The Impact of Starting Price and Market Thickness on Auction Prices: Evidence from a Field Experiment in Online B2B Secondary Market Auctions

Ali Pilehvar
Wedad J. Elmaghraby
Anandasivam Gopal

(apilehva, welmaghr, agopal) @rhsmith.umd.edu
Robert H. Smith School of Business
University of Maryland
College Park MD 20742

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Introduction

In the Business-to-Business (B2B) *secondary market*, large retailers (such as Sears, Target, Walmart, etc.) can liquidate and business buyers (e.g., off-price retailers, eBay power sellers, etc.) can purchase excess and returned inventory at discounted prices. Many retailers have shifted the responsibility of disposing of this 'leftover' inventory to large wholesale liquidators who commonly use B2B *auctions* as the preferred sale mechanism.

Due to the nature of secondary market, used products in secondary markets can arrive to wholesale liquidators in a range of states of quality, from salvage condition to light-used/excellent quality. With fast liquidation a critical part of their daily business model, wholesale liquidators often run several auctions for identical and comparable products, whereby comparable products differ only according to quality condition or models of the product (vertically differentiated products). Although, this practice can increase the speed of the liquidation, its net effect on the wholesale liquidators' total profit is unclear: posting several auctions for identical and/or comparable products can depress overall profits by directly increasing the supply and potentially offering bidders an opportunity to substitute bids on higher end products for lower bids on auctions of lower end products. Further complicating the market dynamics is the price revelation process that is inherent in auctions – the buyer does not dictate a selling price but rather sets the tone for the auction via her starting price and then renders control over to the competitive forces of the market to determine the final price (Bapna et al. 2008).

In such an auction environment, one important and open question to ask is how a seller should manage the product assortment problem so that she auctions off the right mix of products at the right starting price. Although the product assortment problem has received plenty of attention in the marketing and operations literature in recent years (e.g., Kök et al. 2006), it is yet unexplored in the auction literature. Specifically, we seek to understand how cross-category effects that may manifest in the context of multiple, simultaneous auctions of closely linked categories of products may interact to determine the final prices that obtain in the marketplace (Shocker et al. 2004; Kopalle et al. 2009). Since the two levers that the seller can influence are respectively, the starting price of an auction and the supply of auctions of a certain category of products (i.e. thickness), we use a field experiment to better understand how these two levers interact to determine the final prices for auctions in each category. We address this significant gap in the literature in the study reported here.

Research Question and Description of Field Experiment

We report here on the results of a field experiment that we ran in November 2012 – December 2012 on the auction site of one of the nation's largest online auction wholesale liquidation sites. The design of this field experiment was directly aimed at understanding how (i) the starting price of the auction, and (ii) the number of auctions for a specific (model, quality), i.e., the thickness of the market for that product, interact to impact an auction's final price in the presence of an assortment of products being auctioned.

In order to reduce unobservable heterogeneity in the auction environment and to standardize the items for auction to the extent possible, we ran the field experiment on a set of electronic products that were well understood and clearly specifiable – iPad tablets. We conducted the experiment on two sets of products - used 2nd generation iPads (*iPad2*) and 3rd generation iPads (*iPad3*) of varying levels of prior use. The experiment included 24 "days" of auctions excluding the holiday season, and consists of 800 successful auctions totaling over $1.2 million revenues.

The pallet of goods in each auction in the sample consisted of a pallet of similar iPads, in terms of quality and generation, as is common in the secondary B2B market with the average size of 4.2 units (std. dev. = 1.2). The pallet could therefore contain iPads of the same generation (i.e. all iPad3) of two grades of quality: *light-use* and *moderate-use* (a lower quality level). As the quality grade and characteristics of the products are exogenously determined through the seller's production processes, the seller can potentially influence the outcomes of the auctions by manipulating the starting price and determining the total number of auctions to post, i.e., the market thickness, across different models and quality grades. As part of the experimental design, we were allowed the opportunity to randomly set starting prices and the market thicknesses for each set of auctions, across generations and quality levels, on a given day (within acceptable ranges), thereby guaranteeing exogeneity of these parameters. Thus, the design of the experiment allows us to tease out the effects of varying starting prices and market thickness on the recovery rates of auctions across the generational and quality dimensions.

