An Empirical Analysis of Online Auctions for Bordeaux Wine

Abstract:
We analyze online auction prices for premium Bordeaux reds sold on the German eBay site. Our data set reports a total of 2133 transactions completed during November and December 2003. First, we estimate a model which includes only fundamental quality attributes such as vintage conditions, appellation, vineyard classification, and chateau reputation. In a second step, we add quality and reputation indicators due to wine critic Robert Parker. In the third model, we add online-auction specific variables to see whether they have any impact on the final auction price. We evaluate seller reputation scores, auction length, timing of the auction end (day of week, time of day), number of bids, unknown bidder identities (private auctions), initial price per bottle and whether information on Parker ratings is stated in the offer. Our application is unique because eBay auctions (especially for premium wine) have not been analyzed in this detail in the literature. The inclusion of online-auction specific variables adds virtually nothing the overall goodness of fit. However, we observe significant but small effects for auction length, the number of bids, and private auctions. In contrast to many other studies, we estimate an insignificant seller reputation effect on final auction prices.

Key words: online auctions, regional and producer reputation

1. Introduction

The popularity of online auctions is a relatively recent phenomenon. eBay, the leading online auctioneer, is one of the most popular websites and has become synonymous for trading online. Wine is a good well suited for online trading and there is a huge market for it on eBay's websites in France and Germany. Buying and selling Bordeaux reds is especially popular on eBay in Germany where about 2,000 auctions are available at any given time. Many wine enthusiasts and traders have discovered online auctions as a tool to trade wine and availability of Bordeaux wine on eBay.de is even larger than on the French site.

In this paper, we analyze final prices for premium Bordeaux wine auctioned on the German eBay site. For this purpose, we have recorded 2,133 transactions to evaluate whether online specific variables such as auction length, day and time of auction end, or seller reputation have any impact on the final auction price or whether the prices can be explained by more fundamental quality attributes such as vintage conditions, appellations or vineyard classifications or possibly by the quality evaluations of a wine critic. Because of their crucial impact on wine prices in Bordeaux about 40% of all sellers also report Robert Parker's ratings when listing their Bordeaux wine. Therefore, we have also obtained information on Parker points for all the wines at auction and whether this sensory quality information is stated in the offer. We use the auction data in a hedonic pricing model to estimate willingness to pay for product quality attributes of Bordeaux wine correcting it with eBay specific control variables. Dependent variable is the final auction price per bottle including shipping costs. We estimate three different models. In the first model (referred to as M1 or Terroir model), we include only fundamental quality attributes for premium Bordeaux wine: vintage conditions, regional origin (appellations), vineyard classifications (1855/1932), château reputation (brand value) and wine age. In the second model (M2 or Parker model), we add Parker's point ratings and additional château dummies. Finally, in model M3 (or the Online model) we add a number of (eBay specific) online auction control variables to see whether they have any impact on the final auction price. These online control variables include the day and time of the auction end, auction length, number of bids, seller reputation, initial price per bottle, if bidder identities remain undisclosed (private auctions) as well as whether Parker's sensory quality information is stated in the offer. Our application is unique because online auctions (in particular for premium wine) have not been analyzed in this detail in the literature.

2. The (Online-)Auction Literature

Auctions have been extensively studied by economists to understand their properties as a dynamic pricing mechanism (e.g. Vickrey, 1961; Milgrom and Weber, 1982; McAfee and McMillan, 1997). This literature involves both analytical models and empirical testing. The different auction mechanisms studied include the English auction (or ascending-bid auction), the Dutch auction (descending-bid auction), the first-price sealed-bid auction, and the Vickrey auction (second-price sealed-bid auction). For a comprehensive overview of the literature on auction theory refer to Klemperer (1999).

In markets with asymmetric information properties, economists worry about adverse selection (i.e. sellers may have hidden information about the quality of the good). In his seminal paper, Akerlof (1970) demonstrated that if, at the time of sale, only the seller knows whether a used car is a “lemon”, it can be that there is no equilibrium where cars are sold. Thus, Akerlof's analysis is quite pessimistic about whether markets are able to function with adverse selection. Other authors (e.g. Shapiro 1983) have suggested that reputation indicators might be a mechanism that allows markets to function in the presence of adverse selection. If seller gain a reputation for honest behavior, such as making full disclosure of all information about a particular product, then markets can have a positive level of trade. All online auction sites attempt to solve this information problem through some form of a user feedback system. For instance, after an auction is completed, eBay allows both the seller as well as the winning buyer to rate one another in terms of their reliability and timeliness in payment and delivery. The ratings are given as a positive, negative or neutral response. The number of net positive responses is the seller reputation score displayed next to each user's eBay identity which is usually a pseudonym or nickname. By clicking on a seller's eBay ID, potential buyers can view all of the seller's feedback, including all comments as well as statistics totaling the total number of positive, neutral and negative comments.

Bajari and Hortacsu (2004) provide an excellent overview of the recent literature on online auctions. Their paper also includes a review of studies that have used data collected directly from online auction sites to analyze customer-bidding behavior. Lucking-Reiley (2000) present an overview of what is auctioned online and how is auctioned off. Lucking-Reiley et al (2000) analyze online auction prices for collectible one-cent coins on eBay. Their main findings are that the user reputation indicator (i.e. feedback ratings) have a measurable effect on auction prices (negative ratings have a much greater impact than positive ratings), minimum bids and reserve prices have positive effects on the final auction price, and that on average longer lasting auctions result in significantly higher prices. Resnick and Zeckhauser (2001) find that reputation ratings may have a positive price effect. Several studies also provide estimates for the value of reputation in online auctions (e.g. Houser and Wooders, 2000; Lucking-Reiley et al., 2000). A common finding by all authors is that any negative feedback (user reputation) is negatively correlated with the sale price and that the amount of positive feedback has a significant positive impact on the sale price. However, the estimates on how much the winning bid would increase as a function of a seller reputation are rather small. Houser and Wooders (2000) estimate that a ten percent increase in positive feedback points increases the winning bid by only 0.17% and a ten percent increase in negative comments reduces the sale price by 0.24%. Lucking-Reiley et al. (2000) find that a one percent increase in the seller's positive feedback raises prices by 0.03% and a one percent increase in negative feedback decreases prices by 11%.

