ESTIMATING AN AUCTION PLATFORM GAME WITH TWO-SIDED ENTRY

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This paper develops and estimates a structural auction platform model with endogenous entry of buyers and sellers to study the 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. The results also underscore the importance of addressing seller selection when endogenizing (buyer) entry onto auction platforms. Quantifying the welfare effects from (anti-competitive) fee changes through a model that accounts for important user interactions enables antitrust policy to be applied to such markets.

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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 credibly 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.

[1]For example, sellers claiming that eBay charged supra-competitive 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), increasing the urgency of the need for empirical two-sided market studies. See also Bomse and Westrich (2005), Evans and Schmalensee (2013), and Salop et al. (2021).

[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).

The paper also presents the first structural auction model with selective seller entry (see Perrigne and Vuong (forthcoming)), 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 attracted to the platform, so bidder entry depends both on the expected number of sellers that enter and on 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 $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 of platforms in this market; attracting more creditworthy borrowers makes a lending platform more valuable to potential investors. By the same reasoning, platforms in the booming gig economy will be more valuable to job posters when they have a larger pool of qualified freelancers.[7]

I exploit 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, users on one side of the market have private information relevant for the expected surplus of users on the other side, so that entry decisions are interconnected. Reduced-form evidence is presented to support that, in the wine auction setting, 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 specialized warehouse, its provenance, delivery costs, etc.

The two-sided entry setting with seller selection complicates estimating the distribution of seller valuations. First, the support for the distribution of reserve prices depends on the param-

[4]Ellison, Fudenberg, and Mobius (2004) first postulate this entry dynamic to be important.
[5]At a high level, platforms like Prosper, Upwork, Uship, Vinted, and Bondora fit this description.
[6]The market forecast is provided by Predence Research.
[7]While definitions of a *gig worker* vary, Statistica estimates that 38 percent of the US workforce performed freelance work in 2023 (up from 35 percent in 2020), a trend discussed in recent *Forbes* articles *here and here.*

eters 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, as detailed in Section 4.B. The estimated model primitives are used to perform three sets of counterfactual analyses.

First, 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.[8] Consequentially, it is estimated that a £1 increase in the listing fee lowers the expected surplus for sellers who remain on the platform by only £0.60-£0.78. The loss in surplus is less for sellers with lower values and for all infra-marginal sellers when there is greater seller heterogeneity. Moreover, almost all users are better off when the £1 higher listing fee is paired with a budget-neutral bidder entry subsidy, including most sellers, despite paying 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.

Second, I address the canonical two-sided market pricing problem of how to allocate fees to user groups. Alternative fee structures can increase platform revenues by up to 40 percent. It is particularly striking that winning bidders should be given a *discount* on the transaction price when paired with a higher seller commission or listing fee. A negative buyer commission would certainly be innovative for auction platforms but resembles pricing in other two-sided markets, such as cash-back policies of credit card issuers. Below-marginal cost pricing is consistent with subsidizing users who generate larger indirect network effects (Rysman (2009)).

[8]This seller-side externality 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 applies when borrowers have private information about their creditworthiness, as explained in Kawai, Onishi, and Uetake (2022).

Third, I quantify the currently hard-to-measure welfare effects from anticompetitive fee changes. I show that the welfare losses 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. 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.

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

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

Related to the paper are structural analyses accounting for endogenous bidder entry, including Kong (2020), Fang and Tang (2014), Li and Zheng (2012), Athey, Levin, and Seira (2011), and Krasnokutskaya and Seim (2011).[9] 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),

[9]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 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.

and Coey, Larsen, and Platt (2020)).[10] These papers generally focus on dynamic issues for relatively commoditized goods and rely on steady-state requirements for tractability. Here, the listing inspection costs associated with the idiosyncratic nature of the goods are 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 with these papers is that I use a structural auction model 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 micro foundation for the platform's network externalities.[11] 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 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.

[10]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.

[11]These are simulated for counterfactual (fee) policies, resulting in a rich pattern of direct and indirect nonlinear network effects. Typically, the empirical two-sided market literature estimates *linear* effects by using instrumental variables or by relying on quasi-experimental variation. In 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.

2. Online wine auctions

Auction data for the empirical analysis in this paper come from the online auction platform `www.BidforWine.co.uk` (BW). This platform offers a peer-to-peer marketplace for buyers and sellers to trade their wine and caters (currently) to over 20,000 users. BW is one of 8 UK wine auctioneers recognized by The Wine Society.[12] 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.[13] 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 costs of trading on BW.

Items are sold through an English (ascending) auction mechanism with proxy bidding.[14] 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 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. Table 1 summarizes the fee structure on the platform.

As in most empirical auction settings, bidder valuations likely consist 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 the platform's users are reasonably informed about the factors that influence the quality of a bottle of wine.[15] For example, it is widely known that 1961 is a great Bordeaux vintage due to favorable weather conditions, and that low fill levels (ullage) for the age of the wine point

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

[13]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.

[14]Bidders submit their maximum willingness to pay, and the algorithm maintains the current price one bidding increment above the second-highest bid. When the highest bid is less than one increment above the second-highest bid, the transaction price is the second-highest bid. This differs from the eBay pricing rule (see Hickman, Hubbard, and Paarsch (2017)).

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

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	$\leq$ £200
				0.090	£200.01- £1,500
Listing fee	Sellers		c_L	£2.1	

Notes. The platform also charges a reserve price fee that is made up of £0.6 for raising the minimum bid and £0.3 for adding a secret reserve price, but these are not part of the analysis, which focuses on fee structure $c = \{c_B, c_S, c_L\}$. All reported fees include a 20 percent value-added tax.

to potential oxidation.[16] These details and many more are observable on the listing page.[17] 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 associations of wine auctions with luxury, 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 on average, delivery costs are approximately £12-£16, storage is costly, and anticipated future seller fees and the opportunity costs of time reduce the gains from resale further.[18] 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).[19]

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

[16] To highlight the importance of weather conditions for wine quality, Ashenfelter (2008) predicts with surprising accuracy the price of a sample of Bordeaux grand Cru's using weather data.

[17] By contrast, 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.

[18] Only once did a winning bidder sell the wine on BW in my data. This case further refutes a resale motive, as the £55 in revenues from reselling a high-end bottle of *Chateau Lafite Rothschild* from 1991 are depleted after subtracting the £16 shipping costs on the original transaction and seller commission on the second transaction.

[19] 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.

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 observed.

The profile pages of all 15,762 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 263 out of 2,581 potential sellers created a listing during the sample period. This is suggestive of an entry game, where the remaining potential sellers presumably had too high opportunity costs of selling (i.e., drinking the wine) unless they had nothing to sell during that period. As bidder identities are not observed, it cannot be determined how many of the 10,856 observed bidders are the same person.[20] In the structural analysis, bidders and sellers are treated as distinct groups of users,

[20]These statistics are provided for context; population sizes are not used in the estimation of the model primitives.

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. 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 (i.e., 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 as 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.[21] Only 26 percent of listings have an increased minimum bid amount, while 44 percent have a (secret) reserve price, and 3 percent have both. In the rest of the paper, the "reserve price" refers to the maximum of the minimum bid amount and the approximated secret reserve price. One-third of sellers does not set any form of reserve. This is especially salient to bidders by the presence of a "no reserve price" button —observable 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.

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 percent of auctions fall in the lowest seller commission bracket ($\leq$ £200) while having a reserve price lower than £200. 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 heterogeneous impacts of fee changes in different product classes, especially for the counterfac-

[21] 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 approximates well the reserve price distribution obtained in a smaller sample where bids are recorded at 30-second intervals, as documented in Online Appendix G. The 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 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.

Table 3—: Seller-level descriptive statistics

Statistic	N	Mean	St. Dev.	Min	Median	Max
Average number of words in description	254	73.13	83.54	3.00	46.00	772.00
Probability allowing for collection	254	0.60	0.48	0.00	1.00	1.00
Number of sold listings	254	7.43	23.12	0.00	2.00	237.00
Number of bottles per listing	254	3.05	5.62	1.00	1.25	72.00
If multiple listings: number of bottles per listing	143	2.42	2.58	1.00	1.43	13.21
If multiple listings: share with $r > 0$	143	0.56	0.46	0.00	0.75	1.00
If multiple $r > 0$ listings: share with r secret	94	0.54	0.48	0.00	0.75	1.00

Notes. Descriptive statistics across sellers based on the full estimation sample. When excluding three frequent sellers, the maximum number of sold listings drops to 92, and the other statistics are nearly identical.

tual policy simulations in Section 6, the model is estimated separately for "high-end" auctions that have hammer prices between £200 and £800 and reserve prices of at most £800.

B. *Seller side*

Sellers 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 15). To support this, a substantial share of sellers engages very infrequently with the platform: about half of them are only observed once during the sample period. The median seller sells 2 items during the 15 months spanning the sample. The most frequent seller sold 16 listings per month, and when excluding the three sellers that list the most frequently, the maximum sales is only 6 items per month (see Table 3). Moreover, sellers that are observed multiple times typically alternate between setting a positive and a zero reserve price.

In addition, there is substantial heterogeneity in various observable seller traits. For instance, they reside in all corners of the UK and differ in how many words they use to describe a wine — varying 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.[22] These remarks illustrate 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. Moreover, it is compelling that

[22]The most verbose wine description is by a seller residing in South London who has been on the platform since March 2012 and is a stellar seller according to 12 feedback-leaving winning bidders. 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."

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.[23] This implies that counterfactual fee structures affect the *type* of sellers that is attracted to the platform, and not just their number.

C. Bidder side

Selective seller entry has interesting ramifications for bidder entry into such platforms as well, as outlined in Ellison, Fudenberg, and Mobius (2004). For bidders, entry is the act of entering into a listing on the platform. Whether bidders know their value for a wine before entering will affect how profitable it is to attract additional bidders by changing fees. As bidder identities are unknown, I rely on indirect empirical evidence to determine this.

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 higher, markets (months) that attract more *total* bidders for a product do not have significantly different prices.[24] 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.

Nonselective bidder entry describes the case where bidders learn their valuations after inspecting the auction characteristics. That is plausible as the wines offered for sale are preowned by heterogeneous sellers, who report much for bidders to inspect: the wine's storage conditions, provenance, bond status, and other relevant characteristics that are not provided in the brief landing page excerpts. The wine's ullage classification (fill level), also indicated by the seller, provides an important measure of the degree of oxidation.[25]

The data can also speak to the presence of listing inspection costs, which render listings

[23]Online Appendix C contains additional empirical validation, albeit based on limited variation in the data.

[24]See Table B. 1 in the online appendix. 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). This is robust to numerous specifications. In this reduced-form analysis, a market is a month and a product a combination of the high-level filters used on the platform: type of wine, region of origin, and vintage decade.

[25]In Bordeaux-style bottles for instance, the classification "Base of Neck" is better than "Top Shoulder", while Burgundy-style bottles without a pronounced "neck" and "shoulders" have a metric fill level in cm. from the capsule.

Table 4—: 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.

independent of each other even when they have similar product characteristics or end in close proximity to each other. In other words, listing inspection costs deplete the expected surplus from entering another auction after having entered the current one. Indeed, OLS regressions confirm that additional competing listings does not systematically affect the average number of bidders per listing, transaction price, or reserve price.[26]

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.[27] 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, as documented in Table 4. Even with coarse product definitions, 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. 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.

[26]See Table B. 2 in the online appendix. These results are consistent across 18 different competing listing definitions.

[27]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)).

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

Consider a monopoly platform with second-price sealed bid auctions to allocate indivisible goods among bidders with unit demands. Let $\mathcal{N}^B$ and $\mathcal{N}^S$ denote the sets of potential bidders and sellers that consider trading on this platform. F_V and F_{V_0} denote the valuation distributions for potential bidders and sellers, respectively, conditional on auction-level observables introduced below. V_0 is equivalently interpreted as a seller's (marginal) cost of selling. The following assumptions on the conditional valuation distributions are maintained:

Assumption (Two-sided Independent Private Values (IPV))**.** *All* $i = \{1, ..., |\mathcal{N}^B|\}$ *potential bidders independently draw idiosyncratic values* v_i *from* $V \sim F_V$ *and all* $k = \{1, ..., |\mathcal{N}^S|\}$ *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* $\forall k \in \mathcal{N}^S$*.*
Further, F_V *and* F_{V_0} *satisfy:* $supp(V)=[\underline{v}, \overline{v}]$*,* $supp(V_0)=[\underline{v_0}, \overline{v_0}]$*,* F_V *(with density function* f_V*) is absolutely continuous and* $x - \frac{1-F_V(x)}{f_V(x)}$ *is non-decreasing in* x $\forall x \in [\underline{v}, \overline{v}]$*.*

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. Auction subscripts are omitted as this applies to all auctioned items. Note that the two valuation distributions, including their supports, are allowed but not restricted to differ for populations on the two sides of the market (potential sellers and bidders). The final condition states that the distribution of bidder values satisfies Myerson (1981)'s regularity, which is necessary for a unique optimal reserve price.

Accounting for observed auction-level heterogeneity, it is furthermore convenient to assume that values are multiplicative in the idiosyncratic value term and in the valuation that buyers and sellers have for the observed product attributes. Letting the value of the observed attributes be denoted by q, which is interpreted as the item's *quality*, and letting $\tilde{V}_i$ ($\tilde{V_{0k}}$) denote the total valuation of a buyer (seller) for that item, it holds that

Assumption (Common quality). $\tilde{V}_i = qV_i$ *and* $\tilde{V}_{0k} = qV_{0k}$, *with* $q \perp (V_i, V_{0k})$.

This form is convenient because it can be shown that the game scales in q so that the dependence on observed product attributes can be omitted from the equilibrium analysis.[28] The game's equilibrium results are presented in *homogenized value space* (i.e., with $q = 1$), based on the conditional values of bidders and sellers.

This setting is modeled as a two-stage game. In the first stage, potential sellers —owning a good and knowing their valuation for it— decide to create a listing or not, and potential bidders decide to enter or not after observing the number of listings on the platform and whether they have a reserve price.[29] Listings are ex-ante identical up to having a reserve price, so conditional on this bidders are sorted with some constant probability over listings.[30] In the second stage, sellers set a secret reserve price and bidders bid after learning their valuations.[31]

The platform's fee structure $c = \{c_B, c_S, c_L\}$ 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 deterministic opportunity costs of time spent on the platform, on top of any monetary fees charged. For bidders, these are referred to as "listing inspection costs" associated with each listing they enter and denoted by e_B.[32] The opportunity costs of time for

[28]With a common multiplicative quality term, the reserve price is homogeneous of degree one in q, so that also the sale probability is independent of q, and both the seller's expected revenue and listing-level surplus are homogeneous of degree one in q. These properties are derived in Online Appendix A. As a result, the game scales in q up to the additive c_L, and the role of c_L is shown to be minimal in numerical simulations, as documented in Online Appendix J.

[29]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.

[30]When bringing the model to data, listings can be grouped according to additional observables.

[31]In a more general sense, the secret reserve price represents an aspect of the seller side that is imperfectly observed by buyers before entering the platform while being important for their expected surplus. 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 Online Appendix E. 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 presented in Section 2 supports this assumption for the BW platform.

[32]Note 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. Hence, the inter-auction dynamics captured in Kong (2021) and Hendricks and Sorensen (2018) do not arise in this model.

sellers are denoted by e_S and both are also referred to as "entry costs".[33]

The valuation distributions, platform fees, and entry costs, and allocation mechanism are assumed to be common knowledge. To simplify the exposition, the model contains two separate potential bidder populations that differ only by a preference for positive- or zero reserve auctions.[34] As such, $N^B_{r=0}$ and $N^B_{r>0}$ denote the number of potential bidders for no reserve and positive reserve auctions, respectively. The equilibrium results are derived under a large population approximation, which guarantees the empirical tractability of the game and does not require players to know these exact population sizes.

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*

$$f_{N_r}(n;\lambda_r) = \frac{\exp(-\lambda_r)\lambda_r^n}{n!}\ , \forall n \in \mathbb{Z}^+, \tag{1}$$

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

In other words, it is assumed that 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 distributions of the number of bidders per listing are approximately Poisson.[35] The Poisson parameters ($\lambda_{r>0}$, $\lambda_{r=0}$) are determined in equilibrium.

Equilibrium strategies are solved by backward induction. Attention is restricted to symmetric Bayesian-Nash equilibria in weakly undominated strategies requiring that strategies are best-responses given competitors' strategies and that beliefs are consistent with those strategies in equilibrium.

[33]As values scale in q, the outside option of buying or selling a higher-quality item also scales in q, and the scaled opportunity costs are given by $\tilde{e}_S = qe_S$ and $\tilde{e}_B = qe_B$.

[34]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. It is, however, a restriction that all potential bidders draw their values from the same distribution rather than that bidders in positive and zero reserve price auctions are systematically different. 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 enter both types of listings over time.

[35]This assumption, also made in Engelbrecht-Wiggans (2001), Bajari and Hortaçsu (2003), Jehiel and Lamy (2015), and Bodoh-Creed, Boehnke, and Hickman (2021), fits the platform setting (see panel f in Figure 1). Online 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. Proof that the approximation does not drive equilibrium existence and uniqueness is provided in Online Appendix D.

B. Equilibrium strategies: 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 bidding and reserve pricing strategies are therefore derived, as functions of the commissions. In particular, a bidder with valuation v bids

$$b^*(v) \equiv \frac{v}{1+c_B}, \tag{2}$$

with the optimal bid decreasing in c_B. 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)). The threshold is denoted by v_0^R and is taken to be exogenous to simplify the estimation of the game.[36] A seller with valuation $v_0 \geq v_0^R$ sets an optimal reserve price $r^* \equiv r^*(v_0)$ that solves

$$r^* = \frac{v_0}{1-c_S} + \frac{1-F_V\big((1+c_B)r^*\big)}{(1+c_B)f_V\big((1+c_B)r^*\big)}, \tag{3}$$

which is increasing in v_0 and c_S, and decreasing in c_B.[37]. A seller with $v_0 < v_0^R$ sets a zero

[36]Numerical simulations based on the estimated model primitives confirm that changes in c_S and c_L both have a negligible effect on v_0^R compared to the effect that they have on the seller's equilibrium platform entry threshold (v_0^*, characterized in Section 3.C), and that v_0^R moves in the same direction as v_0^* (see Figure H.2 in the online appendix). The latter rules out that endogenizing v_0^R could lead to multiple equilibria —with the caveat that the simulations are based on model primitives that are estimated under equilibrium uniqueness. It also means that letting v_0^R respond to fees would strengthen the importance of seller selection for bidder entry, so one can interpret the results for fixed v_0^R as conservative in that sense. Moreover, endogenizing the threshold to set no reserve would be especially interesting when studying reserve price fees. 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 Jehiel and Lamy (2015) and references in Hasker and Sickles (2010)).

