The Hidden Importance of Wine Scores in Fine Wine Auctions

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ABSTRACT

The aim of this paper is to analyse the impact of wine score on latent bidders’ private valuations in Christie’s live Fine Wine auctions, in ascending price format. In order to achieve this aim, I adopt an indirect inference method to estimate the bidders’ valuation distribution by employing a cross-sectional data set.

My major findings are as follows. Firstly, wine score is a crucial structural element that determines the underlying private valuation distribution. In the secondary wine market, bidders seem to heavily rely on wine scores to make a purchase decision. To be specific, as score increases by one point, the expected private valuation of bidder increases by around 8.02%. Secondly, two non-sensory characteristics - chateau and vintage year - have no significant effect on bidder’s valuation. Thirdly, after characterising the underlying bidder’s valuation distribution, I calculate the optimal reserve price at different levels of seller valuation. I find that the reserve price set by Christie’s is not optimal. My simulation outcomes indicate that a higher reserve price may lead to higher total revenue for sellers.

Keywords: English auction, Wine score, Indirect inference

1 INTRODUCTION

Wine scores have long been regarded as an important numerical quality indicator in the wine retail market. It is a simple and effective method for wine critics to capture their opinions about the real but unknown sensory quality of a wine. Wine scores are widely used as a benchmark for wines, by the first-time wine buyer, who faces a purchase decision with hundreds of options. Several empirical studies, such as San Martin et al. (2008), Bombrun and Sumner (2003), Landon and Smith (1998), Oczkowski (1994), Schamel et al. (2001) and Jones and Storchmann (2001), document that wine scores, as a quality measurement of the sensory characteristics of wine, have a positive impact on the consumers’ willingness to pay in wine retail markets, however there is little research that analyses the effect of wine scores on bidders’ valuation in the secondary market for wine, such as, the wine auctions at Christie’s, where the most expensive wine transactions take place.

Christie’s is one of the world’s leading auction houses for the fine wines and spirits category and has a long history of achieving exceptional auction prices for fine wine. Christie’s employ a traditional English auction format, an auctioneer sells an indivisible item to $N$ potential bidders, commencing with a suggested reserve price.

There are many differences between the primary and secondary market for wines, not only from the aspects of purchasing environment and selling format, but also from the disparity in the consumer’s purchase purpose, the contrast in the values of wine and the differing approaches for consumers to gather information. In the secondary market for wine, most wines are produced from prestigious chateaus, such as, Romanee-Conti and Cheval Blanc of France, but there are also a few wines that have exquisite historical references, such as, wines that were found in the cabin of a sunken shipwreck. Due to the scarcity and uncertain value of wine, sellers prefer to use the auction format, as opposed to posted price, with the expectation of achieving higher profits. In Christie’s wine auctions, bidders are either wine collectors or experienced wine investors who may have the intention of reselling the wine in the future. Contrastingly, in the retail market, the purchase purpose for a consumer is generally for private usage. Both collectors and investors seek out age-worthy wine, wine that improves with age and almost certainly increase in value, however, it is interesting to note that most wines (95% in fact) are not destined to age. It seems that the scarcity of age-worthy wines make wine scores and tasting notes all the more prominent in
the fine wine market. Buyers of fine wine rely on reviews and scores from prestigious critics to form their opinion on wine. Therefore, it is interesting to investigate how wine scores affect a bidder’s valuation in an auction, and whether bidders regard wine scores as an important quality indicator to reveal the unknown sensory characteristics of wine.

There are two major challenges of this paper. Firstly, to analyse the effect of wine scores and other observable heterogeneity on bidder’s valuation, the bidder’s private valuation distribution is required, however, the bidders’ valuation is a latent variable, which is not revealed during the course of an auction. One needs to find a theoretically consistent and empirically tractable method to estimate the bidder’s valuation distribution. Second, it is difficult to get access to a detailed data set for live auctions, especially from leading auction houses, like Christie’s and Sotheby’s. Auction houses will normally publish a simple report on their web-page which summarises the auction outcomes the day after the sales are completed. It only documents the sales title, date, the location of salesroom and the amount of winning bids. Therefore, numerous unobserved variables also cause problems in estimating the bidders valuation distribution.

In this paper, I employ auction data that I collect from completed Christie’s wine auctions. I adopt an indirect inference approach to estimate the bidder’s valuation distribution and analyse the effect of wine scores on bidders’ valuation. There are three major findings according to the outcomes of my empirical analysis. First, wine score is an essential element that characterises the underlying private valuation distribution of bidders. I find that wine score has a predominant effect on the bidder’s valuation. The results from my regression indicate that as wine score increases by one point, the expected private valuation increases by around 8.02%. Second, the regression outcomes contradict other studies of retail wine market that use the hedonic price equation, as certain non-sensory characteristics vineyard location and vintage year of wine do not have an effect on bidder’s valuation. It suggests that bidders in Christie’s wine auctions have no distinct differences in valuation for wines from the most popular vineyard locations in France, namely, Bordeaux, Burgundy, and Rhone. It also suggests that another important non-sensory characteristic indicator vintage year of wine has no effect on bidder’s valuation. Third, by successfully estimating the parameter that characterizes the bidder’s valuation distribution, it allows me to calculate the optimal reserve price following by the framework proposed by Riley and Samuelson (1981). I find that the reserve price set by Christie’s is not optimal; a higher reserve price can yield higher revenue.

This paper is organised as follows. Section 2 introduces some background about wine scores. Section 3 discusses the literature surrounding the relationship between wine scores and consumer’s willingness to pay. Section 4 provides the set-up of the model for Christie’s wine auction under private valuation paradigm. Section 5 presents the structural model for the indirect inference approach. Section 6 presents the data set and summary statistics. Section 7 provides a detailed description of the two-stage indirect inference method. Section 8 reports the outcomes from my indirect inference analysis and tests whether the reserve prices are set at the optimal level. Section 9 concludes the paper with some general remarks.

2 THE IMPORTANCE OF WINE SCORES

The value of a bottle of wine depends on both sensory characteristics and non-sensory characteristics. The sensory characteristics yield utility directly to the wine consumer, in the form of appearance, smell and taste. On the other hand, non-sensory characteristics do not directly generate utility to wine consumers and are attributed to: grape variety, chateau, location, vintage (viticulture), wine-making technique (vinification) and storage – these specifications can normally be found on the label of a bottle of wine. A bottle of wine can be regarded as a complex good, which varies in quality as it matures, as the sensory of characteristics of wine will vary with time elapses and storage conditions. Therefore, first time wine buyers, who do not have the opportunity to taste-test the wines, all encounter the same dilemma in the market – how do they make a rational purchase decision when faced with hundreds of different wines, which vary in taste and are produced in different locations, chateaus, and vintage years.

