

Puzzles: A Look at the Declining Price Anomaly

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December 12, 2015

Abstract

We look at wine auction data from 2014-2015 and test if the declining price anomaly is still present. We will investigate what factors have an affect on the winning bid price in the sequential period.

JEL Classification: D44

1 Introduction

Neoclassical economic theory makes straightforward predictions for prices. If two homogeneous objects are to sold, one subsequent to the other, to risk neutral bidders, equilibrium arguments suggest that on average they should sell at the same price. Otherwise, it would be to the bidders' advantage to bid in the low price period. Weber (1983) proved if one considers a sequential auction with homogeneous objects, risk neutral bidders, and independent private values, then the expected price of the first auction should be equal to the subsequent auctions. Moreover, Milgrom and Weber (1982) had shown, with the standard affiliation value risk neutral model that the expected price in sequential auctions should rise over time. This result arises because early auctions reveal information of the object's value, and thus there is a decrease in the tendency of winner's to overpay (winner's curse) in sequential auctions. However, Ashenfelter (1989), in a novelesque fashion, discovered that prices of homogeneous wine bottles had a tendency to decrease (compared to increase). Furthermore, he analyzed the price data at four distinct auction houses and discovered that as the auction progressed there were multiple cases of the prices decreasing (hence why it is referred as the afternoon effect). Ashenfelter, referred to as the "declining price anomaly".

Our goal will be to verify if a decline in price is still present in wine auctions. A rather ambitious project would be to attempt to explain the price anomaly. Unfortunately, we will not attempt to do so¹. Instead we wish to investigate the effect of the signals (estimates, order, vintage year, etc) on the price of the

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1. Due to time constraints.

sequential period’s hammer (bid) price. We will look at the data from multiple auctions from Hart Davis Hart’s auction house, ranging from Hart Davis Hart’s Auction 1402 (8th of February, 2015) to Hart Davis Hart’s Auction 1510 (October 30-31, 2015). To verify if there is a decline in prices, we will follow the procedure outlined by Ashenfelter. We will compare the price in the second (or more if available) auction to the first and observe if the ratio.

2 Literature Overview

Ashenfelter (1989) identified a declining price anomaly in sequential wine auctions. From this point forward considerable theoretical and empirical research has been conducted to identify and explain the anomaly. As such, we will present the literature review in two sections: empirical and theoretical. For the theoretical models, we will assume risk-averse bidders, stochastic equivalent objects, sequential auctions, and uncertain supply.

2.1 Empirical

The purpose of the empirical research is to identify the existence of an anomaly in prices. As mentioned before, the theoretical model of Weber (1982) suggests that prices in sequential auctions should experience an increasing trend. However, numerous empirical studies (Ashenfelter 1989²; Ashenfelter and Genesove 1992³; Ashenfelter and Graddy 2010⁴; Hui and Ziyu 2014⁵; Kooreman and Haan 2006⁶; Thiel and Petry 1995⁷) suggest that a large portion of auctions experience a decline in prices. More so, Ashenfelter and Graddy (2003) find that the literature is rich with papers on the declining price anomaly. Before we continue we would like to impress that the evidence does not suggest that prices will always fall; the data shows that prices are more likely to fall than to increase. However, Raviv (2006) found evidence of increasing prices in his study of used cars auctions. Moreover, Trifunovic (2014) notes that the 1997 auction of Israeli cable TV licenses is the earliest evidence of increasing prices in sequential auctions.

2.1.1 Wine Auctions and the Beginnings

Ashenfelter (1989) provided the first evidence of declining price anomaly. Ashenfelter discussed that his initial intuition was that each object auctioned should be independent of the sequential one. To this, Ashenfelter expected the price in the second auction to be the same or at most similar in value. Much to

2. Wine and painting auctions
3. Real estate auctions, specifically apartments
4. Art auctions
5. Chinese real estate, specifically houses
6. Used cars auctions
7. Rare stamp auctions

his surprise the price did not always followed his initial intuition. In his study, Ashenfelter examined wine auctions to determine the probability that the price remain the same or changed. Ashenfelter found empirical evidence that the most likely state, to little surprise, is that the price will remain constant. What is more, Ashenfelter found that it was twice more likely for the price to decrease than it was to increase.