[37]This is shown in Online Appendix A. 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. The reserve price does not affect the number of bidders in the seller's listing because it is secret. If sellers compete in public reserve prices (as in McAfee (1993)) the mark-up disappears in equilibrium. The reserve price decreasing in c_B is obvious when F_V has an increasing failure rate ($f_V(x)(1-F_V(x))^{-1}$ increases in x). The model imposes the slightly weaker Myerson's regularity condition on F_V, so numerical simulations confirm that IFR applies and that r^* decreases in c_B in the application.

reserve price. In what follows, the buyer premium-adjusted optimal reserve price is denoted by $\tilde{r} \equiv (1 + c_B)r^*(v_0)$.

Next, the expected listing-level surpluses for bidders and sellers in the auction stage are defined for auctions with and without reserve prices. All listing-level surpluses are zero when there are no bidders. The expected surplus for a bidder in a listing with a positive reserve price, before the bidder knows his valuation, when there are n bidders and the seller has a value of v_0 (to be taken expectations over in the entry stage) equals, for $n \geq 1$

$$\pi_B^{r>0}(n, v_0) \equiv \frac{1}{n}\mathbb{E}\big[V_{n:n} - \max\{V_{n-1:n}, \tilde{r}\}|V_{n:n} \geq \tilde{r}\big]\big[1 - F_{V_{n:n}}(\tilde{r})\big]. \tag{4}$$

$V_{i:n}$ refers to the $(n - i + 1)^{\text{th}}$ highest out of a sample of n draws from random variable V, so $V_{n-1:n}$ denotes the second-highest valuation (equal to zero when $n = 1$), and the last term in (4) is equal to the sale probability. Key properties of $\pi_B^{r>0}(n, v_0)$ are that it decreases in n and v_0, the latter because r^* is increasing in v_0, and decreases in c_S and c_B for a given v_0.[38] In auctions with a zero reserve price, the dependence on v_0 disappears and items are always sold when $n \geq 1$, so the expected bidder surplus in those auctions simplifies to

$$\pi_B^{r=0}(n) \equiv \frac{1}{n}\mathbb{E}\big[V_{n:n} - V_{n-1:n}\big], \tag{5}$$

independent of v_0, c_S, and c_B, and decreasing in n. On the seller side, the expected surplus for a seller with valuation v_0 in positive reserve auctions equals, for $n \geq 1$

$$\pi_S^{r>0}(n, v_0) \equiv \big[(1 - c_S)\mathbb{E}\big[\max\{V_{n-1:n}, \tilde{r}\}|V_{n:n} \geq \tilde{r}\big] - v_0\big]\big[1 - F_{V_{n:n}}(\tilde{r})\big]. \tag{6}$$

In the case without a reserve price, this simplifies to

$$\pi_S^{r=0}(n) \equiv (1 - c_S)\mathbb{E}\left[\frac{V_{n-1:n}}{1 + c_B}\right] - v_0. \tag{7}$$

[38]The expected surplus per bidder decreasing in the number of competitors in the auction is shown by Li (2005) to be without loss of generality when F_V has an increasing failure rate. See also footnote 37.

Both $\pi_S^{r>0}(n, v_0)$ and $\pi_S^{r=0}(n, v_0)$ decrease in v_0, c_B, and c_s, all by reducing gains from trade, increase in n by driving up expected transaction prices and with r^* being independent of n.

C. *Equilibrium strategies: Entry stage*

Sellers adopt the strategy to enter only if their valuation is below an equilibrium threshold value (denoted by v_0^*) because their expected surplus from entering decreases in their valuation, v_0, and because they know v_0 when making their entry decisions. Bidders, on the other hand, learn their valuations after entering and therefore enter with some equilibrium probability (as in Levin and Smith (1994)). Under the large population approximation, the entry equilibrium on the bidder side is fully characterized by the equilibrium mean number of bidders per listing ($\lambda^*_{r=0}$ and $\lambda^*_{r>0}$, defined in (I.5)), depending on the platform's fee structure.[39] A trivial no-trade equilibrium where no bidders and sellers enter is excluded from consideration.

In auctions without a reserve price, $\lambda^*_{r=0}$ is independent of what happens on the seller side because $\pi_B^{r=0}$ is independent of v_0, so the entry equilibrium is defined by a simple zero profit condition. Specifically, the expected bidder surplus from entering the platform into an auction without a reserve price, when the mean number of bidders equals $\lambda_{r=0}$, is given by

$$\Pi_{B,r=0}\big(\lambda_{r=0}\big) \equiv \sum_{n \in \mathbb{Z}^+} \pi_B^{r=0}(n) f_{N_{r=0}}(n; \lambda_{r=0}) - e_B. \tag{8}$$

With $\pi_B(n)$ strictly decreasing in n and $f_{N_{r=0}}(n; \lambda_{r=0})$ increasing in a first-order stochastic dominance sense in $\lambda_{r=0}$, the equilibrium mean number of bidders per listing in zero reserve price auctions ($\lambda^*_{r=0}$) is the unique value of $\lambda_{r=0} \in \mathbb{R}^+$ that solves

$$\Pi_{B,r=0}\big(\lambda^*_{r=0}\big) = 0, \tag{9}$$

decreasing in e_B and independent of the other fees.

The two-sidedness of the platform really manifests itself in positive reserve price auctions.

[39] By the *environmental equivalence* property of the Poisson distribution (Myerson (1998)), it is without loss to use the same density function for the number of bidders n (that matter for sellers) and competing bidders $n-1$ (that matter for bidders).

The equilibrium mean number of bidders per listing in those auctions ($\lambda^*_{r>0}$) responds to v_0^* because bidders expected surplus from entering the platform depends on the distribution of reserve prices on the platform (i.e., because $\pi_B^{r>0}(n, v_0)$ is decreasing in v_0). To derive the entry equilibrium for this case it is first documented that any candidate seller entry threshold ($\tilde{\tilde{v}}_0$) maps into an equilibrium mean number of bidders per listing $\lambda^*_{r>0}(\tilde{\tilde{v}}_0)$. That mapping is used to solve for the equilibrium seller entry threshold v_0^*. It turns out that because $\lambda^*_{r>0}(\tilde{\tilde{v}}_0)$ is strictly decreasing in $\tilde{\tilde{v}}_0$, sellers' best-response entry thresholds satisfy a single-crossing property so that the entry game has a unique equilibrium despite its two-sidedness. These results are derived below.

Two-sided entry: bidder side

The expected bidder surplus from entering the platform into an auction with a reserve price, when the mean number of bidders equals $\lambda_{r>0}$ and given a candidate seller entry threshold $\tilde{\tilde{v}}_0$, is given by

$$(10) \quad \Pi_{B,r>0}\big(\tilde{\tilde{v}}_0; \lambda_{r>0}\big) \equiv \sum_{n \in \mathbb{Z}^+} \underbrace{\left[\int_{v_0^R}^{\tilde{\tilde{v}}_0} \pi_B^{r>0}(n, v_0) \frac{f_{V_0}(v_0)}{F_{V_0}(\tilde{\tilde{v}}_0) - F_{V_0}(v_0^R)} dv_0 \right]}_{\mathbb{E}\left[\pi_B^{r>0}(n+1,c,V_0) \middle| V_0 \in [v_0^R, \tilde{\tilde{v}}_0]\right]} f_{N_{r>0}}(n; \lambda_{r>0}) - e_B.$$

Besides the platform fees and listing inspection costs, $\Pi_{B,r>0}\big(\tilde{\tilde{v}}_0; \lambda_{r>0}\big)$ is made up of the listing-level surplus $\pi_B^{r>0}(n, v_0)$ in expectation over 1) seller-values V_0 given candidate threshold $\tilde{\tilde{v}}_0$, and 2) the Poisson-distributed number of competing bidders. For any candidate seller entry threshold $\tilde{\tilde{v}}_0$, the equilibrium mean number of bidders per listing in positive reserve price auctions ($\lambda^*_{r>0}(\tilde{\tilde{v}}_0)$) is the unique value of $\lambda_{r>0} \in \mathbb{R}^+$ that solves

$$(11) \quad \Pi_{B,r>0}\big(\tilde{\tilde{v}}_0; \lambda_{r>0}\big) = 0,$$

decreasing c_B, c_S, and e_B, given $\tilde{\tilde{v}}_0$. As in the case without reserve prices, the uniqueness of $\lambda^*_{r>0}(\tilde{\tilde{v}}_0)$ follows from $\Pi_B(n, v_0)$ strictly decreasing in n and λ (the latter due to $f_{N_{r>0}}(n; \lambda_{r>0})$

increasing in a first-order stochastic dominance sense in $\lambda_{r>0}$). Moreover, it is crucial to note that $\tilde{\tilde{v}}_0$ affects $\Pi_{B,r=0}\big(\tilde{\tilde{v}}_0;\lambda_{r=0}\big)$ only through the distribution of reserve prices. A higher $\tilde{\tilde{v}}_0$ draws in sellers with higher values that set higher reserve prices, resulting in a lower expected bidder surplus,

$$\mathbb{E}\left[\pi_B^{r>0}(n,V_0)\middle|V_0\in[v_0^R,\tilde{\tilde{v}}_0]\right],$$

for any number of bidders n in the listing, and thus requiring the entry of fewer bidders to break even in expectation. The zero profit condition in (11) therefore dictates that $\lambda^*_{r>0}(\tilde{\tilde{v}}_0)$ strictly decreases in $\tilde{\tilde{v}}_0$. This property is central to the equilibrium uniqueness result on the seller side, as derived below.

Two-sided entry: seller side

The equilibrium entry strategy on the seller side is a threshold strategy, characterized by the value v_0^* that gives a seller with $V_0=v_0^*$ zero expected profit from entering when competing sellers enter the platform $i.f.f$ $V_0\leq v_0^*$.[40] The expected surplus for a seller with $V_0=v_0$ from entering the platform when competing sellers adopt the threshold $\tilde{\tilde{v}}_0$, and given bidders equilibrium best-response to this threshold ($\lambda^*_{r>0}(\tilde{\tilde{v}}_0)$), is given by

$$\Pi_{S,r>0}\big(v_0;\lambda^*_{r>0}(\tilde{\tilde{v}}_0)\big)\equiv\sum_{n\in\mathbb{Z}^+}\pi_S^{r>0}(n,v_0)f_{N_{r>0}}(n;\lambda^*_{r>0}(\tilde{\tilde{v}}_0))-c_L-e_S. \tag{12}$$

The equilibrium entry threshold (v^*) is the unique value of $\tilde{\tilde{v}}_0\in[\underline{v_0},\overline{v_0}]$ that solves

$$\Pi_{S,r>0}\big(\tilde{\tilde{v}}_0;\lambda^*_{r>0}(\tilde{\tilde{v}}_0)\big)=0, \tag{13}$$

with $\lambda^*_{r>0}(\tilde{\tilde{v}}_0)$ the unique value that solves (11). The proof requires three parts. First, sellers have a unique best-response for any competing $\tilde{\tilde{v}}_0$, because $\Pi_{S,r>0}(v_0;\lambda^*_{r>0}(\tilde{\tilde{v}}_0))$ strictly decreases in sellers' own v_0. Second, this best-response function is strictly decreasing in competing sellers' entry threshold, because of the effect that a higher $\tilde{\tilde{v}}_0$ has on lowering $\lambda^*_{r>0}$, and because $\tilde{\tilde{v}}_0$

[40]The strategy is denoted by the threshold itself. As with all equilibrium objects, the dependence of v_0^* on the platform fees is omitted from the notation. In the empirical analysis only fee structures for which $\underline{v_0}<v_0^R<v_0^*<\overline{v_0}$ are considered. The uniqueness result derived below is illustrated graphically in Online Appendix A.

does not affect $\Pi_{S,r>0}\big(v_0; \lambda^*_{r>0}(\tilde{\tilde{v}}_0)\big)$ in other ways. Symmetry then delivers a unique equilibrium threshold, v_0^*, which is the fixed point in seller value space solving (13) i.e., making the marginal seller indifferent between entering and staying out. Moreover, v_0^* is strictly decreasing in c_B, c_S, c_L, and e_S, as they all lower the expected surplus from entering for a seller with $V_0 \geq v_0^R$.

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

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

The values of v_0^**,* $\lambda^*_{r>0}(v_0^*)$*, and* $\lambda^*_{r=0}$ *solve the zero profit conditions of the marginal seller and potential bidders as defined in equations* (13)*,* (11)*, and* (9)*.*

Remark 1. Network effects are nonlinear in this model and, following, e.g., 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. Because bidders are uncertain about the height of the reserve price that they will face upon entering, and because excluding high reserve price setting sellers ("lemons") results in a more favorable reserve price distribution on the platform, in turn encouraging bidder entry, this justifies the labeling of the negative seller-side direct network effect as a *lemons effect* after Akerlof (1970).

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^* 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 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. There are no scale effects in this setting.[41]

[41] These model predictions are summarized in Table B. 3 in the online appendix. The model prediction of constant returns to scale conditional on the seller type distribution can be verified with data from the empirical application, where

Remark 2. The uniqueness of the entry equilibrium relies crucially on the mean number of bidders decreasing in the seller entry threshold. The model applies directly to other two-sided markets where user selection creates a negative own-side network effect.[42] Likewise, a model extension with a match value (as in Deltas and Jeitschko (2007)), where the probability that a bidder finds a suitable item increases in the number of listings, can still result 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.

Remark 3. Additional negative seller-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 than in the presented model. Moreover, when bidders learn 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.[43] 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. By contrast, the model's equilibrium uniqueness does not apply in two-sided markets with a strong positive scale effect.[44]

4. Empirical strategies to recover model primitives

This section discusses the identification and estimation of model primitives (most importantly: valuation distributions and latent entry costs) given the assumptions of the model outlined in

the fee structure is held fixed over the period under consideration. The regression results reported in Table B. 4 in the online appendix confirm 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 idiosyncrasies before knowing how much to value the wine.

[42] For instance, in credit markets such as Prosper.com (see Kawai, Onishi, and Uetake (2022), Liu, Wei, and Xiao (2020), and Freedman and Jin (2017)), borrowers have private information about their creditworthiness and do not internalize the impact of their entry decisions on other platform users. As such, the selection of borrowers with lower creditworthiness is expected to decrease the equilibrium lender/borrower ratio as the market grows.

[43] A full analysis of the case with selective bidder entry is provided in Online Appendix E.

[44] The seller best-response function is not downward-sloping when additional listings increase the expected bidder surplus from each listing beyond the potential decrease in the surplus from the selection of higher-valuation sellers. For instance, game consoles (studied in e.g., Lee (2013)) increase in value to consumers when more games are compatible with them. Ride-hailing services (e.g., Rosaia (2020)) are more attractive to both riders and drivers when there are more total users on the other side, at least until congestion costs outweigh economies of density. Jullien, Pavan, and Rysman (2021) provide more examples of two-sided markets with positive scale effects.

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 (e.g., the "reserve not met" and "reserve almost met" messages). The hammer price (the standing price when the auction closes, irrespective of whether the item is sold) equals the second-highest bid ($B_{n-1:n}$) in auctions without a reserve price when $n \geq 2$.[45]

A. Nonparametric identification

The distribution of bidder valuations F_V is identified from the hammer price and the number of bidders in auctions with $r = 0$ and $n \geq 2$, which follows directly from Athey and Haile (2002, Theorem 1). In those auctions, the hammer price equals the second-highest (equilibrium) bid, which relates to the second-highest value according to (2), so that in the data 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 $\forall v \in [\underline{v}, \overline{v}]$ and $n \geq 2$

$$F_{V_{n-1:n}}(v) = n(n-1) \int_{\underline{v}}^{v} F_V(u)^{n-2}[1 - F_V(u)]du, \tag{14}$$

[45] 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.

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

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.[46]

Next, consider the identification of the distribution of seller values. We focus on the part of the support of $V_0 \in [v_0^R, v_0^*]$ for v_0^* played in the data, because, under the restriction that v_0^R is exogenous, 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. Moreover, without strong entry shifters to vary v_0^*, the population distribution is not nonparametrically identified for $V_0 > v_0^*$.[47] Assuming that sellers play the equilibrium reserve price strategy, each reserve price maps to that seller's value, as can be seen by rearranging (3) to

$$v_0(r) = (1 - c_S)\left(r - \frac{1 - F_V(r(1 + c_B))}{(1 + c_B)f_V(r(1 + c_B))}\right), \tag{15}$$

where, $v_0(r)$ denotes the seller valuation implied by reserve price r. $v_0(r)$ is known as F_V (and hence f_V) is identified and the other elements on the right-hand side of (15) are observed. As such, the distribution of implied seller values, $F_{v_0(r)}$, is equal to the distribution of seller values conditional on entering and setting a positive reserve price. In particular, $\forall v_0 \in [v_0^R, v_0^*]$

$$F_{v_0(r)}(v_0) = \frac{F_{V_0 \geq v_0^R}(v_0)}{F_{V_0 \geq v_0^R}(v_0^*)}. \tag{16}$$

The values of v_0^R and v_0^* are identified as the minimum and maximum seller values implied by (15). Given the identification of F_V and observing all platform fees in c, the entry costs e_S and e_B are identified from the zero profit conditions that govern platform users' entry decisions

[46]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 (2023)). 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.

[47]The counterfactuals show that $V_0 \in [v_0^R, v_0^*]$ is the relevant part of the support in our empirical context, where the *lemons effect* appears important enough to justify modifying the fee structure to exclude more high-v_0 sellers on the platform, rather than decreasing fees to encourage more sellers to enter.

(e.g., (11), (9), and (13)). This follows from $\Pi_{B,r>0}$, $\Pi_{B,r=0}$, and $\Pi_{S,r>0}$ being revealed in the data at equilibrium up to —and strictly decreasing in— the relevant entry costs. In particular, the value of the seller entry costs, e_S, is identified as the value that sets

$$\Pi_{S,r>0}(v_0^*; \lambda_{r>0}^*(v_0^*)) = 0. \tag{17}$$

The bidder listing inspection costs e_B are equal to the value that either sets

$$\Pi_{B,r=0}(\lambda_{r=0}^*) = 0 \tag{18}$$

or that sets

$$\Pi_{B,r>0}(v_0^*; \lambda_{r>0}^*) = 0 \tag{19}$$

so that e_B is overidentified.[48] As (potential) bidders might be censored in auctions with a positive reserve price, the zero profit conditions in (17) and (19) rely on the entry equilibrium.[49] As mentioned, v_0^* is revealed as the maximum of seller values implied by (15). $\lambda_{r>0}^*$ is recovered as the value that maximizes the likelihood of the sample of observed second-highest bids and the number of bidders in positive reserve price auctions, given F_V. This likelihood also depends on an additional parameter ($p_{0,r>0}$) introduced below to allow for any unexplained variation in the entry process causing relatively many zero reserve price 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.