In order to make a rational purchase decision, wine buyers must collect a plethora of information to maximise the probability that they buy a wine that is well matched to their desired sensory characteristics. Buyers in a wine future market also need a reliable predictor for the quality of wine, as they need to minimise the risk caused by uncertainty about the quality of sensory characteristics of wine. Due to imperfect information of sensory characteristics and excess wine options in the market, wine shoppers find they have insufficient time and knowledge to make complex comparisons amongst different wines and make a rational purchase decision. Wine critics, such as, Jancis Robinson and Robert Parker, assign scores and drinking notes for wines. Wine scores help first-time buyers form expectations about the
unknown quality of the sensory characteristics of wine. A higher wine score indicates a higher quality of the wine sensory characteristics, which leads to a higher market price. Therefore, an unbiased wine score, which accurately reflects the wine buyers’ taste preference, is an essential indicator to measure the wine shoppers’ willingness to pay for one additional unit of sensory characteristics. However, it is important to consider that wine scores are only useful to consumers if the scores (and drinking notes) precisely capture the average preferences of wine consumers in the market. Wine scores give consumers accurate information about the wine so they can act and bid as if they have already tasted the wine and have clear knowledge about the wine’s sensory characteristics. Therefore, unbiased scores are a useful tool to guide first time wine buyers, who are uncertain about the sensory characteristics of a wine, when they are making a purchase decision.

3 LITERATURE REVIEW

Several empirical studies use wine scores as a measure of potential quality of sensory characteristics of wines but there are very few that analyse the effect of wine scores on bidder’s valuation in the secondary wine market. To analyse the effect of wine score on consumers’ willingness to pay in the retail market, these studies use hedonic price regressions, which control for a number of observable heterogeneities, such as, vintage year and regions. The main finding of these studies is that there exists a positive relationship between wine score and wine price in the wine retail market.

Oczkowski (1994) find that Australian table wine prices increase with the score given by a popular Australian wine guide. Schamel et al. (2001) use a time-series model to study the effects of the variables, wine score, regional vineyard location and grape variety, on the price of Australian and New Zealand wine. They find that the species of grape and regional vineyard locations from the late nineties have a significant effect on price. Jones and Storchmann (2001) investigates twenty one popular Bordeaux wines and regresses wine price on vintage, grape composition and wine score, measured by Parker-points. They find that wine score has a larger effect on wine prices than the wine’s dominant grape variety. Also vintage year has a larger positive effect on wine prices for Merlot than Cabernet Sauvignon.

There are also three studies that analyse the impact of wine sensory quality on the wine prices in the American wine retail market, which all employ the 100-point wine score system given by Wine Spectator, a popular lifestyle magazine and major wine-buyers guide. Two studies proposed by San Martin et al. (2008), who studied Argentinian wine, and Bombrun and Sumner (2003), who focused on Californian wines, report similar estimations. They find that an increase of one point in wine score increases wine price by 4%. Landon and Smith (1998) study red wine from the Bordeaux region, and find that the purchase decision of a typical consumer is heavily affected by Chateau reputation as opposed to wine score. The impact of wine scores assigned by the wine guide, Wine Spectator, is much smaller; a one point increase in score only leads to an increase in wine price of less than 1%.

4 BIDDING AT CHRISTIE’S WINE AUCTION WITH PRIVATE VALUATION PARADIGM

The wine auctions in Christie’s employ a traditional English ascending price auction, I model it as a non-cooperative game where there is one auctioneer who wants to allocate one indivisible item to N risk neutral bidders under a private valuation paradigm. I assume that the bidders’ valuation distribution is an exponential distribution, with a probability density function, \( f(v|X) \), and a cumulative distribution function, \( F(v|X) \). \( X \) is a d-dimensional vector of auction observable heterogeneity, such as the characteristics of the wine lots. I assume each bidder knows their own valuation but they do not know their opponents’ valuations.

The auctioneer commences the auction at a predetermined reserve price and asks the bidders to raise their bids with discrete and varying size increment. In Christie’s the reserve price for each lot is not published in the auction catalogue and it only becomes known to the bidders as the auction takes place in the salesroom. Only potential bidders who have valuations above the reserve price submit their bids. If no bidder submits a bid, the item goes unsold. If only one bidder submits a bid, the solo bidder wins the auction at the reserve price, conditional on his bid being higher than the secret reservation price of that auction. The secret reservation price is the minimum price a seller is willing to sell his item, which is equivalent to the seller’s valuation. If there are two or more bidders who submit bids, they submit their bids sequentially and the bidder with the highest bid wins the auction at the valuation of the second
highest bidder. Therefore, the probability density function of the winning bid is equal to: zero when the lot is unsold, the reserve price when there is only one bidder and the second highest valuation when there is more than one bidder.

Potential bidders can bid in different ways: they can submit a written absentee bid before an auction commences, which represents the bidder’s highest willingness to pay or they can bid during an auction, either in person or via telephone. It is important to note that all potential bidders must complete a registration form before the auctions commence. Therefore, although Christie’s allow bidders to submit their bids online, only bidders that are already pre-registered can submit their bids online, so the bidding environment is closed with a fixed number of potential bidders after auctions commence. This bidding environment is different from other online auction bidding platforms, for example, on the eBay online platform, where the number of potential bidders is unknown and new bidders can enter the auction at any time during the auction.

Potential bidders can gather information about the wine in upcoming auctions in three ways: using the information provided in a published catalogue, participating in the pre-auction viewing section, (which may include a consultation with a wine specialist), and having past experience or their own private valuation. A wine auction catalogue provides detailed information about each wine lot, such as lot size, bottle size, name of chateau, wine vintage year, wine condition\(^1\) and price estimates for each lot. It also contains conditions of sale and a section on how to place a bid in an auction. However, given the information provided by the wine catalogue, potential bidders are unable to make inferences about the uncertain sensory characteristics of a wine. Bidders who make bids must accept the condition and description of wines, and accordingly, Christie’s allow bidders to personally inspect each wine lot before the auction and make a consultation with a wine specialist from Christie’s.

### 5 STRUCTURAL MODEL FOR INDIRECT INFERENCE APPROACH

To analysis the effect of wine scores on bidders’ valuation, the first step is to characterise the distribution of latent variable, bidder’s private valuation. I need to choose a structure to link the observed variable, winning bids with bidders’ valuation \(V\) under proper data generating process and propose empirical method to estimate the data generating process.

The model proposed by Milgrom and Weber (1982), widely known as the clock model, is prevalently used in modelling English auctions. In the clock model, the auctioneer sets the clock at a pre-determined reserve price. In this model, each bidder knows their valuation, and holds a button to signal that they are still in the auction. As the price rises continuously and exogenously, bidders drop out of the auction as the price reaches their valuation, until only one bidder remains in the auction. The valuation of the second highest bidder is revealed and the last remaining bidder wins the auction with a bid equal to the second highest bidder’s valuation, \(V(2 : N)\), which is equal to the second-order statistic of the valuation, \(V\). Hence, the Milgrom-Weber clock model is often referred to as a form of second-price auction. The dominant strategy of each non-winning bidder is to stay in the auction until the price reaches his private valuation; as a result, the non-winners’ equilibrium bidding strategy is an increasing function of their valuation, \(B_i = \beta(v_i) = v_i\). Therefore in principal, it is possible to estimate the underlying bidders’ valuation by employing an empirical distribution of winning bidders’ bids with a cross-sectional English auction data set.