Ashenfelter mentions that auction houses, specifically wine auction houses, are actively changing their behavior⁸ to use the anomaly to their benefit. Ginsburgh (1998) explored this idea: the role of the auction house and its effects on bidders. Ginsburgh studied four effects: the option effect, the decreasing quality effect, the varying size and quantity effect, and the absentee bidder effect. The decreasing quality effects came from a rule at Christie's to order the sale of lots by decreasing quality. A decline in price is warranted due to first auction objects being more desirable than the sequential objects. The varying size and quantity effect is as follows: auction houses try to hide the decline in prices in latter auctions by auctioning lots with larger quantities of wine. More so, larger bottles (magnum, jeroboam, etc.) are rare and viewed "better" for the wine. Additionally, since later lots have more bottles, "the price per bottle falls as the marginal utility of the additional bottles would be less than that of the initial bottles." (Ashta 2006, 55). As for the absentee bidder effect, Ginsburgh found that 82% of the lots sold went to absentees. From this, it is evident that the auction house should sell the absentee bids in decreasing value since absentees are not there to pick up the signals about the value of the objects and thus alter their bids in sequential auctions. Lastly, the option effect is the option to let the winning bidder take more lots at the price they bid. This leads to the reasoning that the bidders' price includes a premium for risk reduction. To conclude, McAfee and Vincent (1993)⁹ attempted to explain the declining price anomaly through the use of risk aversion and a risk premium¹⁰. McAfee and Vincent found that the average price in the second auction¹¹ of Christie's of Chicago was 1.4% lower than in the first auction. Thus confirming the presence of the declining price anomaly.

2.1.2 Second Auctions for homogeneous or quasi-homogeneous objects

The two papers mentioned in the previous sections paved a path for much of the empirical literature that followed on declining price anomaly. Wine auctions are ideal for constructing a test for declining price anomaly since each object is extremely similar to each other. This allows a direct test without the unease that a possible characteristic may bias the results. Unfortunately, very few objects are homogeneous. Ashenfelter and Genesove (1994) studied auctions for real es-

8. For more on the role of the auction house on sequential auction refer to Picci and Scorcu (2003)

9. More on this in the theoretical literature review

10. Ashenfelter (1989) was the first to conjecture this

11. For the data collected on the sale of wines in June 23, 1990

tate. The study focused on the auctions of apartments. While it is true that no two apartments are the same (similarly wine), the apartments were auctioned in a manner that allowed them to be treated as homogeneous. Ashenfelter and Genesove looked at data where the apartment units were "pooled" together. When the first bidding ends, the highest bidder has the right to choose the unit he or she desires then the bidding restarts and the process repeats. Effectively, the earliest bidder has the right to select a superior product, and therefore naturally pays a higher price for it. This framework of pooled objects auctions innately has a price decline; however, if prices decline more than would be expected, then there is evidence for declining price anomaly. Ashenfelter and Genesove found that the average price decline was 0.27% from one auction to the next, up to 10% from the first auction to the last. Ashenfelter and Genesove attribute most of the declining price to the pooled auction framework. Moreover, the authors infer that the earlier bidders paid a premium¹² for the units sold.

2.1.3 Additional examples of the price anomaly in sequential auctions

Thiel and Petry (1995) found evidence for declining price anomaly in sequential second price auctions in the sale of rare stamp between 1923 and 1937. Berg, Ours, and Pradhan (2001) found evidence for declining price anomaly in rose auctions. Ashenfelter and Graddy (2010) found evidence of price anomaly in art auctions. In addition, Raviv (2006) and Kooreman and Haan (2006) both explain methods for measuring price anomalies in used car auctions.

2.2 Theoretical

The previous empirical results have motivated the search for a model that explains the declining price anomaly. McAfee and Vincent (1993) provide a theoretical model that explains declining prices using risk aversion and a risk premium. They argue if bidders are risk averse and that the expected price in the first auctions is equal to the expected price in the second auction plus a premium for the risk uncertainty in the second auction then the expected price in the first auction is greater than the expected price in the second auction. However, for this argument to hold, McAfee and Vincent assume that bidders have non-decreasing absolute risk aversion. On the contrary, if bidders have decreasing absolute risk then there is no equilibrium in their model. This assumption is justifiable with the data that McAfee and Vincent have. However, intuitively, this does not make sense; a rational thinker would want to reduce their risk.

