Do wine buyers at auction benefit from higher commissions? Welfare estimates from a natural experiment

(Preliminary Results)

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Abstract

Commissions and fees are the main margin on which intermediaries such as auction houses compete; or fail to compete. While negative impacts of uncompetitive fees on bidders' surplus justify compensation of lost value, bidders may also benefit from facing fewer competitors - as has been argued in the theoretical literature. With a model that allows for flexible endogenous entry and optimal reserve price setting, it is shown that the welfare impact of fees depends on two observable factors: the change in the hammer price conditional on selling and the change in the probability of a sale. With a unique dataset of 10.000 online auctions of fine wine that exhibits exogenous variation in fees, the welfare impacts are estimated nonparametrically. For low cost, additional fees are found to indeed increase the bidder's surplus while at high cost the direct negative impact is found to dominate. The reverse holds true for the seller.

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1 Introduction

Buyers and sellers of wine at auction pay a percentage of the hammer price as commission to the auction platform: typically between $0 - 20\%$. These and other fees are a primary source of competition among auction houses, and more generally the amount and structure of user fees are the main margin of on which intermediaries compete. That market power abuse of intermediaries is a reasonable fear for wine auctions is highlighted by the well-known antitrust case of Sotheby's and Christie's. After a period of fierce competition to auction the biggest sales by lowering commissions, they are known to have illegally fixed identical buyer's and seller's premiums in the mid-90s. Resulting from a lawsuit and settlement, everyone who bought (or sold) art or wine through these auction houses in the US between 1993 (1995) and 2000 received in total US$512M as compensation for lost value, most of which went to the buyers (Ashenfelter and Graddy [2003, 2005]). Yet Ashenfelter et al. [2003] and Ashenfelter and Graddy [2003, 2005] hypothesize that this settlement was misguided: higher premiums may have benefitted successful bidders through reduced competition.

With a unique dataset of 10.000 online auctions of fine wine that exhibit exogenous variation in fees, this paper empirically studies the impact of percentage commissions and unit fees on the welfare generated by the auction and how this is distributed among players. Endogenous entry and the optimal setting of the reserve price are essential for how these effects play out, as supported by insights from a structural model that incorporates such equilibrium behavior. Ginsburgh et al. [2010] were the first to model the intermediary in an auction model, and outline conditions under which higher commissions indeed benefit successful buyers. Two relevant abstractions in this paper with respect to Ginsburgh et al. [2010] are: i) allowing for endogenous entry based on an informative signal, and ii) allowing the seller change the reserve price in any direction when facing higher fees.

In this slightly more general model both the direction of the welfare impacts and their magnitude are uncertain. Hence it is argued that the impact of commissions and auction fees on welfare is ultimately an empirical question. The effect is pinned down as the sum of welfare impacts on two observed margins: a change in welfare due to a different hammer price conditional on a successful sale, and a change in the probability of a successful sale. The first margin incorporates changes in entry decisions of potential bidders as well as changes in the reserve price by the seller; which are expected to have opposite impacts as long as the reserve price increases with fees. The sale probability decreases both as a result of a higher reserve price and due to the direct impact of higher additional cost. As the reserve price is secret in the data its sensitivity to changes in fees cannot be separately identified, but the observed choice data is sufficiently rich to analyze the overall welfare impacts including optimal reserve price adjustments.

Identification and estimation of the welfare effects is fully nonparametric. Hence, the findings are robust to misspecification and provide realistic estimates of the magnitude of the impact on wine buyers, sellers, and intermediaries. Results may be of interest to policymakers determining the effects of anticompetitive behavior in this sector, to buyers and sellers of wine choosing among competing auction platforms, to auction houses for optimally designing the auction mechanism, and to economists as an empirical test of implications from a theoretical auction model.

2 Related literature

2.1 Theoretical foundation: competing entry models

Endogenous entry is an essential part of how commissions affect welfare in auctions, so this paper should first and foremost be regarded as a contribution to this literature. Most closely related is the paper by Ginsburgh et al. [2010] who look at commissions in a model of Vickrey auctions with an intermediary. In their model, potential bidders enter when their expected surplus is at least their heterogeneous participation cost. As the entry decision is made before they know their valuation, this falls in the class of models that I denote as "Random entry". Pioneered by Levin and Smith [1994] and McAfee and McMillan [1987], in the standard model bidders enter based on a homogeneous participation cost when observing only an i.i.d. signal that is unrelated to their valuation. Ginsburgh et al. [2010] justify their slight departure from this model by being able to study welfare implications. The heterogeneous cost assumption particularly results in the feature that when fewer potential bidders enter due to higher cost, they will be a *subset* of entrants with lower cost. However, as a feature of Random entry due to valuations being revealed after the entry decision, the distribution of valuations among entrants and non-entrants is assumed identical.

The other polar entry model in the auction literature can be denoted "Selective entry". Introduced by Samuelson [1985], potential bidders enter when their expected surplus based on their fully and privately observed valuation is more than the homogeneous participation cost. In this model, entrants have higher valuations than the full set of players. Many auctions include some form of *value discovery*, for instance procurement auctions where potential bidders must make investments to assess their likely cost and potential profit from winning the tender. But when potential bidders neither know nothing nor everything about their valuation before deciding to enter an auction, both entry models are too restrictive.

In this paper I model entry according to the "Affiliated Signals" (henceforth: AS) model that nests both Random and Selective entry. Bidders decide to enter based on an i.i.d. private signal that is *affiliated* with their value and a homogeneous participation cost (a more formal description follows). Ye [2007] uses this to model indicative bidding in auctions, where potential bidders submit an initial non-binding bid and the highest few are selected to compete in the next round of actual bidding. Roberts and Sweeting [2010] model and estimate this entry process parametrically. They underline the importance of the model permitting both Random and Selective entry by showing how mis-specification of the entry process as one of these cases leads to erroneous policy conclusions and counterfactual analysis. For instance, in a standard second-price auction with Random entry the optimal reserve price equals seller's valuation, while Selective entry requires it to be increasing in the number of entrants and be set higher than the seller's valuation.

From the perspective of a policymaker judging the welfare consequences of unnaturally high participation cost in auctions, the ex-post concern is: would the successful bidder and seller have been better off with competitive participation cost? This is key when anti-competitive behavior has come to light and a fair compensation for lost value of these parties needs to be determined. Underlying any compensation for successful bidders must be the assumption that the same person would have won the auction in the counterfactual auction. This for instance underlies conclusions in Ashenfelter et al. [2003] titled "Auction house settlements - winning twice" regarding the US\$512M settlement in the Sotheby's & Christie's antitrust case. To address this question adequately, the model must be such that the winning bidder in both auctions is likely to be the same person; which is another reason why AS entry is chosen as the preferred entry model in this paper.[1]

A key feature that distinguishes this paper from most auction papers (with the notable exception of Ginsburgh et al. [2010]) is that the seller doesn't design the mechanism; the intermediary does. The intermediary does so to optimize his profits and this could harm both buyer and seller. I think this is an important distinction to make, which has implications for the way the theoretical literature addresses mechanism design, insofar as the intermediary's incentives are not fully aligned with the seller's. In this paper I will formalize the auction outcomes the intermediate (who chooses entry cost and commissions), a profit-maximizing seller (who determines the reserve price) and a surplus-maximizing buyer (who decides on entry and bidding). The paper thus addresses welfare consequences of anti-competitive behavior *among intermediaries* that materializes in higher fees. An interesting extension of the model could be an intermediate who determines the cost structure in each auction optimally

[1] In Ginsburgh et al. [2010], due to the heterogeneous participation cost independent of unknown valuations at the time of entry, this is not guaranteed by the model: it could be that in the low-cost environment someone enters with a valuation higher than the winning bidder in the high-cost environment. Hence, this must be implicitly ruled out. Of course it is also a possibility that the winning bidder in a high-cost environment would be outbid by another bidder in a low-cost environment with the AS model (since Random entry is a nested polar case), but at least *in expectation* the entrant with the highest valuation will be the same in both auctions.

to maximize his profits.

Another policy concern is that higher fees result in a loss of *social efficiency*. Gentry and Li [2014] prove that for AS entry auctions (as for Random entry models and Selective entry models), social welfare is maximized when the seller sets no reserve price and no entry fee. The intuition behind this result is that it allows for the allocation of the good to the potential bidder with the highest valuation. However, unlike the well-known results in Levin and Smith [1994] that a revenue-maximizing seller setting no entry fee coincides with the social optimum, Gentry and Li [2014] show that a revenue-maximizing seller will set a socially inefficient, positive entry fee in the AS model. Together with the result in Moreno and Wooders [2011] that when introducing heterogeneous entry cost in the Random entry model the coincidence between revenue-maximization and social efficiency breaks down, it is clear that both homogeneous entry cost and not knowing valuations at the time of entry are crucial for the conclusions in Levin and Smith [1994]. It is straightforward to see that these results extend to a misalignment between the revenue-maximizing incentives of an intermediary and the social optimum of no barriers to entry in the AS or Selective entry models, because the intermediary's only source of profits are entry fees and commissions.

2.2 Sufficient statistic method

After convincingly modeling the auction mechanism and players' equilibrium behavior, there are two ways to answer the central question of how auction fees affect welfare. The structural approach estimates (or calibrates) the full model including the entry decision of potential bidders, bidding, and the setting of the reserve price. As these equations are interdependent, it is necessary to impose suitable parameterizations of the joint distribution of signals and valuations and of the entry and reserve price functions in terms of the cost, and as mentioned earlier these distributions need to be known to the players. The major benefit of this approach is that besides answering the question for cost levels observed in the data, the behavioral responses to counterfactual policy analysis are pinned down and can thus also be evaluated. Structural models of auctions with entry are developed in Li [2005] (first-price auctions with Random entry specifically allowing for binding reserve prices), Athey et al. [2008] (comparing open and sealed-bid first-price auctions with Random entry) (Li and Zheng [2009, 2012] (first-price auctions, comparing Random - Selective - and AS entry specifications). This literature is also closely related to studies of firm entry into markets, as in e.g. Bresnahan and Reiss [1991] and Berry [1992].

Instead of parameterizing and estimating the full structural model, the *sufficient statistic* approach estimates the components of the relevant total differentials directly from data. This approach is based on the intuition that with adequate variation in the policy variable of interest, and with players optimizing their choices, the realized changes in outcomes reflect the policy impact of interest incorporating behavioral change. While this approach relies on fewer assumptions and can be more feasible, a downside is that counterfactual analysis is less credible for out-of-sample extrapolation (for a great introduction to this approach and the literature see Chetty [2009]). Since Harberger [1964] this has been especially useful to study welfare effects of taxes, which obviously has many similarities to welfare effects of cost in auctions. This paper takes this second approach, using exogenous variation in the fee structure in the data to estimate the policy impacts of interest while relying on the structural model to interpret findings.

