Digital Demand: Demand for digital cameras on eBay

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Abstract

The paper estimates the demand for new digital cameras sold in eBay auctions. EBay data seems to offer significant advantages over traditional transactions data for estimating demand for differentiated products. However, there are a number of concerns including censoring bias and the interpretation of the bidding behavior. This paper discusses these problems as well as possible solutions. The paper presents results from three different methods for estimating demand for differentiated products on eBay. The results suggest that the demand for digital cameras is highly elastic and there isn't a lot of substitution, particularly across brands.

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1 Introduction

Data from eBay and other auction sites seems to have the potential to provide important new information on consumer behavior and the demand for differentiated products.[1] If bidders behave in a way that is consistent with standard auction theory then for each item we get to see a series of consumer values allowing the econometrician to directly identify the distribution of values for that item (demand). On top of this, we are able to observe individual bidders across auctions providing information on substitution preferences. This seems to be a significant benefit over traditional methods of identifying demand for differentiated products from transactions data such as scanner data (Hosken et al. (2002); Nevo (2000)). The growth of eBay and other auctions sites also means that internet auctions have become a significant distribution channel for everything from beanie babies to digital cameras to cars to houses (Lucking-Reiley (2000); Bajari and Hortacsu (2004)).[2] There are however a number of major concerns with interpreting bids from internet auctions. This paper uses data on auctions for new digital cameras and presents results from three different methods for analyzing bidding on eBay. The results suggest that the demand for individual digital cameras is highly elastic and there is not a lot of substitution between cameras.

The paper uses data downloaded from eBay's web site in the first two months of 2001. We observe auctions for 52 models of new cameras manufactured by Canon, Kodak, Fuji, Nikon and Olympus. We separately collected characteristic information for each model. This information includes the number of megapixels, optical zoom length, memory and weight. We also observe other information about the auction such as date, time and day. The first method for analyzing eBay bidding looks at bidding behavior and the "diversion ratio" between cameras. We are able to observe bidders across auctions by tracking their eBay ID. Using this information we can determine the "propensity" with which someone will bid on Camera A given that they

[1]See also Bapna et al. (2005) and Baye et al. (2004) for other internet data sources useful for estimating demand.

[2]Our colleague, Laura Hosken, even bought her wedding dress on eBay!

have bid on Camera B. The second method is a random coefficients model of bids in camera auctions. This model assumes that the highest bid of each bidder in each auction is equal to that bidder's value for the item. The model allows bidders to have different preferences over observable features of the cameras being auctioned. The third method presented in the paper accounts for censoring bias by using is the order statistics approach (Adams (2004); Athey and Haile (2002); Song (2003)). The paper presents estimates from a random coefficients version of the model suggested in Adams (2004).

The biggest and most obvious value of using auction data is that the researcher is not relying on exogenous variation in supply prices to identify demand. The classic simultaneity problem is that price changes may be correlated with changes in demand (Berry et al. (1995); Nevo (2000)). Commonly, promotions and sale prices are used to identify demand, a practice that is likely to over estimate price elasticities either because of consumer inventorying or because of complementary marketing and promotional activities (Hendel and Nevo (2002); van Heerde et al. (2003)). Because eBay uses a second price auction it is an equilibrium for bidders to bid their value, at least at the end of the auction (Hasker et al. (2001); Song (2003)). Theoretically, we directly observe a sample of values for the item that is sold. Unfortunately, there are two concerns with interpreting eBay in this way. The first concern is that some people may not get the opportunity to bid at the end of the auction because the price increases above their value before they get the opportunity to bid. That is some people have their bids censored. The second concern is that people may reduce their bid to account for the option value of bidding on future auctions.[3]

Athey and Haile (2002) present a solution to the problem that observed bidders have their highest bid censored in open call auctions such as eBay. It is shown that when the number of bidders in an auction is known we can think of the bidders in a particular auction as one random sample of the

[3]Another concern is that there is a common values component to the auction (Bajari and Hortacsu (2003); Yin (2005)). However, it is less likely to expect information problems with new digital cameras and the results presented below do not provide any evidence consistent with common values.

population in which a particular order statistic is observed. In the case of a second-price auction such as eBay, we observe the $N-1:N$ order statistic, that is the second highest bid of N bidders, more commonly known as the transaction price. There is a known formula that relates the distribution of a particular order statistic to the underlying distribution.[4] Athey and Haile (2002) show that in a symmetric private value auction where the number of bidders is known, the value distribution is identified when the distribution of the transaction price is known. Unfortunately, while the number of observed bidders is known it is not randomly selected. In particular there is a selection bias as some bidders have all their bids censored by the current price. While the number of potential bidders is randomly selected the number of potential bidders it not observed. Song (2003) suggests one solution to this problem. If the second and third highest bids are observed then we know the number of bidders in the distribution conditional on being above the third highest bid, ie two. Thus we can identify the value distribution conditional on it being above the third highest bid. Song also presents a structural model for bidding in eBay auctions. Song shows that under certain structural assumptions, observing the distribution of two order statistics is enough to identify the value distribution. Adams (2004) presents an alternative solution to the same problem. Adams shows that if the probability distribution over the number of bidders is known then the value distribution is identified. Adams then presents additional assumptions for non-parametrically identifying the value distribution. Here the distributional assumptions allow the probability distribution over the number of bidders and the value distribution to be estimated simultaneously via a maximum likelihood estimator.