Engelbrecht-Wiggans (1994) considered a model where each of the objects were stochastic equivalent. That is, the value of each unit is a random variable from a random jointly distributed probability function. In this model, bidders

12. Which is in line with McAfee and Vincent (1993).

with single object demand obtain information before each auction about the auctioned object. As the supply becomes scarce, relative to demand, bidders will bid more aggressively, which will yield an increasing price trend. Conversely, since bidders have a single object demand, it forces declining prices and thus a decreasing price trend. Engelbrecht-Wiggans showed that if we consider an exponential distribution function, then prices would follow the first case. Alternatively, if we considered a uniform distribution, then the auction will have a decreasing price trend. While there are multiple papers that attempt to explain the anomaly (Bernhardt and Scoones (1994), Weber (1983), Milgrom and Weber (1982), Raviv (2006)) all fall short of fully explaining. They do succeed in showing that under specific cases their theoretical framework works.

3 Data

Auction data for 2014-2015 was collected from the Hart Davis Hart Wine Co. (HDH) website¹³. Table 1 contains the auctions that we used in this paper.

Table 1: Auctions

Auction	Date
Auction 1402	8th of February, 2014
Auction 1410	31st of October and 1st of November, 2014
Auction 1412	December 12-13, 2014
Auction 1502	February 13-14, 2015
Auction 1503	28 of March, 2015
Auction 1505	May 15-16, 2015
Auction 1506	June 26-27, 2015
Auction 1509	September 18-19, 2015
Auction 1510	October 30-31, 2015

Before the auction, HDH releases a catalogue of the lots that are to be sold. In the catalogue, you can find the low and high estimates for the lot as well as the quantity of wine bottles in the lot. You can bid in person¹⁴ or via the Internet. You can bid on a specific lot(s) starting three weeks before the day of the auction. If you are not able to attend an auction in person, you can utilize absentee and live bids online¹⁵ (or on their mobile app). When placing a bid online, you can set a maximum with bid increments¹⁶. Your bid will be

13. "Past Auctions: Auction: Hart Davis Hart Wine Co." Hart Davis Hart Wine Co. Accessed November 26, 2015. <http://www.hdhwine.com/auction-past-auctions>.

14. Usually in the True Restaurant located 676 North St. Clair Street, Chicago, IL 60611. Attendance to the auction is open to the public and free of charge. However you can make a reservation for lunch for \$75.

15. auction.hdhwine.com

16. The increments increase depending on price range, e.g. if the bid is up to \$1000 the increments are by \$50, whereas if the bid is up to \$500 the increments range from \$20 to \$50. However, if the bid is between \$5000 and \$10000 the increments are by \$500. The maximum

executed at the lowest possible price relative to competing bids. That is, if your bid is \$1200 and the only other bid is \$900, you will win the lot at 950. On the day of the auction, bidders can follow the auction in the saleroom, watch a video feed of the auction, and bid against the room (in real time).

Once the auction is completed, HDH’s website releases a pdf file containing: lot number, quantity, description (vintage year and name), estimate range, hammer price (winning bid), and the aggregate price (final price after fees). Table 2 defines the variables found in the data. The reason we choose this data is that, unlike most, it had the variables we were interested in a format we could use. However, one drawback of the data is that we do not know the nature of the winning bid. To clarify, we do not know if the winning bid was from an absentee or from a bidder in real time.

Table 2: Variables in the Data

Variables	Description
Lot	This is the lot number assigned by the auction house corresponding to the order that particular lot will be auctioned.
Qty	The quantity of each wine (same size and model) in the lot.
Year	The year that particular wine was produced (vintage year).
Low Estimate	The auction house’s lowest expected value for the lot.
High Estimate	The auction house’s highest expected value for the lot.
Hammer Price	The highest (winning) bid when the hammer went down.
Aggregate Price	The auction house’s net sale for the lot. This includes additional fees like commission.