3 Model

The mechanism is an English auction where: an intermediary sets both the buyer's commission c_B as a percentage of the hammer price and the amount of entry cost c_E, a seller who has valuation v_0 for the auctioned lot sets reserve price r, and N potential bidders compete to win a single indivisible lot. Let $\mathcal{P}$ denote the set of risk-neutral potential bidders, and X_j and V_j respectively their signal and valuation whose realizations are denoted in lower case.

Assumption: symmetric IPV. *Potential bidders are identical up to signal X_j of their private value V_j. The random pairs $(V_j, X_j) \perp (V_{j'}, X_{j'})\ \forall j \neq j' \in \mathcal{P}$.*

This two-stage equivalent of the standard IPV assumption will in the estimation phase be taken to hold conditional on a set of auction covariates, but rules out any other correlation in valuations such as due to unobserved heterogeneity.[2] Following Gentry and Li [2014] to model AS entry, valuations are assumed to be stochastically increasing in the signal:

Assumption: Stochastic Ordering. *Value-Signal pairs (V_j, X_j) are drawn symmetrically across bidders such that $\forall j \in \mathcal{P}$: the distribution of V_j is stochastically ordered in X_j: $F_{V|X}(v|x') \leq F_{V|X}(v|x)$ when $x' \geq x$ and with $F_{V|X}$ defined on $[\underline{v}, \bar{v}]$.*

This nests Selective entry (as in Samuelson [1985]) when the private signal fully captures the valuation and entry cost can be regarded as bid preparation cost. It also nests the more commonly applied Random entry as a polar case (as in McAfee and McMillan [1987], Levin and Smith [1994]) when the signal is independent of valuations and entry cost can be regarded as bid preparation and valuation discovery cost. Beyond this, the AS model especially allows

[2] This is necessary for nonparametric identification of the second-stage distribution of valuations as shown for no-entry English auctions in Athey and Haile [2002] and in Haile and Tamer [2003] when relaxing the bidding strategies. When this assumption is deemed implausible one can bound bidder surplus and seller profit under the weaker assumption that bidders valuations are non-negatively dependent, following the approach in Aradillas-López et al. [2013] for identification of the distribution of entrant's valuations.

for more moderate entry behavior where potential bidders have some initial idea of their valuation but it is costly to fully discover it, which may be an accurate description of entry in wine auctions.[3]

3.1 Bidder's surplus

In this winner-takes-all auction mechanism, only the successful bidder has a positive surplus. The auction can be modeled as a two-stage game. At the first stage potential bidders decide whether to enter and in the second stage the entrants decide how much to bid. Arguing backwards:

3.1.1 Second stage: bidding

Since the reserve price is secret in these auctions, all entrants place a bid. The bidding stage is rationalized as a Vickrey second-price sealed bid auction where it is optimal for bidders to bid their valuation (Vickrey [1961]), adjusted for additional cost and commissions. The optimal bidding strategy $b^*(.)$ is thus only a function of the private signal and the known cost. So letting $\mathcal{N}$ denote the set of entrants. $\forall i \in \mathcal{N}$:

$$b_i = b^*(v_i, c_B, c_F) = \frac{v_i}{1 + c_B} - c_F \tag{1}$$

Consequently, the entrant with the highest valuation wins the auction and pays the second-highest bid plus additional cost. A distinction is made between commissions and other highest-bid dependent cost c_B and fixed cost c_F independent of the highest bid such as delivery cost. This is to facilitate a close match to the auction data in this study and also to allow for these cost to affect welfare differently. Exogenous variation along these two dimensions will be exploited in the empirical part of this paper.

The winning bidder pays the maximum of the reserve price and the second-highest bid and additional cost, if his valuation is high enough. The number of entrants is an equilibrium outcome from the first-stage entry decision. Denoting the ith highest out of n^* valuations (among the n^* entrants) by $V_{(i:n^*)}$, the second-stage realized surplus for the highest bidder

[3] For example, the private signal can be thought of as the strength of an urge to buy a bottle of red Bordeaux for a special occasion (ranging between none and very strong) and the entry cost as time it takes bidders to compare active lots and look at sold lots to understand the how much the listed Bordeaux are worth to them (nondecreasing in their initial urge) as well as the time it takes to determine the bidding strategy.

is:

$$CS(V_{(n^*:n^*)}, V_{(n^*-1:n^*)}, r^*, c_B, c_F) = \qquad (2)$$
$$\left(V_{(n^*:n^*)} - \max(r^*, \frac{V_{(n^*-1:n^*)}}{1+c_B} - c_F)(1+c_B) - c_F \right) \mathbb{I}\{V_{(n^*:n^*)} \geq r^*(1+c_B)+c_F\}$$

Where $\mathbb{I}\{.\}$ is the indicator function. Also the reserve price is modeled as an equilibrium outcome r^*, as discussed below.

3.1.2 First stage: entry

In the first stage potential bidders decide whether to enter, which is optimal if the expected value of their surplus from doing so exceeds the cost of entry.Due to the stochastic ordering assumption a high signal is "good news" making that equilibrium entry involves a threshold strategy where bidders enter iff their signal is more than some common threshold x^*.[4]

Let $F_V(.;\dot{x})$ be the CDF of valuations among entrants who enter according to some threshold $\dot{x}$.[5] The below will show that there is a unique equilibrium threshold $\dot{x} = x^*$. Let $CS^{1st}(v_i, y_i, c_B, c_F, r^*, N, \dot{x}, F_V(.;\dot{x}))$ be the first-stage expected surplus for an entrant if he would know his valuation v_i when $N-1$ other potential bidders decide to enter according to threshold $\dot{x}$, taking into account all cost and the optimal reserve price as a function of these cost. Furthermore, $y_i = \max_{i' \neq i}(v_{i'})$ indicates the known highest valuation among the other n^*-1 entrants. As in Gentry and Li [2014] the private signal is normalized to be distributed Uniformly on $[0,1]$, without loss of generality and with the aim to simplify the exposition.

$$CS^{1st}(v_i, y_i, c_B, c_F, r^*, N, \dot{x}, F_V(.;\dot{x})) = \qquad (3)$$
$$[\dot{x} + (1-\dot{x})F_V(v_i;\dot{x})]^{(N-1)} CS(V_{(n^*:n^*)} = v_i, V_{(n^*-1:n^*)} = y_i, r^*, c_B, c_F)$$

The first part gives the probability that i's $N-1$ potential competitors either don't enter, or enter but have a valuation less than v_i, and the second part is the amount of profit when the highest competing valuation is y_i.

When the entry decision is made, both v_i and y_i are of course unknown. Let $\mathbb{E}[CS^{1st}(.)|x_i] = \mathbb{E}_{v_i|x_i}[\mathbb{E}_{y_i|v_i}[CS^{1st}(.)]]$ denote the expected value of the CS given observed signal x_i. To be explicit, stating that potential bidders are able to form this expectation implies that they

[4] This is the weakly undominated equilibrium strategy in all entry models except in Random entry with a homogeneous entry cost, and formally shown in e.g. Li and Zheng [2009, 2012], Ginsburgh et al. [2010], Roberts and Sweeting [2010], Moreno and Wooders [2011], Gentry and Li [2014]). For completeness, the optimality of the equilibrium threshold entry strategy is shown for the model here as well.

[5] Notice that $F_V(.;\dot{x})$ equals the distribution of valuations among all potential bidders if signals would be independent of valuations, and that it would be a truncated variant of the CDF of valuations among all potential bidders when there is selective entry.

know the number of potential bidders N, cost c_F and c_B, the optimal (though secret) reserve price set by the seller r^*, entry threshold $\dot{x}$, and most importantly the joint distribution of valuations and signals in the population.[6]

$$\begin{aligned}&\mathbb{E}[CS^{1st}(v_i, y_i, c_B, c_E, r^*, N, \dot{x}, F_V(.;\dot{x}))|x_i] = \\ &\int_{\underline{v}}^{\bar{v}} \left(\int_0^s CS^{1st}(s, t, c_B, c_E, r^*, N, \dot{x}, F_V(.;\dot{x})) f_{Y|V}(t|s) dt \right) f_{V|X}(s|x_i) ds\end{aligned} \tag{4}$$

The inner integral covers possible values of the highest valuation less than v_i, and is based on the conditional density $f_{Y|V}(t|s)$ that gives the probability that the second-highest value entrant has a valuation of t when the highest has a value of s. The outer integral covers possible values of v_i given signal x_i on the compact support of V.

So with c_E being the entry cost, the stage-one entry decision is such that potential bidders enter whenever $\mathbb{E}[CS^{1st}(.)|x_i] \geq c_E$. As $\mathbb{E}[CS^{1st}(.))|x_i]$ is increasing in x_i due to the stochastic ordering assumption and strictly increasing in $\dot{x}$ due to decreasing competition, there exists a unique equilibrium threshold x^* characterized by: $\mathbb{E}[CS^{1st}(.)|x^*] = c_E$: the marginal entrant with $X_i = x^*$ expects to have a surplus equal to the cost of entry. Hence the unique pure Bayes Nash equilibrium in weakly undominated strategies is for all potential bidders $j \in \mathcal{P}$ to enter if and only if $X_j \geq x^*$.[7][8]

The number of entrants is thus a result of the equilibrium entry decision and is therefore also a function of the cost c_B and c_F.[9]

$$n^* = \sum_{j=1}^{N} \mathbb{I}\{\mathbb{E}[CS^{1st}(.)|x_j] \geq c_E\} \tag{5}$$

[6] Such common knowledge assumptions are not uncommon in the auction literature, but nonetheless it seems to ask a lot of bidders and I will relax this assumption when laying out the sufficient statistics approach below.

[7] This is a pure strategy; clearly with this AS model a mixing strategy where all potential bidders enter with probability q is dominated by the pure 'threshold' strategy. Other pure strategies could be for only the potential bidder with the highest signal to enter, but this is not a symmetric equilibrium and also dominated by the 'threshold' strategy for other bidders with a high signal who in expectation forego positive profits by not entering.

[8] As noted earlier this is a standard result. I borrow further intuition from Gentry and Li [2014] who discuss properties of this equilibrium threshold as a function of N and of cost c_E, which I denote as $x^*_N(c_E)$, for general auction settings. First how it relates to cost: $\forall N \geq 1$: $x^*_N(c_E)$ is continuous and weakly increasing in c_E, with strict monotonicity whenever $x^*_N(c_E) \in (0, 1)$. Higher entry cost or higher additional cost thus reduces the number of potential bidders who enter in equilibrium, which is an intuitive result underlying the "entry effect" in Li and Zheng [2009, 2012] for first-price auctions. Second, how it relates to the number of potential bidders: $\forall c^E \geq 0$: $N' > N$ implies $x^*_{N'}(c_E) \geq x^*_N(c_E)$, which holds strictly whenever $x^*_N(c_E) \in (0, 1)$. This implies that auctions with more potential bidders have a higher equilibrium entry threshold, so that entrants must have higher signals and weakly higher values in such auctions as well.

[9] A typical assumption that also underlies the intuition for this entry decision is that each entrant ignores the impact of his own entry decision on other equilibrium outcomes such as r^*.