Adams (2004) also analyzes the effect of future auctions on the bidding behavior of eBay bidders. It is shown that the bidding behavior in single shot auctions can be reinterpreted as bidding as a function of the bidder's

[4] If $N=2$, the formula is $2(1-F(p))f(p)$ where p is the price and f is the marginal distribution. To see this note that the loser bids p which occurs with probability $f(p)$ and the winner bids more than p which occurs with probability $1-F(p)$, and there are 2 permutations (Song (2003)). To see that $F(p)$ is identified when $N=2$, note that if p is at it's lowest value, $F(p)=0$.

value for the item less the bidder's option value for the item. Therefore, the distribution of the item's value plus the option value of the item can be identified using the methods described above. However, if the econometrician wishes to estimate the underlying value distribution independent of the option value then Adams (2004) presents a set assumptions and methods for doing so. This paper ignores this issue, however Arora et al. (2002) uses the same data to analyze the effect of option values on bidding behavior. See Zeithammer (2004) for further discussion of these issues.

The paper proceeds as follows. Section 2 discusses the data and summarizes information about the auctions and bidding behavior. Section 3 presents the assumptions and empirical models. Section 4 presents the result including estimated price elasticities. Section 5 concludes.

2 The Data

The data is collected from eBay auctions for new digital cameras occurring in the first two months of 2001. The data includes auctions for 52 models from the major brands, which are Canon, Nikon, Olympus, Fuji and Kodak. The data collected from eBay includes for each auction, the make and model of the camera, the timing and amount of each bid,[5] and a bidder ID. Attached to this information is data collected from web sites like Cnet.com. These web sites provided characteristic information such as weight, memory, optical zoom length and number of megapixels for each of the 52 models.

Table A1 Camera Characteristics presents information on the characteristics of the digital cameras that are included in the data. At the time, digital cameras were much bigger and had a much smaller number of megapixels and a much smaller memory than today's cameras. Megapixels refers to the quality of the picture that can be taken with the camera. The larger the number of megapixels the better the quality although the cost is that each

[5]The highest bid is reported as the bidding increment over the second highest bid except in those cases where the highest bid is above the second highest bid by an amount less than the bidding increment.

picture requires a larger amount of memory. Optical zoom refers to the type of zoom found on a standard camera. The zoom allows for higher quality close up shots. Digital zoom refers to cropping the shot for a given quality.

Table A2 Auction Statistics presents some basic statistics on the auctions themselves. Overall there are 16,538 bidders whose bids are included in the data and these bidders bid on 4,564 auctions. Although the average number of bidders per auction is just below 5, Graph A1 Bidders Per Auction shows that the distribution is heavily skewed towards 0. Auctions tend to run for either 3 or 5 days and the average price of a new digital camera is just under \$500. The price is important because it shows that the items we are considering are relatively expensive. This table shows that Canon cameras are very popular with relatively more bidders per auction than the other models. The Canon S10 is the most popular model in terms of the number of bidders per auction as well as the total number of auctions and the total number of bidders.

Graph A2 Auctions Per Bidder presents a graph showing the number of auctions each bidder bids in. It shows that the overwhelming majority bid in just one digital camera auction during this two month period. A little over 2,000 bidders or about 1/8 bid in more than one auction and just over 1,400 bid in just two auctions. One person bid in 54 auctions - not sure why.

Graphs A3-A6 are histograms of the number of bidders that have their highest bid in each interval of time conditional on this bid being after a certain time. These graphs show that there is a definite tendency for bidders to bid towards the end of the auction. We see that for bids that occur in the last day the overwhelming majority occur in the last 30 minutes of the auction (Graph A3 Histogram - Bids in the final Day) . Also, for the bids that occur in the last hour the vast majority occur in the last 2 minutes (Graph A4 Histogram - Bids in the final hour). While there is a significant literature on why this occurs, see Roth and Ockenfels (2002) for example, we follow Song (2003) and remain agnostic on the issue. The empirical fact of late bidding does mean that the observed high bids are more likely to be equal to the bidder's actual value for the item (Hasker et al. (2001); Song (2003)). It also means that the censoring problem is likely to be mitigated to some extent (Song (2003)).