However, some potential problems arise from this method above. First, the observed winning bids do not uncover the winning bidders’ true valuation. Second, the Milgrom and Weber model assumes that bidders submit bids with a continuous increment, whereas in Christie’s, and many other auction houses, bidders are required to raise their bids with a discrete increment, which varies in size. Moreover, jump bids, where bids increase by more than the minimum increment, are frequently observed in auctions and also in my data set. The presence of both discrete bidding increments and jump bids makes it possible that the observed winning bid exceeds the second highest bidder’s true valuation. Third, due to the existence of reserve price, only the bidders who have private valuations above the reserve price submit bids, so the empirical distribution of observed winning bids has a truncated sample of data with different truncated points for each cross-sectional observation. Therefore, the Milgrom and Weber model does not provide a suitable data generating procedure to link latent variable \(V\) with the observed winning bids under Christie’s bidding environment.

\(^1\)The condition report issued by Christie’s includes a wide range of factors such as vintage year, previous damage, restoration, repairs and wear and tear.
The theoretical work proposed by Riley and Samuelson (1981) provides a general expression for the winning bidder’s equilibrium bidding strategy for a class of auctions with certain properties, regardless of auction format. The properties include risk-neutral bidders with an independent private paradigm, bidder’s bidding function is an increasing function of their private valuation and the bidder with the highest valuation wins the auction. This general expression well explains the relationship between the latent variable, bidders’ valuations, and the observed variable, winning bids. The Christies’ English auction model proposed in this paper fulfills all these properties. I use this general expression as an empirical structural model to estimate the bidders’ valuation distribution.

Following the framework in Riley and Samuelson (1981), the Bayesian-Nash equilibrium bidding strategy for each winning bidder in Christie’s wine auction is derived as follows.

Without loss of generality, I derive the Bayesian-Nash equilibrium bidding strategy for a specific bidder, winning bidder 1, in auction $k$. In this model, bidder 1, with a private valuation of $v_1$, chooses to report their valuation as $y$. As I assume the bidder’s bidding strategy is solely determined by their valuation, the auctioneer is able to calculate their bid according to their reported valuation. Therefore, the expected payoff for bidder 1 is,

$$\Pi(y, v_1) = v_1 \times \text{Pr}(\text{winning}) - \text{Expected Payment}$$

(1)

Due to the assumption of risk-neutrality, the function of bidders’ utility can be presented as a linear relationship in their monetary payoffs, which makes it possible to separate the probability of winning from the term of expected payment. As bidding behaviour is non-cooperative, an equilibrium bidding strategy for bidder $i$ is, $b_i = b(v_i)$, which is the common expression for the bidding strategy for each bidder. I assume that all bidders will place a bid, $b_i = b(v_i)$, except bidder 1, who reports their private valuation as $y$. Therefore, bidder 1 will submit a bid equal to $bid(y)$, so the payment function of bidder 1 depends not only on $y$, but also on $(v_2, \ldots, v_n)$.

$$\text{Payment}[\text{bid}(y), \text{bid}(v_2), \ldots, \text{bid}(v_n)]$$

(2)

Since the valuation of all the other bidders are unknown to bidder 1, bidder 1 must hold an expectation of other bidders’ types with the joint cumulative distribution function of $(v_2, \ldots, v_n)$. The expected payment of bidder 1, $P(y)$, is equal to,

$$P(y) = \mathbb{E}\{\text{Payment}[\text{bid}(y), \text{bid}(v_2), \ldots, \text{bid}(v_n)]\}$$

(3)

If bidder 1 is the winning bidder in an auction with his reported type $y$ and with $bid(y)$, his reported type must be higher than the rest of $N - 1$ potential bidders, so the probability of winning bid is,

$$\text{Pr}(v_j < y, j \neq 1) = F_v(y)^{N-1}$$

(4)

So bidder 1’s expected profit is,

$$P_1(y, v_1) = v_1 \times F_v(y)^{N-1} - P(y)$$

(5)

Under truth-telling, the first-order condition for bidder 1’s expected profit maximization problem is,

$$\frac{\partial \Pi(y^*, v_1)}{\partial y} = v_1(N-1)F_v(y^*)^{N-2}f_v(y^*) - P'(y^*) = 0$$

(6)

Only when $y^*$ is equal to bidder 1’s true valuation, the $bid(v_1)$ is optimal in equilibrium,

$$P'(v_1) = v_1(N-1)F_v(v_1)^{N-2}f_v(v_1)$$

(7)

The expected payment for a bidder who has a valuation equal to the reserve price, $r$, is,

$$P(r) = rF_v(r)^{N-1}$$

(8)
and the expected payment from bidder 1’s perspective becomes,

\[ P(v_1) = rF_v(r)^N - 1 + \int_r^{v_1} P'(u)du \]

\[ = rF_v(r)^N - 1 + \int_r^{v_1} udF_v(u)N - 1 \]

\[ = rF_v(r)^N - 1 + v_1F_v(v_1)^N - 1 \]

\[ = rF_v(r)^N - 1 + \int_r^{v_1} F_v(u)N - 1 du \]

Bidder 1 wins the auction with his report type, \( v_1 \), if and only if, his valuation \( v_1 \) is higher than the rest \( N - 1 \) potential bidders, therefore the probability of winning bid is equal to,

\[ Pr(v_j < v_1, j \neq 1) = F_v(v_1)^{N - 1} \]

Therefore the equilibrium bidding strategy for the winning bidder in one wine auction can be written as,

\[ b_{i,j} = v_{i,j} - \frac{1}{(F_{v_{i,j}})^{N - 1}} \int_r^{v_{i,j}} F^{N - 1}(h)dh \]

The auction structural model above shows that the bidding strategy for a winning bidder in a wine auction is determined by their private valuation and the number of potential bidders, an exogenous variable. In auction theory, the number of potential bidders \( N \) is assumed to be known. However, in this paper, and in many empirical contexts, it is a latent variable. It would be misleading to assume that the latent variable, the number of potential bidders, is equal to the observed variables, the number of bids or the number of actual bidders, as the relationship between the the number of potential bidders to the two observed variables is ambiguous. Levin and Smith (1994) find that the number of observed bidders in an auction is endogenously determined, given a set reserve price. Only potential bidders who have private valuations above the announced reserve price will place bids. Also, in English auctions, bidders are allowed to submit more than one bid so the number of observed bids tend to be higher than the number of potential bidders. Bajari and Hortacsu (2003) find that in eBay online auctions, the number of potential bidders is large, however only a comparatively small amount of bids are observed, which implies that only a low proportion of potential bidders submit a bid in an auction. This problem is overcome by employing the findings of Guerre et al. (2000) who show that the maximum number of actual bidders is a good proxy for the number of potential bidders, with the assumption that every auction has the same number of potential bidders. In my model, the maximum number of registered bidders in a single auction is equal to 6, therefore the number of potential bidders \( N \) is assumed to be 6.