For each of the 24 experimental "days", we determined the starting price and number of auctions for each of the four sets of iPad products (*iPad2/light-use*, *iPad2/moderate-use*, *iPad3/light-use*, *iPad3/moderate-use*), shown in Figure 1. We synchronized the start of the auctions so as to have them simultaneously open each day, lasting approximately 2 calendar days each. To minimize the effects of simultaneous auctions that are not part of a cohort of auction starting prices and thickness conditions, each set of auctions began after the termination of the previous set of auctions, i.e. there was perfect overlap between auctions that started on the same day and zero overlap with auctions that started on other days as part of the experimental design. The starting prices of auction for each (*generation*, *quality*) pair was fixed within a day and was recommended by the channel manager. Given the relative abundance of iPad2's in inventory compared to iPad3s, we were allowed to manipulate the starting price for iPad2s. In consultation with channel managers, we identified a reasonable low and high starting price for light and moderate-use auctions of iPad2, respectively, rendering us 4 different combinations of starting price pairs. The low (high) starting price for light-use iPad2 were 55% (70%) of retail value ($399); the low (high) starting price for moderate-use iPad2 were 50% (65%) of retail value ($399). All light-use (moderate-use) iPad3 auctions had a starting price of 66% (62%) of retail value ($499 or $599). These experimental settings are shown in Table 1.

While we were able to exert full control over the starting prices, the number of auctions posted was at the occasional mercy of inventory availability. In each given day, on average we had 13 light-use iPad2, (min=0, max=30), 4.6 moderate-use iPad2 (min=0, max=12), 10 light-use iPad3 (min=0, max=19) and 3.7 moderate-use iPad3 (min=0, max=9). The total number of auctions in our dataset number 632, of which 272 are light-use iPad2s, 100 moderate-use iPad2s, 189 light-use iPad3s and 71 moderate-use iPad3s. More details on this distribution are provided in Table 2. To motivate a coherent set of analyses, we postulate some simple hypotheses based on prior research in the next section.

Hypotheses

We know from auction literature (e.g., Bajari and Hortacsu 2000; Lucking-Reiley et al. 2007) that the final price of an auction is influenced by the auction's starting price, as well as the number of similar products being auctioned simultaneously (e.g., Chan et al. 2007). In a departure from prior literature, which has mainly focused on the impact of starting price in isolation of the larger market context, we explicitly account for the substitution/market effects of the starting price of *all* (generation, quality) auctions simultaneously open.

To start with, we posit that *an increase in starting price of a product has a positive effect on the final price of the auction only if the starting price of its lower-quality competitors is sufficiently low*. The first part of hypothesis is a line with that branch of literature which argues that the anchoring effect of starting price will increase the final price of auctions (e.g., Bajari and Hortacsu 2003). However, the second part reveals that the markets for a same product but in two different qualities are now differentiable. If the lower-quality product has a starting price that is closer to that of the higher-quality product, a potential demand substitution effect kicks in, which reduces the impact that a higher starting price may have on final prices for the higher-quality product. In effect, the extent to which the starting price of the two sets of products are closer affects how influential the starting price is in determining the final recovery rate for both sets of products in auction.

Second, we hypothesize that *an increase in the starting price of a high-quality product of an older generation (iPad2) will have a negative effect on the final prices of all auctions for the newer generation of products (iPad3)*. Since the newer generation of products typically tends to be more expensive across all quality levels than the older generation, the likelihood of downward demand substitution is higher when an alternative high-quality but older generation product is made more attractive through a higher starting price. In effect, the light-use iPad2 becomes a viable substitute for all iPad3 products through the signal of the higher starting price on the iPad2. This substitution will likely show up in its effect on the final prices that obtain on the set light-use of iPad2s that are placed on auction simultaneously with higher quality iPad3s.

With regards to market thickness, we conjecture that *an increase in number of auctions for a (generation, quality) class will decrease the final price in auctions of that product*. This is in the same spirit of Chan et al. (2007) who study the negative impact of market thickness on bidders' willingness to pay. The presence of competition from a thicker market and the possibility of fewer bids per auction leads to lower final prices on auctions on average, all else equal.