Table A3 Bidder Switching presents results from an analysis of the auctions which each bidder entered. If we assume that each bidder has the opportunity to bid on every model then the table provides some information on switching behavior. Note that the table only uses information on those bidders that bid in more than one auction which is only about 1/8 of all the bidders. The results suggest that the Canon S10 is the second best substitute for many bidders. Note that this may be due to the large number of auctions for this model rather than any particular preference for the S10. The results don't condition on the probability that a particular camera will be available to bid on. For the Canon S10 the probability that someone who has bid on an S10 will bid again on an S10 is about 80%. This probability is much smaller for the other cameras, ranging between 30% and 65%. For the Canon S10 the probability that a bidder who has bid on the S10 will bid on the "best substitute" is only 4% where that best substitute is the Canon S20. For the other cameras this probability was higher, ranging from 8% up to 31%. It is also worth pointing out that for the two most popular Canon cameras, the S10 and G1, bidders are more likely to bid on another Canon than on some other brand. This is not true for the other brands.

3 Empirical Model

The model and notation closely follow Song (2003). There are N_j "potential" bidders in auction j, with $p_{nj} = \Pr(N_j = n)$, and M_j observed bidders. Each potential bidder's valuation V_j^i is an independent draw from $F(.|X_j)$, where $V_j^i \in [\underline{v}, \bar{v}]$ and X_j is the observed vector of auction characteristics. Each potential bidder knows p_{nj}, $F(.|X_j)$ and their own value V_j^i. The minimum bid is denoted c_j and is set by the auctioneer. I assume that bid increments are small relative to the value of the camera and therefore ignore them. The auction lasts for the interval of time $[0, \tau_j]$. Each potential bidder i is assumed to have a "last opportunity" to bid, $t_j^i \in [0, \tau_j]$, which is a random variable. Let the distribution of t_j^i be denoted $G_j^i(.|X_j)$. Let C_{tj} be the "cut off" price at time t. As eBay is a second price auction, $C_{tj} = B_{tj}^{(M_j-1:M_j)}$, where $B_{tj}^{(M_j-1:M_j)}$ is the second highest bid as of time t. Song (2003) shows that in a Bayesian Nash equilibrium of this game, it must be that for every bidder whose value for the item is greater than C_t at their last opportunity to bid, will bid their value ($B_{t^i j}^i = V_j^i$), if they have not already done so.

To estimate the random coefficients model it is assumed that each potential bidder has the opportunity to bid their value at their "last opportunity". Following Song (2003), we have that $B_i^\tau = V_j^i$, that is for each potential bidder the highest bid at the end of the auction is equal to the value that that bidder places on the item. Bidder i's value for the item available in auction j is

$$V_j^i = X_j^{\beta_i} \epsilon_i \tag{1}$$

where $Log(\epsilon_i)$ is distributed $N(\mu, \sigma^2)$ and β_{ix} is distributed $N(\mu_x, \sigma_x^2)$ and note that the β's and the ϵ are all assumed to be independent and uncorrelated.

The concern with the random coefficients model is that it is unlikely that each potential bidder has the opportunity to bid at their "last opportunity". That is, some bids and some bidders may be censored. To account for the censoring bias, the paper estimates a model based on the model presented in Adams (2004). From above we know that $C_{\tau j} = B_{\tau j}^{(M_j-1:M_j)} = V_j^{N_j-1:N_j}$, or the price at the end of the auction is equal to the value of the second highest potential bidder. We will denote this value V_2. Assume that the probability distribution over the number of potential bidders in the auction is given by $Pr(N|N \geq 2) = (1-p_j)p_j^{n-2}$. Given this assumption Adams (2004) shows that

$$\Pr(V_2|V_2 > c) = \frac{2(1-p_j)(1-F(c))f(V_2)(1-F(V_2))}{(1-(1-p_j)F(c) - p_j F(V_2))^3} \tag{2}$$

where c is the minimum bid amount and V_2 is the price. We can see that the probability of observing a particular price is just a somewhat complicated censored distribution. Note that if c is small, then $F(c) = 0$ and the equation simplifies to something that looks like a censored regression model (Greene (2000)). Adams (2004) shows that $F(V_2)$ is non-parametrically identified. Here V_j^i is assumed to be distributed as in Equation (1). The concern with this estimator is that it makes parametric assumptions on the entry probability which may not be correct. In particular the resulting distribution puts most of the weight on there being a small number of potential bidders in the auction.[6] The value of the distributional assumption is that it leads to a simple formula for the probability function. In fact if the variance on all the β terms is 0, the model is just a slightly complicated censored regression model. Graph A1 Bidders Per Auction shows that the number of *observed* bidders is at least consistent with this distributional assumption on the number of *potential* bidders.[7]

Another important difference between the random coefficients model and the order statistics model is that the observation in the random coefficients model is a bid, while the observation in the order statistics model is an auction.