Another important implication of the Riley and Samuelson model is that it allows sellers to calculate the optimal reserve price for their auctions, assuming that the bidders valuation distribution is common knowledge. As the bidder’s valuation distribution is unknown in this paper, I use the indirect inference approach to estimate the parameter that characterizes the bidder’s valuation distribution, which I employ to calculate the optimal reserve price and empirically test whether the reserve price set by Christie’s is optimal.

The following derivations show how to construct the optimal reserve price for auctions. If the item is sold, sellers have utility that is equal to the sum of expected revenue; if the item is not sold, sellers have the expected utility of retaining the item. The item is not sold if the winning bid is lower than the seller’s valuation, \( v_0 \), which is equal to the secret reservation price. The sum of the seller’s utility is shown in equation (12).

\[ v_0F_v(r)^N + N \int_r^{v_0} [uf_v(u) + F_v(u) - 1]F_v(u)N - 1 du \]

In order to maximise the seller’s expected gain, differentiate equation (12) with respect to the reserve price, \( r \), to give the following first-order condition that holds when \( r \) equals the optimal reserve price \( r^* \):

\[ Nv_0F_v(r)^{N - 1}f_v(r) - N[rF_v(r) + F_v(r) - 1]F_v(r)^{N - 1} = 0 \]
By taking out the common factors, $N$ and $F_v(r)^{N-1}$, the first order condition becomes,

$$v_0 f_v(r) - r f_v(r) - F_v(r) + 1 = 0$$  (14)

So, if buyers are risk neutral and the assumption of a symmetric IPVP holds, the seller’s expected gain is maximized when the optimally-chosen reserve price, $\rho^*$, solves equation (15):

$$\rho^* = v_0 + \frac{1 - F_v(\rho^*)}{f_v(\rho^*)}$$  (15)

Equation (15) shows that to calculate the optimal reserve price $\rho^*$ requires information about the bidders’ valuation distribution $F_v(v)$ and seller’s valuation for the item at auction. Equation 15 also indicate that the optimal reserve price for a specific auction is independent of the number of bidders.

### 6 DATA AND SUMMARY STATISTICS

I collect data from Christie’s’ online auction report, the catalogue book, and video of the auction salesroom provided by Christie’s live wine auctions. The event was categorised under the title, “Fine and Rare Wine”, and the auction was held on the 16th March 2017 at London King Street, with sale number 14365. The total revenue for this sale is equal to 918,426 GBP (excluding the buyer’s premium of 17.5%). The buyer’s premium varies according to the location of salesroom across different countries. For consistency, all the auction realized prices, reserve prices, and presale estimation prices in my data set exclude the buyer’s premium and applicable taxes.

The dataset includes: auction ending prices, reserve prices, the number of bids, and presale estimation prices with an upper and lower bound levels. Presale estimation price of each wine lot is based on the condition, rarity, expected quality, provenance and recent auction realised prices of similar items. Lot information collected includes: the number of wine bottles, carried in each lot, bottle sizes, drinking notes and wine scores.

The dataset consists of 558 wine lots that are categorised under 18 headings according to the type of wine, spirits or liqueurs, and provenance. The headings are namely: Australia, California, Champagne, Claret, Italy, Loire, Madeira, Non-Vintage, Massandra, other Spirits & Liqueurs (Rum), Port, Red Burgundy, Rhone, South America, Spain, Vintage Brandy, White Bordeaux, and White Burgundy.

Figure 1 shows the distribution of wines under different headings. It also indicates that wines from France account for a disproportionately high amount of lots, 359 out of 558 lots, which is around 68% of total lots. In this paper, I focus only on the wine lots from the most popular wine category, the chateau location of France. This eliminates the complication arising from both the wine master’s and bidders’ location preferences.

Parcel lots are prevalent in Christies wine auction, as shown in my data set. Figure 1 illustrates that 90 out of the total 558 lots are parcel lots, which account for around 16%.

A parcel lot is a sequence of several lots which are sold in order, all wine lots in the same parcel are identical and contain wines of the same quantity, condition and bottle size with an identical estimation price for each lot. However, the wines carry in the same lot do not have to be identical and a lot may be composed of several different wines.

When the parcel is auctioned, bidding starts with the first lot in the parcel. At the discretion of the auctioneer, the winner of the first lot can take any or all further lots in the parcel at the same price. Any remaining lots will continue to be sold by auction, starting at the previous second highest bidder’s bid and the next winning bidder will also be able to exercise the option to take any or all the remaining lots in the parcel for the same price. Bidding will continue in this manner until all lots are declared sold or unsold. Christie’s recommend bidders to bid on the first lot of the parcel. Absentee bids that are superseded in any lot in a parcel will be submitted in the next lots in the sequence until the absentee bid is successful or until the end of the parcel.

It is important to note that a number of empirical literature document the existence of a price declining anomaly in various auction settings, where they observe that prices tend to decline over time in parcel lots of live auctions, such as, Buccola (1982) for livestock auctions, Burns (1985) for wool auctions, and Ashenfelter (1989), McAfee and Vincent (1993) and Di Vittorio and Ginsburgh (1994) for wine auctions. In order to avoid the distortion caused by a price declining anomaly, I only include the auction information from the first sold lot in the 90 observations of parcel lots in my data set.
Figure 1. Distribution of lots in Christie’s wine auction categories

![Distribution of lots in Christie’s wine auction categories](image)

Figure 2. Example of Mixed French wines lot

![Example of Mixed French wines lot](image)

It is also important to note that there are several lots that carry a mixture of wines with different characteristics, such as: location, chateau, vintage year, and bottle sizes. These mixed wine lots are not ideal for my empirical analysis. To illustrate, consider an example of a mixed wine lot which contains two bottles of wine that have different vintage years; it would be illogical and misleading to take an average value for the covariate "vintage year" for this lot, and similarly for other covariates such as price per litre and score. Since it is difficult to find suitable values for these observed heterogeneous covariates, I exclude the observations of mixed wine lots and only focus on the lots with either a single bottle or multiple identical bottles. Figure 2 captures lot No. 319, an example of a mixed wine lot which contains 10 regular bottles of French wine that are from different Chateaus in France and with different vintage years.

