstracting from entry. Another take-away is that also buyers experience substantial damages of 7.6 percent of the average hammer price, rather than being unaffected as in the two benchmark scenarios. These damages are also underestimated when shutting down the entry response on both sides (2.1 percent) or when only allowing bidders to enter endogenously (4 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 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

[75]See Ashenfelter and Graddy (2005) and https://casetext.com/case/in-re-auction-houses-antitrust-litigation-61, last accessed December 23, 2021.

[76]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.

[77]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 B.

[78]When fixing entry but letting r^* adjust optimally, the incidence of sellers is estimated to be 80.2 percent (see the "no entry" row in table 9). Although the hammer price is lower in this scenario, even winning bidders are worse off in expectation, as the sale probability also decreases. At the estimated values of the model primitives, the incidence on sellers drops from 80.2 to 75.8 percent when also endogenizing bidder entry while holding the set of listings constant (the "no seller entry" row). 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 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 64.2 percent.

Table 9—: Antitrust damages of doubling the commission index ($c_S + 0.102$)

		Simulated effects			Benchmarks	
		No entry	No seller entry	Two-sided entry	Elastic seller	Pro-rata
Total damage	(1000s pounds)	4	5.9	6.7		
Incidence on sellers	(%)	80.2	75.8	64.2	100	100
Hammer price	(% change)	-0.8	-7.3	-3.4	0	0
Buyer damage	(% post-hammer)	2.1	4	7.6	0	0
Seller damage	(% post-hammer)	8.5	12.6	13.6	10.2	10.2

Notes. 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 (fully) 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.

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, that the selection of sellers with higher valuations depletes much of the indirect network effect on bidders, and that 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 listing fee by one is, for sellers who remain on the platform, less than one as it causes some higher-valuation sellers ("lemons") to choose not to enter. Higher-valuation sellers set higher reserve prices, and as the expected (latent) reserve price affects bidder entry, the number of bidders per listing increases, which drives up transaction prices for the sellers remaining on the platform. 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 arising from the distribution of seller valuations through the use of a separate set of model estimates from a sample of higher-end wines. Increasing the flat 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.

Acknowledgements

I am indebted to Andrew Chesher, Phil Haile, Lars Nesheim, Adam Rosen and Áureo de Paula for fruitful discussions and continued guidance. Suggestions by Dan Ackerberg, Larry Ausubel, Matt Backus, Dirk Bergemann, Thomas Chaney, Natalie Cox, Martin Cripps, Michele Fioretti, Matt Gentry, Jeanne Hagenbach, Emeric Henry, Emel Filiz-Ozbay, Ken Hendricks, Tom Hoe, Hyejin Ku, Laurent Lamy, Kevin Lang, Guy Laroque, Brad Larsen, Thierry Mayer, Konrad Mierendorff, Rob Porter, Imran Rasul, José-Antonio Espín-Sánchez, Andrew Sweeting, Michela Tincani, Jean Tirole, Frank Verboven, Daniel Vincent, Quang Vuong, Martin Weidner, and Mo Xiao also helped improve the paper, for which I am grateful. I also want to thank seminar participants at University College London, Yale University, Duke University, Rice University, Boston University, University of Maryland, Queen's University, University Pompei Fabra, KU Leuven, University of Vienna, University of Surrey, NY FED, Sciences Po, IO^2, and numerous conference participants for thoughtful comments. All errors are my own. I am grateful for financial support from the Economic and Social Research Council (PhD Studentship).

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A. Omitted proofs

A. *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.

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

This joint distribution function can be manipulated to conclude that:

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

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_t} as the distribution is identical for all listings $t = \{1,..,T\}$.

B. Additional tables and figures

Table C. 1—: Independent listings: regression analysis

Dependent variable:	bidders / listing		transaction price		reserve price	
	coef.	s.e.	coef.	s.e.	coef.	s.e.
Product: any wine						
30 days	0.00002	(0.0001)	-0.002	(0.009)	0.009	(0.014)
7 days	0.001**	(0.0003)	0.004	(0.021)	-0.044	(0.039)
2 days	0.001**	(0.0004)	0.032	(0.031)	-0.011	(0.072)
Product: type (e.g., red)						
30 days	0.001	(0.001)	0.012	(0.070)	0.202*	(0.121)
7 days	0.007***	(0.002)	0.099	(0.146)	-0.393	(0.343)
2 days	0.004	(0.003)	0.041	(0.197)	-0.186	(0.494)
Product: region (e.g., Bordeaux)						
30 days	0.0003	(0.0003)	-0.001	(0.022)	0.044	(0.036)
7 days	0.002***	(0.001)	0.035	(0.051)	-0.081	(0.109)
2 days	0.003**	(0.001)	0.095	(0.076)	-0.034	(0.174)
Product: region x type (e.g., red Bordeaux)						
30 days	0.001	(0.001)	0.022	(0.119)	0.090	(0.214)
7 days	0.013***	(0.004)	0.459*	(0.258)	-0.570	(0.604)
2 days	0.002	(0.005)	0.400	(0.366)	-0.786	(0.760)
Product: region x type x vintage (e.g., red Bordeaux 1980s)						
30 days	-0.002	(0.004)	-0.531	(0.401)	-0.521	(0.568)
7 days	-0.003	(0.009)	-0.550	(0.885)	-0.445	(1.187)
2 days	-0.010	(0.011)	-0.300	(1.063)	-0.136	(1.307)
Product: subregion x type x vintage (e.g., red Margaux 1980s)						
30 days	-0.002	(0.002)	0.196	(0.202)	-0.179	(0.320)
7 days	0.005	(0.005)	1.083***	(0.388)	-0.722	(0.758)
2 days	-0.003	(0.006)	0.711	(0.468)	-0.977	(0.861)
Observations	3,481		2,228		2,333	
Sample	all		sold lots		$r > 0$	
Product fixed effects:	✓		✓		✓	

Notes. Standard errors in parenthesis, $^{+}$p<0.1; *p<0.05; **p<0.05; ***p<0.01. Results from 54 separate OLS regressions of how the number of competing listings affects the three 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.

Table C. 2—: Suggestive evidence against bidder selection

Panel A
Dependent variable: sale price (conditional on sale)
Various samples and controls

	(A1)	(A2)	(A3)	(A4)	(A5)	(A6)	(A7)	(A8)	(A9)
Number of bidders in auction	15.661***	13.216***	13.226***	6.847***	5.952***	5.952***	8.806***	7.882***	7.813***
	(1.094)	(1.094)	(1.094)	(0.430)	(0.422)	(0.422)	(0.622)	(0.647)	(0.647)
Total number bidders product/market	−0.186*	−0.097	−0.081	−0.078**	−0.037	−0.033	0.004	−0.037	−0.003
	(0.076)	(0.140)	(0.143)	(0.028)	(0.051)	(0.052)	(0.035)	(0.071)	(0.074)
Product fixed effects:		✓	✓		✓	✓		✓	✓
Time trend (week):			✓			✓			✓
Sample	Full	Full	Full	Main	Main	Main	$r = 0$	$r = 0$	$r = 0$
Observations	2,228	2,228	2,228	1,870	1,870	1,870	984	984	984
Adjusted R^2	0.084	0.305	0.305	0.119	0.362	0.361	0.178	0.329	0.331

Panel B
Dependent variable: hammer price (unconditional on sale)
Various product/market definitions

	(B1)	(B2)	(B3)	(B4)	(B5)	(B6)	(B7)
Number of bidders in auction	10.082***	10.758***	10.764***	10.674***	10.724***	10.129***	8.866***
	(0.668)	(0.612)	(0.619)	(0.614)	(0.627)	(0.692)	(0.719)
Total number bidders product/market	-0.013	0.031	0.009	0.048	0.014	-0.066	0.334+
	(0.074)	(0.026)	(0.035)	(0.050)	(0.103)	(0.218)	(0.202)
Product fixed effects:	✓	✓	✓	✓	✓	✓	✓
Time trend:	✓	✓	✓	✓	✓	✓	✓
Sample	$r = 0$	$r = 0$	$r = 0$	$r = 0$	$r = 0$	$r = 0$	$r = 0$
Observations	988	988	988	988	988	988	988
Adjusted R^2	0.363	0.238	0.293	0.268	0.316	0.363	0.344

Notes. Standard errors in parenthesis, $^{+}$p<0.1; *p<0.05; **p<0.05; ***p<0.01. Product/market specifications in Panel A: All columns: region×type×vintage, 4 weeks. Product/market specifications in Panel B: (B1): region×type×vintage, 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. The results in column (B1) are reported in the main text.