4 Results

Table 1 presents the estimates from the random coefficients model using all the bids made in all of the auctions. The model allows bidders to have different preferences over the characteristics of the cameras including brand, megapixels, optical zoom, as well as for differences between bidders that bid at night and on the weekend. To interpret the numbers note that $\exp(4.82) =$ \$123.96. We see that relative to Olympus, the mean bidder is willing to pay more for the brand Canon and the brand Nikon. We also see that the mean bidder is willing to pay more for cameras that have a larger number of megapixels and have a larger optical zoom. The mean bidder also prefers lighter cameras and cameras which come with more memory.

Table 2 presents the results for the random coefficients order statistics

[6]Thanks to Steve Tenn for pointing this out.

[7]Adams (2004) presents some Monte Carlo comparisons between the models presented in Song (2003) and Adams (2004). Also, in non-presented results, the authors estimate a simpler version of the Adams model and the Song model on each brand separately. In most cases the results are similar.

Variable	β		σ^2	
Canon	0.03	(0.03)	0.25	(0.03)
Fuji	-0.08	(0.02)	0	-
Kodak	-0.21	(0.02)	0.27	(.03)
Nikon	0.11	(0.03)	0.23	(0.04)
Olympus	0	-	0.09	(0.02)
Log(Megapixel)	0.63	(0.04)	0.19	(0.03)
Digital Zoom	-0.15	(0.03)	0.11	(0.03)
Log(Optical Zoom)	0.43	(0.06)	0.06	(0.03)
No Optical Zoom	-0.30	(0.03)	0.13	(0.03)
Log(Weight)	-0.13	(0.06)	0.04	(0.01)
Log(Memory)	0.07	(0.02)	0.05	(0.01)
Friday	-0.01	(0.02)	0	-
Weekend	-0.01	(0.02)	0	-
Night	-0.06	(0.05)	0	-
Const.	4.82	(0.14)	0	-
Residual	-	-	0.21	(0.01)
Number of Observations	20,614			

Table 1: Random Coefficients (standard error)

Variable	β		σ	
Canon	0.28	(0.21,0.30)	0.003	(0,0.010)
Fuji	-0.10	(-0.13,-0.06)	0.003	(0.001,0.010)
Kodak	-0.06	(-0.11,-0.04)	0.007	(0,0.032)
Nikon	0.13	(0.09,.16)	0.003	(0,0.009)
Log(Megapixel)	0.75	(0.71,0.78)	0	(0,0.006)
Log(Optical Zoom)	0.59	(0.44,0.63)	0.011	(0,0.010)
No Optical Zoom	0.29	(0.16,0.33)	0.007	(0,0.014)
Log(Weight)	-0.21	(-0.23,-0.06)	0	(0,0)
Log(Memory)	0.07	(0.05,0.09)	0	(0,0.002)
Const.	4.41	(4.12,4.49)	0.003	(0,0.007)
Residual	-	-	0.51	(0.48,0.55)
p	.94	(0.93,0.95)	-	-
Number of Observations	3,047			

Table 2: Order Statistic Random Coefficients (5%,95%)

model.[8] Note that there are a couple of obvious differences between Table 2 and Table 1. First, in the second model we drop the observed auction characteristics such as night time and weekend. We see from Table 1 that these measures are neither statistically nor economically significant.[9] Second, in the second model there is a new parameter p, which is the parameter on the probability distribution over the number of bidders. Overall, the results in Table 2 are similar to the results presented in Table 1. We see that Canon and Nikon cameras are preferred to Olympus cameras. We also have the consumers value having more megapixels, more optical zoom, more memory and less weight. One difference is that in the second model the coefficient on "no optical zoom" is positive rather than negative. However, this coefficient interacts with the coefficient on log of the optical zoom and so both must be accounted for before comparing how the consumer values a camera without optical zoom to a camera with optical zoom. Finally, the most important difference is that the constant in the second model is estimated to be 4.41 which is lower than 4.81 estimate for the first model. This difference corresponds to a difference of about $40 or a little less than 10% of the average camera price.

Table 3 presents the own price elasticities from each of the empirical models for the top 10 cameras. The table also presents the "best substitute" camera and the "2nd best substitute" and their respective cross elasticities. The cross elasticity is calculated from the percentage decrease in the demand for the camera given a 10% price decrease for the best substitute camera. The best substitute is the camera with the highest percentage that switch from the given camera for a price decrease, and the 2nd best substitute is defined similarly. The random coefficients model suggests that there is large brand effects with bidders more likely to switch to similar products with the same brand. The model also suggests that the cross elasticities are much higher

[8] The percentiles are bootrapped with 100 repetitions. Note also that in the bootstrapped results the likelihood function was assumed to converge even if it had not done so after 5,000 iterations.