Table 1 illustrates the descriptive statistics of my sample, which includes 153 cross-sectional observations that are either single bottle lots or multiple identical-bottle lots. Observations also include the first lot of each parcel lot. The number of bids in each lot differ. Lots that only have one bid indicate that the lot was sold at the reserve price. In the case where only a single bidder participates in the auction, a higher reserve price that is closer to the bidder’s valuation can lead to a higher ending price, which highlights the importance of setting an optimal reserve price.
Table 1. Descriptive statistics for sub-data set

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<th>Variable</th>
<th>Obs</th>
<th>Mean</th>
<th>Std.Dev.</th>
<th>Min</th>
<th>Max</th>
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<tbody>
<tr>
<td>Ending Price (Premium)</td>
<td>153</td>
<td>2914.67</td>
<td>12149.90</td>
<td>106</td>
<td>146875</td>
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<td>Ending Price Per Litre (Premium)</td>
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<td>766.69</td>
<td>2533.59</td>
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<td>18016.67</td>
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<td>Ending Price (Without Premium)</td>
<td>153</td>
<td>2480.46</td>
<td>10340.36</td>
<td>90</td>
<td>125000</td>
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<tr>
<td>Ending Price Per Litre (Without Premium)</td>
<td>153</td>
<td>766.69</td>
<td>2533.59</td>
<td>20.89</td>
<td>18016.67</td>
</tr>
<tr>
<td>Starting Price (Reserve Price)</td>
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<td>14</td>
</tr>
<tr>
<td>Scores</td>
<td>153</td>
<td>17.54</td>
<td>1.03</td>
<td>13</td>
<td>20</td>
</tr>
<tr>
<td>Size (Litre)</td>
<td>153</td>
<td>6.70</td>
<td>5.72</td>
<td>0.75</td>
<td>45</td>
</tr>
<tr>
<td>Lower Bound of Estimation Price</td>
<td>153</td>
<td>2031.24</td>
<td>9163.01</td>
<td>60</td>
<td>11000</td>
</tr>
<tr>
<td>Lower Bound of Estimation Price Per Litre</td>
<td>153</td>
<td>534.91</td>
<td>1984.17</td>
<td>18.52</td>
<td>13333.33</td>
</tr>
<tr>
<td>Upper Bound of Estimation Price</td>
<td>153</td>
<td>2532.09</td>
<td>10849.42</td>
<td>70</td>
<td>130000</td>
</tr>
<tr>
<td>Upper Bound of Estimation Price Per Litre</td>
<td>153</td>
<td>686.50</td>
<td>2531.74</td>
<td>25.93</td>
<td>20000</td>
</tr>
</tbody>
</table>

Table 1 also shows that the average auction realised price per litre is 43.33% higher than the average auction lower bound estimation price per litre, that the average reserve price per litre is around 22% higher than the average lower bound estimation price per litre, and that 69% of auctions have a reserve price higher than the lower bound estimation price. This suggests that the lower bound estimation prices for many lots are set deceivingly low. It can be speculated that auction houses purposefully set at an attractively lower estimation price to attract more potential bidders to register their interest, but set a higher reserve price in order to achieve higher revenues. In Christie’s auctions only registered bidders are allowed to submit bids, so the number of potential bidders in an auction is fixed from the start of the auction. Therefore, it is important to attract more potential bidders to join the salesroom before the auction commences to increase competition.

Figure 3 illustrates the frequency distribution of lots according to different bottle sizes and lot sizes. One wine lot may contain several bottles of wine, thus the lot size varies among different auctions, which makes it difficult to conduct a comparison across lots. In order to facilitate the comparison, I standardize the ending prices, reserve prices and lot estimations to GBP per litre.

Drinking notes and scores for each wine are given by Jancis Robinson, a renowned wine master from the UK, which are taken from her website JancisRobinson.com. Her scores use a 20-point scale which allows for half-scores. Points are given based on the specific sensory characteristics of wine, such as colour, aroma and flavour, as well as more technical qualities including the balance of sugars, acids, tannins and volatile acidity. According to Jancis Robinson’s historical scores and rating records, her wine scores usually fall within the range of 9.5 and 20, with an average score value that is equal to 16.4 points, where around half of the wine tastings have scores between 16 and 17 points.

Table 2 gives an insight into what the numerical scores mean in Jancis Robinson’s 20-Point Scale, as described on her website. Wine buyers should also note that wines scores are given in the context of the particular wine in question, as it is difficult to compare two completely different wines on a linear scale. On her website, she gives the example that a red Burgundy simply cannot be scored on the same scale as a New World Pinot Noir.

Figure 4 illustrates the distribution of wine scores in my sample. The minimum value of scores in the sample is equal to 13, the mean value of scores is equal to 17.5 with a standard deviation 1.03. Both the average and minimum wine scores in the sample is higher than the average and minimum scores listed on the Jancis Robinson website, which suggests that the quality of wine auctioned in Christie’s auction is above average.

There are several reasons why Jancis Robinson’s wine scores are distinguishable from others. Jancis
Figure 3. Distribution of bottle size

Table 2. Jancis Robinson’s 20-Point Scale

<table>
<thead>
<tr>
<th>Score</th>
<th>Explanation</th>
</tr>
</thead>
<tbody>
<tr>
<td>20</td>
<td>Truly exceptional</td>
</tr>
<tr>
<td>19</td>
<td>A humdinger</td>
</tr>
<tr>
<td>18</td>
<td>A cut above superior</td>
</tr>
<tr>
<td>17</td>
<td>Superior</td>
</tr>
<tr>
<td>16</td>
<td>Distinguished</td>
</tr>
<tr>
<td>15</td>
<td>Average</td>
</tr>
<tr>
<td>14</td>
<td>Deadly dull</td>
</tr>
<tr>
<td>13</td>
<td>Borderline faulty or unbalanced</td>
</tr>
<tr>
<td>12</td>
<td>Faulty or unbalanced</td>
</tr>
</tbody>
</table>
Figure 4. Distribution of wine score

Robinson is one of the most respected and renowned wine critics in the UK, with wine buyers worldwide who consider her scores when making a primary purchasing decision. Wine score records on her website are updated frequently, and the majority of wines in my data set are tasted and scored within the short time interval of 2 years. Due to the varying quality of wine characteristics as time elapses, it is essential that the tasting date is close to the time of wine score data collection to better capture the real quality of wines. Also, the quality score given by Jancis Robinson is based on the sensory characteristics of wine, such as taste, aroma and colour, and if the wine has not yet reached its peak maturity, it is also combined with perceived potential. Therefore, a wine that is on the way up to its peak of maturity, such as, a new Burgundy, would likely be assigned a high score due to its high potential performance in the future, however, a wine that is on its way down from its peak will be given a score that denotes the sensory characteristics on the day of the taste testing. Finally, all the wine scores are exclusively given by Jancis Robinson to avoid the problem of measurement error in later analysis. These four characteristics of Jancis Robinson’s wine score system enable us to make reliable and consistent inferences on the impact of wine score on bidders’ private valuation.