3.2 Seller's profit

The seller takes c_B as given: the intermediary decides on the amount of commissions and additional VAT is a fixed percentage depending on the provenance of the bottle (i.e. whether import duties have been paid before). The model also assumes that sellers take c_F as given. These are the actual cost to ship the lot to a mainland UK destination depending only on the seller's own location, in particular it is imposed that the seller doesn't move to reduce these cost and doesn't report higher cost to increase profits. The seller maximizes his profits by optimally setting the reserve price r^*.

It is observed that sellers must pay the intermediary a fixed cost of c_{Fs} for each lot that is sold. If they have a large parcel for sale they can choose to sell the individual lots themselves or arrange for the intermediary to sell the lots. Both c_{Fs} and the commission that the seller pays to the intermediary as a percentage of the hammer price c_S depend on whether a lot is *Seller-managed* or *BfW-managed*. Auctions managed by the intermediary are also subject to a 18% buyer's premium while other lots have none, so this may directly impact the probability of sale. For tractability the seller's problem is however modeled as if the only choice is how to set r^* to maximize profits taken into account the amount of fees.

Let $\pi_S(V_{(n^*:n^*)}, V_{(n^*-1:n^*)}, r^*, c_B, c_F, c_{Fs}, c_S)$ be the profit for the seller if he sets optimal reserve price r^* as a function of all cost and the realized highest - and second-highest valuations of the entrants, and with his valuation for the lot normalized to 0:

$$\begin{aligned} &\pi_S(V_{(n^*:n^*)}, V_{(n^*-1:n^*)}, r^*, c_B, c_F, c_{Fs}, c_S) = \\ &\left[\max(r^*, \frac{V_{(n^*-1:n^*)}}{1+c_B} - c_F)(1-c_S) - c_{Fs}\right] \mathbb{I}\{V_{(n^*:n^*)} \geq r^*(1+c_B) + c_F\} \end{aligned} \tag{6}$$

When setting the optimal reserve, $V_{(n^*:n^*)}$ and $V_{(n^*-1:n^*)}$ are of course unknown, so sellers must form an expectation of (6) ($\mathbb{E}[\pi_S(.)]$). This relies on equilibrium values of x^*, n^*, and most importantly requires them to know the population distribution of valuations among entrants $F_V(.;x^*)$. Let $f_{V_{(n^*-1:n^*)}}(.;x^*)$ be the probability density of the highest valuation among entrants who enter according to equilibrium threshold x^* and $f_{V_{(n^*:n^*)}|V_{(n^*-1:n^*)}}(v|y;x^*)$ the probability that the highest valuation is v when the second-highest valuation equals y. Hence the seller's expected profit is:

$$\begin{aligned} &\mathbb{E}[\pi_S(V_{(n^*:n^*)}, V_{(n^*-1:n^*)}, r^*, c_B, c_F, c_{Fs}, c_S)] = \\ &\int_{\underline{v}}^{\bar{v}} \left(\int_t^{\bar{v}} \pi_S(s, t, r^*, c_B, c_F, c_{Fs}, c_S) f_{V_{(n^*:n^*)}|V_{(n^*-1:n^*)}}(s|t;x^*)ds \right) f_{V_{(n^*-1:n^*)}}(t;x^*)dt \end{aligned} \tag{7}$$

And he sets the optimal reserve price to maximize these expected profits:

$$r^* = \max_r \mathbb{E}[\pi_S(V_{(n^*:n^*)}, V_{(n^*-1:n^*)}, r, c_B, c_F, c_{Fs}, c_S)] \tag{8}$$

Note that it is uncertain in this model what the response of an optimal reserve setting seller would be to an increase in cost c_B and c_F: increasing r^* to make up for a higher probability of no sale or decreasing r^* to increase the probability of a sale. How much r^* changes depends on the probability that the entrant with the highest valuation exceeds the new reserve price and additional cost. These combined effects is what in the optimal tax literature would be the concept of "pass-through", which determines how much of an increase in cost the seller can avert to buyers and which depends on the relative demand and supply elasticities.

This is an important difference with the model in Ginsburgh et al. [2010]; instead of being agnostic about the reserve price change due to a change in fees they model the reserve price such that it increases when (buyer's) commissions go up.

3.3 Intermediary's profit

The intermediary sets the percentage of buyer's commission (which is part of c_B), the percentage of seller's commission (c_F) and the fixed seller's fees (c_{Fs}).[10] These rough prices are not regarded as optimizing the intermediary's immediate profit, which is simply a result of the bidding:

$$\begin{aligned}&\pi_I(V_{(n^*:n^*)}, V_{(n^*-1:n^*)}, r^*, c_B, c_F, c_{Fs}, c_S) = \\ &\left[\max(r^*, \frac{V_{(n^*-1:n^*)}}{1+c_B} - c_F)(c_B + c_F) + c_{Fs}\right] \mathbb{I}\{V_{(n^*:n^*)} \geq r^*(1+c_B) + c_F\}\end{aligned} \tag{9}$$

3.4 Social welfare

Social welfare is made up from the consumer surplus in (2), the seller's profit in (6) and the intermediary's profit in (9). To simplify, let H be the realized hammer price ($H = \max(r^*, \frac{V_{(n^*-1:n^*)}}{1+c_B} - c_F)$ and let $\mathbb{I}\{L=1\}$ equal one if the lot is sold and 0 otherwise. The realized social welfare (SW) is:

$$\begin{aligned}&\left[\left(V_{(n^*:n^*)} - H - Hc_B - c_F\right) + (H - Hc_S - c_{Fs}) + (Hc_B + Hc_F + c_{Fs})\right] \mathbb{I}\{L=1\} \\ &\left[V_{(n^*:n^*)} - c_F\right] \mathbb{I}\{L=1\}\end{aligned} \tag{10}$$

[10] In the data, combinations of (buyer's premium, c_{Fs}) are either (0%, £1.75) for Seller-managed lots, or (18%, £3,00) for BfW-managed lots. The seller's commission is a flat 14% plus 20% VAT for BfW-managed lots, with a minimum of £12+VAT. For Seller-managed lots the commission is stepwise: hammer price up to £200: 8.5%, hammer price £200 to £1500: 7.5%, hammer price £1500 to £2500: 6.5%, and over £2500: 5.5%, all excl. 20% VAT. All fees are only payable for successful sales.

The three components in round brackets are respectively consumer surplus, seller profit and intermediary profit. A couple of aspects are left aside in these surplus and profit specifications, as they will be unobserved in the data and assumed invariant to changes in c_B and c_F so irrelevant to the results. The (unobserved) entry cost c_E technically reduce the buyer's surplus, but they are irrelevant to the social welfare function as they come to the profit of the intermediary. At least a part of these cost cover operational expenses for intermediaries to run the auction service, and these expenses could be subtracted from both the intermediary's profit and the social welfare function (thus the social planner would prefer those platforms with the lowest cost to facilitate the auction). Finally, as mentioned, the seller's valuation is normalized to 0 but otherwise the social planner would weigh the benefits of the seller keeping the lot against the benefits of selling to realize gains from trade.

Among the components that matter to the social planner, the *direct impact* of the fixed cost c_F is arguably the least important. In this model they represent fair delivery cost that would come to the benefit of a shipping company, and one could extend this social welfare function in a way that makes the planner indifferent about the direct effect c_F. The probability of selling the lot, which is the second component of interest, is however negatively affected by a higher c_F, c_B and possibly an increased reserve price as a function of these cost. In a way, failing to sell means that an opportunity to create value is foregone as long as the the highest bidder has a value higher than the seller; this could be thought of as the deadweight loss to society from a higher "tax" rate. Finally, the social planner cares about the value of the highest entrant. Similar to an efficiency argument he would like the potential bidder with the highest valuation to win the auction.

3.5 Implications

The central question is: what are the welfare implications of an increase in the cost c_B and c_F? This effect is captured by the total differentials: $\frac{dCS(.)}{dc_B}$ (for the buyer), $\frac{d\pi_S(.)}{dc_B}$ (for the seller) and $\frac{d\pi_I(.)}{dc_B}$ (for the intermediary) and similarly for changes in c_F. The following partial effects to an increase in fees are relevant in this model:

1. A direct reduction in the probability of a sale and a potential indirect effect due to an increase in the equilibrium r^* as set by the seller to make up for fewer sales.

2. An increase in the entry threshold x^* resulting in reduced entry n^*, and entry of potential bidders with higher signals. Given that the entrants are a subset of those in the low-fee environment, this results in a weakly lower $V_{(n^*-1:n^*)}$ through the AS entry assumption.

3. Due to the opposing effects of higher cost (and possibly r^*) and weakly lower $V_{(n^*-1:n^*)}$

the effect on the hammer price is unclear

Unlike in first-price auctions, since the bid function is independent of both the distribution of valuations among entrants and the number of entrants, there is no direct impact on bids.[11] Instead of calibrating the full structural model including the entry decision and optimal reserve price policy that relies on parameterizations of the joint distributions of signals and values, the approach in this paper is comparable to the sufficient statistic literature on tax effects (as detailed in the literature review). The structural model above is however useful, and in my opinion necessary, as a guidance to interpret the empirical results and to formulate conclusions that stretch beyond the specific auction environment in the data.[12]

The total policy effect of changes in fees depend on only two things: their effect on the hammer price conditional on a successful sale and their effect on the probability of sale. This is based on a key insight from the sufficient statistics approach: due to the Envelope Theorem for optimal entry and for the optimal reserve price, the partial derivatives of behavioral responses to a change in cost are 0; otherwise players are not optimizing. Let these impacts due to changes in c_B be denoted by θ^a with $a = \{$B (buyer), S (seller), I (intermediary), SW (social welfare)$\}$ for the effect on the hammer price given that the lot is sold, and ϕ^a for the welfare effect due to a change in the probability of selling the lot. Similarly, for a change in the highest-bid independent cost c_F: let ψ^a be the impact due to a change in c_F when a sale takes place and let ζ^a be the impact due to not selling the lot as a result to changes in c_F

The set of parameters $\{\theta^a, \phi^a, \psi^a, \zeta^a\}$ explain how cost charged in auctions impact social welfare and its distribution among seller, buyer and intermediary. As the impacts are based on non-linear functions of behavioral responses to them, they are allowed to differ for different levels of cost insofar as this is allowed by the observed variation in the data.[13]

4 Wine auction data

The *Bid for Wine* data (BFW) is collected from the "Closed Auctions" section of the website www.bidforwine.co.uk; a major auction platform where wine sellers and buyers meet. The information is obtained with the 'data extractor' feature of the web-extractor software freely available at www.import.io. With a plethora of relevant auction data available, and a

[11] Li and Zheng [2009, 2012] would call this the "competition effect" in first-price auctions: when more potential bidders increase the optimal bid due to entrants facing more competition in the bidding stage.

[12] A welcome implication of this approach is that some of the assumptions underlying equilibrium behavior in the model can be relaxed. In particular, the information set assumed available to potential bidders may be reduced as long as they decide to enter optimally based on some shared beliefs taking into account the policy variables c_B and c_F, and the same goes for sellers setting the reserve price.