[9] This suggests that there is no evidence of a common values component to these auctions (Yin (2005)).

	Camera Model	Own	Best Sub.	Cross	2nd	Cross
Random	Canon S10	2.62	C. S20	-0.31	C. A50	-0.31
	Olympus D360	3.85	O. D400	-0.20	O. C3000	-0.20
	Nikon CP950	2.33	N. CP880	-0.30	N. CP990	-0.26
	Canon G1	1.49	C. S20	-0.18	N. CP990	-0.08
	Olympus D460	4.06	O. E100	-0.22	O. D400	-0.21
	Kodak DC215	3.00	K. DC210	-0.26	C. A50	-0.16
	Fuji FP1400	3.99	O. D400	-0.18	C. S20	-0.14
	Kodak DC4800	1.68	K. DC3400	-0.08	K. DC290	-0.08
	Nikon CP990	1.63	N. CP880	-0.15	N. CP950	-0.10
	Kodak DC280	2.29	K. DC4800	-0.28	K. DC290	-0.17
Order	Canon S10	4.34	C. S20	-0.20	C. G1	-0.13
	Olympus D360	5.00	C. A50	-0.28	O. C2000	-0.23
	Nikon CP950	4.79	C. S20	-0.20	C. A50	-0.16
	Canon G1	4.71	C. S20	-0.13	C. A50	-0.09
	Olympus D460	5.15	C. S20	-0.23	C. A50	-0.21
	Kodak DC215	5.95	K. DC4800	-0.40	K. DC3800	-0.26
	Fuji FP1400	4.80	C. S20	-0.26	C. A50	-0.21
	Kodak DC4800	4.05	C. S20	-0.14	C. G1	-0.14
	Nikon CP990	5.13	C. S20	-0.13	C. G1	-0.13
	Kodak DC280	4.67	C. S20	-0.19	O. D490	-0.15

Table 3: Elasticity Estimates for Top 10 Models

than what is suggested by the order statistics model. Considering the results from the order statistics model, the demand for the major Canon cameras is very elastic with a 10% decrease in price leading to a 40% to 50% increase in demand. The high value for the Canon cameras in the orders statistics model is reflected in the fact that the Canon brands are likely to be the closest substitutes. In general the cross elasticities estimates are between 0.4 and 0.1 for the best substitutes and between 0.3 and 0.1 for the 2nd best substitutes.

5 Conclusion

Using two months of auction data for new digital cameras, this paper presents results from three methods for analyzing demand for differentiated products sold on eBay. The first method uses the fact it is possible to track individual bidders across different auctions. By looking at what cameras bidders are willing to bid on, we may get some sense of which cameras are closest substitutes. The second approach is to estimate a standard random coefficients model on the highest bids of each bidder in each auction. This approach assumes that we observe each bidder's value for the item while allowing for bidders to have different preferences for individual camera characteristics. The third approach accounts for potential censoring bias by using order statistics. This approach accounts for both the fact that individual bidders have their high bids censored as well as for the possibility that the bidders themselves are censored. The results suggest that the demand for digital cameras on eBay is highly elastic and there is not a lot of substitution between cameras, particularly cameras of different brands.

EBay and other internet auction sites have the potential to provide important new information on consumer behavior in markets for differentiated products. Traditionally, transactions data is used to estimate the demand for differentiated products (Berry et al. (1995); Nevo (2000)). There are a number of concerns with this approach, including simultaneity bias (Berry et al. (1995)) and the tendency to use price promotions to identify price elasticities (van Heerde et al. (2003); Hendel and Nevo (2002)). EBay is a second price auction and so it may be possible to directly observe each bidder's value for the item being sold. Further we are able to observe each bidder's value for items sold in different auctions. There a number of concerns with interpreting bids in this way and this paper presents results from models based on various assumptions on how bidders behave on eBay.