Figure 5 illustrates the frequency distribution for the vintage year of wines in my data set. The wine lots in this data set have vintage years spanning seven decades, with a standard deviation of 15.37. By far, the most common interval for wine vintage year is 1997-2007 with 69 lots, accounting for 45.10% of the total lots in my sub-data set; contrastingly, wine lots from the first five vintage year intervals, 1947 to 1997, only account for 56 lots. It can be noted that the distribution of wine vintage year is skewed heavily to the right with a long left tail, and the reason behind this is that most wines sold at auction have a peak maturity of around 10 to 20 years. The age of peak maturity differs accordingly with wine types: longer for sweet wines as the sugar acts as a preservative, but shorter for white wines as the breakdown of some components can make the wine bitter.

7 EMPIRICAL METHODOLOGY: INDIRECT INFERENCES

I estimate the impact of wine scores on bidder’s private valuation using the structural model of the winning bidder’s equilibrium bidding strategy, derived in section 5. I adopt an indirect inference approach, as proposed by Li (2010), to estimate the parameters of the auction structural model and characterise the underlying bidder’s private valuations.

The indirect inference approach is a simulation-based method, which is used to estimate the parameters
of a model that has latent variables, incomplete data or an analytically intractable likelihood function. Early theoretical work related to indirect inference was proposed by Smith (1993), who used an indirect inference approach in a time series model. Gourieroux et al. (1993) developed the approach further in full generality by using parameter calibration. Then, Gallant and Tauchen (1996) suggested a similar approach, known as the efficient method of moments (EMM).

The approach that I adopt has two stages. The first stage uses ordinary least squares estimation as an auxiliary model to estimate parameters. In the second stage, the estimated parameters from the first stage are used to simulate the latent variable in the structural model. The parameters of the model are estimated by minimising the distance between the simulated variable from the structural model and the same variable in the auxiliary model. I use Mathematica, a mathematical computational software for programming, and conduct a two stage indirect inference analysis for the data set of Christie’s wine auction.

7.1 Indirect inference: Stage one
In the first stage, I run an ordinary least squares estimation to get the estimations of $\hat{\beta}_0$. I regress Log(price per litre) on several observed heterogeneous covariates: vintage year, wine scores, and three dummy variables related to the provenance in France (Burgundy, Rhone, and Bordeaux). I use Bordeaux as a baseline in the regression.

7.2 Indirect inference: Stage two
In the second stage, the estimated parameters of wine characteristics in the first stage are used to simulate the latent variable, the private valuation of winning bidders for each auction. Then, I calculate the winning bidder’s equilibrium bid according to the auction structural model derived in section 5. Then the parameters of the structural model are estimated by minimising the distance between the simulated variable from the structural model and the same variables from the auxiliary model.

Here, I describe the stage two procedure in detail. In the first step, to simulate each winning bidder’s private valuation, I substitute the first-stage estimates of the coefficients of $\theta$ with observed heterogeneity covariates, $x$, into the bidder’s valuation density function 16 by independently drawing their valuation, $v_i$.

$$f(v|X_i) = \frac{1}{\beta} \exp\left[\frac{-v}{\beta}\right], \quad \beta = \frac{1}{\exp(\theta_0 + \theta x_i)}$$
Table 3. first stage auxiliary model estimation for Christie’s wine auctions

\[
\log(\text{price per litre}) = \alpha_0 + \alpha_1 \text{Burgundy}_i + \alpha_2 \text{Rhone}_i + \alpha_3 \text{Scores}_i + \alpha_4 \log(\text{year}) + \epsilon_i, \epsilon_i \sim N(0, \sigma^2)
\]

<table>
<thead>
<tr>
<th>Linear regression</th>
<th>Number of observations: 153</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>F(4, 148) = 47.20</td>
</tr>
<tr>
<td></td>
<td>Probability &gt; F = 0.0000</td>
</tr>
<tr>
<td></td>
<td>R-squared = 0.4245</td>
</tr>
<tr>
<td></td>
<td>Root MSE = 0.3757</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Log (price per litre)</th>
<th>Coef.</th>
<th>Robust Std.Err.</th>
<th>t</th>
<th>p &gt;</th>
<th>95% Conf. Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>Burgundy</td>
<td>0.22</td>
<td>0.05</td>
<td>4.00</td>
<td>0.00</td>
<td>0.11 - 0.32</td>
</tr>
<tr>
<td>Rhone</td>
<td>0.35</td>
<td>0.17</td>
<td>2.03</td>
<td>0.04</td>
<td>0.01 - 0.69</td>
</tr>
<tr>
<td>Scores</td>
<td>0.16</td>
<td>0.03</td>
<td>4.66</td>
<td>0.00</td>
<td>0.09 - 0.23</td>
</tr>
<tr>
<td>Log(year)</td>
<td>-69.60</td>
<td>8.18</td>
<td>8.51</td>
<td>0.00</td>
<td>-85.76 - 53.43</td>
</tr>
<tr>
<td>Constant</td>
<td>231.05</td>
<td>27.06</td>
<td>8.54</td>
<td>0.00</td>
<td>177.58 - 284.52</td>
</tr>
</tbody>
</table>

In the presence of a reserve price, the distribution of observed bids in my sample is truncated: for the observed winning bid in each wine lot, only those bidders who have a valuation higher than the reserve price submit bids, therefore, in each lot, the simulated winning bidders’ valuation must be higher than the reserve price.

I consider 100 simulation paths: \([v_s^i(x_i, \theta), i = 1, \ldots, 153; s = 1, \ldots, 100]\), where I run the simulation 100 times for each of the 153 auctions in my data set, which generate 100 winning bidders’ valuations, \(v_s^i\), for each of the 153 lots.

In the second step, I simulate each winning bidder’s equilibrium bid with 100 simulation paths, \([\hat{y}_s^i(x_i, \theta), i = 1, \ldots, 153; s = 1, \ldots, 100]\), by substituting the correspondent observed covariates \(X\) and the simulated winning bidders’ private valuations, \(v_s^i\), into the structural model derived in equation 11, then I regress \([\hat{y}_s^i]^1\) on \(x_1^1\), for \(s = 1, \ldots, 100\) and get the the estimators, \(\hat{\beta}_s^1\), and is a function of unknown \(\theta_f\).

I solve for equation (17) to find the indirect inference estimator, \(\hat{\theta}\), for the structural parameter, \(\theta_0\).