[13] Ideally, a full distribution of these parameters would be estimated for any reasonable cost amount, but unlike when estimating a full structural model such generous variation needs to be present in the data to facilitate that.

continuous addition of more closed auctions, the data used in this paper is selected as follows. On 24/01/2016 data from the latest 10.000 closed auctions is extracted, going back to 01/03/2015.[14] Not all of these are useful for the analysis in this paper, listings are excluded when they: i) have a "buy now" feature, ii) include multiple listings, iii) do not specify the delivery cost, or iv) auction strong liquor, cigars, or wine accessories. The remaining sample includes 8077 auctions of wine (red, white, rose, sparkling, fortified, or mixed lots) with rich descriptives and information on the number of bidders, the final bid, additional delivery cost and an indication whether the wine is sold "In bond" or "Duty paid". Information on the fixed bidding increment at the final bid is obtained from the website as well. Descriptive statistics can be found in Table 1.

In this data there are three sources of potential additional cost: delivery cost, buyer's premium, and duty / VAT. Delivery cost are specified by the seller and this can be done in any way he deems fit. For comparability, when the seller lists multiple prices for various quantities or distances, or an estimated bracket, the lowest amount is recorded. Higher prices usually correspond to delivery outside mainland-UK, better-insured or professionally packaged, or delivery of multiple cases. Although some sellers emphasize that there is no buyer's premium, this is the rule rather than the exception. The 2165 lots that are sold on behalf of sellers by *Bid for Wine* are subject to a buyer's premium of 18% (including 20%VAT). For "Duty paid" lots, no additional cost are payable. "In bond" purchases are however subject to excise duty and VAT as they are released for consumption. These additional cost are calculated based on official duty percentages from the HM Revenue & Customs website.[15]

As Table 1 shows, the total additional cost are substantial. On average about as much as the hammer price need to be paid, but the share varies widely. The noticeably high maximum share (120 times the hammer price) is for two lots that both have a hammer price under £3. Figure 1 shows for the different wine types the total amount of additional cost in relation to the final bid for the six distinct wine types.

[14] Even though the inflation was minimal over this period, all prices have been adjusted by monthly CPI's published by the UK National Office of Statistics (www.ons.gov.uk) to January 2016 real values.

[15] £273.31 per hectolitre wine (red, white, rose; assuming the alcohol percentage is between $5.5 - 15\%$), £350.07 per hectolitre of sparkling wine (assuming the alcohol percentage is between $8.5 - 15\%$) and £364.37 per hectolitre fortified wine (including port, madeira, sherry, etc.; assuming the alcohol percentage is between $15 - 22\%$). Figures obtained from https://www.gov.uk/government/publications/rates-and-allowance-excise-duty-alcohol-duty/alcohol-duty-rates-from-24-march-2014. VAT is added on both the duty and the final bid. For example, additional duty and 20% VAT on an "in bond" lot of two 750ml bottles of Barolo sold for £200 is calculated as: $0.2 * 200 + 1.2 * ((273.21/100000) * 1500) =$ £44.91 (of which £40 is VAT on the final bid).

Table 1: Descriptive statistics Bid for Wine Auctions

Statistic	N	Mean	St. Dev.	Min	Max
Hammer price (£)	8,077	95.65	88.43	0.99	600.00
Number bids	8,077	7.26	4.75	0	39
Number bidders	8,077	4.11	2.34	0	17
Number bottles	8,077	4.52	5.20	1	58
Vintage	5,818	1,996.09	15.38	1,795	2,014
Lot is sold (1=TRUE)	8,077	0.82	0.38	0	1
Has buyer's premium (1=TRUE)	8,077	0.27	0.44	0	1
In bond (1=TRUE)	8,077	0.26	0.44	0	1
Additional Duty/VAT (£)	8,077	9.72	19.35	0.00	133.79
Delivery cost (£)	8,077	17.00	6.97	0.00	148.80
Buyer's premium (£)	8,077	4.94	11.40	0.00	103.56
Additional cost share	8,077	1.03	3.93	0.00	120.00

The unit of observation is one auctioned lot. The vintage is missing for some non-vintage champagnes as well as for mixed lots with various vintages.“Additional cost share” is the additional cost (duty/VAT, delivery, buyer's premium) as a share of the hammer price. All monetary variables are in January 2016 values.

5 Estimation of impact parameters

The following steps are required to estimate the impact parameters $\{\theta^a, \phi^a, \psi^a, \zeta^a\}$ from a set of $t = \{1, ..., T\}$ independent auctions where the hammer price $H = h^t$, the number of bidders n^t, the additional cost c_B^t, c_F^t, and a vector of auction covariates $\mathbf{Z} = \mathbf{z}^t$ are observed.

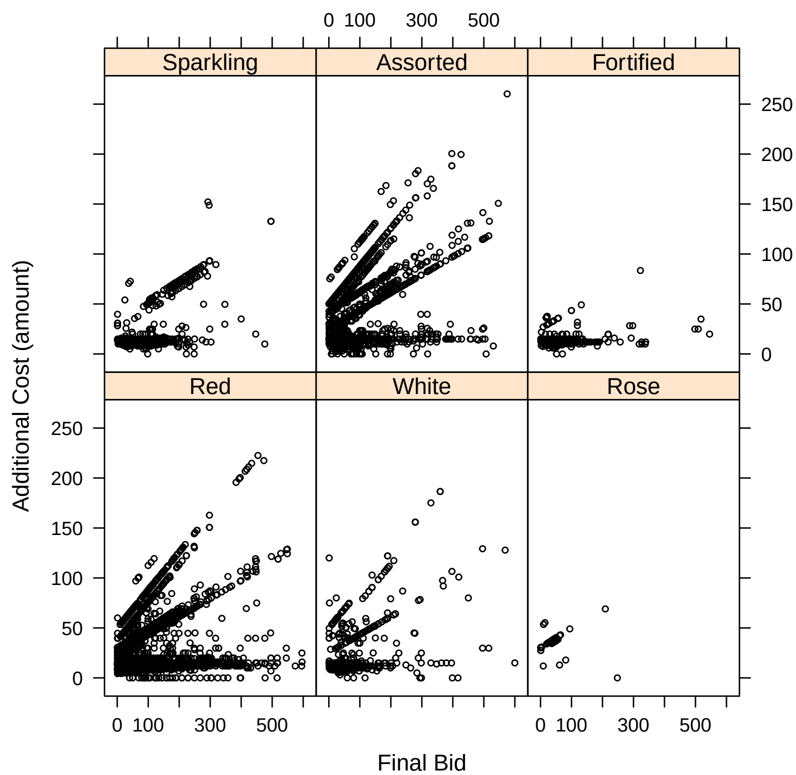
5.1 Step 1: Estimate the valuation of the winning bidder

A key challenge in English auctions is pinning down the highest valuation from bids as the auction stops when the second-highest bidder drops out or when the reserve price is met. The expected value of the highest valuation in each auction ($V^t_{(n^*:n^*)}$) can be estimated using the distribution of valuations among entrants $F_{V|\mathbf{Z}}(.|\mathbf{z}; x^*)$, as:

$$\hat{\mathbb{E}}[V^t_{(n^*:n^*)}] = \int_{h^t(1+c_B^t)+c_F^t}^{\bar{v}} x \frac{\hat{f}_{V|\mathbf{Z}}(x|\mathbf{z}^t; x^*)}{1 - \hat{F}_{V|\mathbf{Z}}(h^t|\mathbf{z}^t; x^*)} dx \tag{11}$$

The distribution of valuations among entrants is obtained from the distribution of the highest bid that is rationalized as the second-highest valuation; and following the standard identification approach using that this distribution is a known function of its parent distribution (as in Athey and Haile [2002]). It is estimated conditional on covariates: the vintage of the wine (older ones are generally more valuable), when the auction was held (to capture

Figure 1: Bid for Wine: Additional cost by final bid and wine type (total)



time or seasonal trends), and the wine's volume in milliliters (higher with more bottles and larger formats). These conditional distributions are estimated separately for the following wine types: Red, White, Rose, Sparkling, Fortified, and Assorted lots, for each of the number of bidders. So a unique distribution is estimated for, say, auctions of red wine with 6 bidders conditional on observed $\mathbf{Z}$ within these auctions and fitted for each auction based on values of $\mathbf{z}^t$. When a certain number of bidders and wine type combination have less than 10 auctions, they are pooled within the wine type, and a distribution is estimated for this remaining group (containing the highest number of bidders). The highest valuation in auctions with 1 bidder is estimated using the distribution of valuations obtained from two-bidder auctions.

Rationale for estimating the distribution separately for different n^t is that entry is endogenous. Without observing the equilibrium signal threshold x^* it is sufficient to assume that the number of potential bidders N is fixed across auctions to identify the distribution among entrants. But not conditioning on n^t implies that the distribution of bidders' valuations would be the same with more entrants; which would be the case with Random entry but not necessarily with AS entry. In particular, with signals normalized as Uniformly distributed on $[0,1]$, $F_V(.;x^*) = \frac{1}{1-x^*}\int_{x^*}^{1} F_V(.|t)dt$, which reduces to $\frac{1}{1-x^*}F_V(.)$ with Random entry as signals are independent of valuations.

Hence, Random entry in these auctions would thus be unlikely when conditional on covariates the distribution of valuations among entrants is significantly different for different number of bidders. This is tested with a series of nonparametric Kolmogorov Smirnov tests for the equality of the conditional distribution functions evaluated at the medians of $\mathbf{Z}$.[16] Table 2 reports p-values of this test which can be interpreted as the probability that the distributions evaluated at their median values of $\mathbf{Z}$ are the same, for all combinations of different number of entrants, and separately for the different wine types. Given that almost all combinations for all wine types have very low p-values makes it highly unlikely that entry decisions are made before potential bidders know something about their valuation. To be more precise, the joint hypothesis of CIPV and Random entry is rejected at least for auctions with median characteristics.

The outlined estimation procedure relies on nonparametric Epanechnikov Kernel estimation of the density and distribution of the second-highest valuation. Cross-validated least-squares bandwidths are selected optimally to minimize the integrated mean squared error, using the method in Li et al. [2013], which can incorporate multi-dimensional, mixed categorical/discrete and continuous conditioning variables and automatically 'smooths out' irrelevant covariates by blowing up their bandwidths.[17] For this reason, the bandwidths themselves are informative about the relevance of the covariates. The bandwidths are therefore reported in Table 3, where the pooled groups are listed separately.

The expected value in equation (11) is approximated by evaluating the estimated density on 1000 equally spaced gridpoints between the highest bid h^t and $\bar{v}$ which is taken to be the maximum plus half a standard deviation of the highest bid in the particular (wine type, number of bidders) combination. In effect, these gridpoints are "weighted" by the estimated probability $\frac{\hat{f}_{V|\mathbf{Z}}(x|\mathbf{z}^t;x^*)}{1-\hat{F}_{V|\mathbf{Z}}(h^t|\mathbf{z^t};x^*)}$ (adjusted slightly to sum to one). The estimated $\mathbb{E}[v^t_{(n^*:n^*)}]$ is used to calculate the consumer surplus in all auctions, including the counterfactual surplus that is foregone in auctions that fail to sell.