We modified the data¹⁷ to include the following parameters: Size, Order, Low Estimate per 750mL, High Estimate per 750mL, Hammer Price per 750mL at time t , Hammer Price per 750mL at time $t + 1$. We chose to have our prices relative to 750mL, as it is the standard size for wine. We did this since we are comparing the lots that contain the same wine, but the lots may contain different sizes and quantities. This way is our comparison is much more straightforward as we are getting the prices per unit quantity. Table 3 describes what these variables are and/or how we constructed them.

increments come for when the bid is greater than \$100000 where the increments are of \$10000

17. With the use of multiple logical statements.

Table 3: Created Variables

Variables	Description
Size	This is the size of the bottle in mL. The data specified if the bottle was not of the standard size (750mL).
Order	We assigned this number to the order identical wine lots were auctioned. Namely, the same vintage year and name. It does not matter if they are different quantities or sizes. It starts with zero for the first wine lot in the sequence and it goes up from there for each sequential wine lot.
Low Estimate per 750mL	This is defined as the ratio of <i>Low Estimate</i> * 750mL to <i>Qty</i> * <i>Size</i> . As the name implies, this quantity gives us the low estimate for every 750mL.
High Estimate per 750mL	This is defined as the ratio of <i>High Estimate</i> * 750mL to <i>Qty</i> * <i>Size</i> . As the name implies, this quantity gives us the high estimate for every 750mL.
Hammer Price per 750mL [$t + 1$]	This is defined as the ratio of <i>Hammer Price</i> * 750mL to <i>Qty</i> * <i>Size</i> . As the name implies, this quantity gives us the hammer price for every 750mL at time $t + 1$.
Hammer Price per 750mL [t]	This variable is created from the previous variable, however lagged one time period. Additionally, we remove the values associated to when the order is zero.

3.1 Statistics

Table 4 and Table 5 gives summary statistics for the data that we collected. The minimum and maximum quantities, sizes, low estimates, high estimates, hammer prices, and aggregate prices. Observe the following: the mean hammer price is less than the mean high estimate (except for Auction 1402). This led us to believe that the high estimate should play a role in in the bid price, however we find that this is not the case.

Table 6 will give us the least order, how many times a lot with the same wine shows up. Table 6 should read as follows. In auction 1402 there were 222 cases where at least two lots containing the same wine were sold sequentially. From this table, the reader should be able to find how lots were sold exactly n times. To do this, consider the following: exactly n is the same as at least n minus at least $n + 1$. Ergo, subtract the frequency you want from its subsequent frequency. For instance, consider Auction 1402. If we want to find out how many lots were sold exactly 5 times, we would subtract $37 - 25 = 12$.

Table 4: Descriptive Statistics of the Different Auctions, part 1

	1402	1410	1412	1502	1503
Min Quantity	1	1	1	1	1
Max Quantity	24	24	24	12	12
Mean Quantity	10.22065 (3.794336)	9.962635 (3.83064)	9.246429 (4.38880)	9.03386 (3.89235)	5.554348 (4.14417)
Min Size	375	375	375	750	750
Max Size	6000	18000	7000	3000	6000
Mean Size	904.8387 (816.5564)	1174.164 (1505.41)	1311.607 (1717.08)	775.395 (221.3278)	988.4511 (706.650)
Min Low Estimate	300	250	250	220	250
Max Low Estimate	50000	40000	26000	15000	28000
Mean Low Estimate	4326.232 (5648.692)	2762.783 (3096.89)	2922.158 (4431.73)	2387.946 (2326.94)	2666.548 (3920.1)
Min High Estimate	450	380	380	320	380
Max High Estimate	75000	60000	38000	22000	42000
Mean High Estimate	6441.458 (8446.287)	4141.622 (4645.674)	4358.022 (6604.866)	3581.151 (3499.965)	3985.589 (5831.051)
Min Hammer Price	500	250	280	300	280
Max Hammer Price	95000	45000	32000	24000	32000
Mean Hammer Price	6735.097 (10037.64)	3133.147 (3433.49)	3428.849 (5265.825)	2599.007 (2830.43)	3310.571 (4693.26)
Min Aggregate Price	597.5	298.75	334.6	358.5	334.6
Max Aggregate Price	113525	53775	38240	28680	38240
Mean Aggregate Price	8048.441 (11994.97)	3744.11 (4103.025)	4097.474 (6292.661)	3105.813 (3382.36)	3956.132 (5608.4)

NOTE: Standard errors are in parenthesis.