Table C. 3—: Reduced form evidence predicted network effects

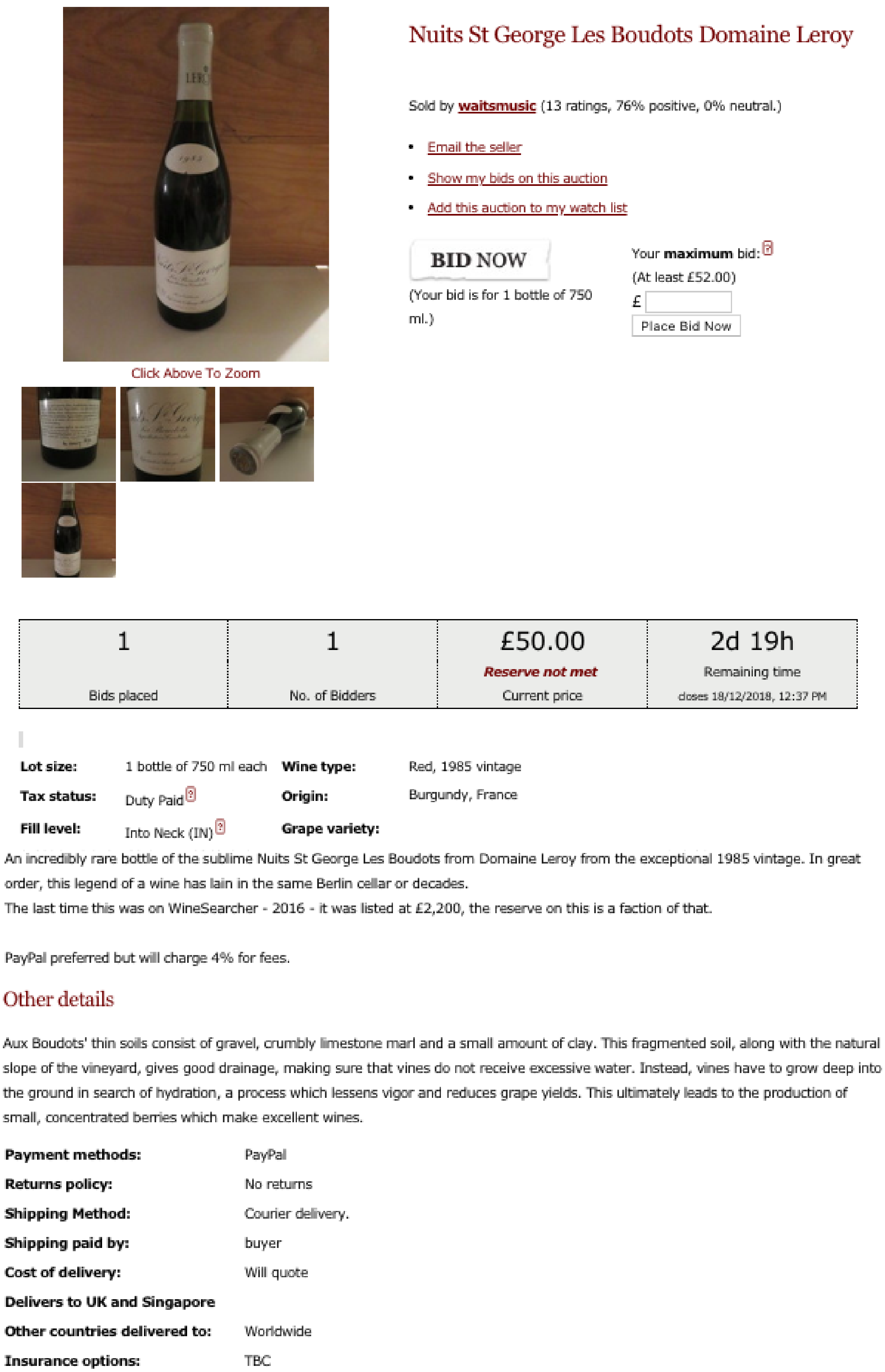
Dependent variable:	Number bidders for product in market				Number bidders per listing of product			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Number listings product/market	3.025***	2.869***	3.018***	2.992***	−0.006	−0.015+	0.004	0.005
	(0.053)	(0.072)	(0.134)	(0.133)	(0.005)	(0.008)	(0.015)	(0.015)
Product fixed effects:		✓	✓	✓		✓	✓	✓
No-reserve only:			✓	✓			✓	✓
Time trend:				✓				✓
Observations	1,229	1,229	457	457	3,481	3,481	1,148	1,148
Adjusted R^2	0.726	0.810	0.867	0.871	0.0001	0.210	0.112	0.112

Notes. Standard errors in parenthesis, $^{+}$p<0.1; *p<0.05; **p<0.05; ***p<0.01. Results from OLS regressions. 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.

Table C. 4—: Antitrust damages of doubling commission index ($c_B + 0.1281$)

	Total damage (1000s pounds)	Incidence on sellers (%)	Hammer price (% change)	Buyer damage (% post-hammer)	Seller damage (% post-hammer)
Benchmark pro-rata		0.0	0.0	12.81	0.0
Benchmark elastic sellers		100.0	-11.36	0.0	12.81
Simulated impacts:					
No entry	4.0	80.2	-12.0	2.4	9.6
No seller entry	5.9	75.8	-17.8	4.5	14.2
Full two-sided entry	6.6	64.2	-14.3	8.5	15.3

Notes. 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 9 in the main text.



Nuits St George Les Boudots Domaine Leroy

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

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

BID NOW

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

Your **maximum** bid:
(At least £52.00)
£
Place Bid Now

Click Above To Zoom

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

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

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

PayPal preferred but will charge 4% for fees.