[16]Specifically, let $\bar{\mathbf{z}}^{t,i}$ denote the medians of sample realizations of $\mathbf{Z}$ when the number of bidders $n^t = i$. The test statistic is: $D_{i,j} = \sup_v |F_{V|\mathbf{Z}}(v|\bar{\mathbf{z}}^{t,i}, n^t = i; x^*) - F_{V|\mathbf{Z}}(v|\bar{\mathbf{z}}^{t,j}, n^t = j; x^*)|$. The null hypothesis that the distributions are equal for $n^* = i$ and $n^* = j$ is rejected at the α-level if $D_{i,j} > c(\alpha)\sqrt{\frac{T_i+T_j}{T_iT_j}}$, where T_i is the number of auctions with $n^t = i$ and values of $c(\alpha)$ are known for each α. So it tests whether the maximum pointwise difference between the two conditional distributions evaluated at their medians are small enough to allow them to be drawn from the same parent distribution.

[17]The "np" package in R is well equipped for nonparametric Kernel estimation and bandwidth selection and it is used for estimation of all ordered bid distributions in this paper. See Hayfield and Racine [2008] for documentation.

Table 2: P-values Kolmogorov-Smirnov tests of (C)IPV & Random entry

(a) IPV

	2	3	4	5	6	7	8	9	10
2		0.01	0	0	0	0	0	0	0
3			0.37	0.05	0	0.02	0.02	0	0.11
4				0.37	0.001	0.08	0.11	0.01	0.70
5					0.21	0.97	0.58	0.58	0.97
6						0.70	0.08	0.99	0.11
7							0.47	0.70	0.81
8								0.16	0.58
9									0.16
10									

(b) CIPV: wine type

	2	3	4	5	6	7	8	9	10
2		0.05	0	0	0	0	0	0	0
3			0.11	0.02	0	0	0.002	0	0.01
4				0.37	0.002	0.02	0.04	0	0.21
5					0.28	0.08	0.37	0.02	0.91
6						0.21	0.11	0.47	0.47
7							0	0.21	0.05
8								0.004	0.08
9									0.02
10									

(c) CIPV: wine type & vintage

	2	3	4	5	6	7	8	9	10
2		0.05	0.01	0.001	0	0	0.001	0	0.001
3			0.02	0.02	0	0	0.004	0	0.002
4				0.81	0.08	0.21	0.02	0.002	0.81
5					0.21	0.05	0.37	0.01	0.70
6						0.16	0	0.37	0.05
7							0	0.21	0.05
8								0.001	0.08
9									0.02
10									

(d) CIPV: wine type & nr. bottles

	2	3	4	5	6	7	8	9	10
2		0.08	0	0	0	0	0	0	0
3			0.001	0	0	0	0	0	0
4				0.28	0	0.001	0.004	0	0.02
5					0.05	0.02	0.37	0.02	0.58
6						0.08	0.21	0.58	0.08
7							0	0.11	0.08
8								0.21	0.28
9									0.04
10									

(e) CIPV: when closed & nr. bottles

	2	3	4	5	6	7	8	9	10
2		0	0.001	0	0.002	0.02	0	0.01	0
3			0.02	0	0.001	0	0.001	0.04	0
4				0.002	0.01	0	0	0.01	0
5					0	0	0	0	0
6						0	0	0	0.04
7							0	0	0
8								0	0
9									0
10									

(f) CIPV: all listed covariates

	2	3	4	5	6	7	8	9	10
2		0	0.001	0.04	0.02	0.02	0.004	0.01	0.04
3			0	0	0	0	0	0	0
4				0	0	0	0	0	0
5					0.21	0.01	0.16	0.16	0.02
6						0.28	0.11	0.28	0.04
7							0	0.21	0.04
8								0.05	0.01
9									0.001
10									

Reports p-values Kolmogorov-Smirnov tests, testing equality unconditional distributions (IPV) and conditional distributions with different covariates (CIPV) *for entrants*. Columns and rows contain different numbers of bidders, so the upper right triangle shows p-values for all combinations of number of bidders (for which at least 50 auctions are in the data). For CIPV, p-values are reported from tests of the equality of the distributions at the median of covariates, which are for the wine type: red wine, for the vintage: 2001, for the number of bottles: 2, for when the auction closed: 170 days ago, and for the bottle size: 750ml. More details in the main text.

5.2 Step 2: Calculate CS, π_S, π_I and SW

For all sold auctions, the consumer surplus is estimated by subtracting the hammer price and additional cost from $\hat{\mathbb{E}}[V^t_{(n^*:n^*)}]$. The entry cost c_E are assumed fixed across auctions and as they are unobserved they are set to 0 for the calculation of the surplus; which is harmless since the *change* in surplus due to a change in fees is of interest. For unsold auctions, although an estimate of the highest value is available, since the highest bid is below the reserve price the surplus is 0.

The unobserved seller's valuation is normalized to 0 and by similar reasoning this doesn't

Table 3: Optimal data-driven bandwidths for red wine

	Number of bidders:											
	2	3	4	5	6	7	8	9	10	11	12	>12
Final bid (Y)	34.11	21.45	5.931	22.51	18.78	16.35	18.83	16.62	17.89	25.81	46.64	37.59
Milliliter (X)	6457	4128	3763	2683	3668	2192	4696	2012	Inf.	3690	Inf.	2683
Days ago closed (X)	42.49	115.5	319.8	Inf.	96.15	93.58	58.14	Inf.	120.7	38.46	26.83	Inf.
Vintage (X)	8.497	28.94	28.21	7.603	7.603	Inf.	Inf.	Inf.	9.839	12.07	4.47	5.367
Observations	613	674	707	617	524	345	216	97	55	33	13	9

Data-driven bandwidths estimated separately for each number of bidders for which at least 10 red wine auctions are recorded, and separately for the remaining red wine auctions. The same procedure is applied for the other wine type categories: White, Rose, Sparkling, Assorted, and Fortified but bandwidths are omitted. The bandwidth is reported as Inf. when it is blown up to eliminate the impact of this co-variate for the estimation of the conditional distribution. In general, higher bandwidths indicate that the covariate is less relevant for explaining variation in the final bid.

impact the results. So the seller's profit is simply calculated as the difference between the observed hammer price and the seller's fee c_{Fs} for sold lots, and 0 otherwise. The intermediary's profit is also easily calculated by multiplying the hammer price by the buyer's commission and adding the seller's fee for all sold lots. Again, fixed and unobserved operational cost to sustain the platform are ignored, and no sale results in 0 profit. These three component are added to obtain the social welfare.

5.3 Step 3: Estimate the impact parameters at different cost levels

Both the endogenous entry decision and the optimal reserve price will react to changes in fees, as predicted by the theoretical model presented in the previous section. Yet from a theoretical standpoint the direction of this effect, and more importantly the resulting impact on welfare and its distribution among players, is uncertain. These questions are addressed empirically by relying on exogenous variation in the fee structure in the BfW auctions, employing the following aspects of the data:

$\mathbf{c_B}$: Discrete jumps in c_B due to *In Bond* lots requiring 20% VAT while *Duty Paid* lots require none.

$\mathbf{c_F}$: Continuous variation in c_F due to the delivery cost depending on the location of the seller, and due to the alcohol levy payable for *In Bond* lots being a function of the type and the amount of wine (and not the final bid).

5.3.1 Exploiting discrete jumps in c_B

The first dimension on which the fee structure differs for lots in the data is whether they are sold by sellers themselves, or whether the intermediary BfW sells them on behalf of the seller. This option is available for sellers who have larger collections of wine for sale.

Therefore, whether the wine is "Seller-managed" or "BfW-managed" is mostly related to the amount of bottles the seller offers. So in principle the welfare effects of charging 18% buyer's commission (as in BfW-managed lots) compared to 0% (in Seller-managed lots) could be estimated by simply comparing the profits among these types of auctions.

There are three concerns for doing so. First of all, potential bidders may interpret it as a signal of good quality when lots are BfW-managed and this may affect their value of these lots and their entry decision; introducing a positive bias favoring the 18% BfW-managed lots. Second, none of these lots in the data remain unsold. This is remarkable since about 25% of the Seller-managed lots remain unsold. On the BfW website the following remark is made regarding commissioned lots: *"If any wines are unsold, Bid for Wine will arrange for them to be relisted. If they have been offered at auction, in some cases it may be necessary to adjust reserves and this will be discussed with you."* (www.bidforwine.co.uk [2016]). This suggests that the platform either 'buys' lots that fail to meet the reserve the first time and re-offers them for sale at a later date with this lower value as reserve or negotiates lower first-time reserve prices than otherwise set for Seller-managed lots. In any case, sellers seem pressured to accept a lower minimum price for their lots and a simple comparison of the profits under these different commission schemes results in biased estimates.[18] The third concern is that BfW-managed lots may be on average more valuable, as will be discussed in more detail at the end of this section.

Bid-dependent fees also differ due to VAT. This is specific to auctions of wine that are either sold *In Bond* or *Duty Free*. For lots that are sold *In Bond*, import duties yet need to be paid; i.e. they have not cleared customs yet but have been stored in a bonded warehouse. Besides the duty cost that are not a function of the final bid but of the wine type and volume (so grouped under c_F), also a 20% VAT on the hammer price is due. So a first estimate of the impact of c_B is to compare the margins of interest along this dimension. Due to the mentioned selection issues of a buyer's commission, the effect of 20% versus 0% additional VAT cost is estimated separately for Seller-managed and BfW-managed lots.

The margins of interest are those usually of interest in both theoretical auction literature as in empirical work: i) the probability of a sale, ii) profits conditional on sale, and iii) the number of bidders. While this last margin sheds light on endogenous entry underlying the results, the other margins combined explain the welfare effects that are ultimately the aim of this study. The results for these margins are reported in Table 4. Besides the means within the relevant c_B-groups, also p values of 2-sample t-tests are reported.

[18] As long as there is indeed no selection on the quality of the auctioned lots, comparing average profits conditional and unconditional on sale of Seller-managed with BfW-managed lots does give an estimate of the added value of an 'active' intermediary relative to wine auctions where buyers and sellers organize sales themselves.