Wilcox (2000) found that more experienced bidders tend to bid more rationally than less experienced bidders. Analyzing eBay data for rare coins, Wood and Kauffman (2001) identified four trends that may explain why auction buyers pay more or less for the same item: weekend, auction length, reputation score, and picture effects. Auctions ending during the weekend yielded higher prices than auctions ending on weekdays (weekend effect). Thus, a weekend effect would be a personal characteristic, not a market characteristic and may indicate that people are willing to pay more for the same item when they have more time to consider the purchase. Auctions that last longer attract more bidders and thus higher prices (auction length effect). Seller reputation may also yield a price premium (reputation score effect). However, since eBay reputation scores tend to increase with time and activity it may in fact measure experience rather than reputation. Moreover, Wood and Kauffman (2001) suggest that items sold online and shown with an actual picture might also sell for a premium (picture effect). As they suggest that this might be due to demanding buyers who expect sellers to present all information available using advanced technology. We would argue that this might no longer be accurate since digital imaging has become almost an everyday household application today.

In addition to the online specific indicators analyzed in other studies, we take a closer look at the effects of the auction ending time during the day on the final bids. We argue that the timing of the final bid *by the seller* has received relatively little attention in the literature. Analyzing buyer behavior, Roth and Ockenfels (2002) have examined the phenomenon that experienced buyers tend to bid during the very final phase of an eBay auction (sniping). Moreover, we also examine an array of distinct product quality attributes which have been analyzed in hedonic models using retail prices. We will argue that an analysis of online auction prices that includes distinct product quality attributes will render most online specific variables to have insignificant impacts on final auction prices. Our application is unique in scope and detail because online specific variables have not been analyzed in conjunction with product quality attributes typically examined in hedonic models using retail prices.

3. Data and Analysis

During the months of November and December 2003, we collected an extensive data set of 2,133 transactions of premium Bordeaux red wine sold on the German eBay site. Our objective is to examine crucial online-specific variables that determine final online auction prices received. In addition to the final auction price per bottle, we recorded measures such as the initial bid, shipping costs, lot size (number of bottles offered), auction length, day and time of auction end, number of bids, buyer interest (page count), seller reputation score (percentage of positive peer evaluations) as well as buyer and seller experience (number of completed transactions, length of membership). We also recorded if the auction was public (sealed bids until the auction ended and with bidder identities known to others) or private (bids and identity of bidders remain unknown even after the auction ends). Because of their crucial impact on wine prices in Bordeaux, many sellers report Parker's point rating when listing their Bordeaux wine. Therefore, we obtained Parker points (PP) for all the wines in the sample and recorded whether this sensory quality information was stated in the offer or not. Figure 1 shows the distribution of Parker ratings in the sample.

Figures 2 through 5 depict specific characteristics of the data set. Figure 2 shows the distribution of lot sizes (number of bottles on offer). In over 80% of all offers only a single bottle is auctioned. Figure 3 depicts the distribution of auction lengths. eBay auctions to last for 1, 3, 5, 7, or 10 days, but most auctions (67%) last a week or more. Figures 4 and 5 are histograms for the day and timing of the auction end. We grouped auction-ending times in the morning and in the afternoon when online time is more expensive and people are typically at work (at least during the week). During the evening, we separate ending times by the hour. Most auctions end on Sundays and in the evening hours between 2100 and 2200 hours CET. Note that the weekday and the time of the auction end are represented as categorical dummy variables in the sample. For the estimation, we chose Sundays and the evening hour between 2100 and 2200 hours CET as the base categories.

Vintages in our sample range from 1926 until 2001. Only 24 observations are from vintages prior to 1960. Thirty-six observations are from the 60's and 201 from the 70's. In the estimation, we include five dummy variables for recent Bordeaux vintages noted to be outstanding. These vintages are 1982, 1989, 1990, 1995, and 2000, representing about 1/3 of the sample. Vineyard classification is a very important quality attribute in Bordeaux, dating back to 1855 when Napoleon III asked the Bordeaux Chamber of Commerce to arrange an exhibit at the Paris World Exposition. In response, the Syndicat of Courtiers, an organization of wine merchants drew up a complete list of all red wines of the Gironde specifying the class they belong up to the fifth growths. The famous list included 58 chateaux: 4 firsts, 12 seconds, 14 thirds, 11 fourths and 17 fifths, with one exception all from the Médoc. Over the years many changes have occurred to the names, owners, vineyards of the chateaux, and because of divisions in the original estates, there are now 61 chateaux on the list. The only formal revision came in 1973, when Baron de Rothschild succeeded in having Chateau Mouton elevated to first growth. In our estimation, we distinguish between second through fifth growths, while all the first growths are characterized by individual chateau dummies.

Other Bordeaux classifications systems represented in the data include the 1932 Cru Bourgeois, “le classement des Graves des vins rouges” and “le classement de St. Emilion.” In the estimation, we distinguish Cru Bourgeois and St. Emilion Premiers Grands Crus Classés by dummy variables. Note that Pomerol is the only famous sub-region in the Bordeaux area that does not have some form of a classification system. In addition to the 1855 first growths (Mouton, Margaux, Latour, Lafite, Haut-Brion), we also include dummies for other famous chateaux (Cheval Blanc, La-Mission-Haut-Brion, Pichon Comtesse de Lalande, and Leoville-Las-Cases). Moreover, because prices of Pomerol reds are inextricably linked to Parker, we add dummies for the two highest ranked chateaux (Le Pin, Pétrus). Figure 6 depicts how the major Bordeaux appellations are represented in the sample. Note that over a third of the sample is from Pauillac, home to three of the five Premiers Crus in the 1855 classification. Since regional origin (appellation) is represented as a categorical dummy variable, we chose the remaining other appellations as the base region in the estimation.