However, in providing a more nuanced understanding to this competitive effect, we also posit that *an increase in the number of low-quality auctions will increase the final price of higher generation or quality product auctions*. Furthermore, we hypothesize that *an increase in the number of auctions of later generation or higher quality will decrease the final price of lower generation or lower quality auctions*. Finally, we posit that *the impact of starting price on final price is negatively moderated by the number of auctions for the similar product in the market*. This prediction is consistent with Dholakia et al. (2002) who find that when the volume of similar listings go up, due to more existing alternatives, the influence from other auctions or bidders (e.g., herding behavior) in bid formation decreases. In the interest of space, we do not provide a full theoretical explanation of these hypotheses but will be able to discuss them at the conference in detail.

Discussion of Results

Given the simple experimental setup, we use a series of linear regressions to test our hypotheses, with the unit of analysis being the auction. Since the auctions in our experimental design naturally fall into cohorts of similar starting prices, we control for this by including the "day" of the experiment in all of our analysis. We also include several control variables in our analysis, shown and described in Table 3. Finally, given the presence of auctions of different categories of products, we conduct our analysis of final prices independently for each market. Therefore, the summary statistics for the four separate markets are shown in Table 4. Figures 5 and 6 respectively show the OLS results for each of these markets. Note that since the iPad3 prices are fixed during the duration of the experiment, they do not appear in any of the analyses. However, the supply of iPad3s per day are included in the analyses.

Our results confirm the expected result that an increase in the starting price of moderate-use iPad2 auctions will positively impact the final price of all auctions for higher quality or later generation iPads. We also find similar patterns of substitution across generations within a quality class. This result implies that business buyers do actively substitute their demand across markets and are directly influenced by the starting prices of lower-end products. If, as is the case with many wholesale liquidators, the objective is the fast removal of lower-quality, lower-generation inventory, then the seller would be advised to set the lower-end product's starting price low so as to minimize the substitution from an inferior product to a superior one. If, however, the seller's objective is to maximize expected daily profit, then it is possible that the seller would be better off increasing the starting price of the low-end product so as to direct bidder traffic to higher-end auctions. We also find that an increase in the number of low-quality auctions increases the final price of higher generation and high-quality product. Finally, we identify a diminishing role of importance for the starting price as the market thickness increases. We discuss these results in more detail in the full paper, available upon request from the authors. We will also discuss these results in more detail at the CIST Conference in 2013.

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Figure 1: Two Categories of Products – Quality Grade and Generation

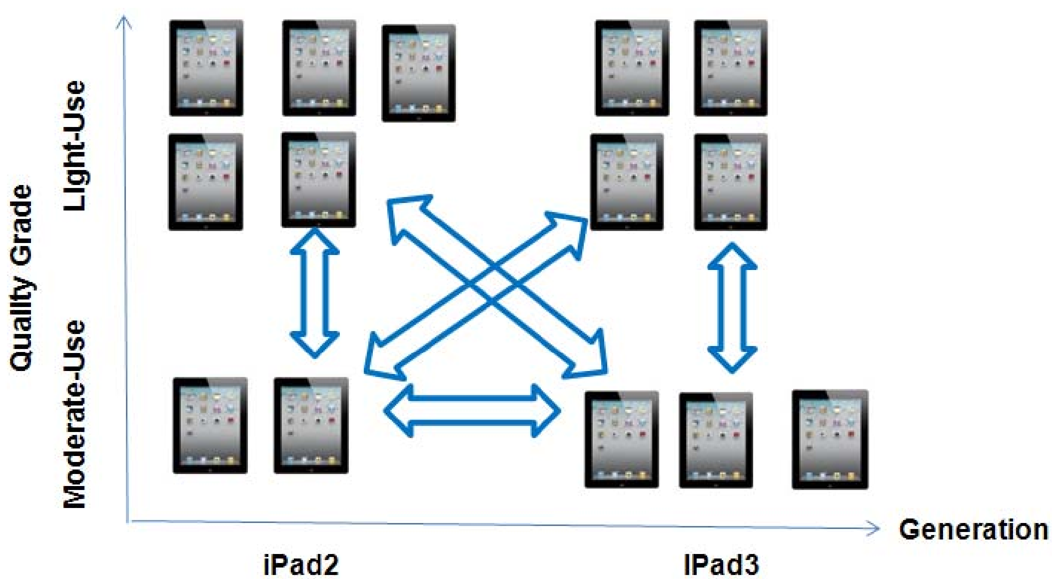

Table 1: Starting Price Levels for All iPad Categories

Quality Grade	iPad2		iPad3 (for Day 4-25)	iPad3 (for Day 1-3)
	Low	*High*	*Fixed*	*Fixed*
Light-use	55%	70%	66%	78%
Moderate-use	50%	65%	62%	75%