Table 5: Descriptive Statistics of the Different Auctions, part 2

	1505	1506	1509	1510
Min Quantity	1	1	1	1
Max Quantity	24	12	16	24
Mean Quantity	6.171569 (4.27834)	9.957806 (3.3086)	7.139219 (4.318246)	8.141337 (4.41994)
Min Size	375	750	375	375
Max Size	12000	3000	6000	18000
Mean Size	1043.199 (1142.465)	800.6329 (253.3036)	990.0255 (787.087)	1428.666 (1685.83)
Min Low Estimate	80	300	120	150
Max Low Estimate	32000	20000	40000	32000
Mean Low Estimate	1768.505 (2466.397)	2397.637 (3482.88)	2629.1 (4241.38)	2583.207 (3193.347)
Min High Estimate	120	450	180	220
Max High Estimate	48000	30000	60000	48000
Mean High Estimate	2645.159 (3686.846)	3596.624 (5224.331)	3924.839 (6322.996)	3863.541 (4770.03)
Min Hammer Price	150	350	200	220
Max Hammer Price	32000	20000	35000	32000
Mean Hammer Price	2103.162 (2584.81)	2712.869 (3725.20)	2939.032 (4230.55)	3021.482 (3620.036)
Min Aggregate Price	179.25	418.25	239	262.9
Max Aggregate Price	38240	23900	41825	38240
Mean Aggregate Price	3088.854 (2513.27)	3241.879 (4451.62)	3512.144 (5055.51)	3610.671 (3610.671)

NOTE: Standard errors are in parenthesis.

Table 6: Least Number of Sequential Lots Sold

Frequency	1402	1410	1412	1502	1503	1505	1506	1509	1510
02	222	269	117	156	159	289	89	238	349
03	120	164	28	62	36	117	27	78	210
04	73	113	10	27	11	57	15	26	140
05	37	72	4	20	2	32	8	7	94
06	25	40	2	8	1	21	3	2	59
07	20	26	0	7	0	7	3	0	40
08	16	19		3		3	1		24
09	10	15		2		1	1		16
10	6	14		2		0	1		10
11	4	9		0			0		7
12	3	2							5
13	2	1							5
14	2	1							2
15	2	1							1
16	1	1							1
17	1	0							1
18	1								1
19	1								1
20	1								1
21	1								0
22	1								
23	1								
24	1								
25	1								
26	1								
27	0								

NOTE: The table should read as follows. In auction 1402 there were 222 cases where at least two lots containing the same wine were sold sequentially. From this table, the reader should be able to find how lots were sold exactly n times. To do this, consider the following: exactly n is the same as at least n minus at least $n + 1$. Ergo, subtract the frequency you want from its subsequent frequency. If there is no value for $n + 1$ assume it is zero.

4 Empirical Model

There are multiple ways to test for the declining price anomaly. One of them is by examining winning bids of an auction of identical objects, as it is in this case. We compare the ratio of the hammer price in the second time period to the hammer price in the first time period. Furthermore, we compare the times price rose, declined, and stayed constant. However, we can also demonstrate the anomaly by examining sequential auctions of randomly assigned objects.

The random assignment implies no correlation between the order in which the object is auctioned and its estimated value. In this case, we can regress the winning bid (or log of winning bid) on a set of covariates along with the order in which the items were auctioned off¹⁸. We will do the following regression for each auction

$$\log Bid750_{t+1} = \alpha + \beta_0 Size_{t+1} + \beta_1 HighEstimate750_{t+1} + \beta_3 Qty_{t+1} + \beta_4 Year_{t+1} + \beta_2 LowEstimate750_{t+1} + \beta_5 Order_{t+1} + \epsilon_t.$$

In this regression, we would expect the coefficient of *Order* to be negative if the declining price anomaly is present. That is because if present, the prices in later stages should decline compared to the prices in the earlier stages. The coefficient of log of the low estimate per 750ml should be positive since this is the least log price the Auction House is expected to sell. On the other hand, the coefficient of log of the high estimate per 750ml should be negative since this is the most log price the Auction House should expect to receive. This should potentially dissuade certain bidders from bidding too high, unless they mistrust the estimates or value the object higher. Table 6 shows us that it is possible that the value of *Order* is not exogenous. It seems that it is an outcome of the behavior of the auction house and may depend on realized prices in earlier auctions. Furthermore, we will investigate if vintage year has an impact on the decline price anomaly.