Using the data set just described in detail, we develop a hedonic pricing model to estimate implicit prices for the distinct quality attributes of Bordeaux wine, adding online specific control variables in a final step. Dependent variable is the final auction price per bottle including shipping costs. The Terroir model M1 only includes fundamental quality attributes for premium Bordeaux wine: vintage conditions, regional origin (appellations), vineyard classifications (1855/1932, St. Emilion), château reputation (brand value) and wine age. The coefficients for the outstanding vintage dummies are expected to be positive and highly significant. We also expect positive coefficients for the selected appellations and vineyard classifications as well as for château reputation (brand value) and wine age. In the Parker model M2, we add dummy variables for certain ranges of Parker ratings that buyers seem to discern as well as two additional chateau dummies (Le Pin, Pétrus from Pomerol) having a strong reputation due to Parker. We expect Parker ratings and the Pomerol chateau dummies to have a particularly strong impact on final auction prices significantly affecting the coefficients estimated in the first model. Finally, the online model M3 includes the following online-specific control variables to see if they have any significant influence on the final auction price received: seller reputation, auction length, day and time of the auction end, number of bids, initial price per bottle, a private auction dummy, and if quality information (Parker points) is stated in the offer. A priori, we cannot state any expectations on how the online-specific control variables will affect the final auction prices. However, we will compare and contrast our results with previous studies on online auction pricing behavior.

4. Results

In Table 1, we present the results of simple OLS regressions for all three models with White heteroskedasticity-consistent standard errors and covariance (t-statistics). The Terroir model M1 yields highly significant coefficients for all fundamental quality attributes with the exception of the Margaux appellation which in the sample is dominated by the Premiers Cru Chateau Margaux. Because of their importance for premium wine prices in Bordeaux, we expect that M1 is not correctly specified (which is also confirmed by the RESET test). Nevertheless, we can use M1 to infer how Parker ratings and online-specific control variables affect online auction prices.

As expected, the Parker model M2 significantly alters the estimation results. The inclusion of Parker ratings adds more than 24% to the overall goodness of fit (adjusted R^2). The dummies for Parker ratings as well as the dummies for Chateaux Le Pin and Pétrus are highly significant. A 100PP wine will receive a 150% premium relative to a wine scoring 82 or below, all other things equal. In terms of magnitude, the coefficients for the Parker rating dummies are in right order. Relative to the results of Terroir model M1, the coefficients for the outstanding five vintages are particularly affected. However, Parker also has an impact on the premiums due to vineyard classifications. The fact that fifth growths receive significantly higher premiums than third and fourth growths may also be linked to Parker who thinks that a number of fifth growths should be upgraded (e.g. Lynch-Bages) while some third and fourth growth should be downgraded (e.g. Prieure-Lichine, Marquis-de-Terme).

Note that the coefficients for the appellations should be interpreted with care. In some sense they do reflect the composition of the sample and the selected vineyard classifications. For example, since Pomerol has no classification system to convey some of the variation in auction prices, its estimated appellation coefficient (about 100%) may be somewhat higher than otherwise, but clearly it also reflects the fact that wines from that region are highly regarded in particular due to Robert Parker. Similarly, the coefficient for Graves/Pessac-Leognan can be somewhat inflated as we do not distinguish classifications within the region. The estimated coefficient for Margaux is relatively low because the sample of wines from this region is largely dominated by the Premiers Cru Chateau Margaux which carries a producer premium of about 140%. Coefficients for the selected chateau dummies largely capture their status according to the vineyard classification system. For example, all Premiers Crus (including St. Emilion's Cheval Blanc) carry estimated premiums above 70% exceeding those of lower ranked chateaux, except for Chateaux Le Pin and Pétrus from Pomerol. Moreover, notice that we estimate only about a 2% premium per year of maturation.

Let us now turn to the Online model (M3) which tests whether a list of online-specific control variables have a significant impact on final auction prices. We look at auction length, seller reputation scores, day and time of the auction end, number of bids, initial price per bottle, a private auction dummy, and if quality information (PP) is stated in the offer. First, note that relative to the Parker model (M2) the inclusion of online-specific control variables adds virtually nothing the overall goodness of fit (adjusted R^2). Figures 7 and 8 compare the virtually parallel trend of the estimated coefficients for Parker ratings and appellation between the Parker and the Online model. In contrast to many other studies, our data suggests that seller reputation (positive vs. negative user feedback) has no significant price effect. In contrast to Wood and Kauffman (2001), we are also unable to confirm a weekend effect. Auctions ending on Mondays and Saturdays command a premium up to 6% (at 1% significance) relative to the Sunday base, while Tuesdays and Wednesdays show no significant difference. As a matter of fact, it seems that buyers may get bargain deals as we observe that most auctions expire on Sunday. The missing weekend effect may be explained by lack of market depth on weekends: not enough buyers might be around to bid during the weekend when many auctions expire such that supply exceeds demand. Moreover, time of day effects are insignificant relative to the base period (21h-22h CET), except for auctions ending during the late evening (22h-23 CET) when prices are about 4% lower.

We also observe no significant picture effect in our sample. While this may seem counterintuitive, we think that it is mainly due to the negligence of many sellers to upload “real” pictures of their items for sale. Often, sellers just use a proxy picture of a wine label collected from the Internet which sometimes does not even show the correct vintage. Thus, many buyers might rather rely on (and pay a premium for) a detailed and knowledgeable description of the wine instead of a picture. However, we do observe a small auction length effect (+1%). Note that this effect could disappear as the online auction market increases in depth: more and more buyers search for deals, thus increasing shorter auctions' ability to attract bidders. Finally, we note that in line with demand analysis, the number of bottles sold in an auction exhibits a negative price impact – selling another bottle decreases the price per bottle by about 2-3%.