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Tabel A1
Camera Characteristics

Brand	Weight (Oz.) Mean	Weight (Oz.) Variance	Megapixels Mean	Megapixels Variance	Optical Zoom Mean	Optical Zoom Variance	Memory (MB) Mean	Memory (MB) Variance	Models with SLR (%)	Models with TIFF Format (%)	Models with Digital Zoom (%)
All	14.38	30.27	2.01	0.63	2.41	2.92	11.15	58.41	4	44	79
Canon	16.90	65.15	2.50	0.85	2.00	1.10	12.00	19.20	17	33	50
Fuji	10.43	7.26	1.75	0.34	2.13	4.16	8.40	19.38	0	20	100
Kodak	14.62	11.81	1.81	0.51	1.93	1.42	10.92	43.08	0	15	77
Nikon	14.20	4.22	2.60	0.45	2.11	1.57	9.60	12.80	0	100	100
Olympus	15.62	45.37	1.96	0.72	3.14	3.99	13.00	116.82	6	67	72
Top 10 Models											
Canon S10	11.20	-	2.11	-	2.00	-	8.00	-	No	No	Yes
Olympus D360	10.70	-	1.30	-	0.00	-	8.00	-	No	No	Yes
Olympus D460	11.90	-	1.30	-	3.00	-	8.00	-	No	Yes	Yes
Kodak DC215	13.30	-	1.00	-	2.00	-	4.00	-	No	No	No
Nikon COOLPIX950	16.80	-	2.11	-	3.02	-	8.00	-	No	Yes	Yes
Nikon COOLPIX990	15.70	-	3.34	-	3.02	-	16.00	-	No	Yes	Yes
Kodak DC4800	12.50	-	3.30	-	3.00	-	16.00	-	No	Yes	Yes
Kodak DC280	14.70	-	2.30	-	2.00	-	20.00	-	No	No	Yes
Kodak DC3200	11.20	-	1.20	-	0.00	-	2.00	-	No	No	Yes
Olympus D490	12.20	-	2.11	-	3.00	-	8.00	-	No	Yes	Yes

Note: -Mean Across Models
-Variance Across Models

Table A2
Auction Statistics

Camera	# of Auctions	# of Bidders	Mean Bidders per Auction	Variance Bidders per Auction	Average length of Auction (Days)	Average Final Prices	Variance-Final Prices
All	4,564	16,538	4.59	18.80	4.88	$389.31	$178.24
Brands							
Canon	609	2,740	8.68	28.95	4.37	$493.28	$165.66
Fuji	594	2,526	4.25	8.64	5.10	$323.34	$155.82
Kodak	1,135	5,131	4.52	25.94	5.49	$315.61	$129.39
Nikon	540	2,150	3.98	8.57	4.81	$548.01	$174.39
Olympus	1,687	5,876	3.48	9.80	4.59	$338.71	$165.50
Top 10 Models*							
Canon S10	382	1,747	9.65	29.58	4.22	$411.42	$56.12
Olympus D360	333	1,193	3.58	16.76	4.34	$230.80	$21.37
Olympus D460	299	1,005	3.36	10.87	4.56	$308.96	$26.96
Kodak DC215	251	984	3.92	11.65	5.47	$215.10	$30.21
Nikon COOLPIX950	216	877	4.06	9.04	4.92	$462.72	$68.99
Nikon COOLPIX990	182	723	3.97	7.60	4.75	$722.20	$116.06
Kodak DC4800	130	716	5.51	57.55	4.75	$533.04	$57.71
Kodak DC280	129	694	5.38	36.83	5.97	$367.86	$50.12
Kodak DC3200	127	662	5.21	10.09	4.86	$170.83	$16.72
Olympus D490	139	585	4.21	6.31	4.22	$412.84	$38.46

*Ordered by total number of Bidders

Table A3
Bidder Switching*

Top 10 Most Popular Models (out of 52 models)

Overall Rank	Brand Model	Megapixels	Optical Zoom	Mean Final Price	Pr(X|Y)**	Best Substitute	Megapixels	Optical Zoom	Mean Final Price	Pr(X|Y)**	2nd Best Substitute	Megapixels	Optical Zoom	Mean Final Price	Pr(X|Y)**
1	Canon S10	2.1	2.0	$ 413.88	80%	Canon S20	3.3	2.0	$ 558.16	4%	Canon G1	3.3	3.0	$ 775.68	3%
2	Olympus D360	1.3	0.0	$ 558.16	37%	Canon S10	2.1	2.0	$ 413.88	17%	Kodak DC3200	1.2	0.0	$ 173.13	6%
3	Nikon Coolpix 950	2.1	3.0	$ 473.77	34%	Canon S10	2.1	2.0	$ 413.88	18%	Kodak DC280	2.3	2.0	$ 382.43	4%
4	Canon G1	3.3	3.0	$ 775.68	65%	Canon S10	2.1	2.0	$ 413.88	17%	Canon S20	3.3	2.0	$ 558.16	4%
5	Olympus D460	1.3	3.0	$ 307.99	41%	Canon S10	2.1	2.0	$ 413.88	12%	Kodak DC280	2.3	2.0	$ 382.43	5%
6	Kodak DC215	1.0	2.0	$ 216.35	42%	Olympus D360	1.3	0.0	$ 229.63	9%	Canon S10	2.1	2.0	$ 413.88	5%
											Fuji FinePix 1400	1.3	3.3	$ 258.88	5%
7	Fuji FinePix 1400	1.3	3.3	$ 258.88	39%	Canon S10	2.1	2.0	$ 413.88	10%	Olympus D360	1.3	0.0	$ 558.16	8%
8	Kodak DC4800	3.3	3.0	$ 543.38	30%	Canon S10	2.1	2.0	$ 413.88	31%	Canon G1	3.3	3.0	$ 775.68	5%
9	Nikon Coolpix 990	3.3	3.0	$ 754.35	40%	Canon S10	2.1	2.0	$ 413.88	8%					
						Canon G1	3.3	3.0	$ 775.68	8%					
10	Kodak DC280	2.3	2.0	$ 382.43	36%	Canon S10	2.1	2.0	$ 413.88	17%	Nikon Coolpix 950	2.1	3.0	$ 473.77	7%