Other details

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

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

Figure C.1. : Listing page example

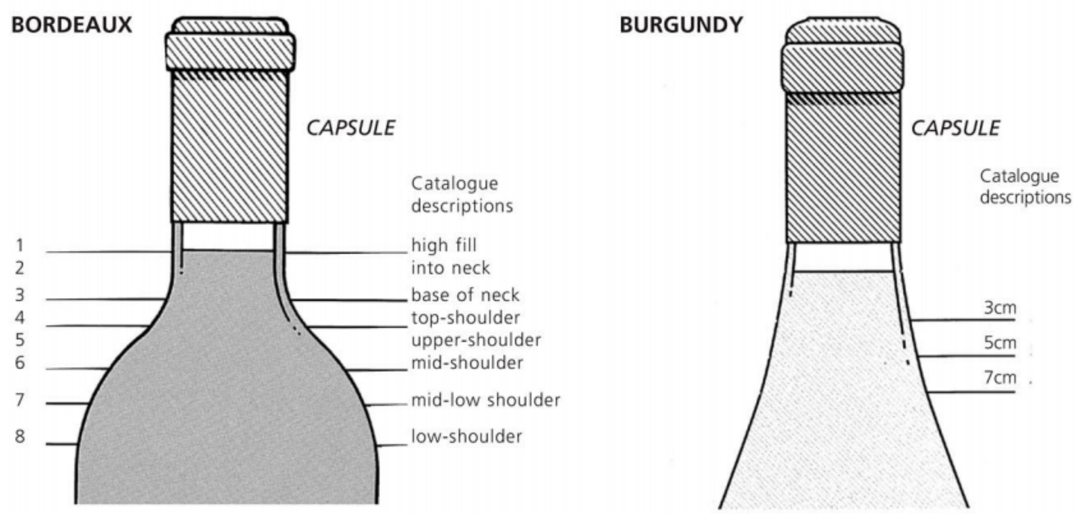
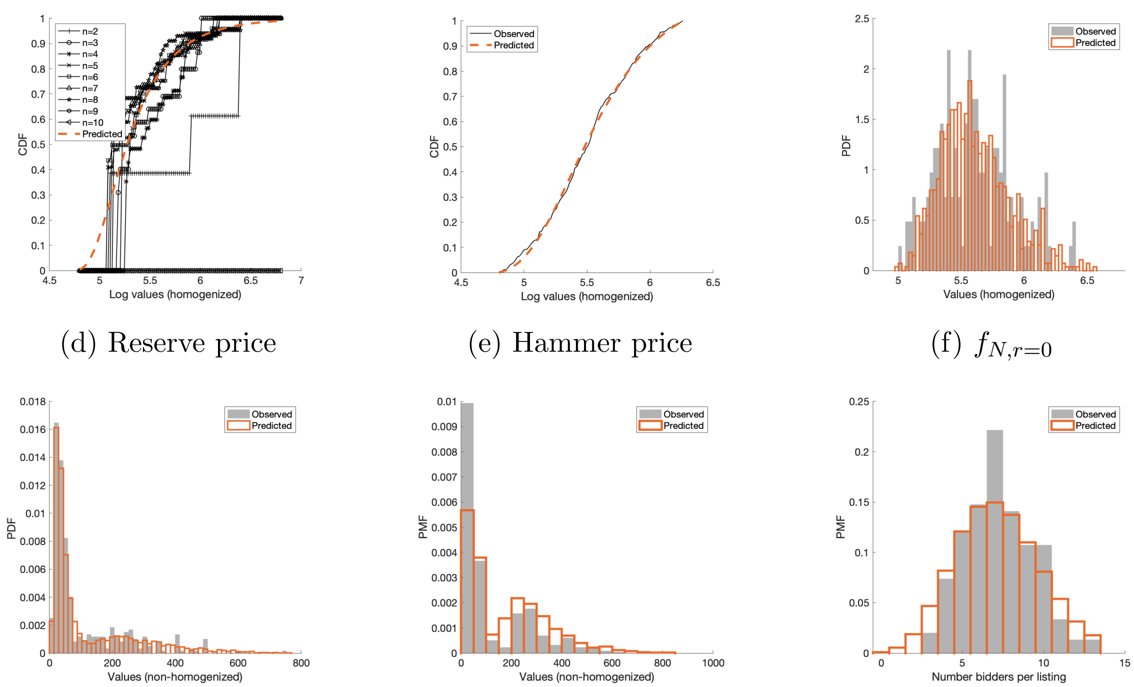


Figure C.2. : Ullage classification and interpretation

Source: https://www.christies.com/Wine/Ullages_2013.pdf, last accessed December 23, 2021.
Notes. 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.



(a) F_V (b) $F_{V_0 \geq v_0^R}$ (c) Second-highest bid

(d) Reserve price (e) Hammer price (f) $f_{N,r=0}$

Figure C.3. : Model fit: high-end sample

Notes. Model predictions and observed values of: (a) F_V, and empirical CDF for $n = 2, ..., 10$ bidders ($r = 0$ auctions), (b) F_{V_0}, and empirical CDF ($r > 0$ auctions), (c) Second-highest bid ($r = 0$ auctions), (d) Reserve price (prediction includes estimated quality, $r > 0$ auctions), (e) Hammer price (prediction includes estimated quality, $r > 0$ auctions), and (f) Number of bidders per listing ($r = 0$ auctions). Simulations of bidder values based on 1000 draws for each bidder and simulation of seller values based on 5000 draws. Observed values are based on the estimation sample. The same plots for the main sample are provided in figure (2) in the paper.

C. Entry equilibrium 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, $\tilde{r} = (1 + c_B)r^*(v_0, c)$, 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 $\Pi_{b,r>0}(c, \tilde{v_0}; p)$ potential bidders' expected surplus from entering the platform as a function of their entry probability p:

$$\Pi_{b,r>0}(c, \tilde{v_0}; p) = \sum_{n=0}^{N^B_{r>0}-1} \mathbb{E}[\pi_b(n + 1, c, v_0)|V_0 \in [v_0^R, \tilde{v_0}]f_{N_{r>0},T_{r>0}}(n; p) - e_B - e^o_{B,r>0} \tag{A.2}$$

It takes the expectation of $\pi_b(n, c, v_0)$ ((5) with optimal r as in (4)) 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 $e^o_{B,r>0}$ are associated with each listing. Components of equation (A.2) are:

$$\mathbb{E}[\pi_b(n + 1, c, v_0)|V_0 \in [v_0^R, \tilde{v_0}]] = \int_{v_0^R}^{\tilde{v_0}} \pi_b(n + 1, c, v_0) f_{V_0|V_0\in[v_0^R,\tilde{v_0}]}(v_0)dv_0 \tag{A.3}$$

$$f_{N_{r>0},T_{r>0}}(n; p) = \binom{N^{B,r>0} - 1}{n} (\frac{p}{T_{r>0}})^n (1 - \frac{p}{T_{r>0}})^{N^{B,r>0}-1-n} \tag{A.4}$$

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.

$\pi_b(n+1, c, v_0)$ 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:

$$p^{*T_{r>0}}(T_{r>0}, f, \tilde{v_0}) \equiv \arg_{p\in(0,1)} \Pi_b^{T_{r>0}}(c, \tilde{v_0}; p) = 0 \tag{A.5}$$

In this equilibrium the number of (competing) bidders per listing follows a Binomial distribution with mean $(N^{B,r>0} - 1)\frac{p^{*T_{r>0}}}{T_{r>0}}$ and variance $(N^{B,r>0} - 1)\frac{p^{*T_{r>0}}}{T_{r>0}}(1 - \frac{p^{*T_{r>0}}}{T_{r>0}})$. Furthermore, a no-trade entry equilibrium at $p = 0$ that trivially solves (A.5) 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 $\frac{p^{*T_{r>0}}}{T_{r>0}}$ 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 $\mathbb{E}[\pi_b(n+1, c, v_0)|V_0 \in [v_0^R, \tilde{v_0}]]$. The zero profit condition therefore guarantees that in equilibrium a change in $T_{r>0}$ causes $p^{*T_{r>0}}$ to adjust to keep $f_{N_{r>0},T_{r>0}}(.)$ constant.