[48]The model assumes e_B to be the same in auctions with and without a reserve price as the costs of inspecting a listing are not expected to differ between these two listing types. The fact that e_B can be identified using either subset exploits a degree of freedom in the data and allows for validating this assertion empirically.

[49]Instead, with the number of bidders ($N_{r=0}$) observed and F_V identified, the expected bidder surplus in zero reserve auctions in (18) is simply the average of the expected listing-level surplus in (5).

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. In addition, the estimation of the distributions of the bidder and seller values is based on data from auctions of heterogeneous items, so the value homogenization step introduced in Haile, Hong, and Shum (2003) is applied to account for observed auction heterogeneity. Further details are given below.

Estimation of the distribution of bidder values

The parameters of the distribution of bidder values (denoted by θ_b) are obtained using maximum likelihood estimation in line with previous analyses of ascending auction data. First, to pool across auctions with different observed characteristics (denoted by the vector $\mathbf{Z}$), the quality of the item in auction t is specified as[50]

$$q_t = e^{g(\mathbf{z}_t)}, \tag{20}$$

with $g(.)$ a linear additive function and imposing that $\mathbb{E}[g(\mathbf{z}_t)] = 0$ so that $g(\mathbf{z}_t)$ measures the quality of the item in auction t relative to the average quality of items on the platform. It follows from Section 4.A (with $c_B = 0$ in the data) that

$$\log\big(H_t\big) = g(\mathbf{z}_t) + \epsilon_t(n_t) \tag{21}$$

with $\epsilon_t(n_t) \perp g(\mathbf{z}_t)$, for all t where $n_t \geq 2$ and $H_t \neq r_t$ (this set of auctions is denoted by $\mathcal{T}_q$).[51] Accordingly, $\hat{g}(\mathbf{z}_t)$ is obtained by regressing the log of the hammer price on $\mathbf{Z}$ and dummies for the number of bidders (denoted by $d(n_t)$) for all auctions in $\mathcal{T}_q$.

[50] In the empirical application, auctions are classified according to a binary type $\tau = \{\tau_1, \tau_2\}$ (being in the main vs. high-end sample) and all model primitives (including $g^\tau()$ and F_V^τ) can vary across τ. The dependence on τ is omitted from notation but two sets of estimation results are presented.

[51] The homogenization argument is usually applied only to auctions without a reserve price, in which case $\log(H_t) = \log B_{n_t-1:n_t} = g(\mathbf{z}_t) + log(V_{n_t-1:n_t})$, but it also applies to auctions with secret reserve prices as long as the hammer price is not equal to the reserve price (as shown in Online Appendix A).

In all observations with a zero reserve price, the residuals of this regression (plus the n_t-specific intercepts $d(n_t)$) deliver the (logarithm of the) homogenized second-highest values $V_{n-1:n}$. These are used to estimate the distribution of F_V by MLE, deriving the likelihood function from the relationship between $F_{V_{n-1:n}}$ and F_V given in (14).

Estimation of the distribution of seller values

Estimating the parameters of the distribution of seller values (denoted by θ_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 ((13)), 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 the resulting equilibrium v_0^*. The steps are detailed below.

Let $\mathcal{T}_{r>0}$ denote the set of auctions with positive reserve prices. Using the mapping between the reserve price (r_t) and seller's valuations from (15) and accounting for auction heterogeneity according to (20), the homogenized seller value in auction t equals:[52]

$$\hat{v}_{0t} = \frac{(1-c_S)}{e^{\hat{g}(\mathbf{z}_t)}}\left(r_t - \frac{1-F_V\left(\frac{r_t}{e^{\hat{g}(\mathbf{z}_t)}};\hat{\theta}_b\right)}{\frac{1}{e^{\hat{g}(\mathbf{z}_t)}}f_V\left(\frac{r_t}{e^{\hat{g}(\mathbf{z}_t)}};\hat{\theta}_b\right)}\right) \tag{22}$$

$\forall t \in \mathcal{T}_{r>0}$ and when $c_B = 0$ as in the data. The density of implied seller values given entry threshold v_0^*, r_t, and $\mathbf{z_t}$ equals, $\forall t \in \mathcal{T}_{r>0}$[53]

$$h(\hat{v}_{0t}|v_0^*, r_t, \mathbf{z}_t; \theta_s) = \frac{f_{V_0 \geq v_0^R}(\hat{v}_{0t};\theta_s)}{F_{V_0 \geq v_0^R}(v_0^*;\theta_s)}. \tag{23}$$

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 initial estimate of the seller entry

[52]The reserve price for the case with general q and generic F_V is derived in the online appendix, see equation (A.9).
[53]The no-reserve screening value that determines the lower bound on the support is simply $\hat{v}_0^R = \min(\{\hat{v}_{0,t}\}_{t\in\mathcal{T}_{r>0}})$.

threshold; $\hat{\upsilon}_{T_{r>0}} = \max(\{\hat{\upsilon}_{0,t}\}_{t\in\mathcal{T}_{r>0}})$:[54]

$$\mathcal{L}\big(\theta_s; \{\hat{\upsilon}_{0,t}, r_t, \mathbf{z}_t\}_{t\in\mathcal{T}_{r>0}}, \hat{\upsilon}_{T_{r>0}}\big) = \sum_{t\in\mathcal{T}_{r>0}} ln(h(\hat{\upsilon}_{0t}|v_0^* = \hat{\upsilon}_{T_{r>0}}, r_t, \mathbf{z}_t; \theta_s)\big) \tag{24}$$

$$\hat{\theta}_s^0 = \arg\max \mathcal{L}\big(\theta_s; \{\hat{\upsilon}_{0,t}, r_t, \mathbf{z}_t\}_{t\in\mathcal{T}_{r>0}}, \hat{\upsilon}_{T_{r>0}}\big) \tag{25}$$

The next step is to compute the entry equilibrium using the estimated taste parameters ($\hat{\theta}_b$, $\hat{\theta}_s^0$) to determine the value at which a seller is indifferent between entering and staying out of the platform. Then, the updated seller parameters are obtained by plugging the resulting equilibrium entry threshold into (25). This is done in an iterated fashion until convergence in the entry probability, meaning that for $k = 1, \ldots$

$$\hat{\theta}_s^k = \arg\max \mathcal{L}(\theta_s; \{\hat{\upsilon}_{0,t}, r_t, \mathbf{z}_t\}_{t\in\mathcal{T}_{r>0}}, v_0^{*k}(\hat{\theta}_s^{k-1})). \tag{26}$$

As the expected seller surplus and the equilibrium v_0^* are functions of the latent entry costs, the estimation algorithm is detailed further at the end of this section. The described estimator resembles the Aguirregabiria and Mira (2002, 2007) nested pseudo-likelihood (NPL) estimator, albeit with a nested concentrated likelihood estimator derived from the optimal reserve price strategy to recover structural parameters.[55]

Parameterization of valuation distributions

The parameterization of the valuation distributions is 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. The distributions appear unimodal and continuous but not symmetric, and the Generalized Gaussian Distribution ($\mathcal{GGD}$) appears suitable to capture the variation in

[54] $\hat{\upsilon}_{T_{r>0}}$ is a consistent initial estimate of v_0^* with $\hat{\upsilon}_{T_{r>0}} \to v_0^*$ as $T_{r>0} \to \infty$ at the true population parameters, by the law of large numbers, asymptotically over multiple iterations of the game.

[55] NPL is 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 the NPL estimator to an auction setting with bidder entry. In my model, the entry game reduces to a single agent (marginal seller) discrete choice problem with a unique equilibrium, satisfying the stability condition for convergence of the estimator in theory (Pesendorfer and Schmidt-Dengler (2010), Kasahara and Shimotsu (2012)). Egesdal, Lai, and Su (2015) and Aguirregabiria and Marcoux (2021) show that convergence in small samples from stable processes is not guaranteed. In my data, the estimator converges within a few iterations, but it does not converge in all bootstrap samples used for inference. See also the footnote of Table 5.

log values (see plots a and b in Figure 1). The estimation results are therefore based on the following parameterization:

$$V \sim \log \mathcal{GGD}(\mu_b, \sigma_b^2, \kappa_b) \tag{27}$$

$$V_0 | V_0 \geq v_0^R \sim \log \mathcal{GGD}(\mu_s, \sigma_s^2, \kappa_s). \tag{28}$$

The $\log \mathcal{GGD}$ distribution allows for additional flexibility relative to the often-imposed log-normal distribution, with values of $\kappa > 0$ ($\kappa < 0$) introducing skewness to the left (right).

Estimation of entry parameters and algorithm

Estimation of the entry costs requires solving for the values that satisfy the zero profit conditions in (17), (18), and (19) given the estimated taste parameters and the computed entry equilibrium, following the steps outlined in the identification section. The bidder listing inspection costs are estimated separately from the subsets of auctions with and without a reserve price (resulting in $\hat{e}_{B,r>0}$ and $\hat{e}_{B,r=0}$) to verify the assertion that the two are equal. The additional share ($p_{0,r>0} \geq 0$) of listings in positive reserve price auctions attracts zero bidders 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 $N_{r>0}$. 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 1).

It should be noted that $\hat{e}_S$ and $\hat{\theta}_s$ are determined jointly, as e_S is the amount that makes the marginal seller indifferent and the marginal seller is defined depending on how costly it is to enter. To address this, the estimation approach starts from an initial guess of the seller entry costs ($\hat{e}_S^0$) and the initial $\hat{\theta}_S^0$ (defined in (25)) and then updates both the equilibrium seller entry threshold and the seller valuation parameters iteratively. The pseudo-code of these steps is as follows. After obtaining $\hat{e}_S^0$ and $\hat{\theta}_S^0$, for each iteration $k = 1, \ldots$:

- solve for the unique $v_0^{*k}(\hat{\theta}_s^{k-1}, \hat{e}_S^{k-1})$ and the associated $\lambda_{r>0}^{*k}$ (equation 13)
- estimate $\hat{\theta}_s^k(v_0^{*k})$ by maximum concentrated likelihood (equation 26),

- solve for the $\hat{e}_S^k = e_S^*(v_0^{*k}, \hat{\theta}_s^k, \lambda_{r>0}^{*k})$ satisfying the zero profit entry condition (equation 17),

and iterate on these steps until convergence, omitting from the notation above any parameters that remain fixed throughout.[56]

5. Estimation results

This section describes the estimation results that are reported in Table 5. Unless otherwise noted, the discussion in this section refers to the estimates from the main estimation sample that are of primary interest.

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, as collectively denoted by $\mathbf{Z}$ in Section 4.B. Obtaining the data by scraping the content of the listing pages results in an unusually rich dataset that contains much of what bidders also observe. To fully exploit this information, text mining techniques are applied to the wine's description. Words are identified that relate to the *expert opinion* of wine critics Robert Parker or Janice Robinson, the wine being bought *en primeur*, and the delivery or shipment of the wine.[57] 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.

The observables explain a strikingly large share of the price variation.[58] In the main sample

[56]Following Dearing and Blevins (2023) and Aguirregabiria and Mira (2007), the algorithm has converged when

$$||(\hat{\theta}_S^k - \hat{\theta}_S^{k-1}, \hat{e}_S^k - \hat{e}_S^{k-1}, \hat{P}^k - \hat{P}^{k-1})||_\infty \tag{29}$$

is less than $10^{-2}/4$ (given 4 parameters, or when $k = 100$), and with $\hat{P}$ indicating the estimated seller entry probability

$$\hat{P}^k = F_{V_0|V_0 \geq v_0^R}(v_0^{*k}(\hat{\theta}_S^{k-1}); \hat{\theta}_S^{k-1}). \tag{30}$$

Further details about the computation of the entry equilibrium and estimation of the entry parameters are provided in online appendices F-I.

[57]For example, words related to expert opinion include "advocate", "points", "color", and "tannin" (related to the wine's taste), words related to *en primeur* status include "temperature", "member", "facility", and "society" (related to the wine's provenance and the professionalism of the seller), and words related to delivery and storage include "insurance", "arrange", "quote", "wales", and "invoice". *En primeur* is French for "in advance" or "first" and indicates the practice of buying Bordeaux wines on the basis of young barrel samples (before the wine has been bottled and matured).

[58]Column 1 in Tables H. 1-H. 2 in the online appendix report estimation results from these regressions for the main sample and high-end sample, respectively. They also provide a comparison with alternative specifications; estimated on

Table 5—: Estimated structural parameters

Valuation distributions		$\hat{\mu}_b$	$\hat{\sigma}^2_b$	$\hat{\kappa}_b$	$\hat{\mu}_s$	$\hat{\sigma}^2_s$	$\hat{\kappa}_s$
	est.	2.420	0.878	0.013	2.624	0.782	0.112
Main sample	*s.e.*	(0.025)	(0.004)	(0.004)	(0.029)	(0.010)	(0.006)
	est.	5.316	0.338	-0.465	5.495	0.359	-0.078
High-end sample	*s.e.*	(0.032)	(0.003)	(0.011)	(0.034)	(0.018)	(0.019)
Entry parameters		$\hat{e}_{B,r>0}$	$\hat{e}_{B,r=0}$	$\hat{e}_S$	$\hat{p}_{0,r>0}$	$\hat{v}^R_0$	
	est.	1.831	2.283	2.277	0.049	0.345	
Main sample	*s.e.*	(0.230)	(0.211)	(0.217)	(0.001)	(0.033)	
	est.	13.782	14.493	14.463	0.115	4.705	
High-end sample	*s.e.*	(0.587)	(0.653)	(0.678)	(0.004)	(0.034)	

Notes. The parameters in the top panel describe the location (μ), scale (σ^2), and shape (κ) of $\mathcal{GGD}$-distributed log-values. The table reports point estimates (*est.*) and standard errors based on 250 nonparametric bootstrap repetitions (*s.e.*). Estimation of θ_s excludes the 8.3 percent percent of sellers (3.7 in the high-end sample) for which $\hat{v}_{0t}$ is estimated to be negative. Both $\hat{v}_{0,t}$ and $\hat{g}(\mathbf{Z})$ are trimmed at their 1^{st} and 99^{th} percentiles to minimize the impact of outliers; before trimming the estimation sample has 2,787 observations (618 in the high-end sample). Moreover, the standard errors are based on draws that generate a stable equilibrium, thereby excluding 7 draws (46 from the smaller high-end sample) where the estimator did not converge. See Egesdal, Lai, and Su (2015) and Aguirregabiria and Marcoux (2021) on the issue of non-convergence of the NPL estimator in small samples based on stable data generating processes.

the R^2 is 0.55, and in the high-end sample the R^2 is 0.91. 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 using innovative methods to recover information otherwise unobservable to the econometrician (see, e.g., Bodoh-Creed, Boehnke, and Hickman (2017) and Kong (2020)). As such, unobserved heterogeneity likely plays a minor role in the current context. In addition, the impact of key variables is 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 description, or having a longer description, is favorable for the price, as is fast shipping.

Table 5 reports the remaining estimated structural parameters. The estimated taste distribution parameters imply that, on average, tastes in the populations of potential bidders and sellers (for positive reserve price auctions) are very similar; in levels, the mean idiosyncratic value is about £11 for bidders and £13 for sellers in the main sample. The sunk opportunity costs of

the sample with zero reserve prices only (column 2), excluding dummies for the number of bidders (column 3), based on the level (rather than the log) of the hammer price (column 4), and excluding all seller and shipping-related variables from **Z** (column 5).

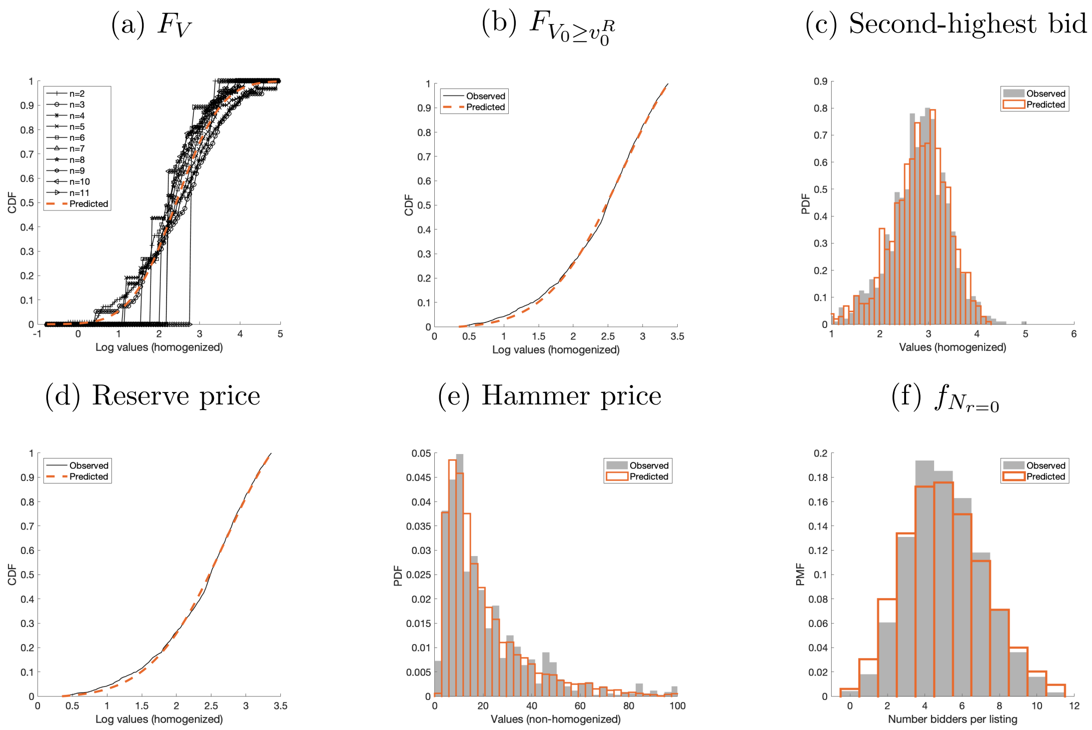

Figure 1. : Model fit: main sample

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 (prediction includes estimated quality, $r > 0$ auctions), and (f) Number of bidders per listing ($r = 0$ auctions). Simulations of bidder values based on 1,000 draws for each bidder and simulations of seller values based on 5,000 draws. Observed values are based on the estimation sample.

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 £11 as well. 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. In the high-end sample, both distributions are right-skewed with especially some bidders having particularly high values.