Additionally, we wish to investigate the following equation,

$$\begin{aligned} Bid750_{t+1} = & \alpha + \beta_0 Bid750_t + \beta_1 Size_{t+1} + \beta_2 HighEstimate750_{t+1} \\ & + \beta_3 LowEstimate750_{t+1} + \beta_4 Qty_{t+1} + u + \epsilon_{t+1} \end{aligned} \quad (1)$$

for the pooled data, where $Bid750_{t+1}$ is the hammer price per 750ml at time $t + 1$, $Bid750_t$ is the hammer price per 750ml at time t , $Size_{t+1}$ is the size of the lot at time $t + 1$, $HighEstimate750_{t+1}$ is the high estimate per 750ml at time $t + 1$, $LowEstimate750_{t+1}$ is the low estimate per 750ml at time $t + 1$, and Qty_{t+1} is the quantity in the lot at time $t + 1$. From Table 6, it should be apparent that we have plenty of data to run this model for two lag periods. The bid price for a given sequential auction is not typically independent i.e. we have lag variables. This mean we have to deal with fixed effects. We will first difference (1) and use only two lag periods.

5 Results

In this section we will discuss results. We follow Ashenfelter (1989) procedure to deduce if there is a declining price anomaly by comparing the instances the hammer price in the second auction to the first. Table 7 has the distribution of

18. Raviv (2006) used this method for quasi-homogeneous objects

the price pattern for identical wines that were sold in the same auction.

Table 7: Distribution of Price Patterns for Identical Wines Sold in the Same Auction

	1402	1410	1412	1502	1503	1505	1506	1509	1510
Price Decline	215	269	60	83	36	249	68	109	367
Price Same	157	294	62	28	43	14	54	60	214
Price Rose	177	181	39	113	83	212	27	99	318

Mean hammer price of the pooled data at time $t + 1$: 491.9336 (14.34497)

Mean hammer price of the pooled data at time t : 504.231 (13.88092)

Instances that price decreased: 1590

Instances that price increased: 1227

Instances that price remained constant: 880

From Table 7 it is apparent that the declining price anomaly present. We see that 43% of the time the bid in the sequential period decreases. Moreover, we see that the ratio of the mean hammer price for the pooled data (second price to first) is 0.975604, which implies that on average the price decreased by 2.44%.

Table 8 and Table 9 give the results of the preliminary regression analysis. The model we are estimating is,

$$\begin{aligned} \log Bid750 = & \alpha + \beta_0 Size + \beta_1 \log HE750 + \beta_4 Year + \beta_5 Order \\ & + \beta_2 \log LE750 + \beta_3 Qty + \epsilon, \end{aligned}$$

where $Bid750$ is the hammer price, $Size$ is the size of each wine bottle in the lot, $HE750$ is the high estimate per 750ml of the lot, $LE750$ is the low estimate per 750ml of the lot, $Year$ is the vintage year of the wine, $Order$ is the sequential order of homogeneous lots, Qty is the quantity of wine in a lot.

Table 8: OLS for the log of the Hammer Price, part 1

	1402	1410	1412	1502	1503	1505
α	13.847** (2.8901)	-.4345565 (.9628847)	3.014915 (2.440319)	8.394662 (9.339531)	3.31868 (3.755713)	-.7215162 (2.220723)
$\log LE750$	1.490132** (.4134828)	.894185** (.1657674)	.7281679 (.4653085)	2.636804** (1.333185)	1.577883** (.4323559)	.6886199** (.3154708)
$\log HE750$	-.5378023 (.4143161)	.0777921 (.1654235)	.2811474 (.4657491)	-2.019529 (1.329262)	-.5881055 (.4339479)	.2626936 (.315506)
$Year$	-.0065387** (.0014566)	.0003783 (.0004834)	-.0015229 (.0012084)	-.0020801 (.0046519)	-.0013798 (.0018616)	.0006115 (.0011108)
$Order$	-.0106828** (.0042326)	-.0046856** (.0018065)	-.0191176 (.0127889)	-.0127052 (.026501)	-.0560911** (.0129148)	-.006861 (.0074932)
$Size$.0000409** (.0000183)	1.72e-06 (3.78e-06)	.0000195* (.0000117)	-.0004666** (.0001652)	.0000155 (.0000172)	-.000018** (.0024738)
Qty	7.40e-06 (.0033788)	-.0055887** (.0016308)	.0005182 (.0035909)	-.1054106** (.0118452)	-.0067246* (.0035555)	-.0178523** (.0024738)
Observations	770	1016	263	426	364	784
R^2	0.9346	0.9799	0.9749	0.6369	0.9747	0.9657

NOTE: Standard errors are in parenthesis.