We also looked at a number of other indicators. First, the number of bids place in an auction showed a significant but very small impact on the final price (about 1%). Second, when the bidder identity remains unknown to non-bidders (private auctions), the final auction price is 6.8% higher on average. Third, we examine whether quality information (PP) stated in the offer has an impact on final prices, but are unable to confirm a significant information disclosure effect. Although sellers could be inclined to only reveal higher Parker ratings, we did not observe that this was more likely. It seems that buyers in the market are informed enough that disclosing verifiable quality information in the offer will not make a difference in the final auction prices received. Fourth, we estimate that the initial price per bottle contributes a significant but tiny 0.1% premium to the final auction price. In auxiliary regressions not documented in this paper we also looked at the logarithm of the page count as a measure of potential buyer interest[1] and buyer experience measured by the logarithm of the completed transaction count.[2] We estimate an elasticity of buyer interest equal to 0.28 (which is significant at the 10% level) and a non-significant elasticity of buyer experience.

[1] Note that including potential buyer interest only marginally affects the results obtained in model M3. The usable sample size is reduced by about 430 as a page count is not available for all auctions.

[2] Including buyer experience reduces the usable sample size by about 600 as for private auctions the identity of the buyer and thus the number of completed transactions remains undisclosed to non-bidders. The results of both auxiliary regressions are available from the author upon request.

5. Summary and Conclusions

This paper is relevant as it sheds some light on potential factors determining online auction prices for wine as well as on the economics of online auction prices in general. We observe that the variation in final online auction prices can be explained by the Parker model without adding online-specific control variables. The inclusion of online-specific control variables adds virtually nothing the overall goodness of fit (adjusted R^2) of the Parker model. In contrast to many other studies examining online auction prices, the seller reputation score showed no significant impact on final auction prices in our sample. Moreover, we could not find a significant weekend effect. As a matter of fact, it seems that buyers will find bargains on Sundays when most auctions expire. The missing weekend effect might be explained by lack of market depth on weekends with not enough buyers around to bid up prices during the weekend when too many auctions expire and thus supply exceeds demand. However, one would need to examine a measure of relative traffic on the relevant auction pages to confirm this hypothesis. Time of day effects are insignificant relative to the base period (21h-22h CET), except for auctions ending during the late evening (22h-23 CET).

We observe no significant picture effect, but a significant although small auction length effect (+1%). Other online specific indicators with significant but small price impacts include the number of bids place in an auction (+1%) and the private auction effect (+6.8%) higher on average. In contrast, we are unable to confirm a significant information disclosure effect (PP stated in the offer). Finally, we note that the initial price per bottle contributes a significant but tiny 0.1% premium to the final auction price and the number of bottles sold in an auction exhibits a negative price impact – selling another bottle decreases the price per bottle by about 2-3%. In light of these results, we may recommend sellers to offer *single* bottles in a 10 day *private* auction that expires on Saturdays but not late in the evening. Buyers should bid for *multiple* bottles on offer in a 1-day *public* auction that expires Sundays during the late evening.

There are a number of possible extensions to this empirical modeling effort. For example, the data set may be used to check the winner's curse hypothesis. If as it seems that auction prices are systematically below retail prices, we would hypothesize that this price difference is in part a risk premium for improper storage and handling that the buyer will accept only in form of a lower price relative to retail outlets.

Table 1: Results [Dependent variable = log(Final Price/Bottle)]

	M1: Terroir		**M2: Parker**		**M3: Online**	
Parameter	Estimate	t-Stat.[a]	Estimate	t-Stat.[a]	Estimate	t-Stat.[a]
CONSTANT	2.506*	29.86	2.407*	36.76	1.976*	6.74
100 PP			1.492*	48.11	1.442*	44.81
99-98 PP			1.379*	28.30	1.316*	26.60
97-96 PP			0.968*	32.53	0.932*	31.19
95-94 PP			0.833*	28.60	0.806*	27.96
93-92 PP			0.652*	23.26	0.619*	22.58
91-90 PP			0.482*	19.64	0.460*	19.22
89-87 PP			0.264*	10.75	0.260*	11.02
86-83 PP			0.156*	5.87	0.153*	6.02
Vintage 2000	0.653*	18.54	0.152*	6.79	0.137*	6.03
Vintage 1995	0.224*	5.56	0.071*	3.20	0.071*	3.26
Vintage 1990	0.442*	10.31	0.233*	9.75	0.205*	8.88
Vintage 1989	0.330*	7.31	0.192*	9.19	0.177*	8.20
Vintage 1982	0.607*	8.62	0.174*	6.17	0.142*	4.88
Seconds Crus	0.829*	9.19	0.569*	9.09	0.514*	8.21
Troisièmes Crus	0.515*	5.60	0.438*	6.65	0.404*	6.17
Quatrièmes Crus	0.431*	4.59	0.358*	5.57	0.328*	5.09
Cinquièmes Crus	0.536*	5.93	0.489*	7.80	0.449*	7.15
St Emilion Premier Cru	0.294*	4.27	0.418*	8.10	0.418*	8.65
Cru Bourgeois	0.348*	4.02	0.296*	4.78	0.261*	4.19
Pomerol	1.814*	16.42	1.022*	15.38	0.958*	14.39
Graves/Pessac-Léognan	0.794*	7.42	0.614*	8.72	0.576*	8.08
St. Emilion	0.894*	9.53	0.570*	8.72	0.521*	8.00
St. Estephe	0.364*	6.45	0.247*	6.34	0.252*	6.68
St. Julien	0.288*	5.26	0.211*	5.72	0.216*	5.89
Pauillac	0.299*	5.85	0.183*	5.43	0.192*	5.65
Margaux	0.048	0.80	0.131*	3.17	0.139*	3.46
Ch. Le Pin			1.762*	17.72	1.751*	17.83
Ch. Pétrus			1.627*	24.94	1.557*	24.10
Ch. Mouton	1.607*	17.13	1.408*	22.04	1.330*	20.62
Ch. Margaux	2.033*	19.27	1.404*	19.94	1.305*	18.37
Ch. Latour	1.608*	15.91	1.258*	18.20	1.175*	17.07
Ch. Lafite	1.721*	17.66	1.227*	18.58	1.152*	17.36
Ch. Cheval Blanc	0.980*	10.93	0.725*	14.01	0.682*	13.89
Ch. Palmer	0.858*	13.61	0.630*	14.01	0.600*	13.91
Ch. Haut-Brion	1.206*	15.14	0.781*	17.06	0.750*	15.95
Ch. La Mission-Haut-Brion	1.026*	9.74	0.643*	12.00	0.606*	11.27
Ch. Pichon-Comtesse	0.305*	5.70	0.216*	6.34	0.219*	6.51
Ch. Léoville-Las-Cases	0.368*	7.70	0.196*	6.93	0.195*	7.18
Wine Age	0.018*	10.18	0.019*	16.13	0.017*	15.36
Number of Bottles	-0.033*	-7.97	-0.022*	-8.89	-0.028*	-10.85