*Only bidders that bid in 2 or more auctions.
**Pr(X|Y) is defined as the percentage of the total bids on a given model by a bidder who bids on two or more auctions. For example, of the bidders who bid on the Canon S10 and bid in 2 or more auctions, 80% of their total bids were on the Canon S10, 4% of their total bids were on the Canon S20, and 3% of their total bids were on the Canon G1.

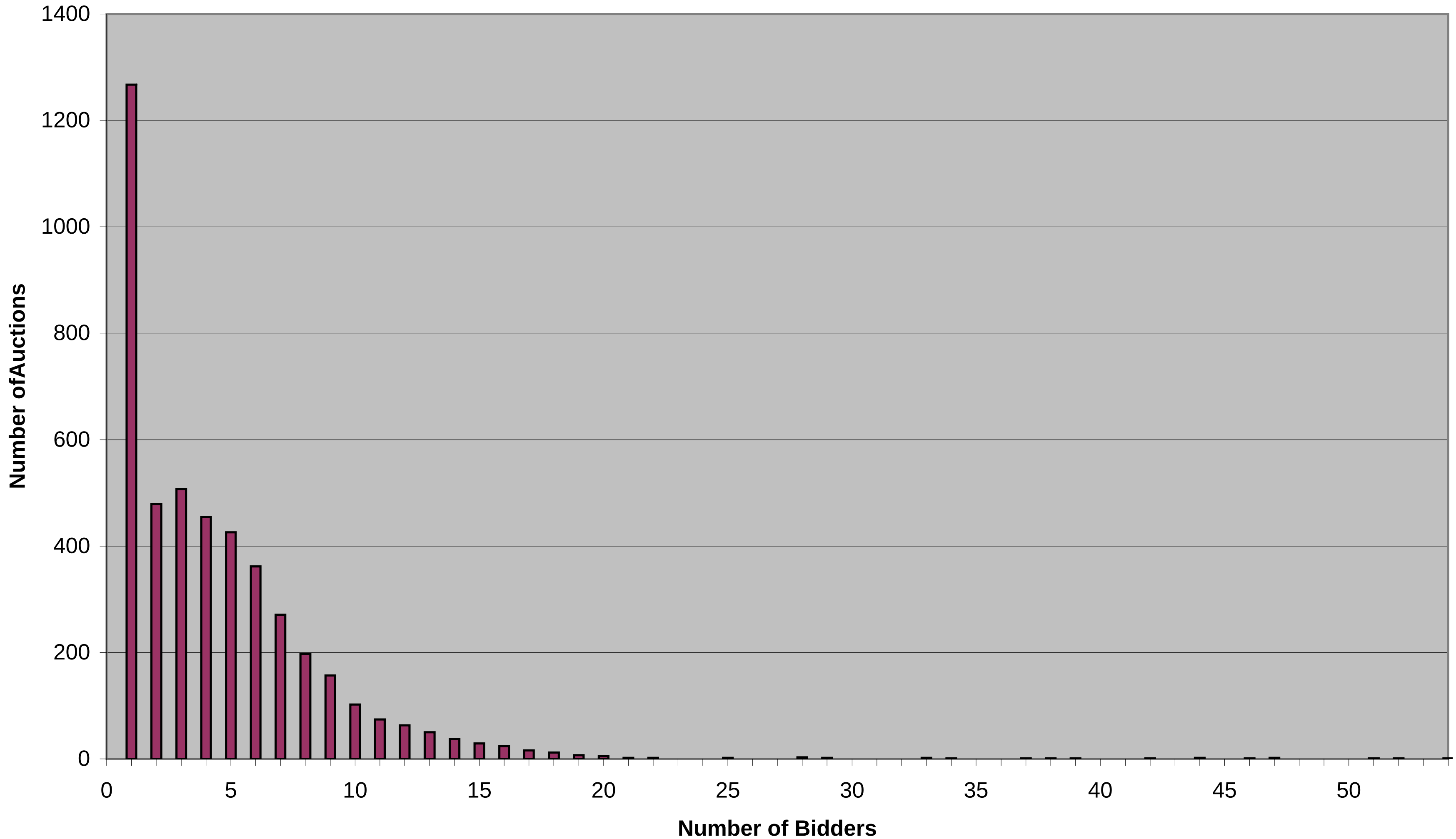
Table A4
Marginal Value Distributions

			Adams				Song				Vogt		
Brand	Model	Mean	Standard Deviation	Min	Max	Mean	Standard Deviation	Min	Max	Mean	Standard Deviation	Min	Max
CANON	A50	239.99	38.71	114.90	482.44	245.99	49.61	103.30	596.25	307.80	400.89	2.28	11966.83
CANON	G1	656.50	105.68	337.37	1255.24	427.15	86.31	190.79	936.86	714.54	1440.11	1.20	66315.35
CANON	PRO70	428.21	69.11	207.23	838.87	234.88	47.40	101.35	581.95	363.95	585.16	1.37	23655.43
CANON	S10	358.18	57.61	167.19	728.93	282.26	57.26	120.11	679.03	356.93	536.13	1.89	18412.35
CANON	S20	476.79	76.88	229.82	934.16	432.40	87.26	183.03	945.59	590.76	1120.33	1.19	50787.15
FUJI	DX10	64.28	33.30	6.58	426.98	92.87	32.56	19.98	367.65	77.18	78.24	1.29	1675.11
FUJI	FINEPIX1300	89.32	46.64	10.85	617.65	144.06	50.38	32.58	558.66	115.62	134.62	1.05	4716.03
FUJI	FINEPIX1400	115.07	59.97	13.07	991.48	187.24	65.51	39.46	761.04	226.89	246.12	4.03	6165.81
FUJI	FINEPIX2400	168.18	87.87	19.37	1240.00	276.72	96.71	45.27	1192.82	319.25	396.13	3.24	11850.47
FUJI	FINEPIX4700	242.86	125.79	26.09	1491.05	379.00	132.72	64.45	1730.79	433.83	630.86	2.35	23224.22