The result shows that the estimator, \(\hat{\theta}\), depends on the positive definite matrix A, which serves as a weighted matrix.

\[
\min_{\theta \in \Theta} [\hat{\beta}_n - \frac{1}{s} \sum_{s=1}^{100} \hat{\beta}_n^s(\theta)] A [\hat{\beta}_n - \frac{1}{s} \sum_{s=1}^{100} \hat{\beta}_n^s(\hat{\theta})]
\]

(17)

The problem of finding the indirect inference estimator, \(\hat{\theta}\), is simplified when the number of the auxiliary parameters is the same as number of the structural parameters. Equation (18) is the solution to the reduced equation:

\[
\hat{\beta}_n - \frac{1}{s} \sum_{s=1}^{100} \hat{\beta}_n^s(\hat{\theta}) = 0
\]

(18)

By solving equation (18), I get the estimators, \(\hat{\theta}\) that determine bidders’ valuation distribution.

8 EMPIRICAL RESULTS AND ESTIMATES OF THE OPTIMAL RESERVE PRICE

8.1 First stage: OLS estimation of auxiliary model

Table 3 illustrates the first stage auxiliary model regression outcome, and all the coefficients are statistically significant at the 5% level. The regression outcomes suggest that wine scores serve as a particularly good quality indicator for wine sensory characteristics; consequently, wine scores have a significant impact on auction ending prices. From my OLS regression, an increase of one point in wine score results in an increase in auction end prices by a substantial 16.19%.

The regression outcome suggests that there are distinct preferences for the vineyard location of wine. The outcomes indicate Rhone is the most preferred location in my sample, as the auction ending prices of
wine from vineyards in Rhone is 34.79% higher than Bordeaux, while the wines from Burgundy have prices that are 21.72% higher than Bordeaux.

The vintage year of wine is also a crucial determinant of auction ending prices; an increase in vintage year by one percentage point will decrease auction ending prices by 69.10%. The negative sign is consistent with my expectations; amongst the top quality age-worthy wines in the fine wine market, newer wines are relatively more common and generally of lesser value, in comparison to the older collectible wines.

8.2 Second stage: Structural model analysis

Table 4 presents the estimates obtained from the one hundred simulations in stage two of my indirect inference analysis. Wine scores, the indicator for sensory characteristics, is significant at the 5% level with a positive effect on bidder’s valuation, however the magnitude decreases from 16.19% to 8.02%, so an increase in wine score by one point will increase the expected private valuation of a typical bidder in Christie’s by around 8.02%.

The regression outcomes suggest that when bidders are uncertain about the quality of sensory characteristics of age-worthy wines, they may heavily rely on the wine scores. In particular, the wine scores given by Jancis Robinson well capture the average preferences of wine collector and investor in the fine wine market. Wine scores seem to be a good guide for the first time buyers, who are uncertain about quality of sensory characteristics of a bottle of wine. Table 4 also shows that the estimators for the non-sensory characteristics, chateau, location and vintage are not significant at the 5% significant level in the second stage of the indirect inference approach. These results contradict those obtained by the auxiliary model and also to a number of empirical studies of the wine market. One possible explanation of this result is that all the wines in my data set are from most famous regions and prestigious vineyards of France, and all vineyards in the data set are located in a relatively small area. Therefore, the differences in the non-sensory characteristics are less important to the potential bidder. Another explanation is that wine scores provide a strong enough indicator of quality to that affects and shapes the consumer’s preferences and persuading consumers to acquire a taste for certain sensory characteristics.

The calculation of the asymptotic variance-covariance matrix in my case is computationally complicated due to the approximation of derivatives of functions and integrations, therefore I employ bootstrap method to get an estimate for the asymptotic variance and covariance matrix. The standard errors in table 4 are computed using the following bootstrap procedure.

First, I substitute the structural estimators $\hat{\theta}$ and observed heterogeneous covariates $X$ into auxiliary model in stage 1 and retain the fitted values $\tilde{y}_i = \hat{\theta}_0 + \hat{\theta}_1 x_{i1} + \hat{\theta}_2 x_{i2} + \hat{\theta}_3 x_{i3} + \hat{\theta}_4 x_{i4}$ and obtain the corresponding residual $\tilde{\epsilon}_i = y_i - \tilde{y}_i$, $[i=1,...,153]$.

Second, use each $\tilde{y}_i$ add a random resampled residual $(\tilde{\epsilon}_j - \mathbb{E}(\tilde{\epsilon}_j))$, $[j=1,...,153]$ to get synthetic response variables $y^* = \tilde{y}_i + (\tilde{\epsilon}_j - \mathbb{E}(\tilde{\epsilon}_j))$, where j is selected randomly from the list $(1,...,153)$ for every i.

Third, I regress $y^*$ on $X$ to obtain the coefficient $\hat{\theta}^*$.

Fourth, repeat step two and step three for 800 times and calculate standard error for each coefficient $\hat{\theta}^*$.

The above indirect inference estimation characterises the underlying bidder’s private valuation distribution, which allowed me to calculate the optimal reserve price for each auction at different level of seller’s valuation $v_0$.

---

Table 4. Second stage: structural model outcome adopting OLS as auxiliary model of Christie’s wine auctions

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Burgundy</td>
<td>0.01</td>
<td>0.19</td>
</tr>
<tr>
<td>Rhone</td>
<td>-0.08</td>
<td>0.11</td>
</tr>
<tr>
<td>Scores</td>
<td>0.08</td>
<td>0.04</td>
</tr>
<tr>
<td>Log(year)</td>
<td>-16.39</td>
<td>11.22</td>
</tr>
<tr>
<td>Constant</td>
<td>53.13</td>
<td>37.05</td>
</tr>
</tbody>
</table>

[2] Since ordinary least square estimation requires zero conditional mean of error terms.
I follow the same assumption that each bidder’s private valuation is draw from a exponential distribution, by substitute the structural estimator $\theta_{score}$ and covariates $x_{score}$) in equation 15 in section 5, by simplifying, equation 15 can be rewritten as:

$$P_0 = \frac{1}{\beta} + v_0, \quad \text{where} \quad \beta = \frac{1}{\exp(\theta_{score}) \cdot x_{score}} \quad (19)$$

Equation 19 shows that the optimal reserve price $p_0$ for each wine lot in my case is simply determined by a) wine score, ($\theta_{score}$), the structural estimator, b) a score $x_{score}$, for each wine lot and c) the sellers’ valuation, $v_0$. However, $v_0$, is a latent variable, which is not revealed during the course of an auction. In many cases (and empirical studies) of sealed bid and English auctions, such as, timber auctions, the auctioneer sets the reserve price equal to the seller’s valuation, $v_0$, which is the lowest price a seller is willing to sell their item, usually at a fair market price.

However, in Christie’s auctions, it would be misleading to directly assume the reserve price to be equal to the seller’s valuation. Christie’s catalogue book provides a high and low estimate for each wine lot, which states, "Unless otherwise indicated, all lots are subject to a secret reserve price which cannot be more than the lot’s low estimate." Here, the secret reserve price is the lowest price a seller is willing to sell their item, which I assume is equal to the each seller’s valuation, $v_0$. In Christies’ each wine lot has a secret reservation price, so it is possible that the highest bidder in an auction fails to win the lot if their bid is below the secret reservation price, in which case, the item goes unsold. This statement allows us to make inferences about the possible range of sellers’ valuations. According to the catalogue book the maximum secret reservation price, (which is equal to the seller’s valuation), cannot exceed the low estimates stated in the catalogue book. Therefore, if the reserve price of a wine lot is higher than its low estimate, it must also be higher than both the secret reservation price and the seller’s valuation.