[Table continued on the following page].

Table 1 Con't: Results [Dependent variable = log(Final Price/Bottle)]

Parameter	Estimate	t-Stat.[a]	Estimate	t-Stat.[a]	Estimate	t-Stat.[a]
Seller Reputation					0.003	1.15
Auction Length					0.010*	4.62
Monday					0.052*	3.18
Tuesday					0.028	1.60
Wednesday					0.027	1.61
Thursday					0.042†	2.24
Friday					0.043†	2.02
Saturday					0.062*	3.34
Picture					-0.018	-1.51
Number of Bids					0.010*	8.86
Private Auction					0.068*	5.47
PP disclosed					-0.009	-0.68
Time 23p-08a					-0.002	-0.06
Time 08a-12p					-0.010	-0.38
Time 12p-17p					-0.015	-0.84
Time 17-18					-0.009	-0.42
Time 18-19					-0.035‡	-1.77
Time 19-20					-0.002	-0.09
Time 20-21					-0.014	-0.72
Time 22-23					-0.042†	-1.97
Initial Price/Bottle					0.001*	6.81
R^2 (adj. R^2)	0.664	(0.659)	0.906	(0.905)	0.914	(0.912)
F-Statistic	138.60		506.01		361.71	
RESET-test	51.0		13.7		16.5	

Note: ‡, †, and * indicate significance at the 10%, 5%, and 1% level, respectively.
Red indicates no significance. [a] Heteroskedasticity consistent.

Figure 1: Distribution of Parker Ratings

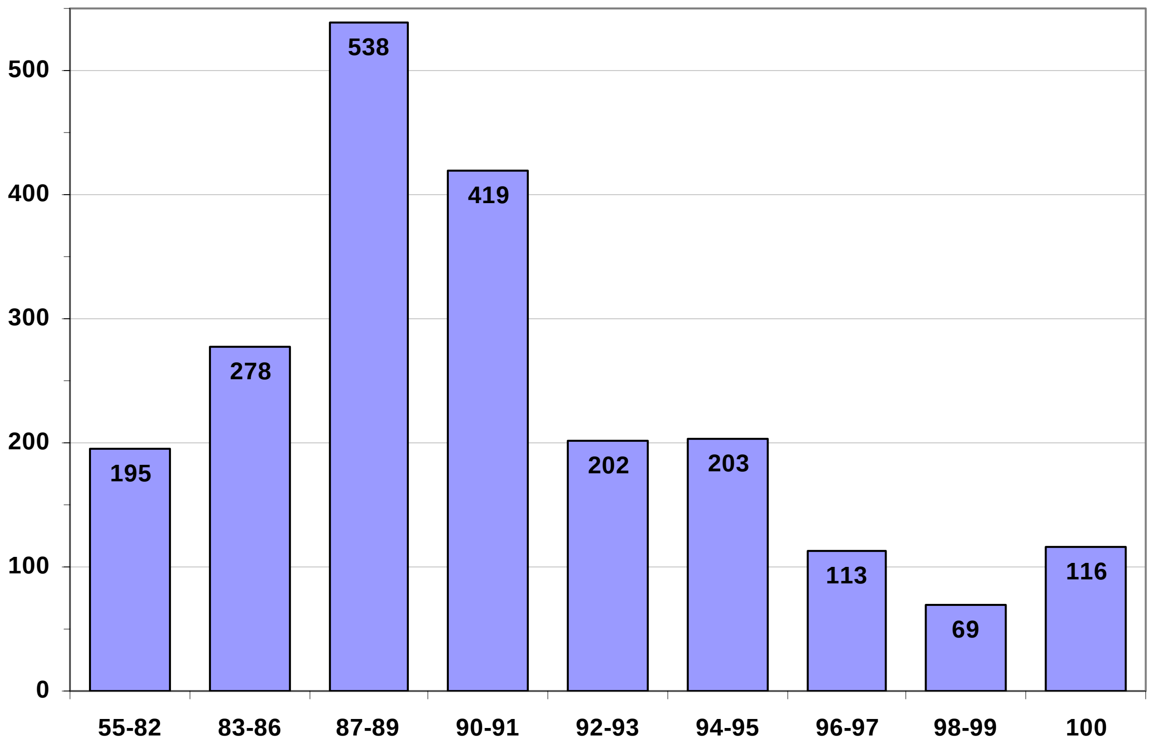


Figure 2: Lot Size (# of Bottles)