** denotes a variable that is significant at the 5% level.

* denotes a variable that is significant at the 10% level.

We are estimating:

$$\log Bid750 = \alpha + \beta_0 Size + \beta_1 \log HE750 + \beta_4 Year + \beta_5 Order + \beta_2 \log LE750 + \beta_3 Qty + \epsilon.$$

Table 9: OLS for the log of the Hammer Price, part 2

	1506	1509	1510
α	-2.834537 (2.491972)	-.8501842 (1.642908)	1.390938 (1.113616)
$\log LE750$.8867682** (.3668314)	.3598205 (.3322419)	.7541457** (.2002937)
$\log HE750$.0906804 (.3675826)	.6097872* (.3331538)	.2244649 (.2005299)
$Year$.0015765 (.0012292)	.0004824 (.0008218)	-.0005656 (.0005562)
$Order$	-.0090767 (.0073126)	-.024511** (.010189)	-.0075125** (.0029888)
$Size$	-5.92e-06 (.0000439)	.0000133 (.0000108)	-4.60e-06 (4.02e-06)
Qty	-.009094** (.0042622)	-.0042898* (.0025378)	-.0061742** (.0015616)
Observations	232	463	1290
R^2	0.9823	0.9793	0.9692

NOTE: Standard errors are in parenthesis.

** denotes a variable that is significant at the 5% level.

* denotes a variable that is significant at the 10% level.

At a first glance, it seems that vintage year is not significant since only in Auction 1402 is it significantly different from zero. However, this might be due to under-sampling. Next, log of the low estimate per 750 ml was significant save for Auction 1412 and Auction 1509 and surprisingly, log of the high estimate per 750 ml was not significant in any of the auctions. We would think that the high estimate might have an impact on the bid price as it gives a notion of the maximum expected price the Auction House would be willing to pay for. We would like to note the sign of the order coefficient is negative in every auction. This leads us to the conclusion that as the order increases the log of the hammer price decreases in each auction. However, the magnitude of *Order* was not always significant.

We investigate if vintage year and the declining price anomaly are related. For this we, once more, regress

$$\log Bid750_{t+1} = \alpha + \beta_0 Size_{t+1} + \beta_1 HighEstimate750_{t+1} + \beta_4 Year_{t+1} + \beta_5 Order_{t+1} + \beta_2 LowEstimate750_{t+1} + \beta_3 Qty_{t+1} + \epsilon_t,$$

however, we will pool all the data. Table 10 and Table 11 give the results of the regression.

Table 10: OLS for the log of the Hammer Price Controlling for Vintage Year, part 1

	<i>Year</i> \in [1949, 1969]		<i>Year</i> \in [1970, 1989]	
α	71.1046** (17.28309)	1.751128 (.6389533)	30.29318** (3.961251)	.7385948** (.1742902)
$\log LE750$	-1.246631 (1.227226)	.2668026 (1.274786)	1.305716** (.3817852)	1.336052** (.3890007)
$\log HE750$	2.027633 (1.233255)	.4891806 (1.279497)	-.3652212 (.3821864)	-.1856449 (.1761986)
<i>Year</i>	-.0357217** (.0088969)		-.0149009** (.0019953)	
<i>Order</i>	.0238371 (.0238962)	.0119022 (.0258805)	.0059685 (.0042758)	.004218 (.0043503)
<i>Size</i>	.0000475 (.0000421)	.0000506 (.000046)	-.0000167 (.0000114)	-6.96e-06 (.0000116)
<i>Qty</i>	-.0299623** (.0086383)	-.0330063** (.0093925)	-.0004459 (.0026541)	-.001278 (.002702)
Observations	85	85	1437	1437
R^2	0.8925	0.8702	0.8904	0.8861

NOTE: Standard errors are in parenthesis.