The estimated scaled listing inspection costs are £2 for each unit of quality in the main sample and £14 in the high-end sample (for both $r = 0$ and $r > 0$ listings, see Table 5). In relative terms, the median unscaled listing inspection costs as a share of the hammer price per bottle are 7-8 percent for auctions in the main sample and 5 percent in the high-end sample. Estimates do in both cases correspond to the idea that the costs of inspecting a listing to prepare for bidding are significant, justified by the heterogeneous nature of the goods and by a platform setting of unvetted listings generated by individual sellers.[59] Obtaining similar $\hat{e}_{B,r=0}$ and $\hat{e}_{B,r>0}$ in both samples also provides a key source of model validation, confirming that the presence of a reserve price does not affect how time intensive it is to inspect listings (of a certain quality level) as it does not reveal any information about the quality of the item. Moreover, these costs 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, using different estimation methods. The opportunity costs of time for sellers are estimated to be similar, too, indicating that it takes about the same time for sellers to provide the detailed item description as it takes for bidders to inspect and bid.

The model also fits the data well on the usual dimensions, as illustrated by the various plots in Figure 1. It is particularly convincing that predicted hammer prices in positive reserve price auctions match the observed values closely —given that the distribution of bidder values is estimated from the 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. The mean absolute deviation between the observed and predicted second-highest bids in zero reserve price auctions is computed separately for $n = \{2, 3.., 10\}$ bidders: the mean absolute deviations are small and there is no clear pattern by the number of bidders. Furthermore, a two-sample Kolmogorov–Smirnov test cannot reject the null hypothesis that the observed and predicted reserve prices are drawn from the same population distribution (p-value 0.25).

Plot f of Figure 1 displays the goodness of fit of the assumed Poisson distribution of the number of bidders per listing, given the estimated level of $\lambda^*_{r=0}$ played in the data, relative to it's empirical distribution. Notably, the data do not reveal any substantial overdispersion relative to the Poisson distribution. While preferences for high-level characteristics (filters) might vary

[59]By comparison, entry costs average 2 percent of the winning bid in USFS timber auctions (Roberts and Sweeting (2013)).

Table 6—: Estimated indirect network effects

	Main sample				High-end	
Changing the number of sellers ($T_{r>0}$) by	-50	-10	+10	+50	-50	+50
Effect on $\Pi_{B,r>0}$ (selection)	-0.015	-0.002	0.002	0.009	-0.446	0.597
Effect on $\Pi_{B,r>0}$ (no selection)	-0.034	-0.007	0.007	0.034	-0.741	0.688
	Main sample				High-end	
Changing the number of bidders ($M_{r>0}$) by	-50	-10	+10	+50	-50	+50
Effect on $\Pi_{S,r>0}$ (marginal seller)	-0.033	-0.007	0.007	0.033	-0.437	0.437
Effect on $\Pi_{S,r>0}$ (median seller)	-0.057	-0.011	0.011	0.056	-1.343	1.335

Notes. Simulations are based on $r > 0$ homogenized auctions. In the main (high-end) sample, $T_{r>0}$ equals 1,586 (434), $M_{r>0}$ equals 8,137 (2,279), and the marginal seller has a valuation at the 84^{th} (96^{th}) percentile of the estimated seller valuation distribution.

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.[60] The estimation results underscore the importance of accounting for censoring in positive reserve price auctions, even when the reserve price is (partly) hidden. The estimated baseline level of $\lambda^*_{r>0}$ played in the data equals 4.9, whereas an average of 2 actual bidders are observed in these auctions.

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. This section estimates their magnitudes on the BW platform as follows. First, homogenized auctions are simulated by applying equilibrium strategies to the estimated parameters. Then I alter either the total number of bidders (denoted by $M_{r>0}$) or sellers (denoted by $T_{r>0}$) in positive reserve price auctions by various amounts. Marginal sellers are added (or removed) when accounting for seller selection, and otherwise sellers are added or removed randomly. The expected bidder and seller surplus are re-estimated after updating the mean number of bidders per listing to the

[60] A chi-squared goodness-of-fit test fails to reject the hypothesis that N is generated by a Poisson distribution, but only marginally, with a p-value of 0.06.

new $\lambda_{r>0} = \frac{M_{r>0}}{T_{r>0}}$. The results are reported in Table 6 for various exogenous changes to $M_{r>0}$ and $T_{r>0}$, and separately for the high-end sample.

Indirect network effects have the following magnitude: adding 10 additional bidders to the platform increases the expected surplus of the marginal seller by £0.007, and this effect more than 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. The results display heterogeneity, as sellers with lower valuations for the item on sale benefit more. Increasing the number of sellers also has a different effect on bidders than decreasing the number of sellers.

These results are driven by the estimated bidder and seller valuation parameters, which impact the importance of the seller selection channel. For example, a lower level of dispersion in seller values would increase the indirect network effect of attracting additional sellers. The estimates indicate that conditional value 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 74 percent because sellers in these listings set relatively high reserve prices.

C. Commission index and revenue-volume trade-off

The model's estimates shed light on two key market features. Firstly, it highlights the significance of the "commission index," denoted as $\alpha = \frac{c_B + c_S}{1 + c_B}$. Ginsburgh, Legros, and Sahuguet (2010) demonstrate that expected platform revenue (and bidder and seller surplus) is independent of (c_B, c_S) when α stays constant, which applies to the two-sided market setting as well. Thus, only the commission index and flat fees affect the platform revenue-maximization problem. Figure 2 (a) confirms that the simulated counterfactual platform revenue levels align perfectly with the theoretical commission-index level lines (in orange). However, theory alone cannot inform beyond the combinations of c_B and c_S that keep outcomes constant.

Secondly, the platform faces a trade-off between maximizing revenues and maximizing sales

(a) Platform revenue (b) Sales volume

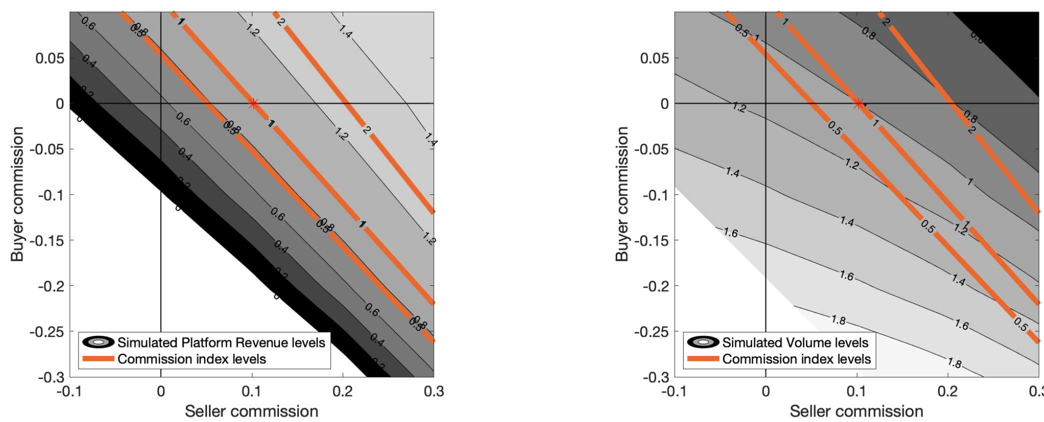

Figure 2. : Illustrating the commission index and revenue-volume trade-off

Notes. Displaying two overlapping contour plots. The grey contour plot reflects, in panel (a) simulated platform revenues normalized by baseline revenues, and in panel (b) the simulated volume of sales normalized by the baseline volume of sales. The thick orange lines indicate combinations of c_B and c_S where the commission index is either half as large as (level=0.5), equal to (level=1), or twice as large (level=2) as the baseline commission index. 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. Simulations are based on parameter estimates from the main sample.

volume. Increasing fees reduces the sales volume but increases the share paid to the platform. Even when the commission index remains constant, altering fees affects the sales volume. For instance, increasing c_B and decreasing c_S such that α remains unchanged decreases volume as bidders scale down bids, while the reserve price and sale probability remain unaffected (Ginsburgh, Legros, and Sahuguet, 2010). Plot b of Figure 2 illustrates this, showing decreasing simulated volume levels when moving up along the commission index level lines. Similarly, raising the listing fee boosts revenue but diminishes sales volume by reducing platform listings. Such fee structures that prioritize revenue over volume are typically considered unattractive, particularly when volume impacts future revenues through factors like word of mouth or brand awareness (Evans and Schmalensee, 2010). To address this, a nonparametric volume constraint is reported alongside platform revenues.

6. Counterfactuals

I first use the model estimates illustrate the *lemons effect* of two-sided markets with seller (listing) heterogeneity. To do so, I simulate the effect on sellers when the listing fee is increased

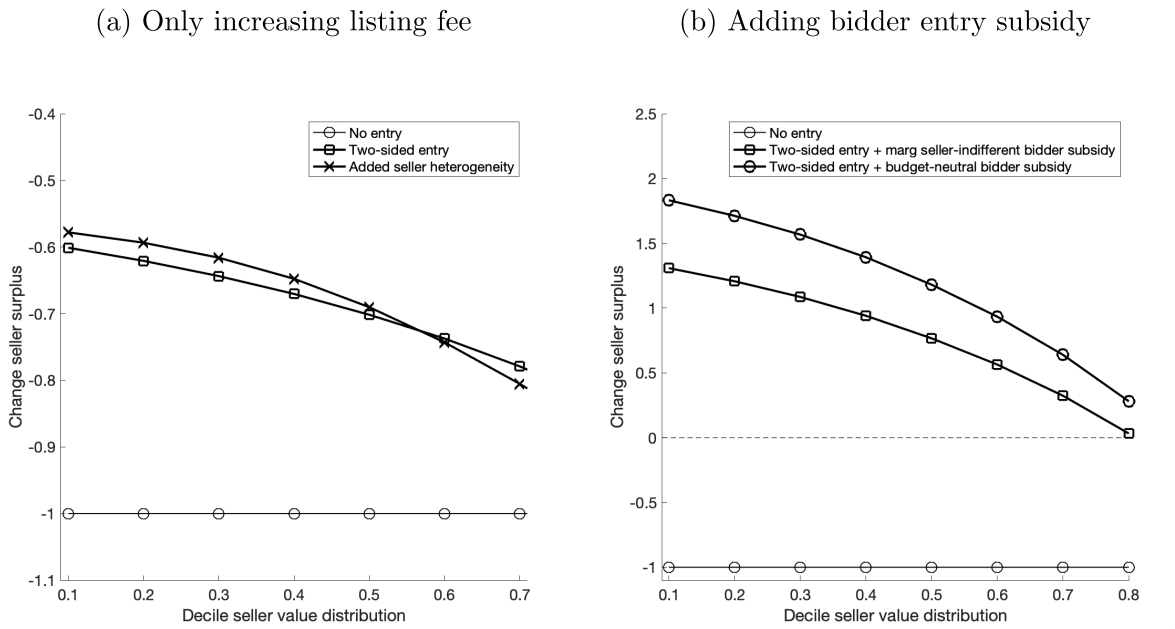

Figure 3. : Lemons effect: heterogeneous change in expected seller surplus when increasing the listing fee by £1.

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

by £1. In a model that ignores entry, the expected surplus for all sellers on the platform would decrease by £1, 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. The higher listing fee excludes some of the highest-valuation (v_0) sellers from the platform, increasing the expected surplus for potential bidders and driving up the number of bidders per listing. Figure 3 shows that the magnitude of the lemons effect is inversely related to the infra-marginal seller's value draw. The expected seller surplus reduces by 22-40 percentage points *less* than when the two-sided entry is not taken into account. The bias 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 40 percent (the line that is labelled "additional seller heterogeneity").[61]

Furthermore, plot (b) of Figure 3 demonstrates that the network effects can be exploited

[61] Sellers who set no reserve price simply experience the full £1 loss in surplus, while the expected surplus of the 6 percent of sellers who are pushed out of the market must be lower in the counterfactual scenario.

to make sellers better off despite paying a £1 higher listing fee, when using the proceeds to subsidize bidder entry. The marginal seller remains indifferent when combining the £1 higher listing fee with a £0.19 bidder subsidy. All infra-marginal sellers with $V_0 \in [v_0^R, v_0^*)$ are better off; their expected surplus increases by up to £1.3. These results provide evidence for the special circumstance in two-sided markets that (some) users could be better off when paying higher fees. 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. To see this, an even higher bidder subsidy of £0.23 would be budget neutral for the platform, depleting all additional platform revenues raised through the higher listing fee.

In general, subsidizing user entry on the side that generates stronger positive externalities proves profitable in two-sided markets (Rochet and Tirole (2006)). As bidders create stronger indirect network effects than sellers on BW (see Table 6), the platform is right to set $c_B = 0$ and change no bidder entry fee. The preceding section discussed the benefits of subsidizing bidder entry, implementable by lowering listing inspection costs or offering cash back to winning bidders. Here, I consider a negative buyer commission that gives winning bidders a percentage discount on the sale price. Such a fee policy would be innovative in the auction platform sphere but is akin to temporary discount vouchers on eBay or cash-back policies of credit cards.

To assess the impacts of fee changes on the composition of listings on the platform, the following results include homogenized auctions based on parameter estimates from the high-end sample. Figure 4 shows that a self-imposed non-negativity constraint on c_B remains binding. Platform revenues cannot increase by changing the allocation of commissions to buyers and sellers *unless* buyers are subsidized through a negative c_B. Paired with a larger increase in c_S (to finance the winning bidder discount), volume-constrained revenues rise by up to 40 percent.

Next, I use the model to simulate the impact of (anti-competitive) commission changes, as this is closely tied to assumptions about entry and sellers' pricing strategies. I compare the results to two benchmark rules-of-thumb. In the first, based on theories posited by McAfee

(1993), Ashenfelter and Graddy (2005), and Marks (2009), winning bidders remain unaffected by changes in buyer or seller commissions. This can be shown to hold only in markets devoid of entry barriers and with fully elastic sellers. In the second, based on common practice in antitrust cases, damages are considered pro-rata. For instance, in the 2001 Sotheby's and Christie's commission-fixing case, the pro-rata rule resulted in most of the $512 million settlement going to winning bidders who were overcharged the most.[62] The presented framework allows for precise estimation of welfare impacts in platform antitrust cases without reliance on such simplistic rules of thumb. This is demonstrated through a simulation doubling the commission index from 0.102 to 0.204, revealing biases in simpler models that overlook seller entry. Notably, in the auction model with two-sided entry, only 60 percent of the incidence of seller commission increases falls on sellers, deviating significantly from the expected 100 percent in both benchmark scenarios. Furthermore, considering market entry increases the total welfare loss for sellers by 25 percent, while buyers also incur a substantial welfare loss, contrary to assumptions in conventional scenarios. These findings underscore the necessity for comprehensive modeling to accurately assess the ramifications of fee adjustments.[63]

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 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

[62] See Ashenfelter and Graddy (2005) and https://casetext.com/case/in-re-auction-houses-antitrust-litigation-61.

[63] The estimated welfare impacts capture the true economic impact of increased fees, including equilibrium effects from changes in entry on the other side of the market. This is in line with the notion of antitrust damages in two-sided markets since recent developments in US antitrust law (see footnote 1). The simulation results referenced in this paragraph are presented in Table B. 5 in the online appendix.

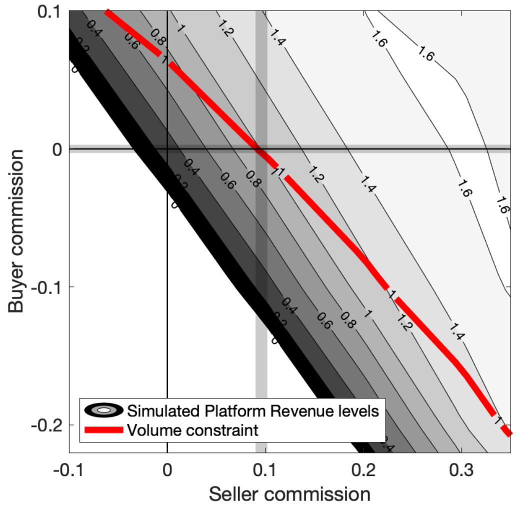

Figure 4. : Platform revenue at alternative fee structures

Notes. Displaying a contour plot of simulated platform revenues normalized by baseline values, and indicating the volume constraint where the simulated volume of sales is equal to the baseline volume. The grey vertical bar corresponds to $c_S \in [0.9$ (high-end), 0.102 (main sample)], the horizontal bar indicates the baseline $c_B = 0$. 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.

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 (e.g., *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. Moreover, platform revenues can be increased by pairing a bidder discount (negative buyer commission) with higher seller fees.

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. An auction platform could combine high fees on one side of the market with below-marginal cost prices on the other side. Both practices could be considered predatory when evaluated in isolation, but they prove to be socially optimal in the two-sided market in this paper. In recent years, competition authorities and courts have also recognized that the regulation of platform markets requires new empirical models, but the perceived difficulty of quantifying user interactions has been a bottleneck for the practical application of these ideas. While the empirical results presented here are based on a specific platform, this paper provides the tools necessary to make much-needed progress in applying antitrust policy to two-sided markets.

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For Online Publication

A. Additional results

Optimal reserve price with fees

This section derives the optimal reserve price for sellers with $V_0 = v_0$. Hat and check notation is defined as: $\hat{x} = x(1 + c_B)$ and $\check{x} = \frac{x}{1+c_B}$. Let R denote expected revenue for a seller with valuation v_0 when setting reserve price r in an auction with n bidders. It equals

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

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

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

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

$$r = \frac{v_0}{1 - c_S} + \frac{1 - F_V(r(1 + c_B))}{(1 + c_B) f_V(r(1 + c_B))}. \tag{A.3}$$

The optimal reserve price is unique $\forall(v_0, c_B, c_S)$ given IFR of F_V, increasing in v_0, independent of n, increasing in c_S, and decreasing in c_B given IFR of F_V.