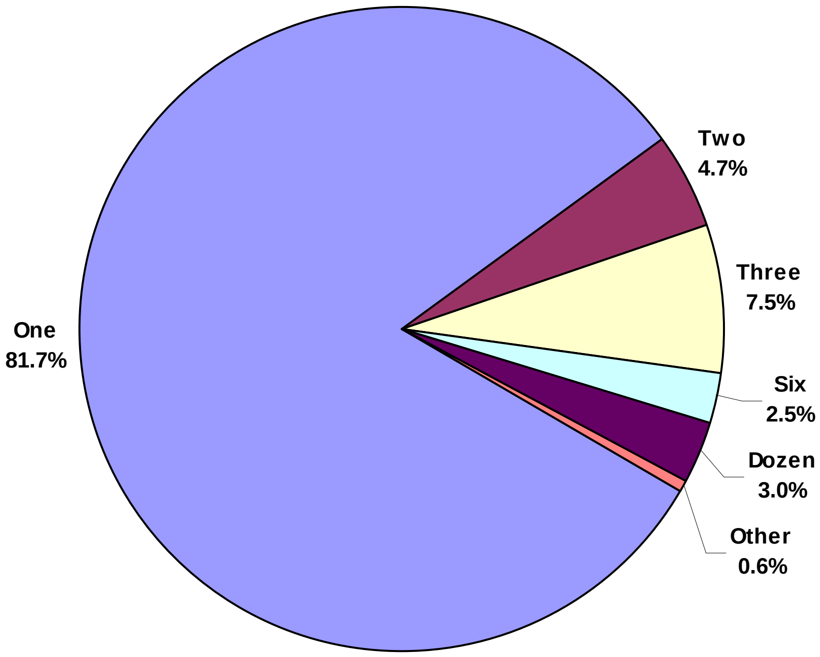


Figure 3: Auction Length

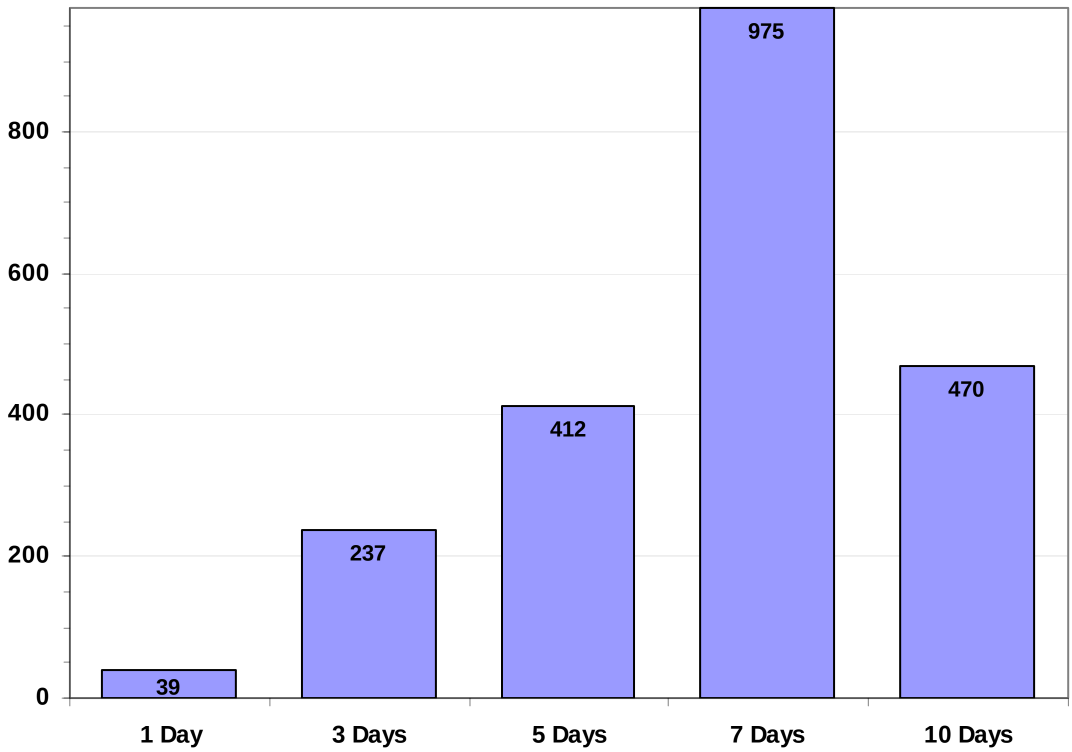


Figure 4: Auction End Day

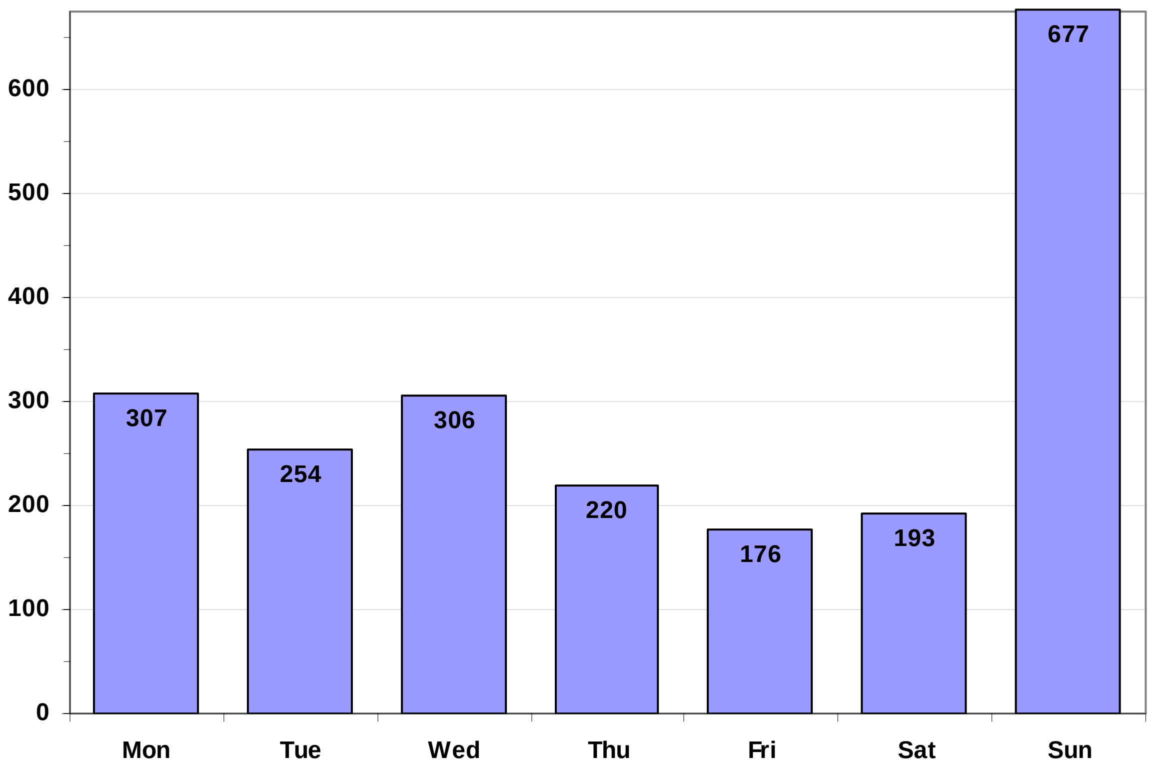