Table 4: Profits by c_B category (Buyer's commission (c) and VAT (V))

	Seller-managed lots			BfW-managed lots		
	(0%c, 0%V)	(0%c,20%V)	p value	(18%c,0%V)	(18%c,20%V)	p value
Number of auctions	4851	1061		1159	1006	
Number of bidders	4.29	2.34	0.00	4.79	4.31	0.00
	[0.04]	[0.04]		[0.06]	[0.07]	
Hammer price	87.77	118.05	0.00	113.24	89.76	0.00
	[1.25]	[2.95]		[2.70]	[2.38]	
Probability of sale	0.83	0.41	0.00	1.00	1.00	1.00
Profits if sold:						
Consumer Surplus	138.44	106.22	0.00	132.25	124.45	0.00
	[0.78]	[2.28]		[1.41]	[1.47]	
Profit Seller	75.66	111.12	0.00	95.65	71.81	0.00
	[1.28]	[4.32]		[2.72]	[2.41]	
Profit Intermediary	10.71	13.27	0.00	37.97	34.12	0.00
	[0.13]	[0.45]		[0.55]	[0.53]	
Social Welfare	223.88	227.40	0.40	262.83	226.85	0.00
	[1.26]	[3.92]		[2.49]	[2.33]	

Reports average profits conditional upon sale by auction type. P-values are reported for two-sample t-tests, with values less than 0.05 indicating that with at least 95% certainty the equality of the means can be rejected. Standard errors reported in square brackets.

A few things stand out. For Seller-managed auctions, the probability of a sale drops from 83.34% for 0%VAT to 41.47% with 20%VAT. Conditional on selling, the average CS is significantly lower for lots with VAT, but the profit of the seller is significantly higher. Since the seller's fee is equivalent for both types of auctions, this must be due to an increase in the average hammer price; which indeed increases from about £88 to about £118. A significantly lower number of bidders reflects equilibrium behavior where potential bidders (rightly) take into account that higher c_B reduces the probability of a sale, and with fewer entrants and a significantly lower surplus conditional on sale this suggests that the reserve price has increased to make up for fewer expected profits due to reduced sales for the seller as well. There is no change in the profit for the Intermediary, and since the Social Welfare conditional on sale doesn't change the higher c_B has merely shifted surplus from the successful buyer to the seller.

For BfW-managed auctions, the probability of a sale remains unchanged at 100% as detailed above. There are fewer bidders in the 20%VAT auctions, but the drop is much less than for Seller-managed auctions. In other words: entry is less sensitive to changes in c_B in these auctions managed by the platform. The reserve price policy described on www.bidforwine.co.uk [2016] suggests that sellers are encouraged not to increase their reserve price by as much as they would otherwise do. The lower sensitivity in entry could thus be explained by potential bidders being able to (rightfully) expect their surplus to decrease by less than in the Seller-managed case.

Similar to findings in the tax literature, this shows that in auctions the relative elasticity of the reserve price to changes in the fee structure is important for its welfare consequences. When the increase in reserve price is less as a response to higher auction fees, either because this is optimal for a profit maximizing seller or because the auction platform imposes such a policy upon the seller, more of the drop in total surplus will be born by the seller. All else equal, when more comparable lots are auctioned at the same time or when auctioning a less unique lot, the seller has less market power and will bear more of the burden of a drop in total surplus. In the BfW-managed auctions, the seller's profit goes down even conditional on sale so the hammer price must be lower; it indeed drops from about £113 to about £90.

With this type of variation in the data, the impact parameters $\{\theta^a, \psi^a\}$ cannot be interpreted as slope parameters reflecting the effect of infinitesimal changes in c_B on the consumer surplus, and profits of the seller and intermediate. Instead, we have to focus on the total impact from changing hammer-price dependent fees from 0% to 20%, and assume that the impact is linear in order to interpret the parameters as the change in profits due to a one percentage point change in bid-dependent fees c_B. This assumption is not uncommon in the sufficient statistics literature, and will be maintained for this section but relaxed when analyzing the effects of c_F for which richer variation is available. The impact parameters are calculated separately for Seller-managed and BfW-managed auctions. For example, for the impact of a one percentagepoint change in c_B on the average consumer surplus in Seller-managed auctions, it then suffices to follow the calculation (where $P[\{L = 1\}]$ denotes the probability that the auction is sold):

$$
\begin{aligned}
&\frac{dCS(.)}{dc_B} = \theta^B + \phi^B = \\
&\frac{\mathbb{E}[CS|c_B = 20\%] - \mathbb{E}[CS|c_B = 0\%]}{20} = \\
&\frac{\mathbb{E}[CS|c_B = 20\% \cap \{L = 1\}] - \mathbb{E}[CS|c_B = 0\% \cap \{L = 1\}]}{20} \\
&+ \frac{\mathbb{E}[CS|c_B = 0\% \cap \{L = 1\}] * (P[\{L = 1\}|c_B = 20\%] - P[\{L = 1\}|c_B = 0\%])}{20} = \\
&\frac{106.22 - 138.44}{20} + \frac{138 * (0.41 - 0.83)}{20} = -1.611 - 2.898 = -4.509
\end{aligned}
\tag{12}
$$

The estimated impact under the linearity assumption is a decrease in consumer surplus of £4.509 for every percentage point increase in c_B. This includes £1.611 ($= \theta^B$) of surplus loss due to a higher hammer price (including endogenous entry effects and reserve price effects) and $-$£2.898 ($= \psi^B$) due to a lower probability of sale. To be clear, without the linearity assumption we only know that the change in c_B from 0% to 20% results in a loss for the average successful bidder of £4.509 $*$ 20 = £90.18. This loss is about as high as the original hammer price! But it can be argued that when thinking about compensating the successful bidder in the high-c_B auction, only the loss due to a decreased surplus needs to be considered. If he would have won the low-c_B auction as well, his surplus would on average have been £1.611 $*$ 20 = £32.22 higher; or about 27% of the average hammer price in the high c_B auction.

The impacts are different for BfW-managed auctions and, by the reasoning above, the lower sensitivity of the reserve price to changes in c_B underly this diverging impact. An alternative explanation could be that lots auctioned by the BfW platform are themselves significantly different. One dimension in which they differ could be the amount they are expected to sell for. Since sellers have to pay a seller's commission of 14% with a minimum of £12 (plus VAT) for each lot sold by BfW, while they pay stepwise fees between 8.5%-5.5% (plus VAT) *without a minimum amount*, those auctions sold through BfW may be on average more valuable.

To account for this possibility, the impacts are also calculated for lots with hammer prices of at least £86: the maximum value at which the fixed £14.40 seller's commission for BfW-managed lots has to be paid. In other words, for lots having a lower hammer price than £86 it is especially unattractive to sell through BfW with the disadvantage compared to Seller-managed increasing with lower the hammer prices. Results are presented in Table 5. The impact parameters are precisely estimated since they are simply based on the mean calculations, as shown in Equation (12).

5.3.2 Exploiting continuous variation in c_F

Another dimension along which the fee structure differs is the shipping fees. An estimate of the shipping fees is given by the seller when bids are Seller-managed; and shipping fees for BfW-managed lots are fixed. The sample of auctions only includes auctions where the seller has specified a delivery estimate. When an estimate bracket is given or when multiple amounts are quoted the lowest value is used as this typically corresponds to standard delivery to a "mainland UK" postcode. These fees are interesting for the current analysis because they depend on the location of the seller, and therefore these fees are exogenous and independent of the value of the lot. Moreover, with continuous variation in estimated shipping fees this will deliver estimates of local effects of increasing fees, and thus allows for non-linear impacts on social welfare and its distribution among players.

To fully utilize local variation a k-nearest-neighbor type of nonparametric estimation, LOESS, is employed. This fits a polynomial on a moving window around the estimation

Table 5: Estimated impact parameters: $c_B = 20\%$ versus $c_B = 0\%$.

	Bidder	Seller	Intermediary	Social Welfare
Lots with any hammer price:				
Seller-managed: θ	-1.61	1.77	0.13	0.18
	[0.01]	[0.01]	[0.00]	[0.01]
Seller-managed: ϕ	-2.90	-1.59	-0.22	-4.69
	[0.00]	[0.00]	[0.00]	[0.00]
Seller-managed: $\theta + \phi$	-4.51	0.19	-0.10	-4.52
	[0.01]	[0.01]	[0.00]	[0.01]
BfW-managed: θ	-0.39	-1.19	-0.19	-1.80
	[0.00]	[0.00]	[0.00]	[0.00]
BfW-managed:ϕ	0.00	0.00	0.00	0.00
	[0.00]	[0.00]	[0.00]	[0.00]
BfW-managed: $\theta + \phi$	-0.39	-1.19	-0.19	-1.80
	[0.00]	[0.00]	[0.00]	[0.00]
Lots with hammer price $\geq$ £86:				
Seller-managed: θ	-1.26	-0.02	0.14	-1.25
	[0.01]	[0.02]	[0.00]	[0.01]
Seller-managed: ϕ	-2.20	-2.73	-0.18	-5.08
	[0.00]	[0.00]	[0.00]	[0.00]
Seller-managed: $\theta + \phi$	-3.47	-2.75	-0.04	-6.34
	[0.01]	[0.02]	[0.00]	[0.01]
BfW-managed: θ	-0.19	-1.27	-0.21	-1.69
	[0.01]	[0.01]	[0.00]	[0.01]
BfW-managed: ϕ	0.00	0.00	0.00	0.00
	[0.00]	[0.00]	[0.00]	[0.00]
BfW-managed: $\theta + \phi$	-0.19	-1.27	-0.21	-1.69
	[0.01]	[0.01]	[0.00]	[0.01]

Estimated impact parameters of the welfare effects of a unit increase in c_B, assuming that the effect is linear, and as estimated from the total impact on profits of a change in c_B from 0% to 20%. Standard errors are reported in square brackets. More details in the main text.

point x containing a proportion α of the data, with estimation weights higher for data nearer to x. The main results are based on a locally linear fit with smoothing parameter $\alpha = 0.75$ and uses the standard tri-cube weight function: $w(x) = (1 - |x|^3)\mathbb{I}\{|x| < 1\}$.

Considerate variation in shipping fees allows for local estimation of impact parameters $\{\psi^a(c), \zeta^a(c)\}$ at various cost levels c. For instance, $\psi^B(1)$ is the effect of an infinitesimal change in the additional cost c_F at $c_F =$ £1 on the expected Consumer Surplus due to a change in the hammer price. This is estimated as the derivative of the fitted nonparametric LOESS regression of CS on c_F for auctions that resulted in a sale at $c_F =$ £1. Similarly, $\zeta^B(1)$ is the impact on the CS at $c_F = 1$ due to a change in the probability of sale estimated from the derivative of the fitted regression of $P[\mathbb{I}\{L = 1\}]$ on c_F at $c_F = £1$ and multiplied by the local average CS.

The main impact parameters are estimated from Seller-managed lots that are sold *Duty paid*. As said, these lots have rich exogenous variation in shipping fees.

Estimates are provided only for Seller-managed lots to exclude possible clouding of the results through unnatural low elasticity of the BfW-manged reserve price to changes in fees or due to higher-value lots being sold through BfW. Another concern could be that *In bond* lots are incomparable to *Duty paid* lots, on a relevant dimension such as there being less uncertainty about the quality of *In bond* lots due to their more controlled provenance. Notice that this would at least imply that the the estimates of $\{\theta^a, \psi^a\}$ are subject to bias and at worst it renders them invalid. Here, while being agnostic about the direction of such an effect, any difference is accounted for by estimating the impact parameters $\{\psi^a(c), \zeta^a(c)\}$ solely for *Duty paid* lots. Finally, all results are based on shipping fees less than the 99th percentile of fees to reduce the impact of a few high cost estimates.