Optimal reserve price with fees and common quality term

Here, I consider the optimal reserve price for an item with quality $q = e^{g(\mathbf{Z})}$ valued equally by buyers and sellers, when the seller has an idiosyncratic value of $V_0 = v_0$. As in the main text, let bidder and seller values be given by

$$\tilde{V} = qV \tag{A.4}$$

$$\tilde{V_0} = qV_0, \tag{A.5}$$

Hat and check notation is used as in the derivation above, $\hat{x} = x(1 + c_B)$ and $\check{x} = \frac{x}{1+c_B}$. The expected revenue for a seller with valuation v_0 and an item with quality q when setting reserve price r in an auction with n bidders is given by

$$\begin{aligned} R = qv_0 F_{\tilde{V}}(\hat{r})^n + (1 - c_S) rn F_{\tilde{V}}(\hat{r})^{n-1}[1 - F_{\tilde{V}}(\hat{r})] + \\ (1 - c_S) \int_{\hat{r}}^{\overline{v}} \check{x} n(n-1) F_{\tilde{V}}(x)^{n-2}[1 - F_{\tilde{V}}(x)] f_{\tilde{V}}(x) dx. \end{aligned} \tag{A.6}$$

The following transformation makes the dependence on q explicit

$$F_{\tilde{V}}(\hat{r}) = P[\tilde{V} \leq \hat{r}] = P[qV \leq \hat{r}] = F_V(\frac{\hat{r}}{q}). \tag{A.7}$$

Solving for r we get

$$\begin{aligned} \frac{\partial R}{\partial r} = qv_0 n F_V(\frac{\hat{r}}{q})^{n-1} f_V(\frac{\hat{r}}{q})(1 + c_B)\frac{1}{q} + (1 - c_S) n F_V(\frac{\hat{r}}{q})^{n-1}[1 - F_V(\frac{\hat{r}}{q})] \\ -(1 - c_S) rn F_V(\frac{\hat{r}}{q})^{n-1} f_V(\frac{\hat{r}}{q})(1 + c_B)\frac{1}{q}. \end{aligned} \tag{A.8}$$

Setting this equation to zero and re-arranging, the optimal reserve price in the presence of a common multiplicative quality term q solves

$$r = \frac{qv_0}{1 - c_S} + \frac{1 - F_V(\frac{r(1+c_B)}{q})}{\frac{1}{q}(1 + c_B) f_V(\frac{r(1+c_B)}{q})}, \tag{A.9}$$

which can also be presented as

$$\text{(A.10)} \qquad \frac{r}{q} = \frac{v_0}{1-c_S} + \frac{1-F_V(\frac{r}{q}(1+c_B))}{(1+c_B)f_V(\frac{r}{q}(1+c_B))}.$$

From here, we can see that the optimal reserve price in this specification is homogeneous of degree one in q. Specifically, denoting the solution to (A.10) by $r^*(q, v_0)$, we can see that $r^*(\alpha q, v_0) = \alpha r^*(q, v_0)$. We get the reserve price in homogenized value space by setting $q = 1$. Moreover, $r^*(v_0)$ is unique $\forall v_0$ given IFR of F_V, increasing in v_0 and c_S, decreasing in c_B, and independent of n.

Sale probability independent of q

The sale probability is independent of q when sellers set an optimal reserve price. This is simply because $P[\tilde{V} \leq \hat{r}^*] = F_V(\frac{\hat{r}^*}{q})$, with r^* the optimal reserve price that is homogeneous of degree one in q, as established above, so we get $F_V(\frac{\alpha\hat{r}^*}{\alpha q}) = F_V(\frac{\hat{r}^*}{q})$. As a result, the mark-up in the optimal reserve price is also independent of q.

Seller revenues homogeneous of degree one in q

With the sale probability being independent of q, we can also show that the expected seller revenues are homogeneous of degree one in q. To see this, take the revenue function (A.6) and denote terms that are obviously independent of q with Λ_i and Λ_{ii}.

$$\text{(A.11)} \qquad R(q, v_0) = qv_0 \underbrace{F_{\tilde{v}}(\frac{\hat{r}^*}{q})^n}_{\Lambda_i} + r \underbrace{(1-c_S)nF_{\tilde{v}}(\frac{\hat{r}^*}{q})^{n-1}[1-F_{\tilde{v}}(\frac{\hat{r}^*}{q})]}_{\Lambda_{ii}} + (1-c_S)\int_{\hat{r}^*}^{\overline{v}} q\check{x}n(n-1)F_{\tilde{v}}(\frac{x}{q})^{n-2}[1-F_{\tilde{v}}(\frac{x}{q})]f_{\tilde{v}}(\frac{x}{q})dx.$$

The second line represents the expected second-highest bidder valuation conditional on exceeding $\hat{r}$. We can write this as $\mathbb{E}[qv_{n-1:n}|qv_{n-1:n} \geq \hat{r}^*]$, and since $P[qv_{n-1:n} \geq \hat{r}^*]$ is independent of q when r^* is the optimal reserve price, the full revenue equation simplifies to

$$\text{(A.12)} \qquad R(q, v_0) = qv_0\Lambda_i + r^*\Lambda_{ii} + q\Lambda_{iii},$$

where $\Lambda_{iii} = (1-c_S)\int_{\hat{r}^*}^{\overline{v}} \check{x}n(n-1)F_{\tilde{v}}(\frac{x}{q})^{n-2}[1-F_{\tilde{v}}(\frac{x}{q})]f_{\tilde{v}}(\frac{x}{q})dx$. This proves that also $R(q, v_0)$ is homogeneous of degree one in q, as

$$R(\alpha q, v_0) = \alpha q v_0 \Lambda_i + \alpha r^* \Lambda_{ii} + \alpha q \Lambda_{iii} = \alpha R(q, v_0). \tag{A.13}$$

Seller surplus homogeneous of degree one in q

The expected seller surplus function as defined in (12) is equal to the expected revenue function as defined in (A.6) minus the seller's cost of selling the wine. Specifically, maintaining that $\tilde{v} = qv$ and $\tilde{v_0} = qv_0$, and making the dependence on q and v_0 explicit, we have that

$$\pi_S(v_0, q) = R(q, v_0) - qv_0. \tag{A.14}$$

This shows that $\pi_S(v_0, \alpha q) = \alpha R(q, v_0) - \alpha q v_0 = \alpha \pi_S(v_0, q)$.

Optimal reserve price : non-common quality term

Here, I solve for the optimal reserve price when bidders and sellers have different appreciation of the auction characteristics, assuming that a bidder's (seller's) valuation is equivalent to $q_B v$ ($q_B v_0$). In this setting, the $F_{\tilde{V}}(\hat{r})$ depends on q_B only, whereas the reserve price must be increasing in q_S to correspond to a higher seller valuation. The optimal reserve price, in the presence of a multiplicative quality term that differs between bidders and sellers, solves:

$$\frac{r}{q_S} = \frac{v_0}{1-c_S} + \frac{1 - F_V(\frac{r}{q_B}(1+c_B))}{\frac{q_S}{q_B}(1+c_B)f_V(\frac{r}{q_B}(1+c_B))}. \tag{A.15}$$

From here, we can see that when $q_B \neq q_S$, the optimal reserve price is not homogenous of degree one in either quality term. The mark-up is decreasing in $\frac{q_S}{q_B}$.

Optimal reserve price : additive common quality term

Here, I solve for the optimal reserve price when bidders and sellers have the same appreciation of the auction characteristics but this enters their valuations additively. Sticking to the same notation as above, the assumption is that a bidder's (seller's) valuation is equivalent to $q + v$

$(q+v_0)$. The optimal reserve price, in the presence of a common additive quality term, solves:

(A.16) $$r = \frac{v_0 + q}{1 - c_S} + \frac{1 - F_V(r(1+c_B) - q)}{(1+c_B) f_V(r(1+c_B) - q)}.$$

Only when there is no distortion from the commissions, i.e., in the case that $c_B = c_S = 0$, is the optimal reserve price homogeneous of degree one in q, as then we can rewrite (A.16) as

(A.17) $$r - q = v_0 + \frac{1 - F_V(r-q)}{f_V(r-q)}.$$

.

Poisson decomposition property for number of bidders per listing

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

(A.18) $$f_{N_t, N_{-t}}(m,n) = \frac{\exp(-\lambda)\lambda^{(m+n)}}{(m+n)!} \frac{(m+n)!}{m!n!} (q)^m (1-q)^{(n)}$$

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 $t = \{1, .., T\}$.

Illustration of equilibrium uniqueness in two-sided market

Figure A.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 described in Section 3.C, the best-response function $\bar{v_0}_i^{BR}(\lambda^*_{r>0}(\bar{v}_{0-i}))$ is downward-sloping: a higher competing seller entry threshold decreases expected seller surplus for any v_0, lowering the threshold $\bar{v_{0i}}^{BR}$ 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 A.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 $\bar{v_0}$, $\lambda > \lambda^*_{r>0}$ can only be sustained by some $\bar{v_0} < v_0^*(\lambda^*_{r>0})$. In turn, the latter leaves money on the table for sellers with values $\in [\bar{v_0}, v_0^*(\lambda_{r>0})]$ and is therefore also excluded as an equilibrium. For the

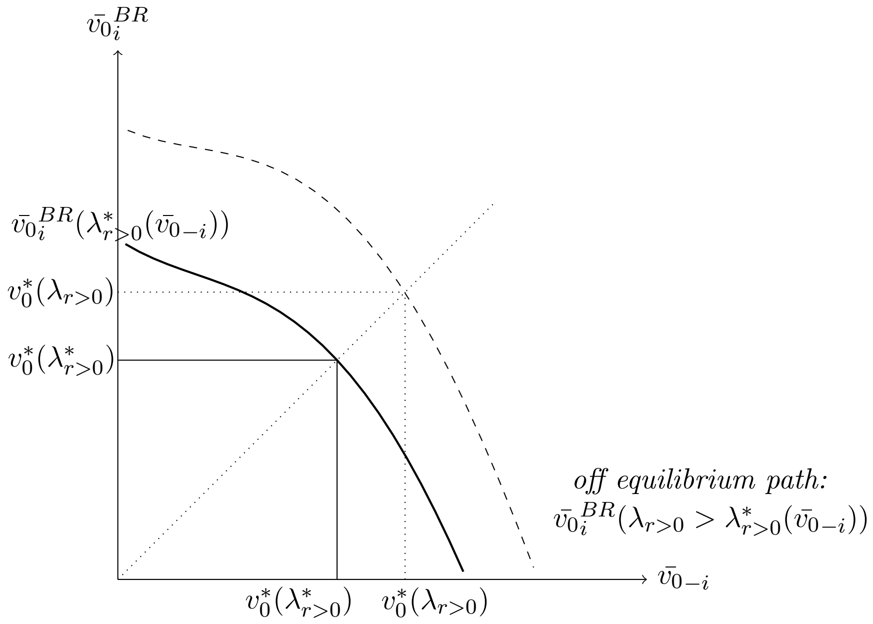


Figure A.1. : Graphic representation of unique entry equilibrium result

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 $\bar{v_0}_i^{BR}(\lambda^*_{r>0}(\bar{v_0}_{-i}))$.

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.

Estimating the quality term

The quality term $q = g(\mathbf{Z})$ is estimated using a linear regression of the hammer price on $\mathbf{Z}$ in auctions with at least two bidders, irrespective of whether they have a positive or no reserve price, but for positive reserve price auctions only using those that are unsold or that have a hammer price exceeding the reserve price. Using more observations (compared to when restricting the estimation sample to zero reserve prices only) results in more precise estimates. To see why this is a valid approach, the hammer price when $n \geq 2$ and $c_B = 0$ is composed of

$$H = \begin{cases} \tilde{V}_{n-1:n} & \text{if } r = 0 \\ \tilde{V}_{n:n} & \text{if } r > 0 \text{ and } \tilde{V}_{n:n} < r \\ \max(\tilde{V}_{n-1:n}, r) & \text{if } r > 0 \text{ and } \tilde{V}_{n:n} \geq r \end{cases}$$

When also making the dependence on data including $\mathbf{z}_t$ explicit and when $n_t \geq 2$, $\log(H_t)$ equals

$$\log(H_t) = \begin{cases} g(\mathbf{z}_t) + \ln(V_{n_t-1:n_t}) & \text{if } r_t = 0 \\ g(\mathbf{z}_t) + \ln(V_{n_t:n_t}) & \text{if } r_t > 0 \text{ and } \tilde{V}_{n_t:n_t} < r_t \\ \max\left(g(\mathbf{z}_t) + \ln(V_{n_t-1:n_t}), \log\left(\frac{e^{g(\mathbf{z}_t)}V_{0t}}{(1-c_S)} + mup_t\right)\right) & \text{if } r_t > 0 \text{ and } \tilde{V}_{n_t:n_t} \geq r_t \end{cases}$$

where mup_t denotes the reserve price mark-up in auction t, independent of $\mathbf{z}_t$ as shown above. Because $mup_t \geq 0$, the log hammer price is not linear in $g(\mathbf{z})$ if $H_t = r_t$ and the good remains unsold (which happens when the second-highest valuation is below the reserve price but the highest valuation exceeds the reserve price). The largest set of auctions where the log hammer price is linear in $g(\mathbf{z})$ is those where either the reserve price is zero, the reserve price is positive and the item is unsold, or the reserve price is positive but the hammer price exceeds the reserve, and all three cases conditional on the number of bidders exceeding one. The log hammer price then consists of

$$\log(H_t) = \begin{cases} g(\mathbf{z}_t) + \ln(V_{n_t-1:n_t}) & \text{if } r_t = 0 \\ g(\mathbf{z}_t) + \ln(V_{n_t:n_t}) & \text{if } r_t > 0 \text{ and } \tilde{V}_{n_t:n_t} < r_t \\ g(\mathbf{z}_t) + \ln(V_{n_t-1:n_t}) & \text{if } r_t > 0 \text{ and } \tilde{V}_{n_t:n_t} \geq r_t \text{ and } H_t > r_t \end{cases}$$

The conditions above can be summarized as $n_t > 1$ and $H_t \neq r_t$. As such, $\hat{g}(\mathbf{z}_t)$ is obtained from the following linear regression equation using auctions that satisfy those conditions

$$\log(H_t) = g(\mathbf{z}_t) + \epsilon_t, \tag{A.19}$$

where ϵ_t denotes the residual that is independent of $g(\mathbf{z}_t)$.

B. Auxiliary tables and figures

This section presents auxiliary results that further illustrate the empirical setting and the underlying mechanisms highlighted in the paper. Tables B. 1-B. 2 and Figures B.1-B.2 support the notion that bidders face substantial listing inspection costs and thus are modelled to enter randomly, as discussed in Section 2 of the paper. B. 3 summarizes the direct and indirect network effects generated in the model (see Remark 1 in the paper) for the case when $r > 0$

Table B. 1—: 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<0.01; ***p<0.001. 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.

and the benchmark when either $r = 0$ or v_0^* is fixed, and Table B. 4 presents reduced form evidence consistent with these effects (for the benchmark case). Table B. 5 presents the results of the counterfactual simulations designed to mimic the platform increasing the seller commission (anti-competitively), which are discussed in the counterfactual section of the paper. The reduced form evidence consistent with sellers entering the platform selectively requires some additional explanation, as provided in the next Section.

Table B. 2—: 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<0.01; ***p<0.001. 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.

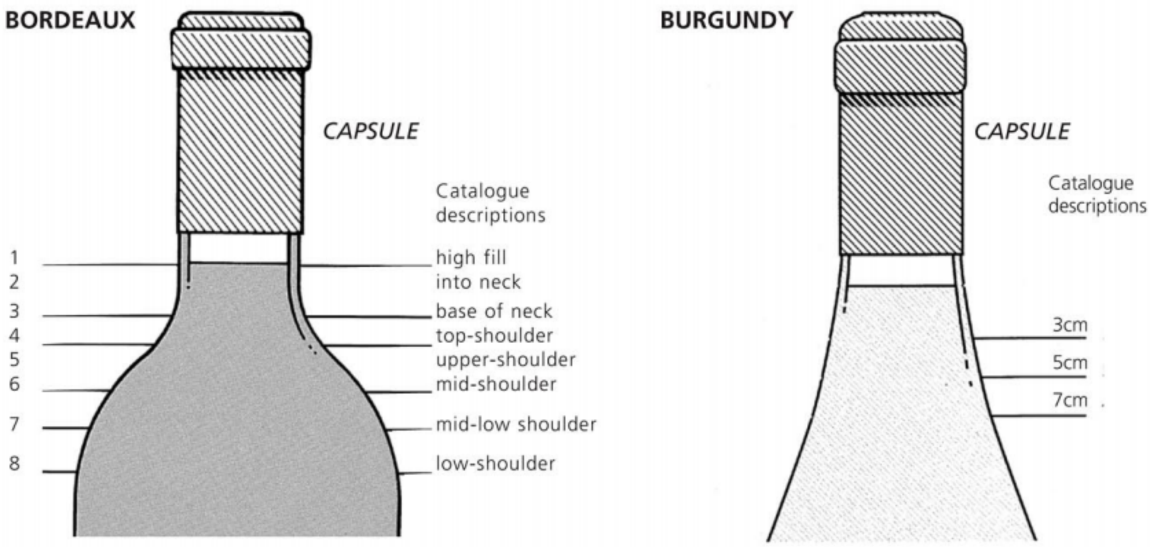
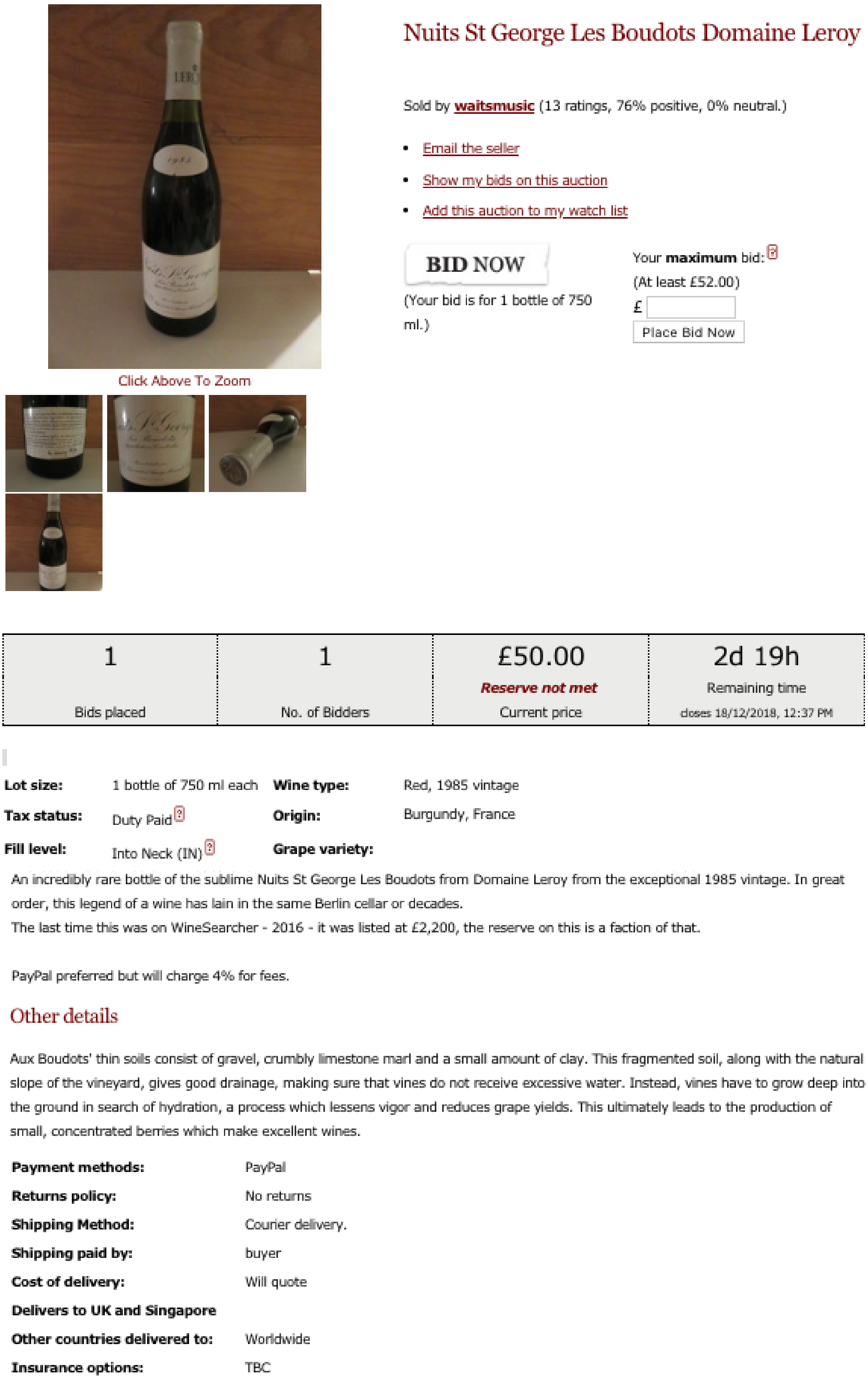


Figure B.1. : Ullage classification and interpretation

Source: https://www.christies.com/Wine/Ullages_2013.pdf.
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.