Figure 5: Auction Ending Time

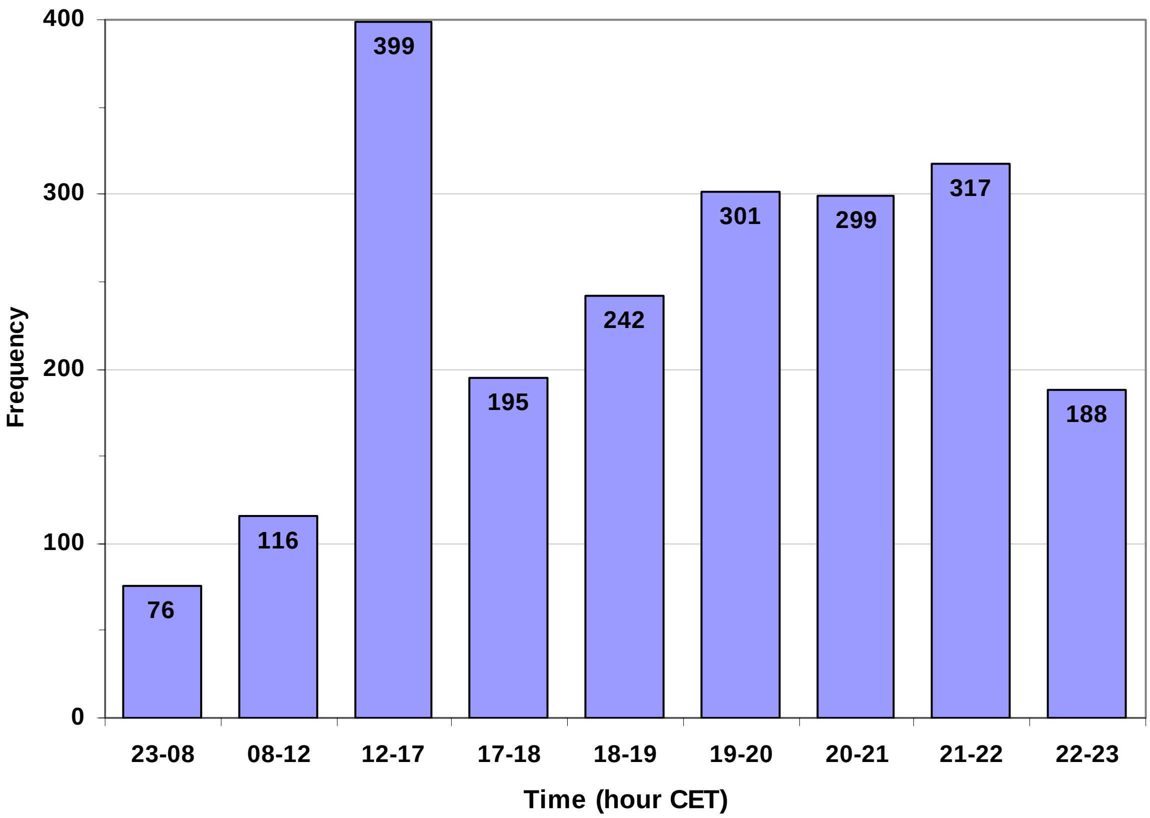


Figure 6: Major Bordeaux Appellations

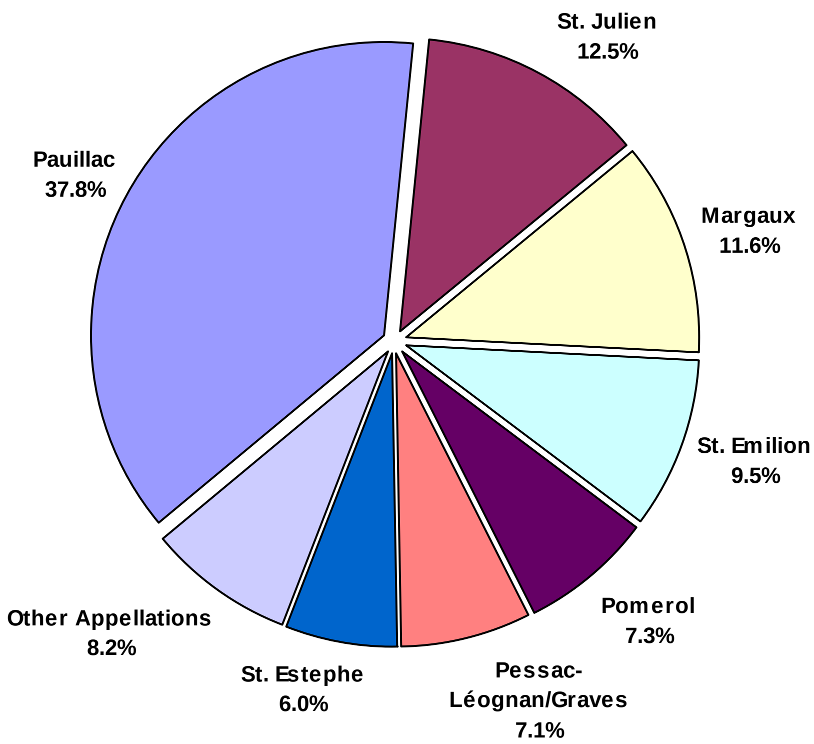


Figure 7: Estimated Parker Coefficients