D. 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 $\forall v \in [v^*, \bar{v}]$:

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

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 (5)-(7). The listing-level expected surplus for a bidder with valuation v_i in a listing with $n-1$ competing bidders, fee structure c, when the seller has a private value of v_0, and conditional on $v_i \geq \tilde{r}$:

(B.2)
$$\pi_b(v_i, n, f, v_0, v^*) = F_{V|V \geq v^*}(v_i)^{n-1} \mathbb{E}^{v^*}[v_i - \max(V_{n-1}, \tilde{r})|V_{n-1} \leq v_i, v_i \geq \tilde{r}]$$

$\pi_b(v_i, n, f, v_0, v^*)$ 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 $F_{V|V \geq v^*}(v)$:

(B.3)
$$\pi_s(n, f, v_0, v^*) \equiv \left(\mathbb{E}^{v^*}[\max(V_{n-1:n}, \tilde{r})|V_{n:n} \geq \tilde{r}](1 - c_S) - v_0\right)[1 - F^{v^*}_{V_{(n:n)}}(\tilde{r})]$$

where $F^{v^*}_{V_{(n:n)}}$ 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:

$$\text{(B.4)} \qquad \Pi_{b,r>0}(v_i, f, \tilde{v_0}; \tilde{v}) = \\ \sum_{n=0}^{N^B_{r>0}-1} \mathbb{E}[\pi_b(v_i, n+1, f, v_0, \tilde{v})|V_0 \in [v_0^R, \tilde{v_0}]] f_{N^B_{r>0}, T_{r>0}}(n; \tilde{v}) dn - e_B - e^o_{B,r>0}$$

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

$$\text{(B.5)} \qquad f_{N^B_{r>0}, T_{r>0}}(n; \tilde{v}) = \binom{N^B_{r>0}-1}{n} \binom{1}{T_{r>0}} (1 - F_V(\tilde{v}))^n (\frac{1}{T_{r>0}} F_V(\tilde{v}))^{N^B_{r>0}-1-n}$$

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 4. *A unique entry equilibrium bidder entry threshold solves the marginal bidder's zero profit condition:*

$$\text{(B.6)} \qquad v^*(f, \tilde{v_0}) \equiv \arg_{\tilde{v} \in [\underline{v}, \bar{v}]} \{\Pi_{b,r>0}(\tilde{v}, f, \tilde{v_0}; \tilde{v}) = 0\}$$

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 $v^*(\bar{v})$ 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 $\bar{v_0}$. As in the baseline model, whether also a unique seller entry equilibrium exists depends on how the expected surplus of sellers is affected by $v^*(f, \bar{v})$. We know that v^* decreases in $\bar{v}$ 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 2. In what follows, $f_{N^B_{r>0}, T_{r>0}}(n; v^*(\tilde{v_0}))$ 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 $\Pi_s(c, v_0; \lambda^*_{r>0}(c, \tilde{v_0}), \tilde{v_0})$ 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 $\tilde{v_0}$:

$$\Pi_s(c, v_0; f_{N^B_{r>0}, T_{r>0}}(n; v^*(\tilde{v_0})), \tilde{v_0}) = \sum_{T_{r>0}=1}^{N^S} \sum_{n=0}^{N^B} \pi_s(n, f, v_0, v^*(\tilde{v_0})) f_{N^B_{r>0}, T_{r>0}}(n; v^*(\tilde{v_0})) - e_S - e_S^o \tag{B.7}$$

Lemma 5. *A unique equilibrium seller entry threshold solves the marginal seller's zero profit condition:*

$$v_0^*(c) \equiv \arg_{\tilde{v_0} s.t. F_{V_0}(\tilde{v_0}) \in (0,1)} \{\Pi_s(c, \tilde{v_0}; f_{N^B_{r>0}, T_{r>0}}(n; v^*(\tilde{v_0})), \tilde{v_0}) = 0\} \tag{B.8}$$

The proof requires three parts. First, sellers have a unique best-response for any competing $\tilde{v_0}$, because $\Pi_s(c, \tilde{v_0}; f_{N^B_{r>0}, T_{r>0}}(n; v^*(\tilde{v_0})), \tilde{v_0})$ strictly decreases in their own v_0. Second, given that $\Pi_s(c, \tilde{v_0}; f_{N^B_{r>0}, T_{r>0}}(n; v^*(\tilde{v_0})), \tilde{v_0})$ 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 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, $v_0^*(c)$, 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.

E. Additional details estimation algorithm

This section provides details about the estimation of structural parameters not included in the main text. This regards especially $\hat{e}^o_{B,r>0}$, $\hat{e}^o_{B,r=0}$, $\hat{e}^o_S$, and $\hat{p}_{0,r>0}$, as well as details about the iteration algorithm.

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 at least 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 ($\hat{e}^{o,0}_{B,r>0}$ and $\hat{e}^{o,0}_S$) as detailed below. After obtaining these initial values, for each iteration $k = 1, \ldots$:

- solve for the unique $v_0^{*k}(\hat{\theta}_s^{k-1}, \hat{e}_S^{o,k-1})$ that pins down the marginal seller (equation (14)),
- estimate $\hat{\theta}_s^k(v_0^{*k})$ by maximum concentrated likelihood (equation (31)),
- and solve for the $\hat{e}_S^{o,k} = e_S^{o*}(v_0^{*k})$ that satisfies the zero profit entry condition (equation (19)),

until convergence of the entry probability (using a tolerance level of $1e-3$), omitting from the notation above any parameters that remain fixed throughout. The results in the main body of the paper are based on just one iteration, which also corresponds to the iteration with the lowest function value (highest likelihood) across iterations, and the results are similar when iterating until convergence.

For $\hat{e}^{o,0}_{B,r>0}$ and $\hat{e}^o_{B,r=0}$, the initial estimator is the same as the final estimator although $\hat{e}^{o,0}_{B,r>0}$ 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 $\Pi_{b,r>0}(.)$ and $\Pi_{b,r=0}(.)$ equal to 0 as dictated by the two zero profit entry conditions for potential bidders. This clearly depends on the relevant distribution of the number of bidders per listing, and hence on $\hat{\lambda}^*_{r>0}$, $\hat{p}_{0,r=0}$, and $\hat{\lambda}^*_{r=0}$. In auctions with no reserve price, the mean observed N is a consistent estimator of $\lambda^*_{r=0}$:

$$\hat{\lambda}^*_{r=0} = \frac{1}{|\mathcal{T}_{r=0}|} \sum_{t \in \mathcal{T}_{r=0}} n_t \tag{B.9}$$

Note that $\hat{\lambda}^*_{r=0}$ 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 $\hat{\lambda}^*_{r>0}$.

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 partially secret, but in that case 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 $\tilde{r}_t = r_t(1 + c_B)$, $\forall t \in \mathcal{T}_{r>0}$:

$$\begin{aligned} h(b_t, a_t | n_t, r_t, \mathbf{z}_t, \hat{\theta}_b) = \{F_V(\tilde{r}_t; \hat{\theta}_b)^{n_t}\}\mathbb{I}\{a_t = 0\} \\ \{n_t F_V(\tilde{r}_t; \hat{\theta}_b)^{n_t - 1}[1 - F_V(\tilde{r}_t; \hat{\theta}_b)]\}\mathbb{I}\{a_t = 1\} \\ \{\binom{n_t}{n_t - a_t} F_V(\tilde{r}_t; \hat{\theta}_b)^{n_t - a_t}[1 - F_V(\tilde{r}_t; \hat{\theta}_b)]^{a_t} \\ a_t(a_t - 1)F_V(\tilde{b}_t; \hat{\theta}_b)^{a_t - 2}[1 - F_V(\tilde{b}_t; \hat{\theta}_b)]F_V(\tilde{b}_t; \hat{\theta}_b)\}\mathbb{I}\{a_t \geq 2\} \end{aligned} \tag{B.10}$$

Note that $h(b_t, a_t | n_t, r_t, \hat{\theta}_b) = 0$ 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 draw 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 $N \sim$ generalized $Pois(\lambda^*_{r>0}, p_{0,r>0})$.[79] Using the more flexible two-parameter Poisson distribution allows for an unspecified reason for observing no bids, in addition to all values being below the reserve price or no bidders entering the auction.