** denotes a variable that is significant at the 5% level.

Table 11: OLS for the log of the Hammer Price Controlling for Vintage Year, part 2

<i>Year</i> $\in [1990, 2014]$		
α	7.002864** (1.503758)	.5716184** (.0804137)
$\log LE750$	1.145549** (.0013126)	1.157437** (.1764179)
$\log HE750$	-.1856449 (3.99e-06)	-.1946674 (.1765601)
<i>Year</i>	-.0032056** (.0007485)	
<i>Order</i>	-.0026775 (.0026356)	-.0038746 (.0026263)
<i>Size</i>	-.0000129** (3.99e-06)	-.0000129** (4.00e-06)
<i>Qty</i>	-.0126254** (.0013126)	-.0125037** (.0013151)
Observations	4086	4086
R^2	0.9363	0.9360

NOTE: Standard errors are in parenthesis.

** denotes a variable that is significant at the 5% level.

We now run a regression with first difference of (1). Namely,

$$\begin{aligned}\Delta Bid750_{t+1} = & \beta_0 \Delta Bid750_t + \beta_1 \Delta Size_{t+1} + \beta_2 \Delta HighEstimate750_{t+1} \\ & + \beta_3 \Delta LowEstimate750_{t+1} + \beta_4 \Delta Qty_{t+1} + \Delta \epsilon_{t+1}\end{aligned}$$

Table 12 gives the results of the regression.

Table 12: OLS for the difference of the Hammer Price at time $t+1$

$\Delta Bid750_t$	-.1200584** (.014093)
$\Delta LE750_{t+1}$.9206421** (.4401685)
$\Delta HE750_{t+1}$.0936203 (.2904878)
$\Delta Size_{t+1}$	-.0119246** (.0052538)
ΔQty_{t+1}	-9.323723** (2.041329)
Observations	1782
R^2	0.6497

NOTE: Standard errors are in parenthesis.
** denotes a variable that is significant at the 5% level.

We can see that coefficient of $\Delta Bid750_t$ is statistical significant and the sign is as we expected if the declining price anomaly is present.

6 Conclusion

In this paper, we tested for the declining price anomaly in wine auction data from 2014-2015. Since the objects in the auction are homogeneous, we tested the ratio of the second hammer price to the first. We found that on average the second price declined by 2.44%. Moreover, 43% of the time the decreased. One interesting thing to note is that the prices were more likely to change than to stay the same. This is different from what McAfee and Vincent (1993) and Ashenfelter (1989). One explanation could be that at the time of their research publication, the declining price anomaly was not known and now that it is. Another explanation along these lines is that the Auction House could be using the price anomaly to their benefit. This would be in-line with the research of Picci and Scorcu (2003). It is also possible that absentee bidder could be playing a bigger role. Unfortunately, our data has no way of determining what type of bidder won the sale. If it is the case of an absentee bidder then *Order* and the hammer price in the previous period play no role in determining the hammer price in the second period.

In the OLS model for the log of the hammer price, we find that order is indeed significant in most auctions. Moreover, the sign on order is negative, as expected. *Order* serves as an indicator of the price decline anomaly since as the

order increases, if price decline anomaly is present then log price should decrease. Lastly, while vintage year is significant when we control for vintage year, we have no evidence that it is a factor that is associated with the declining price anomaly. Interestingly, size and quantity do play a role; both of are negative in value and significant. It suggest that that larger quantities and sizes lead to a decline in log of winning bids. It could be that the Auction House is hiding the price anomaly with the use of lots that contain large sizes and/or quantities. Furthermore, this is verified when we first difference the hammer price levels. Most surprising was that high estimate per 750 is not significant. Although, it can be argued that the low estimate gives an indicator for when the bidder and the Auction House of the lowest price they would be expected to buy and sell, respectively. Therefore, low estimate being positive would make sense.

Acknowledgements

We would like to thank Dr. Gagan Ghosh for suggesting this neat little problem and for advising. We also would like to thank Dr. Andrew Gill who suggested to see how vintage year and the price anomaly interact. Lastly, we would like to thank the following students (from Physics 226L and 212L, Fall 2015) who helped sort the large data set: Joe Ampuero, Eduardo Ramirez, Thang Dao, Luis Landy, Chimezie Mbanu, Zhongxiu Yang, Robert Hare, Melanie Garcia, Angel Alvarez, and Eduardo Ramirez.

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