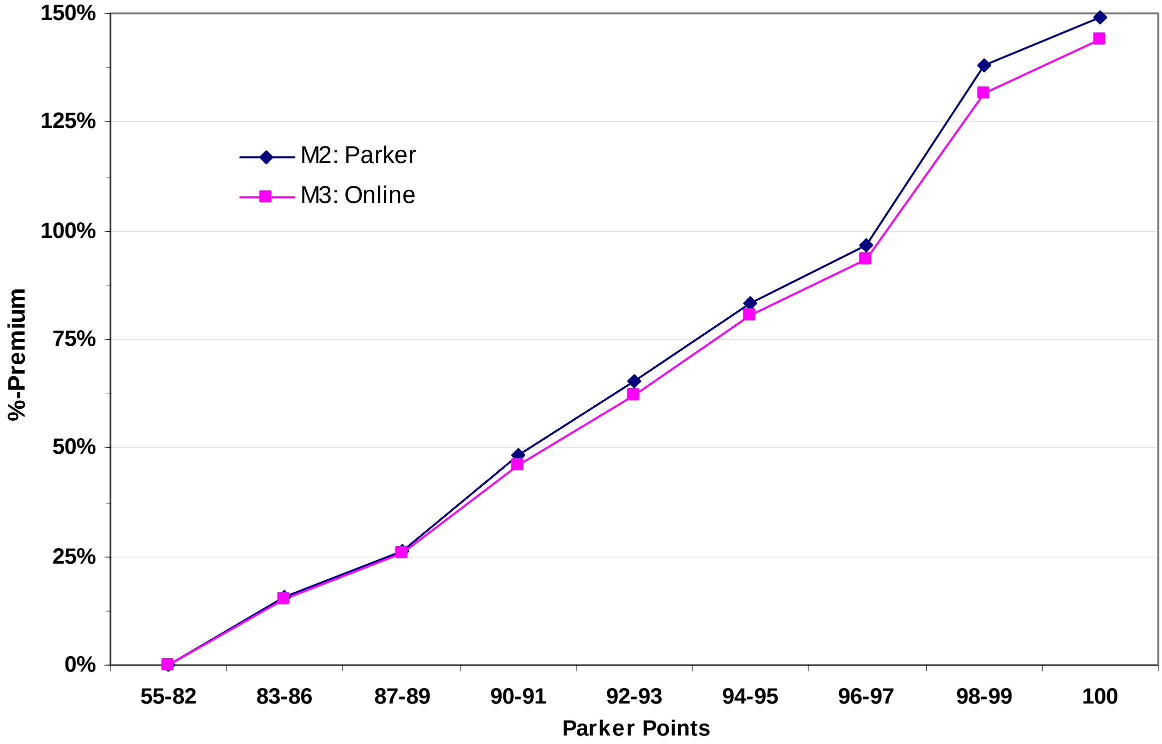
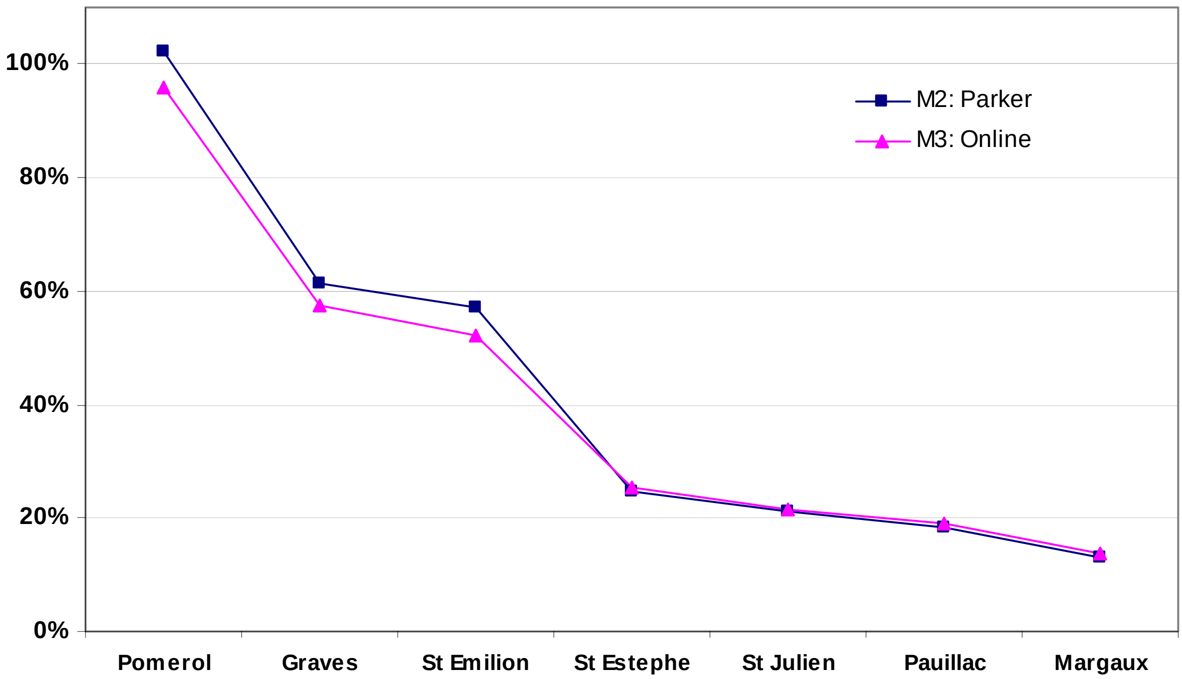


Figure 8: Estimated Regional Premiums



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