[79] The generalized Poisson distribution has PDF:

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

which reduces to a standard Poisson distribution for $p_{0,r>0} = 0$.

This feasible specification is the basis of the likelihood function that $(\hat{\lambda}^*_{r>0}, \hat{p}_{0,r>0})$ maximizes:

$$g(b_t, a_t | r_t, \mathbf{z}_t, \hat{\theta}_b; \lambda^*_{r>0}, p_{0,r>0}) = \sum_{k=a_t}^{\infty} h(b_t, a_t | n_t = k, r_t, \mathbf{z}_t, \hat{\theta}_b) f_{N_{r>0}|N_{r>0} \geq A}(k; \lambda^*_{r>0}, p_{0,r>0}) \tag{B.11}$$

$$\mathcal{L}(\lambda^*_{r>0}, p_{0,r>0}; \{b_t, a_t, r_t, \mathbf{z}_t\}_{t \in \mathcal{T}_{r>0}}) = \sum_{t \in \mathcal{T}_{r>0}} ln(g(b_t, a_t | r_t, \mathbf{z}_t, \hat{\theta}_b; \lambda^*_{r>0}, p_{0,r>0})) \tag{B.12}$$

$$(\hat{\lambda}^*_{r>0}, \hat{p}_{0,r>0}) = \arg\max \mathcal{L}(\lambda^*_{r>0}, p_{0,r>0}; \{b_t, a_t, r_t, \mathbf{z}_t\}_{t \in \mathcal{T}_{r>0}}) \tag{B.13}$$

The estimator does not require interpretation of losing bids. While the resulting estimator does capture the censoring of bidders to some extent, it does not address potential intra-auction dynamics to the extent that some other estimators do.[80] Specifically, 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 minimized in the presented model with endogenous two-sided entry, relative to a model without entry. To see why, consider a scenario where the true $\lambda^*_{r>0}$ would be larger than estimated due to some bidders entering after the standing price exceeds their valuation. In that scenario, the true F_V would be stochastically dominated by the estimated distribution as the hammer price is really the second-highest out of *more* draws from F_V than what is captured in the analysis. The true $\hat{e}_{B,r>0}$ in that case would also have to be lower than estimated, as the per-bidder expected surplus from entering the platform is lower. Hence, without changing the fee structure but with endogenous entry, simulating entry decisions of lower-value potential bidders facing lower entry cost would result in the exact same outcomes. That is to say, the abstraction from intra-auction dynamics is therefore internally consistent. Nonetheless, the direction of the effect of the abstraction when changing fees cannot be signed ex-ante due to nonlinearities in the system. Given that the effects of overestimating bidder values and overestimating the bidder entry cost, relative to the scenario with intra-auction dyanamics, offset each other at least partially, this abstraction is considered not to be of first order importance in the model with two-sided entry.[81]

[80] Hickman, Hubbard, and Paarsch (2017) (for the case of non-binding reserve prices) and Bodoh-Creed, Boehnke, and Hickman (2021) (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 $p_{0,r>0} = 0$.

[81] This assertion is supported by results from a robustness analysis based on the filtering described in Platt (2017). Specifically,

The above describes how initial values $\hat{e}^{o,0}_{B,r=0}$ and $\hat{e}^{o,0}_{B,r>0}$ are estimated. The initial value $\hat{e_S}^{o,0}$ is estimated as follows. $\hat{v}_{T_{r>0}}$ is the sample *maximum* of a noisy first stage estimator and likely overestimates the true v_0^*.[82] This is confirmed numerically. Starting from a relatively high $\hat{e_S}^{o,0} = \max(\hat{e}^{o,0}_{B,r>0}, \hat{e}^{o}_{B,r=0})$ —which will be an overestimate if bidders need to spend more time inspecting a listing and bidding on it than that sellers require to create it—, and implementing the NPL algorithm, both $\hat{e_S}^k$ and v_0^{*k} converge downwards. The final estimate $\hat{e_S}^o$ is lower than its starting value. One benefit of the NPL algorithm to estimate $\hat{\theta}_S$ is that the initial values do not have to be close to the truth nor consistent estimates of their population counterparts (Aguirregabiria and Mira (2002)), as the equilibrium conditions of the game improve the estimates throughout until it converges at the (unique) equilibrium.

After convergence of $F_{V_0|V_0\geq v_0^R}(v_0^*; \hat{\theta}_S)$, $\hat{e}^o_{B,r>0}$ is also updated as the value that solves the zero profit condition for $\mathcal{N}^B_{r>0}$ at the equilibrium solution. Note finally that $\hat{\theta}_b$, $\hat{v}_0^R$, $\hat{p}_{0,r>0}$, $\hat{\lambda^*_{r>0}}$, $\hat{\lambda}^*_{r=0}$, and $\hat{e}_{B,r=0}$ are never updated in the estimation algorithm.

F. 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. Shorthand notation $\tilde{r} = (1 + c_B)r^*(v_0, c)$ 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 $\{\lambda^*_{r>0}(c, v_0^*),\ \lambda^*_{r=0}(c),\ v_0^*(c)\}$ as respectively defined in (11), (12), and (14) in the main text. This requires computing the expected surplus from entering the platform for bidders and sellers as a function of λ and $\tilde{v_0}$, and then solving for the equilibrium values that satisfy the zero profit entry conditions.

To compute $\Pi_{b,r>0}(c, \tilde{v_0}; \lambda_{r>0})$ we need to obtain $\pi_b(n, c, v_0)$ defined in (5) in expectation over v_0 and n, minus entry cost:

the model is re-estimated assuming that all potential bidders in both $r > 0$ and $r = 0$ auctions arrive at a Poisson rate (non-generalized, hence with $p_{r>0} = 0$), observe the standing price, and place a bid that is equal to their valuation when the standing price is below it. While this obviously results in a higher implied $\lambda^*_{r>0}$ and $\lambda^*_{r=0}$ and lower entry costs and bidder values, the main counterfactual of increasing c_L by one pound gives similar results.

[82] $\hat{v}_{T_{r>0}}$ is certainly $\geq v_0^*$ when the population $N^S \to \infty$ and no trimming is applied, in which case the maximum $\hat{v}_{0t} = v_0^*$.