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 B.2. : Listing page example

Table B. 3—: Summary of network effects generated by the model

	Two-sided entry $r > 0$ Seller selection	Benchmark $r = 0$ No seller selection
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 captures how the entry of an additional user affects users on the other side, before any equilibrium adjustments. A direct network effect 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. The direct network effect on the seller-side is described in the text. The indirect network effect of sellers on bidders is ambiguous in positive reserve price auctions 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.

Table B. 4—: 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<0.01; ***p<0.001. 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 B. 5—: Effects of doubling the commission index ($c_S + 0.102$)

	Simulated welfare effects			Simple benchmarks	
	No entry	Bidder entry	Two-sided entry	Elastic seller	Pro-rata
Total effect (£1000)	3.8	5.4	5.8		
Incidence on sellers (%)	92.3	77.2	60.3	100	100
Hammer price (% change)	-3.2	-6.5	-1.0	0	0
Buyer "damage" (% price)	0.8	3.7	8.2	0	0
Seller "damage" (% price)	9.3	12.4	12.4	10.2	10.2

Notes. Simulations are based on homogenized auctions with $r > 0$ in the main sample. The welfare effects are computed as a share of the counterfactual expected hammer price (the expected sale probability multiplied by the expected transaction price conditional on a sale). The effects are computed in expectation for groups of buyers and sellers, with a buyer being the in-expectation winning bidder, including in unsold listings, and therefore include allocative inefficiency. This may depart from the more narrow interpretation of antitrust damages in courts, depending on the jurisdiction (hence the quotation marks). In the pro-rata benchmark common for typical markets, the damage to buyers (sellers) equals simply 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. Increasing the buyer commission from 0 to 0.1281 (keeping c_S at 0.102) also doubles the commission index and results in the same welfare effects as in this table. In that scenario, the pro-rata benchmark is 0% incidence on sellers and a 12.81% buyer damage.

C. Empirical results supporting selective seller entry

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. If some observable traits shift the surplus from entering upwards, entry is worthwhile for sellers with a higher latent marginal cost of selling. This in turn would be reflected by a positive association between the reserve price and those traits, under the appropriate exclusion restrictions.

Recall that all 2,581 registered users who have ever listed a wine for sale are labeled as potential sellers. With the number of potential sellers fixed, the time dimension of the data must 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

$$y_{hmi} = X_{hm}\beta - v_{hmi}, \tag{C.1}$$

where the expected surplus for seller h to enter market m and list item i (y_{hmi}) is strictly decreasing in its unobserved idiosyncratic valuation v_{hmi} —reducing gains from trade— and may also be a function of observed seller and market characteristics X_{hm}. Seller h enters market m to list item i *iff* $y_{hmi} > 0$, a process that is formalised in the structural model.

Estimation results for the selection equation in (C.1) are reported in Table C. 1 and reveal some interesting empirical facts.[64] Seller-level variables in X_{hm} 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 a (fleeting) interest in the platform would also explain the negative effect of the number of members that joined the platform in the same month. Having more listings in

[64] The analysis is also repeated with as dependent variable the *number* of listings that are created by a potential seller in a market (see columns 4-6 of Table C. 1), using as preferred specification is the zero-inflated Poisson count model that accounts for the abundance of seller-market observations with zero listings.

Table C. 1—: Potential sellers: predicting entry (first-stage)

Dependent variable:	$1(y_{hmi} > 0)$ =“dummy”			Number $y_{hmi} > 0$ = “count”		
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<0.01; ***p<0.001. Based on the main sample only.

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.

The predicted entry probability $X_{hm}\hat{\beta}$ is used in a second stage to assess whether seller selection can be detected in the data.[65] For sellers with a higher expected utility from entering based on observed characteristics ($X_{hm}\hat{\beta}$), higher values of v_{hmi} will satisfy $y_{hmi} > 0$. This will be picked up by a positive association between the (average) reserve price and $X_{hm}\hat{\beta}$ for all sellers that did enter.[66] A key identifying assumption for interpreting such a positive association as seller selection is that X_{hm} is independent of v_{hmi}, so that that conditional on entry, X_{hm}

[65] 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 $X_{hm}\hat{\beta}$ (columns 3 and 6 of Table C. 1). Specifically, 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 costs 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. 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.

[66] It is well-known that reserve prices and the benefit of setting a positive reserve price are both increasing in v_{hmi} (Riley and Samuelson (1981), Jehiel and Lamy (2015)).

Table C. 2—: Sellers: suggestive evidence for selection (second-stage)

Dependent variable:	Reserve price				1(Reserve price >0)		
Regression model:	*OLS*	*Tobit*	*OLS*	*OLS*	*OLS*	*Probit*	*OLS*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Predicted $X_{hm}\hat{\beta}$	1,076.515***	1,076.515***	106.781***	−46.585^{+}	10.539***	10.539***	0.033
	(119.392)	(119.310)	(15.464)	(26.295)	(0.828)	(0.828)	(0.145)
Observations	1,471	1,471	1,471	1,471	2,322	2,322	2,322
Auction-level observables (**Z**):				✓			✓
First-stage model = dummy or count	dummy	dummy	count	count	dummy	dummy	count
Adjusted R^2	0.052		0.031	0.435	0.065		
Log Likelihood		−7,840.082				−1,522.049	−834.253

Notes. Standard errors in parenthesis, $^{+}$p<0.1; *p<0.05; **p<0.01; ***p<0.001. Based on the main sample only, omitting 465 observations where the seller id is missing. Auction-level observables (**Z**) are those used for the homogenization of auctions in the structural analysis, listed in Table H. 1. The first-stage model = "dummy" refers to an entry model with a binary left-hand side variable $1(y_{hmi} > 0)$ indicating whether seller h entered market m with item i, corresponding to column 3 of Table C. 1. The first-stage model = "count" refers to an entry model with a numeric left-hand side variable y_{hmi} indicating the number of listings that seller h has in market m, corresponding to column 6 of Table C. 1.

does not affect the reserve price.[67]

The estimation results from the second stage, reported in Table C. 2, 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.[68] 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 columns 4 and 7 of Table C. 2). 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. Finally, the descriptive analysis in this section considers whether variation in the data is *consistent with selective seller entry*, but the structural analysis is developed separately and does not rely on information about potential sellers. For instance, due to the absence of strong seller entry shifters, the data from different months is

[67] This is similar to the reduced form analysis of selective bidder entry in Roberts and Sweeting (2011), which also relies on the fact that in a selective entry model the set of entrants is a non-random sample of the set of potential entrants. Differences are that, in Roberts and Sweeting (2011), bidders observe a signal of their valuation before entry and this signal is assumed to be normally distributed.

[68] 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 $X_{hm}\hat{\beta}$ from the zero-inflated Poisson count model based on the number of listings that seller h created in market m.

pooled in the structural estimation of the model and only one equilibrium seller entry threshold is obtained.

D. 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 positive reserve prices as they provide the more interesting case with two-sided entry. As before, $\tilde{r}$ denotes the optimal reserve price increased with buyer premium, $\tilde{r} = (1 + c_B)r^*(v_0)$, 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:

$$\Pi_{B,r>0}(c, \tilde{v_0}; p) = \sum_{n=0}^{N^B_{r>0}-1} \mathbb{E}[\pi_B(n+1, c, v_0)|V_0 \in [v_0^R, \tilde{v_0}]f_{N_{r>0},T_{r>0}}(n; p) - e_{B,r>0} \tag{D.1}$$

It takes the expectation of $\Pi_B(n, v_0)$ ((4) with optimal r as in (3)) 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 costs $e_{B,r>0}$ are associated with each listing. Components of equation (D.1) are:

$$\mathbb{E}[\pi_B(n+1, c, v_0)|V_0 \in [v_0^R, \tilde{v_0}]] = \int_{v_0^R}^{\tilde{v_0}} \pi_B(n+1, c, v_0) f_{V_0|V_0 \in [v_0^R, \tilde{v_0}]}(v_0) dv_0 \tag{D.2}$$

$$f_{N_{r>0},T_{r>0}}(n; p) = \binom{N^{B,r>0}-1}{n} (\frac{p}{T_{r>0}})^n (1 - \frac{p}{T_{r>0}})^{N^{B,r>0}-1-n} \tag{D.3}$$

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. 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:

$$p^{*T_{r>0}}(T_{r>0}, f, \tilde{v_0}) \equiv \arg_{p\in(0,1)} \pi_B^{T_{r>0}}(c, \tilde{v_0}; p) = 0 \tag{D.4}$$

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 (D.4) always exists, and it is excluded from the analysis based on the empirical observation that bidders currently play the positive trade equilibrium.

A key property is that $\frac{p^{*T_{r>0}}}{T_{r>0}}$ 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.

E. 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 $\forall v \in [v^*, \overline{v}]$:

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

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 (4)-(5). 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 $v_i \geq \tilde{r}$:

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

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

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

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:

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

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 $T_{r>0}$:

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

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 $\frac{1}{T_{r>0}}$). Hence, a unique entry equilibrium bidder entry threshold solves the marginal bidder's zero profit condition:

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

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 $v^*(\overline{v})$ 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 (E.6) that makes the marginal bidder indifferent between entering and staying out.

The result holds for any realization of $T_{r>0}$ given $\overline{v_0}$. As in the baseline model, whether also a unique seller entry equilibrium exists depends on how the expected surplus of sellers is affected by $v^*(f, \overline{v})$. We know that v^* decreases in $\overline{v}$ 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 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 $\pi_S(c, v_0; \lambda^*_{r>0}(\tilde{v_0}), \tilde{v_0})$ 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 $\tilde{v_0}$:

$$\text{(E.7)} \qquad \pi_S(c, v_0; f_{N^B_{r>0},T_{r>0}}(n; v^*(\tilde{v_0})), \tilde{v_0}) = \sum_{T_{r>0}=1}^{N^S} \sum_{n=0}^{N^B} \pi_S(n, f, v_0, v^*(\tilde{v_0})) f_{N^B_{r>0},T_{r>0}}(n; v^*(\tilde{v_0})) - c_L - e_S$$

A unique equilibrium seller entry threshold solves the marginal seller's zero profit condition:

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

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 the 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^*, which is the fixed point in seller value space solving (E.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.

F. Additional details estimation algorithm

This section provides details about the estimation of structural parameters not included in the main text, including especially $\hat{e}_{B,r>0}$, $\hat{e}_{B,r=0}$, $\hat{e}_S$, and $\hat{p}_{0,r>0}$. The estimated entry costs (opportunity costs 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 costs estimates ($\hat{e}_{B,r>0}^0$ and $\hat{e}_S^0$) as detailed below. After obtaining these initial values, for each iteration $k = 1, \ldots$:

- solve for the unique $v_0^{*k}(\hat{\theta}_s^{k-1}, \hat{e}_S^{k-1})$ and the associated $\lambda_{r>0}^{*k}$ which pin down the marginal seller (equation (13)),
- estimate $\hat{\theta}_s^k(v_0^{*k})$ by maximum concentrated likelihood (equation (26)),
- solve for the $\hat{e}_S^k = e_S^*(v_0^{*k}, \hat{\theta}_s^k, \lambda_{r>0}^{*k})$ that satisfies the zero profit entry condition (equation (17)),

until convergence, omitting from the notation above any parameters that remain fixed throughout. For $\hat{e}_{B,r>0}$ and $\hat{e}_{B,r=0}$, the initial estimator is the same as the final estimator although finally $\hat{e}_{B,r>0}$ is based on the updated $\hat{\theta}_s$. They are estimated as the value of the entry costs 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 the estimated values of $\lambda_{r>0}^*$, $p_{0,r=0}$, and $\lambda_{r=0}^*$. In auctions with no reserve price, the mean observed N is a consistent estimator of $\lambda^*_{r=0}$:

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

Note that $\hat{\lambda}^*_{r=0}$ and $\hat{\lambda}^*_{r>0}$ are only obtained to estimate entry costs and they are not treated as structural parameters. We now turn to the estimation of $\hat{\lambda}^*_{r>0}$.

In positive reserve price auctions, 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 the 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 $\tilde{r}_t = r_t(1+c_B)$, $\forall t \in \mathcal{T}_{r>0}$:

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

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

$$g(b_t, a_t | r_t, \mathbf{z}_t, \hat{\theta}_b; \lambda^*_{r>0}, p_{0,r>0}) = \sum_{k=a_t}^{\infty} h(b_t, a_t | n_t = k, r_t, \mathbf{z}_t, \hat{\theta}_b) f_{N_{r>0}|N_{r>0} \geq A}(k; \lambda^*_{r>0}, p_{0,r>0}) \tag{F.3}$$

$$\mathcal{L}(\lambda^*_{r>0}, p_{0,r>0}; \{b_t, a_t, r_t, \mathbf{z}_t\}_{t \in \mathcal{T}_{r>0}}) = \sum_{t \in \mathcal{T}_{r>0}} ln(g(b_t, a_t | r_t, \mathbf{z}_t, \hat{\theta}_b; \lambda^*_{r>0}, p_{0,r>0})) \tag{F.4}$$

$$(\hat{\lambda}^*_{r>0}, \hat{p}_{0,r>0}) = \arg\max \mathcal{L}(\lambda^*_{r>0}, p_{0,r>0}; \{b_t, a_t, r_t, \mathbf{z}_t\}_{t \in \mathcal{T}_{r>0}}) \tag{F.5}$$

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.[69] 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 two-sided entry, simulating entry decisions of lower-value potential bidders facing a lower entry costs would result in the exact same outcomes. Moreover, in a model without seller entry and with a Levin and Smith (1994) bidder entry process, the effect of higher entry and lower bidder

[69] 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 $p_{0,r>0} = 0$ and if bidders arrive stochastically over time at a constant rate and bid only once.

values also cancel out (Platt (2017)) even when changing the fee structure. Given that the effects of overestimating bidder values and overestimating the bidder entry costs, relative to the scenario with intra-auction dynamics, offset each other at least partially, this abstraction is also not considered to be of first-order importance in the model with two-sided entry.[70]

The above describes how initial values $\hat{e}^0_{B,r=0}$ and $\hat{e}^0_{B,r>0}$ are estimated. The initial value $\hat{e_S}^0$ 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.[71] This is confirmed numerically. Starting from a relatively high $\hat{e_S}^0 = \max(\hat{e}^0_{B,r>0}, \hat{e}_{B,r=0})$ —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^{*k}_0 converge downwards. The final estimate $\hat{e_S}$ is lower than its starting value, but not by much.

One benefit of the NPL algorithm to estimate $\hat{\theta}_S$ is that the initial values do not have to be consistent estimates of their population counterparts ((Aguirregabiria and Mira, 2002, Proposition 2)) when there is a unique stable equilibrium (see also Aguirregabiria and Mira (2010) and Aguirregabiria and Marcoux (2021)). Imposing the equilibrium conditions of the game in the recursive algorithm improves the estimates throughout until it converges at the equilibrium.

Note finally that $\hat{\theta}_b$, $\hat{v}^R_0$, $\hat{p}_{0,r>0}$, $\hat{\lambda}^*_{r=0}$, and $\hat{e}_{B,r=0}$ are never updated in the estimation algorithm. In terms of the selected parametric families, the generalized (or zero-inflated) Poisson

[70]However, seller selection does introduce nonlinearities into the system so that the direction of the bias (if any) cannot be signed ex-ante. The assertion that intra-auction dynamics are less important in our setting with endogenous two-sided entry is therefore supported with results from a robustness analysis based on the filtering described in Platt (2017). Specifically, the model is re-estimated assuming that all potential bidders in both positive and zero reserve price 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. Estimating the model with these additional assumptions results in more numerous entrants ($\lambda^*_{r>0}$ and $\lambda^*_{r=0}$) and lower entry costs and bidder values, as explained above. However, as expected, these effects almost fully offset each other when looking at the effect of changing the fee structure. Figure H.1 illustrates this for the main counterfactual policy simulation that increases c_L by £1. The figure supports the robustness of the lemons effect to this and other alternative assumptions, as detailed in Online Appendix H.

[71]$\hat{v}_{T_{r>0}}$ is certainly $\geq v^*_0$ when the population $N^S \to \infty$ and no trimming is applied, in which case the maximum $\hat{v}_{0t} = v^*_0$. In finite samples, $\hat{v}_{T_{r>0}} \geq v^*_0$ only if the noise introduced from having estimated $\hat{\theta}_b$ and $\hat{g}(\mathbf{Z})$, is larger than the true "gap" between the highest seller valuation in the data and the equilibrium threshold v^*_0. Letting θ^P_s and $g^P(\mathbf{Z})$ denote the true population values of the parameters and $v_{0t}(\theta^P_s, g^P(\mathbf{Z}))$ the true seller value draw in listing t, then $\hat{v}_{T,r>0}$ is an overestimate if and only if

$$\underbrace{\max(\hat{v}_{0t}) - \max(v_{0t}(\theta^P_s, g^P(\mathbf{Z})))}_{\text{estimation noise gap}} > \underbrace{v^*_0 - \max(v_{0t}(\theta^P_s, g^P(\mathbf{Z})))}_{\text{value draw gap}}. \tag{F.6}$$

The sample maximum is known to be a biased but super-consistent estimator of its population counterpart so the bias, or the value draw gap, goes to 0 at a rate of $O(\frac{1}{T})$ when T is the sample size. Hence it depletes faster than the estimation noise gap.