Figure 2 displays the LOESS estimates evaluated on 50 equally spaced points x between the observed shipping cost extremes, as well as the 95% Confidence Interval from 100 bootstrap repetitions. It is not surprising that the estimates are particularly precise in the middle since half of the lots in this sample has a shipping fee between £11.90 and £14.88. The first thing that stands out is that, conditional on the lot being sold, successful bidders initially benefit from an increasing c_F but after a precisely estimated tipping point higher c_F reduces their surplus. The reverse pattern emerges for the seller.

This is reinforced by the estimates of the derivatives of these profit functions in Figure 3: low shipping cost increase the bidder's surplus conditional on winning the auction while above-average shipping cost are generally harmful, and the reverse is true for the seller. Less clear-cut are the implications of c_F for the intermediary's profits. The derivatives are simply calculated as the estimated effect at node $x + 1$ minus the effect at node x; resulting in 49 estimates of the slope of how profits vary with c_F that will approach the truth when both the number of nodes is high enough and the LOESS estimates approach the true profit function.

Also the probability of a sale increases with positive shipping cost compared to none, which is surprising. It peaks at below-average shipping cost, after which the probability reduces sharply so that generally it holds that for above-average shipping cost the probability of a sale is lower than for below-average shipping cost. These estimates are displayed in Figure 4, also with a 95%CI from 100 bootstrap repetitions.

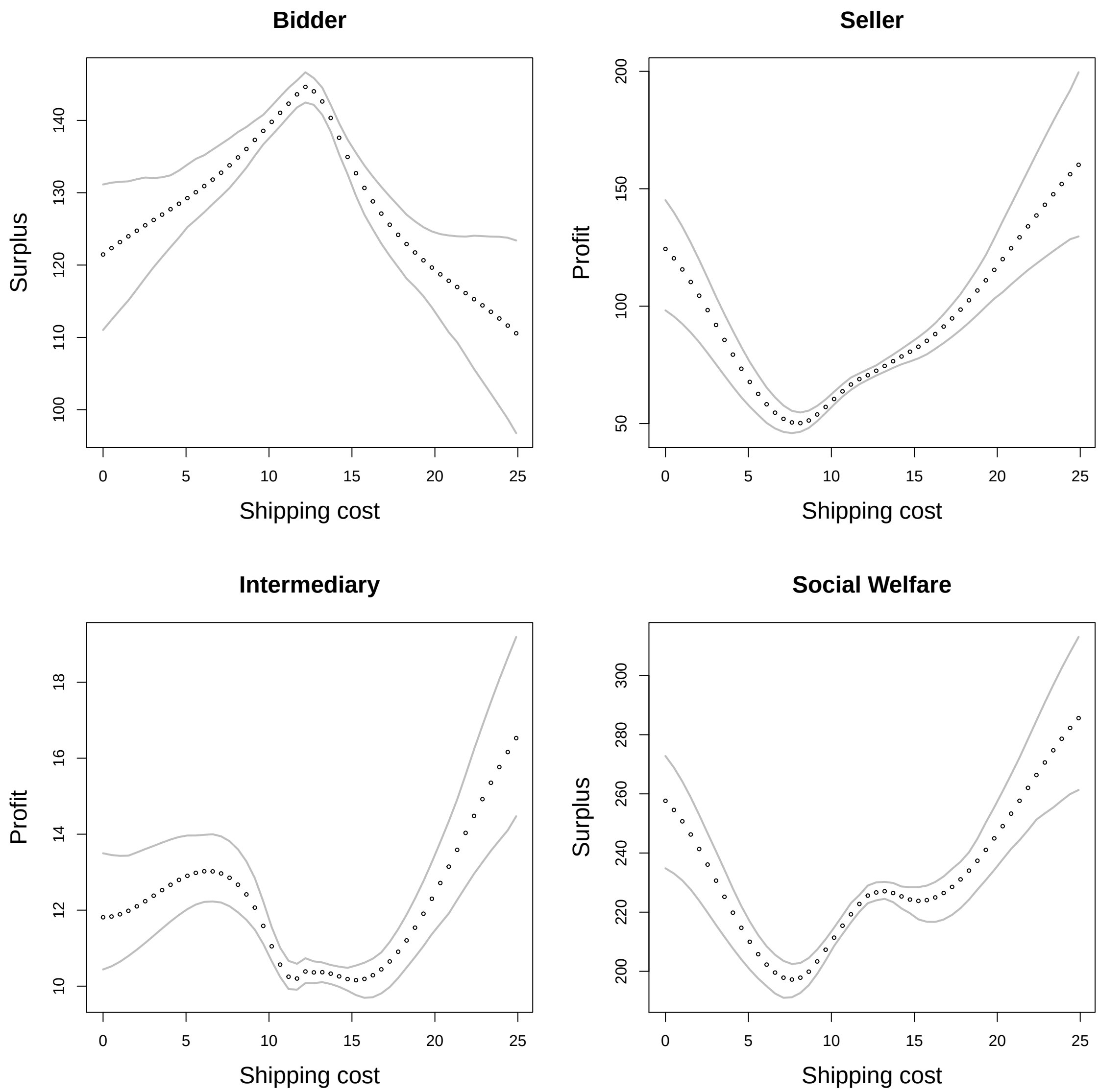
These combined effects are easily translated into impact parameters $\{\psi^a(c), \zeta^a(c)\}$ at all 49 points (c). $\psi^B(c)$ is simply the estimated partial derivative of the Consumer Surplus to c_F at $c_F = c$; thus *exactly* the derivatives in Figure 3. The loss in Consumer Surplus due to an infinitesimal change in c_F at $c_F = c$ ($=\zeta^B(c)$) is simply the estimated by multiplying the derivative of the Probability of a sale to c_F at $c_F = c$ (as in Figure 4) by the average Surplus at $c_F = c$ if there would have been a sale. The estimates are combined to obtain the total effect in 5, which give a clear result. For low fees, successful bidders benefit from increasing fees while at high fees this harms them. In other words: at low amount, an increase in fees increases the surplus of the successful bidder by reducing competition while at high amounts the negative direct effect from paying higher additional cost dominates. This conclusion remains solid even when adding conservative confidence intervals that combine the outer CI regions of *both* $\psi^a(c)$ and $\zeta^a(c)$. Intuitively, the result is reversed for the seller; at lower amounts higher fees reduce his profits, as can be explained by the same endogenous entry effect. Although less clear-cut, at higher amounts fees seem to benefit the seller. For the intermediary, at most of the cost range it cannot be excluded that the cost leave his profits unchanged. In fact, this suggests that the fee structure (or the allowable fees insofar as they are set by the seller) are optimal for their profits. Only at high fees seems increasing fees be more beneficial to the intermediary.

6 Conclusions

This paper models auctions with a flexible AS entry that nests as special cases Selective entry when the private signal fully captures the valuation and entry cost can be regarded as bid preparation cost, as well as Random entry when the signal is independent of valuations and entry cost can be regarded as bid preparation and valuation discovery cost. Beyond this, the AS model especially allows for more moderate entry behavior where potential bidders have some initial idea of their valuation but it is costly to fully discover it, which may be an accurate description of entry in wine auctions. The model is agnostic as to how sellers change their reserve price when facing higher commissions and additional cost. Clearly, the equilibrium response depends also on the probability that the entrant with the highest valuation exceeds the new reserve price and additional cost, which is related to the concept of "pass-through" in the optimal tax literature. Results from numerous Kolmogorov-Smirnov tests reject the joint hypothesis that wine auctions in the data are the result of Random entry where entrants have conditionally independent private values.

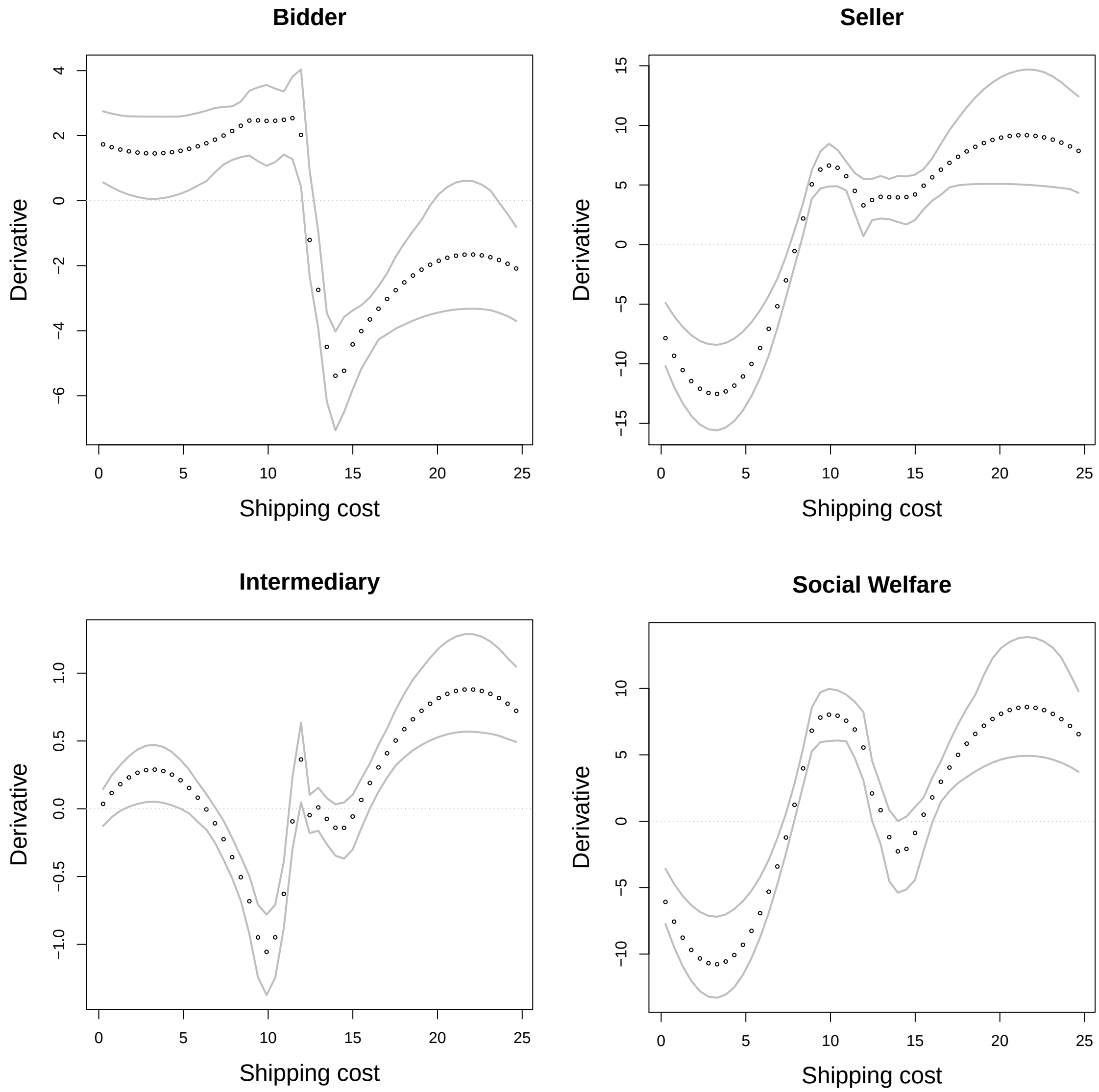
Two sources of variation in the data are exploited to address the central question: What are the welfare impacts of commissions and fees in auctions? First, differences in profits for auctions with and without 20%VAT are compared ("high-c_B" versus "low-c_B"); supported by the idea that the equilibrium response of both potential bidders and sellers should be revealed by the resulting choice data. Conclusions appear to depend critically on whether sellers manage the lot themselves or whether the auction platform handles the sales for them.