(B.14)
$$\Pi_{b,r>0,T_{r>0}}(c,\tilde{v_0};\lambda) = \sum_{n=0}^{\max(n)-1}\left[\int_{v_0^R}^{\tilde{v_0}} \pi_b(n+1,c,v_0)\frac{f_{V_0|V_0\geq v_0^R}(v_0)}{F_{V_0|V_0\geq v_0^R}(\tilde{v_0})}dv_0\right]\times f_{N_{r>0}}(n;\lambda_{r>0}) - e_B - e^o_{B,r>0}$$

(B.15)
$$\pi_b(n,c,v_0) = \frac{1}{n}\int_{\tilde{r}}^{\bar{v}} v_n - \max(\tilde{r}, \int_{\underline{v}}^{v_n} v_{n-1}dF_{V_{n-1}|V_n=v_n}(v_{n-1}))dF_{V_n}(v_n)$$

(B.16)
$$F_{V_n}(v_n) = \int_{\underline{v}}^{v_n} nF_V(x)^{n-1}f_V(x)dx$$

(B.17)
$$F_{V_{n-1}|V_n=v_n}(v_{n-1}) = \int_{\underline{v}}^{v_n} \frac{(n-1)F_V(y)^{n-2}f_V(y)}{F_V(v_n)^{n-1}}dy$$

and $f_{N_{r>0}}(n;\lambda_{r>0})$ defined in (2). This is then sufficient to compute $\lambda^*_{r>0}$ for any value of $\tilde{v_0}$:

(B.18)
$$\lambda^*_{r>0}(\tilde{v_0}) \equiv \arg_\lambda \{\Pi_{b,r>0}(c,\tilde{v_0};\lambda) = 0\}$$

As $\Pi_{b,r>0}(c,\tilde{v_0};\lambda)$ strictly decreases in λ, $\lambda^*_{r>0}$ solves a threshold-crossing condition that is nested in the fixed point problem that defines $v_0^*(c)$. 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 $\Pi_{b,r=0}$:

(B.19)
$$\Pi_{b,r=0}(f,\lambda_{r=0}) = \sum_{n=0}^{\max(n)-1} \pi_b(n+1,c,0)f_{N,r=0}(n;\lambda_{r=0}) - e_B - e^o_{B,r=0}$$

with $\pi_b(n+1,c,0)$ defined in (7).

Computing $\Pi_s(c,\tilde{v_0};\lambda_{r>0})$ relies on $\pi_s(n,c,v_0)$ defined in (6) in expectation over the number of bidders, minus entry cost:

$$\Pi_s(c, v_0; \lambda^*(\tilde{v_0})) = \sum_{n=0}^{N^B_{r>0}} \pi_s(n, c, v_0) f_{N_{r>0}}(n, \lambda^*_{r>0}(\tilde{v_0})) - e_S - e^o_S \tag{B.20}$$

$$\pi_s(n, c, v_0) = (\max(r, \frac{1}{1+c_B}\int_{\underline{v}}^{\bar{v}} v_{n-1} dF_{V_{n-1}|V_n \geq \tilde{r}}(v_{n-1}))\times \\ (1-c_S) - v_0)[1 - F_{V_{(n)}}(\tilde{r})] \tag{B.21}$$

$$F_{V_{n-1}|V_n \geq \tilde{r}}(v_{n-1}) = \int_{\tilde{r}}^{\bar{v}} F_{V_{n-1}|V_n = x}(v_{n-1}) dF_{V_n}(x) \tag{B.22}$$

This is then sufficient to compute $v^*_0(c)$ for any fee structure and given potential bidders' best-response characterized by $\lambda^*_{r>0}(c, \tilde{v_0})$:

$$v^*_0 \equiv \arg_{\tilde{v_0}} \{\Pi_s(c, \tilde{v_0}; \lambda^*_{r>0}(\tilde{v_0})) = 0\} \tag{B.23}$$

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

- Importance sampling of $V_{n:n}$ and $V_{n-1:n}|V_{n:n}$. Set $\bar{v} = F^-_V 1(1-1e^{-9}; \hat{\theta_b})$ and $\underline{v} = 0$. Code the distributions in (B.16) and (B.17). For each $n = 1, .., 15$, simulate 250 values from the two distributions. For the highest valuation, solve for $F^{-1}_{V_n:n}($**v_probs**$; \hat{\theta_b})$, separately for each n, resulting in matrix **h_mat** of dimension $[250 \times 15]$. For the second-highest valuation, solve for $F^{-1}_{V_n-1:n|V_n:n=v_n}($**v_probs**$; \hat{\theta_b})$, where for each entry j in **v_probs** v_n equals the jth entry in **h_mat** from the relevant n column. Doing this separately for each $n > 1$ results in matrix **sh_mat** of dimension $[250 \times 15]$ with the first column made up of zeros.

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

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

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

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

- Repeat the five previous steps only once for each new $\hat{\theta}_s$ or fee structure. With the pre-calculated listing-level surplus matrices as functions of v_0 and n, the computation of v_0^* as a fixed point problem with a nested threshold-crossing problem to find $\lambda_{r>0}^*$ for each candidate $\tilde{v_0}$ is fast and straightforward.

- Coding equation (B.20) with nested in it equation (B.18). Make sure that for every candidate $\tilde{v_0}$, the entries of **pdf_v0_mat** that function as weights of the listing-level bidder surplus (the $\frac{f_{V_0|V_0 \geq v_0^R}(v_0)}{F_{V_0|V_0 \geq v_0^R}(\tilde{v_0})}$ in (B.14)) sum to one. The $\lambda^*(\tilde{v_0})$ in (B.18) is obtained as the root of $(\Pi_b(c, \tilde{v_0}; \lambda))^2$. Matlab's fzero function is used with tolerance levels for the function and parameter of $1e^{-}6$, which delivers stable results. Then (B.20) 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 Π_s through its effect on 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 Π_s is decreasing in the seller's v_0^j, the resulting $v_0'(v_0^{-j}) < v_0^{-j} < v_0^*$. We conclude that $\Pi_s(v_0^{-j}, v_0^{-j})$ is not an equilibrium.

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

- The final case is the unique fixed point in seller 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 (B.23) is a contraction mapping.

G. Reserve price approximation

Reserve prices are defined as the maximum of the increased minimum bid amount and the secret reserve price. The increased minimum bid amount is recovered as the standing bid when the number of bidders is zero. The secret reserve price is 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. A limitation of this approach is that the reserve price approximation could be more than half a bidding increment off if the bids are not placed at regular intervals. To compromise between too many data requests and accuracy, a separate dataset is collected that accesses all open listings at 30-second intervals but only for the duration of two weeks. This high-frequency dataset is used to verify the reserve price approximation in the paper.

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 $F_R^{\mathcal{F}}$ and $F_R^{\mathcal{R}}$ respectively denote the empirical distribution of right truncated approximated reserve prices in the high frequency ($\mathcal{F}$) and regular ($\mathcal{R}$) samples, the Kolmogorov-Smirnov test statistic is defined as:

$$D_{f,r} = \sup_x |F_R^{\mathcal{F}}(x) - F_R^{\mathcal{R}}(x)|, \tag{B.24}$$

with $\sup_x$ the supremum function over x values and f and r respectively denoting the relevant number of observations in the high frequency and regular samples, which are 330 in the high-frequency sample and $1,079$ in the regular sample. With $D_{f,r} = 0.072$, the null cannot be rejected at the 5 percent level ($D_{f,r} > 1.36\sqrt{(\frac{f+r}{fr}})$, the p-value $= 0.1441$).

The associated empirical distributions are plotted in panel (a) of figure C.4. As the approximation only delivers a lower bound on secret reserve prices in auctions that do not lead to a sale, omitting such lots generates a slightly different approximation of the reserve price distribution (plotted in panel (b) of figure C.4). The two-sample Kolmogorov-Smirnov test is therefore repeated when excluding unsold lots from the regular sample. With $D_{f,r} = 0.059$, also in this sample the null that the two distributions are equal cannot be rejected at any reasonable level (the p-value $= 0.4456$). This second test is based on a lower number of observations ($r = 596$).