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 $p_{0,r>0} = 0$. The $\log\mathcal{GGD}(\mu,\sigma^2,\kappa)$ has PDF:

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

reducing to the Normal distribution for $\kappa = 0$.

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. It is useful to note here that the gap between the highest bid for which the reserve price is unmet and the lowest for which it is met is indeed smaller in the high-frequency (£7) than in the main (£44) sample.

The presented estimation method requires that the estimated distribution of reserve prices is consistent for its population counterpart. Equality of the distribution of approximated reserve prices in the main sample and the distribution of (approximated) reserve prices in the smaller high frequency sample is tested with a two sample nonparametric Kolmogorov-Smirnov test. To account for different listing compositions the empirical reserve price distributions are right-truncated at the 90^th 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:

$$D_{f,r} = \sup_x |F_R^{\mathcal{F}}(x) - F_R^{\mathcal{R}}(x)|, \tag{G.1}$$

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 446 in the high-frequency sample and $1,147$ in the regular sample. With $D_{f,r} = 0.060$, the null cannot be rejected at the 5 percent level ($D_{f,r} > 1.36\sqrt(\frac{f+r}{fr})$, the p-value = 0.1996).

The associated empirical distributions are plotted in panel (a) of Figure G.1. 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 G.1). The two-sample Kolmogorov-Smirnov test is therefore repeated when excluding unsold lots from the regular sample. With $D_{f,r} = 0.066$, also in this sample the null that the two distributions are equal cannot be rejected at any reasonable level (the p-value = 0.2015). This second test is based on a lower number of observations ($r = 627$).

H. Robustness to model assumptions and estimation algorithm

The main counterfactual analysis in Section 6 builds on the model estimates and highlights the role of the negative seller-side network effect in this two-sided platform setting with seller selection. To consider the impact of various choices made in modeling and in estimation, the model is re-estimated under various alternative assumptions, and the lemons effect is evaluated

(a) regular sample: all (b) regular sample: sold

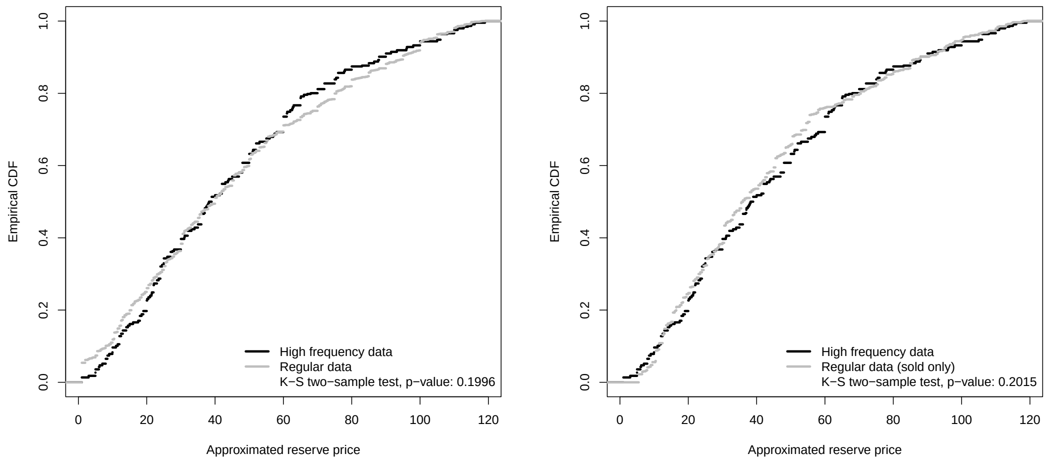


Figure G.1. : Empirical distributions underlying the presented Kolmogorov-Smirnov tests

with the alternative sets of structural parameters. The results of this exercise are displayed in Figure H.1. The dark solid line represents the results based on the model and estimation algorithm presented in the main body of the paper. Overall, it can be concluded that changing the listing fee has a similar effect under all alternative simulations, with only small differences in the magnitudes across specifications. The following alternative specifications are considered:

- The alternative "One-step NPL" only computes the equilibrium once, rather than estimating until convergence.
- The alternative "Iterate NPL, lowest funcval" selects the estimates that achieve the lowest function value / highest likelihood of implied seller values as given in (24), after iterating until convergence of the algorithm. It can be seen that this achieves the exact same results as taking the final, converged, values as is done in the main body of the paper.
- The alternative "Platt" adopts the filtering process described in Platt (2017) based on an argument of inter-auction dynamics, as discussed in Online Appendix F. To adopt this algorithm, the following additional restrictions are placed on the data. The number of participants n is Poisson distributed with mean λ (and $p_0 = 0$), and arrive in a random order with each permutation of the arrival order being equally likely. Once a participant

arrives, it immediately places a bid equal to its valuation whenever the standing price is below it. Platt (2017) shows that under these assumptions the observed mean number of bidders per listing (denoted by $\overline{a}$) relates to λ according to

$$\overline{a}(\lambda) = 2(\ln(\lambda) + \gamma + \Gamma(0, \lambda)) - 1 + \exp(-\lambda). \tag{H.1}$$

Under these restrictions, the simulation exercise thus solves for the λ that satisfies (H.1). In zero reserve price auctions, $\overline{a}(\lambda)$ is observed as the sample mean number of bidders per listing as in (F.1). In positive reserve price auctions, there is additional censoring by the (secret) reserve price, and $\overline{a}(\lambda)$ is taken to be the maximum likelihood estimate of the number of bidders in the baseline model without intra-auction dynamics, e.g. the $\lambda^*_{r>0}$ in (F.2).

- The alternative "minimal gZ" excludes in the homogenization step all variables from **Z** that relate to seller ratings, delivery costs and delivery options, and payment options.[72] The variables that are retained are listed in column 4 of Table H. 1, which contains the estimates of $\hat{g}(\mathbf{Z})$ for the minimal model.

- The alternative "sold only" uses only sold auctions to estimate seller parameters θ_s. To do so, the estimator adjusts the likelihood function in (24) for the fact that sold listings are not a random sample of all listings. Specifically, the original estimator is based on the unconditional probability of observing the sample of $\hat{v}_{0t}$ on the platform given v_0^*, e.g. based on the $h(\hat{v}_{0t}|v_0^*, r_t, \mathbf{z}_t; \theta_s)$ defined in (23) and uses all $t \in \mathcal{T}_{r>0}$. The alternative estimator labeled "sold only" is thus based on the subset of positive reserve price auctions that resulted in a sale, where the contribution to the likelihood for observation t, $\forall t \in \mathcal{T}_{r>0}$

[72] For completeness, the omitted variables in the "smaller" subset of **Z** are the following: whether the buyer can collect the wine, whether the buyer can *only* collect the wine, whether returns are accepted by the seller, whether insurance is included in the delivery costs quote, whether the seller ships to the UK, whether payment by bank is allowed, whether payment via PayPall is allowed, whether payment by cheque is allowed, whether payment in cash is allowed, whether the item is shipped with Royal Mail, whether the item is shipped with ParcelForce, whether the seller mentions fast shipping, the estimated alcohol duty, the estimate VAT, the estimated shipping costs, whether the seller has ratings from previous transactions, the number of seller ratings from previous transactions, and the number of ratings squared.

s.t. $1(sale)_t = 1$, equals

(H.2)

$$\sum_{n \geq a_t} h(\hat{v}_{0t}|v_0^*, r_t, \mathbf{z}_t; \theta_s) p(sale|r_t, n) f_{N_{r>0}}(n; \hat{\lambda}^*_{r>0}, \hat{p}_{0,r>0}) / (1 - F_{N_{r>0}}(a_t; \hat{\lambda}^*_{r>0}, \hat{p}_{0,r>0}))$$

multiplying $h(\hat{v}_{0t}|v_0^*, r_t, \mathbf{z}_t; \theta_s)$ by the sale probability given r_t, which is computed as:

$$p(sale|r_t, n) = 1 - F_V(\log(r_t) - \hat{g}(\mathbf{z}_t); \hat{\theta}_b)^n \quad \text{(H.3)}$$

and taking the expectation over $N_{r>0}$ given the realization of actual bidders a_t. The rest of the estimation procedure is unchanged.

- The alternative "without N dummies" presents the results when excluding only the number of bidders from the estimation of $g(\mathbf{Z})$. Column 3 of Table H. 1 reports the estimates of the homogenization step for this specification.

- The alternative "Only secret r" excludes observations from auctions that have a publicly observed increased minimum bid amount when estimating the seller valuation parameters.

The results from all alternative model specifications point towards the same pattern and roughly the magnitude of the lemons effect.

The next robustness analysis considers the effect of keeping the threshold beyond which sellers set a positive reserve price, v_0^R, fixed in the analysis (see also footnote 36). The expected surplus for sellers is simulated as a function of V_0 and separately when setting a positive reserve price and when setting no reserve price, given the estimated structural parameters in the main sample. Figure H.2 displays the results. The solid lines with marker show the expected seller surplus when setting a reserve price, and the plain solid lines show the expected surplus when setting $r = 0$. The black pairs correspond to the baseline fee structure, and the grey pairs are simulated based on increasing the listing fee by £1 (in panel a) increasing the seller commission by 5 percentage points (in panel b). The expected seller surplus is scaled by the average hammer price in the estimation sample.

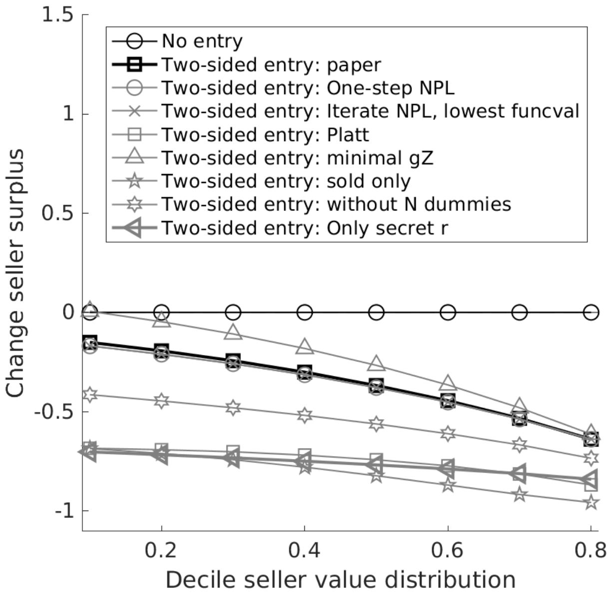


Figure H.1. : Robustness of lemons effect to alternative assumptions

The results confirm that low-v_0 sellers are better off setting a zero reserve, and also that the level beyond which it is optimal to set a positive reserve price (v_0^R) is little affected by changes in the fee structure, whereas the threshold beyond which it is optimal not to enter (v_0^*) varies much more. This is because changes in the platform's fee structure affect sellers in both $r > 0$ and $r = 0$ listings, but not sellers who don't enter.

The simulations are also useful to assess the role of fixing the threshold for the uniqeness of the entry equilibrium, because 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 in equilibrium. The fact that the simulations show that v_0^R and v_0^* move in the same direction when the fee structure changes confirms that, in this setting, even when v_0^R would be endogenized there remains a unique entry equilibrium.[73]

[73] One caveat is that the simulations are based on model primitives that are estimated under the assumption of a unique equilibrium. If in reality there are multiple equilibria, it cannot be ruled out that the true F_V is different in a way that undermines the conclusions in this paragraph.

(a) Increasing c_L (b) Increasing c_S

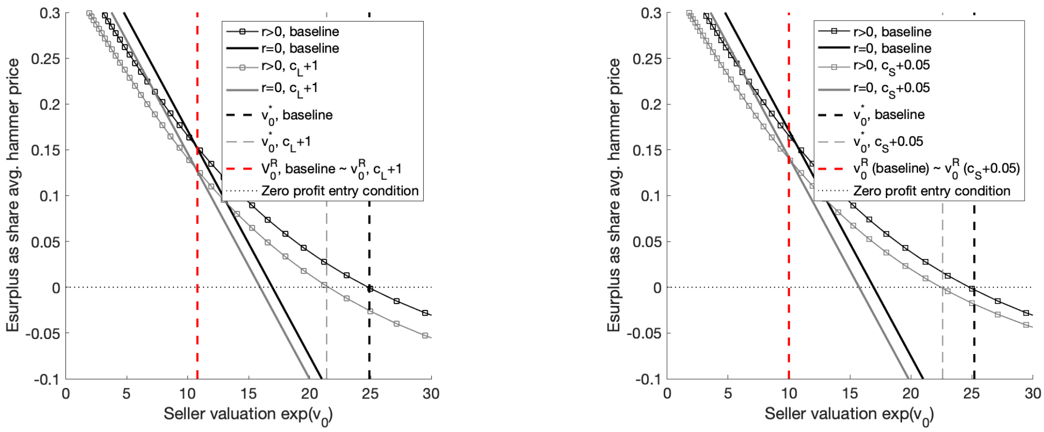


Figure H.2. : Numerical simulations: minimal effect endogenizing v_0^R

Table H. 1—: Results from homogenization step (main sample), with alternative specifications

	(1)	(2)	(3)	(4)	(5)
Number bottles	−0.523***	−0.601***	−0.490***	−0.498***	−17.701***
	(0.092)	(0.108)	(0.099)	(0.094)	(4.627)
Number bottles, squared	0.029***	0.040***	0.027***	0.028***	1.090**
	(0.010)	(0.012)	(0.010)	(0.010)	(0.483)
Case of 6	0.680***	0.756***	0.666***	0.688***	17.543**
	(0.143)	(0.171)	(0.154)	(0.146)	(7.206)
Case of 12	0.633	−0.105	0.544	0.557	15.985
	(0.613)	(0.823)	(0.659)	(0.609)	(30.830)
Special format bottle	0.102	0.286***	0.076	0.055	−0.651
	(0.076)	(0.102)	(0.082)	(0.077)	(3.847)
One bottle	0.150	0.049	0.123	0.242**	18.081***
	(0.099)	(0.115)	(0.106)	(0.097)	(4.963)
Stored in warehouse	−0.113	−0.590	−0.099	−0.001	7.954
	(0.275)	(0.504)	(0.296)	(0.112)	(13.836)
Description: En Primeur	0.121**	0.018	0.144***	0.163***	4.460*
	(0.050)	(0.060)	(0.054)	(0.049)	(2.519)
Description: Parker	−0.002	−0.001	−0.007	−0.031	−0.065
	(0.040)	(0.049)	(0.043)	(0.039)	(2.010)
Description: Number words	0.207***	0.086	0.191***	0.287***	3.828*
	(0.044)	(0.057)	(0.047)	(0.043)	(2.222)
Description: Delivery	0.006***	0.004	0.011***	0.007***	0.278**
	(0.002)	(0.003)	(0.003)	(0.002)	(0.119)
Can Collect	0.064	0.207***	0.114**		4.979**
	(0.045)	(0.058)	(0.048)		(2.280)
Can only Collect	−0.144	0.001	−0.306**		0.300
	(0.122)	(0.141)	(0.131)		(6.126)
Returns Accepted	−0.103	−0.183	−0.394**		2.101
	(0.165)	(0.380)	(0.176)		(8.299)
Insurance Included	0.049	0.060	0.104**		3.626*
	(0.043)	(0.053)	(0.046)		(2.159)
Delivers to UK	0.050	−0.137**	0.003		4.213
	(0.051)	(0.063)	(0.055)		(2.585)
Ships with Royal Mail	−0.055	−0.142**	−0.058		−1.905
	(0.052)	(0.064)	(0.055)		(2.600)
Ships with Parcelforce	−0.207***	−0.152***	−0.175***		−7.554***
	(0.048)	(0.053)	(0.052)		(2.419)
Shipping estimate	0.018***	0.020***	0.014***		0.573***
	(0.004)	(0.006)	(0.005)		(0.217)
Mentions fast shipping	0.282***	0.460***	0.440***		17.633***
	(0.071)	(0.082)	(0.076)		(3.595)
Payment by bank	0.161*	−0.043	0.237***		6.586
	(0.085)	(0.114)	(0.091)		(4.272)
Payment by Paypall	−0.108**	−0.179***	−0.155***		−4.290*
	(0.048)	(0.064)	(0.051)		(2.412)
Payment by cheque	0.026	0.025	0.026		−0.140
	(0.052)	(0.068)	(0.056)		(2.608)
Payment in cash	−0.095	−0.206*	−0.029		−3.830
	(0.114)	(0.125)	(0.123)		(5.752)
Alcohol duty estimate	−0.001	0.021	0.003		−0.550
	(0.016)	(0.037)	(0.017)		(0.805)
VAT estimate	0.006	−0.006	0.003		0.157
	(0.007)	(0.024)	(0.007)		(0.332)
Seller has ratings	−0.039	0.040	−0.022		−0.344
	(0.047)	(0.056)	(0.050)		(2.341)
Number seller ratings	−0.030*	−0.060***	−0.058***		−2.278**
	(0.018)	(0.022)	(0.019)		(0.904)
Number seller ratings, squared	0.001	0.002**	0.002***		0.095**
	(0.001)	(0.001)	(0.001)		(0.038)
Constant	3.134***	2.474***	3.282***	3.198***	25.816*
	(0.285)	(0.373)	(0.305)	(0.257)	(14.355)
Sample (n≥ 2 and) :	$H\neq r$	r=0	$H\neq r$	$H\neq r$	$H\neq r$
Dependent variable:	ln(H)	ln(H)	ln(H)	ln(H)	H
N dummies:	✓	✓		✓	✓
Observations	1,621	967	1,621	1,621	1,621
R^2	0.573	0.666	0.500	0.543	0.491
Adjusted R^2	0.548	0.634	0.475	0.523	0.462

Notes. Standard errors in parenthesis, $^{+}$p<0.1; *p<0.05; **p<0.01; ***p<0.001. Results from OLS regressions. The dependent variable is the (log) of the hammer price normalized by the number of bottles in the auction. All specifications include dummies for the type of wine, ullage level, wine region, and month. The structural estimates are based on the model specification in column (1).