Table 2: Breakdown of Auctions Across Treatments of iPad2 Starting Prices

	Combination 1	Combination 2	Combination 3	Combination 4
Light-use *IPAD2* (Starting price level)	*High*	*High*	*Low*	*Low*
Moderate-use *IPAD2* (Starting price level)	*High*	*Low*	*Low*	*High*
Number of days in experiment	4	5	4	6
Total Number of light-use *iPad2* Auctions	63	69	70	70
Total Number of moderate-use *iPad2* Auctions	20	24	30	26
Total Number of light-use *iPad3* Auctions	42	25	43	40
Total Number of moderate-use *iPad3* Auctions	14	16	19	21
Avg. Number of Daily light-use *iPad2* Auctions	15.8	13.8	17.5	11.7
Avg. Number of Daily moderate-use *iPad2* Auctions	5	4.8	7.5	4.3
Avg. Number of Daily light-use *iPad3* Auctions	10.5	5	10.8	6.7
Avg. Number of Daily moderate-use *iPad3* Auctions	3.5	3.2	4.8	3.5

Table 3: Variables and Measurement

Variable	Definition
Final Price	The price of the second-highest maximum-willingness-to-pay on the auction as a % of E
N	The final number of unique bidders in the same auction
Q	The number of items in each pallet
E	$ declared/retail price of all items in each pallet
Y	Avg. per-unit $ declared/retail price in each pallet (E/Q)
$iPad2Light_{high}$	Dummy variable indicating whether light-use *iPad2* auction has high starting price (=1) or low starting price (=0)
$iPad2Mod_{high}$	Dummy variable indicating whether moderate-use *iPad2* auction has high starting price (=1) or low starting price (=0)
$NiPad2Light$	Number of daily posted light-use *iPad2* auctions
$NiPad3Mod$	Number of daily posted moderate-use *iPad2* auctions
$NiPad3Light$	Number of daily posted light-use *iPad3* auctions
$NiPad3Mod$	Number of daily posted moderate-use *iPad3* auctions