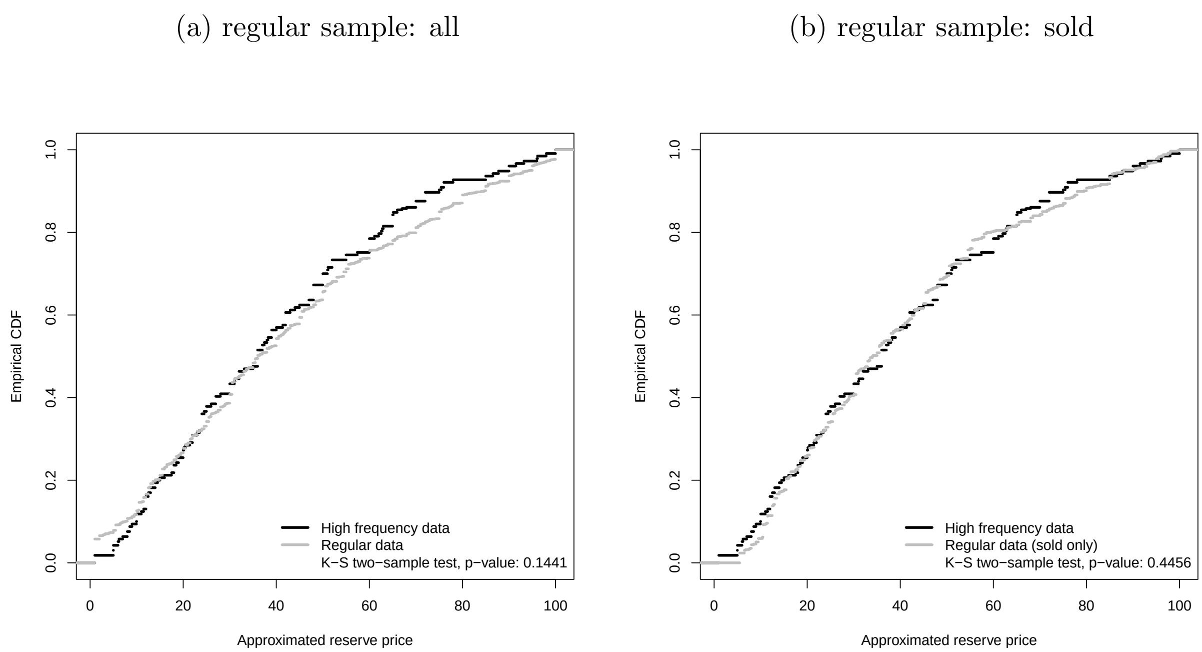


Figure C.4. : Empirical distributions underlying the presented Kolmogorov-Smirnov tests

Table C. 5—: Results from homogenization step (main sample), with alterantive specifications

	Log(Hammerprice)					Hammerprice
	(1)	(2)	(3)	(4)	(5)	(6)
Number bottles	−0.355***	−0.654***	−0.601***	−0.388***	−0.349***	−11.459***
	(0.056)	(0.135)	(0.108)	(0.052)	(0.057)	(2.664)
Number bottles, squared	0.015***	0.048**	0.040***	0.017***	0.015***	0.547**
	(0.004)	(0.015)	(0.012)	(0.003)	(0.004)	(0.169)
Case of 6 bottles	0.458***	0.804***	0.756***	0.562***	0.431***	11.517+
	(0.126)	(0.214)	(0.171)	(0.118)	(0.128)	(6.017)
Case of 12 bottles	0.763***	−0.683	−0.105	0.933***	0.508*	28.724**
	(0.230)	(1.033)	(0.823)	(0.216)	(0.226)	(11.028)
Special format bottles	0.073	0.253*	0.286**	0.098	0.001	−0.869
	(0.069)	(0.127)	(0.102)	(0.065)	(0.069)	(3.329)
One bottle	0.218**	−0.096	0.049	0.234**	0.322***	20.739***
	(0.080)	(0.145)	(0.115)	(0.075)	(0.078)	(3.831)
Stored in temperature-controlled warehouse	0.252	0.156	−0.590	0.119	−0.019	14.775
	(0.207)	(0.631)	(0.504)	(0.194)	(0.082)	(9.906)
Description relates to *En Primeur*	0.186***	0.092	0.018	0.147**	0.182***	8.091***
	(0.049)	(0.075)	(0.060)	(0.046)	(0.048)	(2.363)
Description relates to expert opinion	0.171***	0.146*	0.086	0.189***	0.243***	3.164
	(0.041)	(0.071)	(0.057)	(0.039)	(0.040)	(1.981)
Number of words in description	0.011***	0.008*	0.004	0.007***	0.014***	0.432***
	(0.002)	(0.004)	(0.003)	(0.002)	(0.002)	(0.109)
Description relates to shipping	0.00005	−0.066	−0.001	0.001	0.004	−0.764
	(0.039)	(0.062)	(0.049)	(0.036)	(0.038)	(1.860)
Buyer can only collect the wine	−0.001	−0.370*	0.001	0.195+		6.934
	(0.109)	(0.175)	(0.141)	(0.103)		(5.224)
Returns are accepted	−0.184	−1.506**	−0.183	0.043		−3.070
	(0.144)	(0.472)	(0.380)	(0.135)		(6.886)
Insurance included in delivery quote	0.138**	0.099	0.060	0.079*		7.804***
	(0.042)	(0.066)	(0.053)	(0.040)		(2.013)
Buyer can collect the wine	0.071	−0.155+	−0.137*	0.112*		6.135**
	(0.049)	(0.079)	(0.063)	(0.046)		(2.348)
Sellers ships to the UK	0.091*	0.332***	0.207***	0.052		6.674**
	(0.044)	(0.073)	(0.058)	(0.042)		(2.130)
Payment by bank	0.262**	0.023	−0.043	0.209*		10.685*
	(0.088)	(0.144)	(0.114)	(0.083)		(4.227)
Payment via PayPall	−0.111*	−0.252**	−0.179**	−0.071		−4.130+
	(0.047)	(0.080)	(0.064)	(0.044)		(2.245)
Payment by cheque	0.037	−0.005	0.025	0.043		−0.755
	(0.050)	(0.086)	(0.068)	(0.047)		(2.395)
Payment in cash	0.059	−0.272+	−0.206+	−0.006		2.646
	(0.112)	(0.157)	(0.125)	(0.105)		(5.382)
Shipped with Royal Mail	−0.028	−0.188*	−0.142*	−0.020		−0.253
	(0.050)	(0.080)	(0.064)	(0.047)		(2.415)
Shipped with ParcelForce	−0.179***	−0.174**	−0.152**	−0.228***		−7.172**
	(0.048)	(0.067)	(0.053)	(0.045)		(2.284)
Mentions fast shipping	0.402***	0.685***	0.460***	0.250***		21.253***
	(0.069)	(0.102)	(0.082)	(0.065)		(3.286)
Estimated Alcohol Duty	−0.021*	−0.022	0.021	−0.021*		−0.895*
	(0.009)	(0.046)	(0.037)	(0.008)		(0.427)
Estimated VAT	0.010+	0.018	−0.006	0.012*		0.161
	(0.006)	(0.030)	(0.024)	(0.006)		(0.290)
Shipping cost	0.008+	0.015*	0.020***	0.013**		0.185
	(0.004)	(0.007)	(0.006)	(0.004)		(0.203)
Seller has ratings	−0.0004	−0.017	0.040	−0.030		0.410
	(0.046)	(0.071)	(0.056)	(0.043)		(2.217)
Number of seller ratings	−0.058**	−0.082**	−0.060**	−0.034*		−3.006***
	(0.018)	(0.027)	(0.022)	(0.017)		(0.863)
Number of seller ratings, squared	0.003***	0.003**	0.002*	0.001+		0.136***
	(0.001)	(0.001)	(0.001)	(0.001)		(0.036)
Constant	2.915***	3.742***	2.474***	2.852***	3.162***	11.584
	(0.262)	(0.457)	(0.373)	(0.246)	(0.231)	(12.549)
Sample:	$n > 1$	$n > 1, r = 0$	$n > 1, r = 0$	n>1	n>1	n>1
Wine type fixed effects:	✓	✓	✓	✓	✓	✓
Region fixed effects:	✓	✓	✓	✓	✓	✓
Ullage fixed effects:	✓	✓	✓	✓	✓	✓
Time trend:	✓	✓	✓	✓	✓	✓
N (A) dummies:			✓	✓		
Observations	1,998	967	967	1,998	1,998	1,998
R^2	0.510	0.462	0.666	0.573	0.475	0.444
Adjusted R^2	0.490	0.419	0.634	0.554	0.459	0.422
Note:	+ p¡0.1; * p¡0.05; ** p¡0.01; *** p¡0.001					

Notes. Standard errors in parenthesis, $^{+}p<0.1$; $^{*}p<0.05$; $^{**}p<0.05$; $^{***}p<0.01$. Results from OLS regressions. The dependent variable is the (log) of the hammer price normalized by the number of bottles in the auction.