Table H. 2—: Results from homogenization step (high-end sample), with alternative specifications

	(1)	(2)	(3)	(4)	(5)
Number bottles	−0.240***	−0.822***	−0.242***	−0.249***	−18.692*
	(0.032)	(0.248)	(0.032)	(0.031)	(10.048)
Number bottles, squared	0.005***	0.048**	0.005***	0.005***	0.414
	(0.001)	(0.019)	(0.001)	(0.001)	(0.313)
Case of 6	−0.167	0.199	−0.170*	−0.160	−19.843
	(0.104)	(0.385)	(0.101)	(0.099)	(32.195)
Case of 12	0.155	−0.208	0.167	0.160	12.086
	(0.179)	(0.492)	(0.175)	(0.171)	(55.338)
Special format bottle	0.121	0.727***	0.106	0.093	10.465
	(0.116)	(0.253)	(0.114)	(0.112)	(36.030)
One bottle	0.431***	−0.238	0.423***	0.449***	139.407***
	(0.098)	(0.318)	(0.095)	(0.096)	(30.348)
Stored in warehouse	−0.278	−1.961**	−0.214	−0.145*	−50.837
	(0.222)	(0.789)	(0.213)	(0.085)	(68.666)
Description: En Primeur	−0.073	−0.214*	−0.081	−0.054	−23.331
	(0.058)	(0.111)	(0.055)	(0.055)	(17.869)
Description: Parker	−0.014	−0.072	−0.006	0.001	−4.361
	(0.050)	(0.089)	(0.049)	(0.047)	(15.320)
Description: Number words	−0.107*	−0.470***	−0.105*	−0.053	−41.798**
	(0.062)	(0.151)	(0.060)	(0.056)	(19.156)
Description: Delivery	0.002	0.014***	0.001	0.001	0.852
	(0.003)	(0.004)	(0.003)	(0.003)	(0.978)
Can Collect	−0.002	−0.111	−0.005		6.192
	(0.061)	(0.123)	(0.059)		(18.737)
Can only Collect	−0.429**	−0.934**	−0.423**		−91.617
	(0.201)	(0.397)	(0.197)		(62.133)
Returns Accepted	−0.071		−0.078		−11.630
	(0.122)		(0.118)		(37.821)
Insurance Included	−0.020	−0.116	−0.019		−16.406
	(0.054)	(0.092)	(0.053)		(16.656)
Delivers to UK	−0.137**	−0.195*	−0.115*		−31.564
	(0.064)	(0.101)	(0.062)		(19.849)
Ships with Royal Mail	0.106	0.412***	0.118		35.498
	(0.075)	(0.149)	(0.074)		(23.316)
Ships with Parcelforce	−0.184**	−0.301	−0.196**		−51.695**
	(0.084)	(0.186)	(0.082)		(26.010)
Shipping estimate	0.002	−0.010	0.003		0.168
	(0.003)	(0.008)	(0.003)		(0.966)
Mentions fast shipping	−0.112	−0.182	−0.115		−46.553
	(0.105)	(0.215)	(0.100)		(32.338)
Payment by bank	−0.137	0.080	−0.119		−55.260
	(0.124)	(0.219)	(0.121)		(38.359)
Payment by Paypall	−0.110*	−0.067	−0.096		−22.052
	(0.062)	(0.139)	(0.060)		(19.097)
Payment by cheque	−0.025	0.086	−0.026		−9.820
	(0.069)	(0.157)	(0.067)		(21.331)
Payment in cash	0.437*	0.202	0.401*		21.667
	(0.243)	(0.361)	(0.235)		(75.312)
Alcohol duty estimate	0.006	0.075**	0.003		0.665
	(0.009)	(0.032)	(0.009)		(2.865)
VAT estimate	−0.001	0.0001	−0.002		0.132
	(0.003)	(0.005)	(0.002)		(0.788)
Seller has ratings	0.022	0.092	0.006		13.565
	(0.054)	(0.097)	(0.052)		(16.769)
Number seller ratings	−0.049	−0.205**	−0.049		−2.150
	(0.037)	(0.098)	(0.035)		(11.293)
Number seller ratings, squared	0.002	0.009**	0.002		0.189
	(0.002)	(0.004)	(0.001)		(0.474)
Constant	6.032***	8.616***	5.849***	5.597***	393.941***
	(0.427)	(1.084)	(0.408)	(0.378)	(132.080)
Sample (n≥ 2 and) :	H≠ r	r=0	H≠ r	H≠ r	H≠ r
Dependent variable:	ln(H)	ln(H)	ln(H)	ln(H)	H
N dummies:	✓	✓		✓	✓
Observations	299	151	299	299	299
R^2	0.935	0.930	0.933	0.927	0.738
Adjusted R^2	0.914	0.876	0.915	0.911	0.653

Notes. Standard errors in parenthesis, $^+$p<0.1; *p<0.05; **p<0.01; ***p<0.001. Results from OLS regressions. The dependent variable is the (log) of the hammer price normalized by the number of bottles in the auction. All specifications include dummies for the type of wine, ullage level, wine region, and month. The structural estimates are based on the model specification in column (1).

Table H. 3—: Differences $g(\mathbf{Z})$ above vs. below median hammer price in main sample

Number bottles	−0.173
	(0.533)
Number bottles, squared	0.065
	(0.094)
Case of 6	−0.849
	(1.030)
Case of 12	
Special format bottle	0.223**
	(0.111)
One bottle	−0.291
	(0.283)
Stored in warehouse	0.356
	(0.575)
Description: En Primeur	0.097
	(0.075)
Description: Parker	−0.024
	(0.058)
Description: Number words	0.191***
	(0.066)
Description: Delivery	0.002
	(0.004)
Can Collect	−0.009
	(0.070)
Can only Collect	−0.028
	(0.235)
Returns Accepted	−0.498
	(0.370)
Insurance Included	−0.054
	(0.064)
Delivers to UK	0.004
	(0.078)
Ships with Royal Mail	0.027
	(0.080)
Ships with Parcelforce	0.031
	(0.075)
Shipping estimate	0.004
	(0.006)
Mentions fast shipping	−0.062
	(0.145)
Payment by bank	0.131
	(0.130)
Payment by Paypall	0.063
	(0.072)
Payment by cheque	0.021
	(0.079)
Payment in cash	−0.149
	(0.173)
Alcohol duty estimate	−0.042
	(0.049)
VAT estimate	0.034
	(0.025)
Seller has ratings	−0.090
	(0.068)
Number seller ratings	0.100***
	(0.026)
Number seller ratings, squared	−0.004***
	(0.001)
Constant	−1.723**
	(0.796)
Sample ($n \geq 2$ and)	H$\neq r$
Dependent variable:	ln(H)
N dummies:	✓
Observations	1,621
R^2	0.801
Adjusted R^2	0.778

Notes. Standard errors in parenthesis, $^+$p<0.1; *p<0.05; **p<0.01; ***p<0.001. Results from OLS regressions. The dependent variable is the (log) of the hammer price normalized by the number of bottles in the auction. The specification includes dummies for the type of wine, ullage level, wine region, and month as in column (1) of Table H. 1. In addition, the variables are interacted with a binary variable indicating that the hammer price exceeds the median hammer price in the sample. Only the interaction terms and the intercept for above-median hammer prices are reported.

I. 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 does not make explicit that these distributions are in fact the estimated conditional value distributions. Shorthand notation $\tilde{r} = (1 + c_B)r^*$ 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 $\{\lambda^*_{r>0}(v^*_0),\ \lambda^*_{r=0},\ v^*_0\}$ as respectively defined in (11), (9), and (13) 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 $\Pi_{B,r>0}(\tilde{v_0};\lambda_{r>0})$ we need to obtain $\pi^{r>0}_B(n, v_0)$ defined in (4) in expectation over v_0 and n, minus entry costs, as in

$$\Pi_{B,r>0}(\tilde{v_0};\lambda) = \sum_{n=0}^{\max(n)} \left[\int_{v_0^R}^{\tilde{v_0}} \pi^{r>0}_B(n, v_0) \frac{f_{V_0|V_0 \geq v_0^R}(v_0)}{F_{V_0|V_0 \geq v_0^R}(\tilde{v_0})} dv_0 \right] \times f_{N_{r>0}}(n;\lambda_{r>0}) - e_B, \tag{I.1}$$

where

$$\pi^{r>0}_B(n, v_0) = \frac{1}{n} \int_{\tilde{r}}^{\overline{v}} v_n - \max\left(\tilde{r}, \int_{\underline{v}}^{v_n} v_{n-1} dF_{V_{n-1}|V_n=v_n}(v_{n-1})\right) dF_{V_n}(v_n), \tag{I.2}$$

$$F_{V_n}(v_n) = \int_{\underline{v}}^{v_n} nF_V(x)^{n-1} f_V(x) dx, \tag{I.3}$$

$$F_{V_{n-1}|V_n=v_n}(v_{n-1}) = \int_{\underline{v}}^{v_n} \frac{(n-1)F_V(y)^{n-2} f_V(y)}{F_V(v_n)^{n-1}} dy, \tag{I.4}$$

and $f_{N_{r>0}}(n;\lambda_{r>0})$ is defined in (1). This is sufficient to compute $\lambda^*_{r>0}$ for any value of $\tilde{v_0}$, as the unique value $\lambda \in [0, \max(n)]$ that sets

$$\Pi_{B,r>0}(\tilde{v_0}; \lambda) = 0. \tag{I.5}$$

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

$$\Pi_{B,r=0}(\lambda_{r=0}) = \sum_{n=0}^{\max(n)} \pi_B^{r=0}(n) f_{N_{r=0}}(n; \lambda_{r=0}) - e_B, \tag{I.6}$$

with $\pi_B^{r=0}(n)$ defined in (5).

Computing $\Pi_{S,r>0}(v_0; \lambda^*_{r>0}(\tilde{v_0}))$ relies on $\pi_S^{r>0}(n, v_0)$ defined in (6) in expectation over the number of bidders, minus entry costs:

$$\Pi_{S,r>0}(v_0; \lambda^*_{r>0}(\tilde{v_0})) = \sum_{n=0}^{\max(n)} \pi_S^{r>0}(n, v_0) f_{N_{r>0}}(n, \lambda^*_{r>0}(\tilde{v_0})) - c_L - e_S \tag{I.7}$$

$$\pi_S^{r>0}(n, v_0) = \Bigg(\max\Big(r, \frac{1}{1+c_B} \int_{\underline{v}}^{\overline{v}} v_{n-1} dF_{V_{n-1}|V_n \geq \tilde{r}}(v_{n-1})\Big) \times (1 - c_S) - v_0 \Bigg) \Big[1 - F_{V_{(n)}}(\tilde{r})\Big] \tag{I.8}$$

$$F_{V_{n-1}|V_n \geq \tilde{r}}(v_{n-1}) = \int_{\tilde{r}}^{\overline{v}} F_{V_{n-1}|V_n = x}(v_{n-1}) dF_{V_n}(x) \tag{I.9}$$

This is sufficient to compute v_0^* for any fee structure and given potential bidders' best-response characterized by $\lambda^*_{r>0}(\tilde{v_0})$, as the value that sets

$$\Pi_{S,r>0}(\tilde{v_0}; \lambda^*_{r>0}(\tilde{v_0})) = 0 \tag{I.10}$$

Given the 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 $\overline{v} = F_V^{-1}(1-1e^{-9};\hat{\theta}_b)$ and $\underline{v} = 0$. Code the distributions in (I.3) and (I.4). For each $n = 1,..,15$, simulate 250 values from the two distributions. For the highest valuation, solve for $F^{-1}_{V_{n:n}}(\mathbf{v\_probs};\hat{\theta}_b)$, separately for each n, resulting in matrix **h_mat** of dimension $[250 \times 15]$. For the second-highest valuation, solve for $F^{-1}_{V_{n-1:n}|V_{n:n}=v_n}(\mathbf{v\_probs};\hat{\theta}_b)$, 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 $F^{-1}_{V_0}(\mathbf{v0\_probs};\hat{\theta}_s)$ 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**. $\Pi_{B,r>0}(2, v_0)$ is approximated as the mean of the second column of **h_mat_fine** including only all values exceeding **r_mat**$(v0idx, 2) \times (1 + c_B)$, minus the mean of the same entries in **sh_mat_fine** or minus **r_mat**$(v0idx, 2) \times (1 + c_B)$ if that is higher, and multiplied by the sale probability $(1 - F_V(\log((1 + c_B)\textbf{r\_mat}(v0idx, 2)); \hat{\theta}_b)^2)$, all divided by two.

- Linear interpolation of listing-level surplus on **v0_probs_fine**. This results in listing-level surplus matrices of dimensions $[25000 \times 15]$ for bidders in positive reserve price auctions (**pib_posr_mat**), for sellers in positive reserve price auctions (**pis_posr_mat**), and for sellers in no reserve price auctions (**pis_nor_mat**). For bidders in auctions with no reserve price (**pib_nor_vec**) we obtain a vector of dimension $[1 \times 15]$ as their listing-level surplus is independent of the seller's value. Also pre-calculate a vector of probabilities that $V_0 = v_0$ using $F^{-1}_{V_0|V_0 \geq v_0^R}$(**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 (I.7) with nested in it equation (I.5). 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 (I.1)) sum to one. The $\lambda^*(\tilde{v_0})$ in (I.5) is obtained as the root of $(\Pi_{B,r>0}(\tilde{v_0}; \lambda))^2$. MATLAB's fzero function is used with tolerance levels for the function and parameter of $1e^{-}6$, which delivers stable results. Then (I.7) 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 if and only if $v_0 \leq v_0'(v_0^{-j})$. 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 (I.10) is a contraction mapping.

J. Sensitivity of entry equilibrium to scaling of c_L

The expected bidder and seller profits in the presented model are independent of the quality of the item, due to $q = e^{g(\mathbf{Z})}$ entering values multiplicatively, up to the additive listing fee c_L. This section shows numerically that the impact of c_L on the equilibrium is small in the empirical setting, justifying the omission of q from the derivation of the game's properties. In particular, the thought experiment is that the game scales in q if, at least for values of q found in a reasonably wide interval around v_0^*, the difference between using c_L and $\frac{c_L}{q}$ has little effect on the resulting entry equilibrium.

Hence, the numerical simulations are based on the estimated parameters at $q = 1$ and consider the effect of introducing auction heterogeneity for the estimation of the entry equilibrium. Quality is continuous and estimated with noise, so this requires some averaging of the estimated quality across auctions with similar estimated seller values. Average estimated qualities in a grid of successive distance bins (of various widths) from the seller entry threshold v_0^* are constructed, as the analysis might depend on the width of the bin and how different the auction's $\hat{v}_{0t}$ is from the marginal auction. The following averages are computed:

$$\overline{q}(i,j) = \mathbb{E}\Big[\hat{q}_t | t : \hat{v}_{0t} \in (v_0^* - i \times 0.1j, v_0^* - (i-1) \times 0.1j]\Big], \tag{I.1}$$

for $i = \{1, 2, \ldots, 10\}$ and $j = \{1, 2, 3, 4\}$. For example, $\overline{q}(1,2)$ is the average estimated quality term across all auctions for which the estimated $\hat{v}_{0t}$ is between the maximum value (v_0^*) and 0.2 (first window of two times 0.1) below it.

The (i,j) notation also relates to the indices of matrices with simulation results, with the (i,j)th entry in all six matrices in Table J. 1 referring to the bin definition with the i^{th} distance band of width $0.1j$ from v_0^*. In other words, going from left to right, the matrix entries contain increasingly wide distance bins so that more variation in $\hat{q}_t$ is smoothed out across auctions. Going from top to bottom, the matrix entries contain results for adjacent bandwidths.

The least smoothing occurs with bins of width 0.1, e.g. the first columns in all matrices of

Table J. 1. Bins of this width all contain between 195 and 167 auctions (see the first column in matrix b). The estimated quality for the marginal listing is 1.44, meaning that the unscaled listing fee for that bin is £1.5 (compared to £2.1 at q=1), as documented in entry (1,1) of matrix c). Considering adjacent bins of $\hat{v}_{0t}$, the largest differences are for $\overline{q}(10,1) = 1.53$. Taking into account the scaled entry costs (matrix c) and the equilibrium adjustment of bidder entry (matrix d), the equilibrium seller entry threshold adjusts only slightly in all cases (matrix e). Matrix f is the most important output of this exercise, interpretting the equilibrium results relative to what would be the threshold for the marginal sellers (e.g., the entries in the first row). No absolute adjustments of v_0^* larger than 2.1 percent are found across all bin sizes and distances from the threshold.[74] These results motivate the omission of the dependence of the entry equilibrium on q.

Table J. 1—: Sensitivity of equilibrium to scaling c_L, distance bins from $\hat{v}$.

(a) $\overline{q}(i,j)$

1.44	1.39	1.37	1.4
1.34	1.41	1.42	1.41
1.34	1.4	1.42	1.43
1.47	1.41	1.43	1.35
1.37	1.49	1.38	1.26
1.44	1.37	1.24	1.28
1.39	1.39	1.27	1.12
1.44	1.31	1.42	1.32
1.45	1.2	1.12	1.02
1.53	1.38	1.45	1.19

(b) Number auctions in bin

143	274	422	575
131	301	474	613
148	321	390	353
153	292	255	169
167	193	127	69
154	160	87	26
146	94	30	9
146	75	20	17
98	45	8	22
95	24	13	32

(c) $\frac{c_L}{\overline{q}(i,j)}$

1.5	1.5	1.5	1.5
1.6	1.5	1.5	1.5
1.6	1.5	1.5	1.5
1.4	1.5	1.5	1.6
1.5	1.4	1.5	1.7
1.5	1.5	1.7	1.6
1.5	1.5	1.7	1.9
1.5	1.6	1.5	1.6
1.4	1.8	1.9	2.1
1.4	1.5	1.4	1.8

(d) $\lambda^*_{r>0}(\frac{c_L}{\overline{q}(i,j)})$

4.99	4.88	4.65	4.65
4.88	4.42	5.57	5.45
4.42	5.69	5.11	4.99
4.2	5.34	4.99	4.2
6.04	4.99	4.31	4.31
5.11	4.99	4.2	4.31
5.22	4.42	4.31	4.2
5.34	4.09	4.31	4.31
4.99	4.2	4.2	4.54
4.99	4.31	4.31	4.42

(e) $v_0^*(\frac{c_L}{\overline{q}(i,j)})$

3.31	3.31	3.31	3.31
3.3	3.31	3.31	3.31
3.3	3.31	3.31	3.31
3.32	3.31	3.31	3.3
3.31	3.32	3.31	3.29
3.31	3.31	3.29	3.3
3.31	3.31	3.29	3.27
3.31	3.3	3.31	3.3
3.32	3.28	3.27	3.24
3.32	3.31	3.32	3.28

(f) v_0^* change w.r.t. i=1 (%)

0	0	0	0
-0.3	0	0	0
-0.3	0	0	0
0.3	0	0	-0.3
0	0.3	0	-0.6
0	0	-0.6	-0.3
0	0	-0.6	-1.2
0	-0.3	0	-0.3
0.3	-0.9	-1.2	-2.1
0.3	0	0.3	-0.9

[74] Note that different bin sizes and distances from the marginal seller are considered so that some configuration will capture sufficiently many auctions at reasonable smoothing levels.