Table 4: Summary Statistics and Correlation Matrix

Market		Variable	Observations	Mean	Std. Dev.	1	2	3	4	5	6	7	8	9
	1	Final Price	272	0.77	0.04									
	2	N	272	2.84	0.74	0.52*								
	3	Q	272	4.39	0.84	-0.05	-0.29*							
	4	Y[1]	272	399	0									
Light-use	5	$iPad2Light_{high}$	272	0.49	0.50	0.15*	-0.30*	0.16*						
iPad2	6	$iPad2Mod_{high}$	272	0.49	0.50	0.21*	0.15*	0.032		-0.023				
	7	$NiPad2Light$	272	17.19	5.95	-0.41*	-0.28*	0.23*		-0.17*	-0.15*			
	8	$NiPad2Mod$	272	6.00	3.57	0.04	0.24*	0.00		-0.22*	-0.28*	0.25*		
	9	$NiPad3Light$	272	10.53	4.71	-0.34*	-0.27*	0.35*		-0.22*	0.24*	0.69*	-0.1	
	10	$NiPad3Mod$	272	4.10	2.60	0.15*	0.30*	-0.11*		-0.05	-0.13*	0.14*	0.72*	0.05
	1	Final Price	100	0.74	0.05									
	2	N	100	2.70	0.70	0.28*								
	3	Q	100	4.85	0.58	-0.06	-0.33*							
	4	Y[1]	100	399	0									
Moderate-use	5	$iPad2Light_{high}$	100	0.44	0.50	0.20*	-0.13	-0.15						
iPad2	6	$iPad2Mod_{high}$	100	0.46	0.50	0.25*	-0.1	0.06		-0.01				
	7	$NiPad2Light$	100	15.82	5.91	-0.44*	-0.35*	-0.01		-0.14	-0.25*			
	8	$NiPad2Mod$	100	7.64	3.07	-0.17*	-0.18*	0.08		-0.41*	-0.1	0.36*		
	9	$NiPad3Light$	100	9.37	3.54	-0.22*	-0.18*	0.1		-0.40*	0.1	0.61*	0.35*	
	10	$NiPad3Mod$	100	5.02	2.53	-0.1	-0.24*	0.01		-0.26*	-0.1	0.10	0.68*	0.32*
	1	Final Price	189	0.73	0.03									
	2	N	189	2.57	0.78	0.89*								
	3	Q	189	4.25	0.73	0.30*	0.11							
	4	Y	189	529.16	46.02	-0.38*	-0.37*	-0.51*						
Light-use	5	$iPad2Light_{high}$	189	0.35	0.48	-0.12*	-0.21*	0.21*	-0.01					
iPad3	6	$iPad2Mod_{high}$	189	0.43	0.50	0.21*	0.17*	0.12*	0.03	0.28*				
	7	$NiPad2Light$	189	13.79	8.84	-0.18*	-0.25*	0.18*	0.02	0.23*	0.27*			
	8	$NiPad2Mod$	189	4.60	4.02	0.10	0.01	-0.06	0.03	0.06	0.02	0.50*		
	9	$NiPad3Light$	189	12.68	4.26	-0.36*	-0.26*	-0.03	-0.01	-0.24*	-0.05	0.02	-0.5*	
	10	$NiPad3Mod$	189	3.90	2.37	0.18*	0.20*	-0.29*	-0.03	0.11	-0.04	0.12*	0.68	-0.34*
	1	Final Price	71	0.70	0.04									
	2	N	71	2.48	0.69	0.73*								
	3	Q	71	4.56	0.58	0.27*	0.03							
	4	Y	71	532.80	47.64	-0.42*	-0.10	-0.75*						
Moderate-use	5	$iPad2Light_{high}$	71	0.42	0.50	0.05	-0.14	0.01	-0.01					
iPad3	6	$iPad2Mod_{high}$	71	0.49	0.50	0.48*	0.33*	0.25*	-0.10	-0.05				
	7	$NiPad2Light$	71	14.52	6.76	-0.25*	-0.20*	-0.12	0.03	0.03	-0.27*			
	8	$NiPad2Mod$	71	7.07	3.55	-0.28*	-0.171	-0.04	0.05	-0.32*	-0.28*	0.45*		
	9	$NiPad3Light$	71	9.66	3.18	-0.26*	-0.15	-0.01	0.15	-0.23*	0.01	0.50*	0.14	
	10	$NiPad3Mod$	71	5.68	2.04	-0.27*	-0.13	-0.05	0.11	-0.45*	-0.16	0.05	0.62*	0.14

Notes. [1] Y for *iPad2* is fixed and \$399. All correlations significant at $p<0.1$ is denoted by *.