Table C. 6—: Results from homogenization step (high-end sample), with alternative specifications

	Log(Hammerprice)					Hammerprice
	(1)	(2)	(3)	(4)	(5)	(6)
Number bottles	-0.221^{***}	-0.699^{**}	-0.822^{**}	-0.220^{***}	-0.217^{***}	-18.134^{*}
	(0.026)	(0.235)	(0.248)	(0.027)	(0.023)	(7.702)
Number bottles, squared	0.005^{***}	0.039^{*}	0.048^{*}	0.005^{***}	0.004^{***}	0.439
	(0.001)	(0.018)	(0.019)	(0.001)	(0.001)	(0.268)
Case of 6 bottles	-0.244^{**}	0.052	0.199	-0.239^{**}	-0.257^{**}	−25.836
	(0.088)	(0.363)	(0.385)	(0.090)	(0.083)	(25.918)
Case of 12 bottles	0.069	−0.111	−0.208	0.064	0.002	14.543
	(0.131)	(0.489)	(0.492)	(0.133)	(0.118)	(38.300)
Special format bottles	0.161^{+}	0.725^{**}	0.727^{**}	0.172^{+}	0.118	23.656
	(0.091)	(0.250)	(0.253)	(0.092)	(0.086)	(26.511)
One bottle	0.502^{***}	−0.100	−0.238	0.506^{***}	0.523^{***}	144.599^{***}
	(0.083)	(0.298)	(0.318)	(0.084)	(0.078)	(24.227)
Stored in temperature-controlled warehouse	−0.153	-1.218^{+}	-1.961^{*}	−0.168	-0.167^{*}	−30.804
	(0.175)	(0.724)	(0.789)	(0.181)	(0.071)	(51.246)
Description relates to *En Primeur*	−0.052	-0.211^{*}	-0.214^{+}	−0.056	−0.029	−12.369
	(0.052)	(0.105)	(0.111)	(0.054)	(0.049)	(15.262)
Description relates to expert opinion	−0.032	-0.450^{**}	-0.470^{**}	−0.037	0.022	-32.795^{*}
	(0.053)	(0.147)	(0.151)	(0.055)	(0.047)	(15.604)
Number of words in description	0.003	0.015^{***}	0.014^{**}	0.003	0.003	1.481^{+}
	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)	(0.865)
Description relates to shipping	−0.014	−0.058	−0.072	−0.024	−0.022	0.376
	(0.045)	(0.088)	(0.089)	(0.046)	(0.042)	(13.298)
Buyer can only collect the wine	-0.253^{*}	-0.963^{*}	-0.934^{*}	-0.252^{*}		−57.578
	(0.124)	(0.392)	(0.397)	(0.128)		(36.369)
Returns are accepted	−0.002			−0.007		−5.409
	(0.104)			(0.108)		(30.537)
Insurance included in delivery quote	−0.005	−0.108	−0.116	−0.002		−11.669
	(0.049)	(0.091)	(0.092)	(0.050)		(14.311)
Buyer can collect the wine	-0.105^{+}	−0.132	-0.195^{+}	-0.123^{*}		−26.498
	(0.058)	(0.100)	(0.101)	(0.060)		(16.976)
Sellers ships to the UK	−0.035	−0.146	−0.111	−0.028		−0.617
	(0.054)	(0.117)	(0.123)	(0.056)		(15.904)
Payment by bank	−0.102	0.081	0.080	−0.120		−42.227
	(0.117)	(0.215)	(0.219)	(0.119)		(34.167)
Payment via PayPall	-0.111^{+}	−0.007	−0.067	-0.124^{*}		-28.008^{+}
	(0.057)	(0.133)	(0.139)	(0.058)		(16.604)
Payment by cheque	0.012	0.115	0.086	0.001		−6.385
	(0.058)	(0.153)	(0.157)	(0.060)		(17.003)
Payment in cash	0.176	0.194	0.202	0.180		−12.800
	(0.133)	(0.360)	(0.361)	(0.136)		(38.855)
Shipped with Royal Mail	0.118^{+}	0.436^{**}	0.412^{**}	0.108		31.478
	(0.068)	(0.145)	(0.149)	(0.069)		(19.822)
Shipped with ParcelForce	-0.210^{**}	−0.244	−0.301	-0.207^{*}		-56.560^{*}
	(0.079)	(0.180)	(0.186)	(0.080)		(23.101)
Mentions fast shipping	−0.123	−0.238	−0.182	−0.115		−42.361
	(0.097)	(0.201)	(0.215)	(0.101)		(28.363)
Estimated Alcohol Duty	−0.003	0.045	0.075^{*}	−0.003		−0.236
	(0.007)	(0.029)	(0.032)	(0.007)		(2.122)
Estimated VAT	−0.002	−0.0004	0.0001	−0.002		0.119
	(0.002)	(0.005)	(0.005)	(0.002)		(0.665)
Shipping cost	0.005^{+}	−0.008	−0.010	0.005		0.635
	(0.003)	(0.007)	(0.008)	(0.003)		(0.819)
Seller has ratings	0.019	0.097	0.092	0.027		10.090
	(0.048)	(0.092)	(0.097)	(0.049)		(13.980)
Number of seller ratings	−0.049	-0.258^{**}	-0.205^{*}	−0.047		−3.930
	(0.032)	(0.093)	(0.098)	(0.033)		(9.344)
Number of seller ratings, squared	0.002^{+}	0.011^{**}	0.009^{*}	0.002		0.261
	(0.001)	(0.004)	(0.004)	(0.001)		(0.393)
Constant	5.618^{***}	7.444^{***}	8.616^{***}	5.710^{***}	5.234^{***}	332.830^{**}
	(0.396)	(0.919)	(1.084)	(0.410)	(0.355)	(115.940)
Sample:	$n > 1$	$n > 1, r = 0$	$n > 1, r = 0$	n>1	n>1	n>1
Wine type fixed effects:	✓	✓	✓	✓	✓	✓
Region fixed effects:	✓	✓	✓	✓	✓	✓
Ullage fixed effects:	✓	✓	✓	✓	✓	✓
Time trend:	✓	✓	✓	✓	✓	✓
N dummies:			✓	✓		
Observations	370	151	151	370	370	370
R^2	0.935	0.920	0.930	0.936	0.928	0.749
Adjusted R^2	0.921	0.872	0.876	0.920	0.918	0.696
Note:			+ p¡0.1; * p¡0.05; ** p¡0.01; *** p¡0.001			

Notes. Standard errors in parenthesis, $^{+}p<0.1$; $^{*}p<0.05$; $^{**}p<0.05$; $^{***}p<0.01$. Results from OLS regressions. The dependent variable is the (log) of the hammer price normalized by the number of bottles in the auction.