I compare the reserve price for each wine lot with the corresponding low estimates and find that 69% of wine lots in my sample have reserve prices that are above the maximum secret reservation price, and only the remaining 31% of wine lots have reserve prices that are below or equal to the maximum secret reservation price. This contradicts the statement in Christie’s catalogue book, which suggests that auctioneers commence each auction at a price below the low estimates.

The prevalent existence of absentee bids is a possible explanation behind the higher reserve prices, which are above the low estimate, observed in a large proportion of auctions in my data set. Other researchers also observe the existence of absentee bids in live auctions, for example, Ginsburgh (1998), report that a large number of bidders in Christie’s and Sotheby’s auctions submit absentee bids. Some bidders choose to submit absentee bids before the start of the auction and the auctioneer bids on behalf of them. The reasons why bidders choose to submit absentee bids differ, but it is usually a combination of the value of the lot being relatively inexpensive and high added costs of participating in the auction in person, such as travel and time costs.

It would be interesting to explain why absentee bids affect the reserve price. Christie’s allows bidders to submit absentee bids 24 hours before the auction commences, therefore the reserve price can only be confirmed the day before the sale takes place. There are three ways in which submitted absentee bids can affect the reserve price of an auction. I assume that the auctioneer sets the original reserve price at the sellers’ valuation. First, if the auctioneer only receives one absentee bid which is lower than the original reserve price, the reserve price does not change. Second, if he receives an absentee bid that is higher than the original reserve price, the new reserve price is equal to the original reserve price plus a minimum increment. Finally, if the auctioneer receives a few registered absentee bids (more than 1), which are higher than the original reserve price, the auction will normally commence at the price equal to the second highest bidder’s absentee bid plus a minimum increment. The existence of absentee bids explains why there are a number of observed reserve prices that are considerably higher than the seller’s valuation. If I take all observed reserve prices as a proxy for the seller’s valuation to calculate the optimal reserve prices, the results would be biased. However according to the analysis above, it is reasonable to believe that the reserve prices of the remaining 31% of lots are closer to the seller valuations $v_0$, so it is interesting to test whether the reserve prices in those listings are high enough. I calculate the optimal reserve prices for those 31% wine lots at different levels of seller valuations and follows equation (19). Table 5 reports the average simulated revenue and average sell through rate at different level of optimal reserve prices, $p_0$, with 800 simulations.
Table 5. Simulations of auctions with optional reserve price at different levels of seller’s valuations

<table>
<thead>
<tr>
<th>Optimal reserve price at average percentage increase in original reserve price</th>
<th>Total revenue at different level of optimal starting price</th>
<th>Sell through rate at different levels of optimal starting price</th>
</tr>
</thead>
<tbody>
<tr>
<td>41.6%</td>
<td>570,241</td>
<td>65.60%</td>
</tr>
<tr>
<td>36.6%</td>
<td>474,165</td>
<td>70%</td>
</tr>
<tr>
<td>0%</td>
<td>418,455</td>
<td>100%</td>
</tr>
</tbody>
</table>

In order for the simulation outcomes at different reserve levels to be comparable, all the winning bidders’ simulated valuations are drawn from the same distribution that is truncated at the observed original reserve price, for each wine lot. The simulated bidders’ valuations are identical at different level of reserve prices. Therefore, if the reserve price is above the simulated winning bidder’s valuation, the item is unsold.

The problem I encounter is that secret reservation prices are unknown, which makes it difficult to distinguish whether a lot is sold or unsold. However, the upper bound of the secret reservation price is known to be the lot’s low estimate. Therefore, it is possible to form a criterion to decide whether an item is sold or unsold, at different levels of seller valuation and increasing levels of reserve prices, according to the simulated auction ending prices.

I distinguish the sold and unsold items according to the simulation outcomes in the following way. First, I compare the calculated optimal reserve prices that correspond to different seller valuations, with the lot’s low estimate. For auctions with an optimal reserve price above the low estimate, all auctions with a placed bid is sold.

For auctions with an optimal reserve price below the low estimate: all those lots with simulated ending prices above the low estimate are sold. If simulated ending prices are below the low estimate, I compare the simulated ending prices with actual (observed) auction ending prices, as all 46 lots in my data set are sold lots, so the unobserved secret reservation price must be below the observed auction ending prices.

In my sample, 15 out of 46 lots have observed auction ending prices that are lower than the lots’ low estimates, which helps me to narrow down the possible upper bound of secret reservation prices for these 15 wine lots. If the simulated ending price is higher than the new upper bound of secret reservation prices, I regard the lot as a sold lot.

According to the selection principal and simulation outcomes, I find that an increase in the reserve price tends to increase the frequency of some lots being unsold, however, the average total revenue increases dramatically. For example, if a higher reserve price level is used, which is 36.6% higher than the original reserve prices, the seller’s average total revenue would expect to be 474,165 GBP, with a decreased sell through rate equal to 70%. The average total revenue of the 46 lots increases by 55,710 GBP, which is an increase of around 13%, in comparison with the average total revenue of 418,455 GBP yielded from auctions with the original reserve price level. Evidently, this suggests that the reserve price for Christie’s auctions is set below the optimal level, as an increase in the reserve price level will increase the ending prices for these auctions and result in higher revenue.

9 SUMMARY AND CONCLUSION

In this paper, I empirically analysed the effect of wine scores on the bidder’s private valuation in Christie’s wine auctions. Firstly, due to the bidder’s private valuation being a latent variable, I used an indirect inference approach to estimate the bidder’s private valuation distribution. I found that wine score is the essential structural element that determines the underlying private valuation distribution of bidders in Christie’s wine auction. The expected private valuation of bidders increases by 8.02% for every one-point increase in wine score, based on the 20-point scale by Jancis Robinson. This result indicates that, when faced with a purchase decision, bidders heavily rely on the wine scores when they are uncertain about the quality of fine wines in the auction market. It also indicates that wine scores capture the average preferences of buyers in the fine wine market well.

I also found that the coefficients of two of the most popular vineyard locations, Bordeaux and Burgundy, are not significant, which conflicts with other empirical findings in wine retail market. After revealing the bidder’s private valuation distribution, I calculated the optimal reserve price for each auction
and found that the original reserve price set by Christie’s is not optimal; an increase in reserve price may lead to a higher total revenue.

This paper contributes to the literature of structural model analysis of English auction with a bundle of identical items. It also contributes to the empirical literature of effect of wine characteristics on bidder’s valuation in auction market.

REFERENCES