Figure 2: Estimated localized relation between profits conditional on sale and c_F



Estimated relation profits conditional on sale and c_F using LOESS local linear regression with $\alpha = 0.75$ and tri-weight weighing, using only Seller-managed auctions of *Duty paid* lots. Grey lines show 95% Confidence Interval obtained with 100 bootstrap repetitions.

Figure 3: Derivative of relation between profits conditional on sale and c_F



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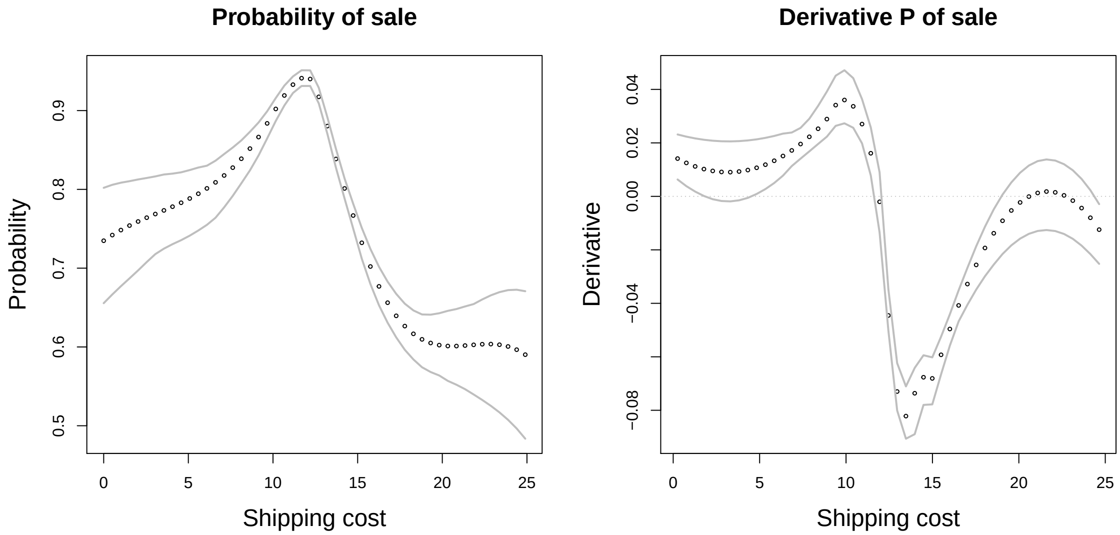
Derivative of relation profits conditional on sale and c_F (as estimated using LOESS local linear regression with $\alpha = 0.75$ and tri-weight weighing, using only Seller-managed auctions of *Duty paid* lots (see Figure 2). Grey lines show 95% Confidence Interval obtained with 100 bootstrap repetitions.

Figure 4: Probability of sale by c_F and its derivative

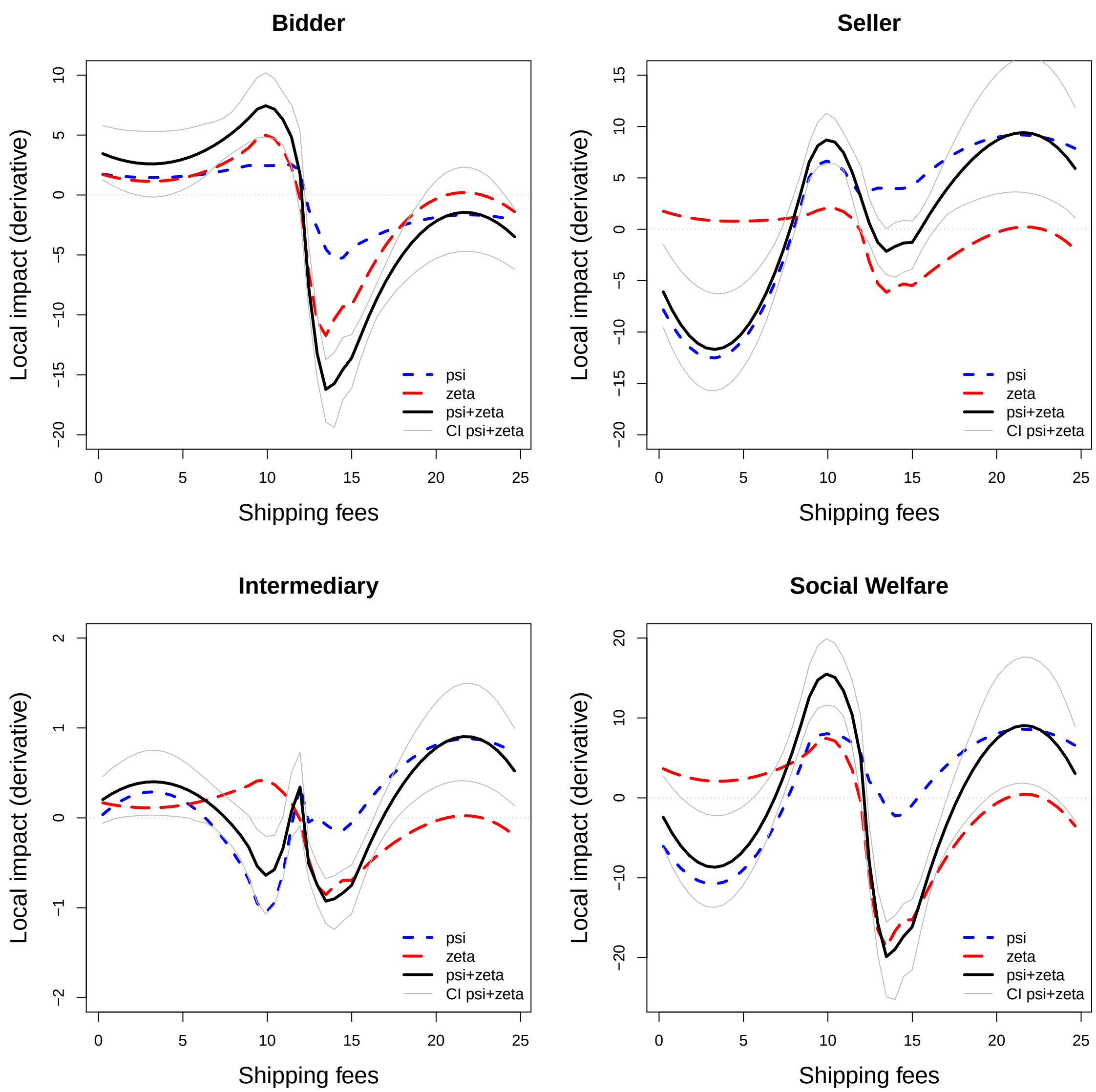


Estimated relation between the probability of selling a lot and c_F using LOESS local linear regression with $\alpha = 0.75$ and a standard tri-weight weighing function, and its derivative (right-hand panel). Grey lines show 95% Confidence Interval obtained with 100 bootstrap repetitions.

It is shown that for Seller-managed auctions, the probability of a sale drops significantly from 83.34% for low-c_B to 41.47% for high-c_B. Conditional on selling, the average consumer surplus is significantly lower for high-c_B lots, but the profit of the seller is significantly higher. Since the seller's fees are equivalent for both types of auctions, this must be due to an increase in the average hammer price; which is indeed found to increase from about £88 to about £118. A significantly lower number of bidders could be explained by potential bidders taking into account that with higher commissions it is less likely that they are willing to pay the cost-adjusted reserve price. Fewer entrants and a significantly lower surplus conditional on sale in turn suggests that the reserve price has increased to make up for fewer expected profits. Higher commissions appear have shifted surplus from the successful buyer to the seller.

For auctions managed by the intermediary, the probability of a sale in the data remained unchanged at 100%, which is surprising since Seller-managed auctions only sell in about 75% of listed auctions. Comments on the auction website suggest that sellers are encouraged to accept lower reserve prices when failing to sell, which is equivalent to having an environment where sellers respond by increasing the reserve price less steeply as fees increase (i.e. they are less price sensitive). The results show that although there are fewer bidders in the high-c_B auctions, the drop is much less than for Seller-managed auctions. In other words: also entry seems to be less sensitive to changes in commissions in these auctions managed by the platform. One explanation of this lower entry sensitivity in line with the theoretical model

Figure 5: Estimated impact parameters $c_F(c)$



Estimated impact parameters of welfare impact due to local changes in c_F, combining estimates in Figures 2-4, and with a conservative Confidence Interval (grey thin lines) for the combined impact as described in the main text.

could is that potential bidders are able to forecast their surplus decreasing by less than in the Seller-managed case. The seller's profit goes down even conditional on sale as the hammer price drops from about £113 to about £90.

This emphasizes that in auctions the relative elasticity of the reserve price to changes in the fee structure is important for its welfare consequences. When the increase in reserve price is less as a response to higher auction fees, either because this is optimal for a profit maximizing seller or because the auction platform imposes such a policy upon the seller, more of the drop in total surplus will be cut from the seller's profit. All else equal, when more comparable lots are auctioned at the same time or when auctioning a less unique lot, the seller has less market power and will bear more of the burden of a drop in total surplus.

A second source of variation arises due to sellers independently providing an estimate of the shipping cost. As these cost are based on their location, they are exogenous from the point of view of the potential bidder and can thus be used to estimate the impact of changing fees on welfare. Furthermore, these cost vary continuously and therefore the impacts can be estimated locally to draw conclusions at various cost levels. LOESS, a nonparametric k-nearest-neighbor estimation procedure, is adopted. Results are estimated on a more restricted sample to facilitate a clean interpretation of the results: only Seller-managed auctions of *Duty paid* lots are considered. Hence, even if the impact parameters above (from the discrete jump in c_B) would be biased due to relevant unobservables related to *In bond* lots compared to *Duty free* ones, the local impact parameters obtained from continuous changes in shipping fees are robust to this.

At below-average amounts, the estimates show that successful bidders benefit from an increase in fees, while at higher amounts their surplus decreases with an increase in fees. This can be explained by the model if at low fees the positive indirect effect of less competition dominates the negative direct effect of higher additional cost, while the reverse is true for higher fees.

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