Table 5: Regression Results for iPad2 Pallets, Dependent Variable = Final Price

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Light-used iPad2						Moderate used iPad2				
Q	0.0057	0.0075**	0.0041	0.0038	0.0065*	0.0077**	-0.0236**	-0.0219**	-0.0224**	-0.0218**	-0.0228**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
iPad2Lighthigh	0.0141**	0.0903***	0.0213***	0.0211***	0.0155**	0.0112	0.0030	0.0013	0.0105	0.0014	0.0118
	(0.007)	(0.018)	(0.007)	(0.007)	(0.008)	(0.008)	(0.015)	(0.014)	(0.016)	(0.014)	(0.016)
iPad2modhigh	0.0249***	0.0350***	0.0319***	0.0306***	0.0341***	0.0331***	0.0107	0.0028	0.0021	0.0026	0.0027
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.014)	(0.013)	(0.013)	(0.014)	(0.013)
iPad2Lighthigh* iPad2modhigh	-0.0228**	-0.0262**	-0.0270**	-0.0265**	-0.0227**	-0.0188*	0.0021	0.0077	-0.0001	0.0076	-0.0012
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.020)	(0.019)	(0.020)	(0.019)	(0.020)
NiPad2Light	-0.0030***	-0.0021***	-0.0032***	-0.0030***	-0.0024***	-0.0014*		-0.0027***	-0.0035***	-0.0027***	-0.0038***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)		(0.001)	(0.001)	(0.001)	(0.001)
NiPad2Light* iPad2Lighthigh		-0.0046***		0.0016							
		(0.001)		(0.001)							
NiPad2Mod			0.0030***		0.0023***	-0.0007	-0.0030	-0.0011	-0.0009	-0.0013	-0.0001
			(0.001)		(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
NiPad3Light					-0.0017*	-0.0029***			0.0023		0.0027
					(0.001)	(0.001)			(0.002)		(0.002)
NiPad3Mod				0.0026		0.0050**				0.0005	-0.0017
				(0.002)		(0.002)				(0.003)	(0.004)
Constant	0.7890***	0.7685***	0.7796***	0.7650***	0.7804***	0.7528***	0.8386***	0.8661***	0.8542***	0.8625***	0.8639***
	(0.029)	(0.029)	(0.029)	(0.030)	(0.028)	(0.030)	(0.066)	(0.063)	(0.064)	(0.068)	(0.067)
Dummies (location/auction time)	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	272	272	272	272	272	272	100	100	100	100	100
F stat	10.16***	11.97***	11.48***	10.75***	10.57***	10.54***	3.97***	5.31***	4.98***	4.73***	4.51***
R-squared	0.236	0.291	0.283	0.288	0.292	0.308	0.258	0.347	0.359	0.347	0.360

Table 6: Regression Results for iPad3 Pallets, Dependent Variable = Final Price

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
			Light-used iPad3					Moderate used iPad3		
Q	0.0178***	0.0180***	0.0161***	0.0160***	0.0157***	-0.0256*	-0.0206	-0.0210	-0.0205	-0.0208
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
iPad2Lighthigh	-0.0304***	-0.0299***	-0.0209***	-0.0339***	-0.0286***	0.0043	-0.0104	-0.0101	-0.0109	-0.0105
	(0.007)	(0.007)	(0.006)	(0.006)	(0.007)	(0.011)	(0.012)	(0.012)	(0.012)	(0.013)
iPad2modhigh	0.0254***	0.0244***	0.0263***	0.0157***	0.0189***	0.0361***	0.0321***	0.0316***	0.0312***	0.0312***
	(0.006)	(0.006)	(0.005)	(0.005)	(0.006)	(0.010)	(0.010)	(0.010)	(0.011)	(0.011)
iPad2Lighthigh* iPad2modhigh	-0.0017	-0.0016	-0.0059	0.0072	0.0028	-0.0044	0.0128	0.0127	0.0136	0.0132
	(0.009)	(0.009)	(0.008)	(0.008)	(0.009)	(0.014)	(0.015)	(0.016)	(0.016)	(0.017)
NiPad2Light			-0.0012***		-0.0006*			-0.0001		-0.0001
			(0.000)		(0.000)			(0.001)		(0.001)
NiPad2Mod				-0.0048***	-0.0035***				-0.0003	-0.0002
				(0.001)	(0.001)				(0.001)	(0.002)
NiPad3Light	-0.0042***	-0.0037***	-0.0023***	-0.0036***	-0.0029***		-0.0036**	-0.0035**	-0.0036**	-0.0035*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)		(0.001)	(0.002)	(0.001)	(0.002)
NiPad3Mod		0.0013	0.0040***	0.0091***	0.0083***	-0.0034	-0.0053**	-0.0053**	-0.0050	-0.0051
		(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)
Constant	0.8289***	0.8120***	0.8061***	0.8021***	0.8019***	1.1444***	1.1648***	1.1678***	1.1618***	1.1649***
	(0.045)	(0.047)	(0.044)	(0.044)	(0.043)	(0.133)	(0.128)	(0.130)	(0.130)	(0.136)
Dummies (location/auction time)	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	189	189	189	189	189	71	71	71	71	71
F stat	18.61***	16.94***	19.54***	16.94***	20.97***	5.99***	6.48***	5.78***	5.8***	5.58***
R-squared	0.483	0.488	0.548	0.566	0.574	0.469	0.519	0.520	0.520	0.520