FUJI	FINEPIX4900	335.33	174.45	33.06	2598.79	593.04	207.15	123.89	2525.12	614.46	1036.87	1.96	39375.29
FUJI	MX1200	83.32	43.48	8.55	705.59	148.34	52.01	33.18	542.90	104.03	108.46	1.46	3284.23
FUJI	MX1700	158.45	82.62	14.89	1063.45	229.55	80.16	53.35	826.74	268.33	311.63	3.35	8330.22
FUJI	MX2700	139.70	72.80	16.19	1049.38	276.51	97.36	63.49	1218.49	175.17	225.55	1.33	11622.34
FUJI	MX2900	167.36	87.32	16.80	1276.67	306.41	106.87	67.89	1266.67	364.95	484.96	2.80	15497.47
KODAK	DC200	80.90	50.15	5.84	1191.61	143.80	72.95	12.53	961.31	95.89	125.16	0.98	4079.11
KODAK	DC210	90.68	56.43	8.17	914.16	149.97	76.17	17.67	1161.55	184.92	246.19	1.73	7078.10
KODAK	DC215	91.51	56.86	6.03	1308.06	138.79	70.70	15.28	857.14	166.48	199.07	1.84	6209.95
KODAK	DC240	128.49	79.28	9.16	1471.85	182.29	92.66	20.86	1598.97	243.79	373.03	1.47	10535.59
KODAK	DC265	161.87	100.08	10.40	1280.80	210.85	107.79	20.07	1352.72	281.75	455.43	1.65	14227.42
KODAK	DC280	173.95	107.81	9.07	1487.71	290.92	149.14	26.78	2175.06	362.86	669.91	1.23	28011.44
KODAK	DC290	210.19	131.63	14.03	3320.15	297.00	151.00	29.75	1875.73	441.77	870.66	1.24	34642.20
KODAK	DC3200	90.76	55.95	7.27	799.12	149.23	75.57	13.11	1138.43	91.35	119.18	0.75	4712.84
KODAK	DC3400	173.34	107.58	12.94	1570.35	290.69	148.42	30.98	1944.53	362.86	669.91	1.23	28011.44
KODAK	DC3800	129.00	80.28	9.01	1233.03	264.93	134.60	24.06	1808.28	179.50	276.07	0.97	9746.39
KODAK	DC4800	253.41	157.90	19.29	3286.39	365.74	186.34	41.76	2655.37	567.64	1096.16	1.28	52808.34
KODAK	DC5000	178.56	109.98	13.05	1713.43	283.42	144.06	31.45	1840.83	345.67	620.24	1.19	25711.39

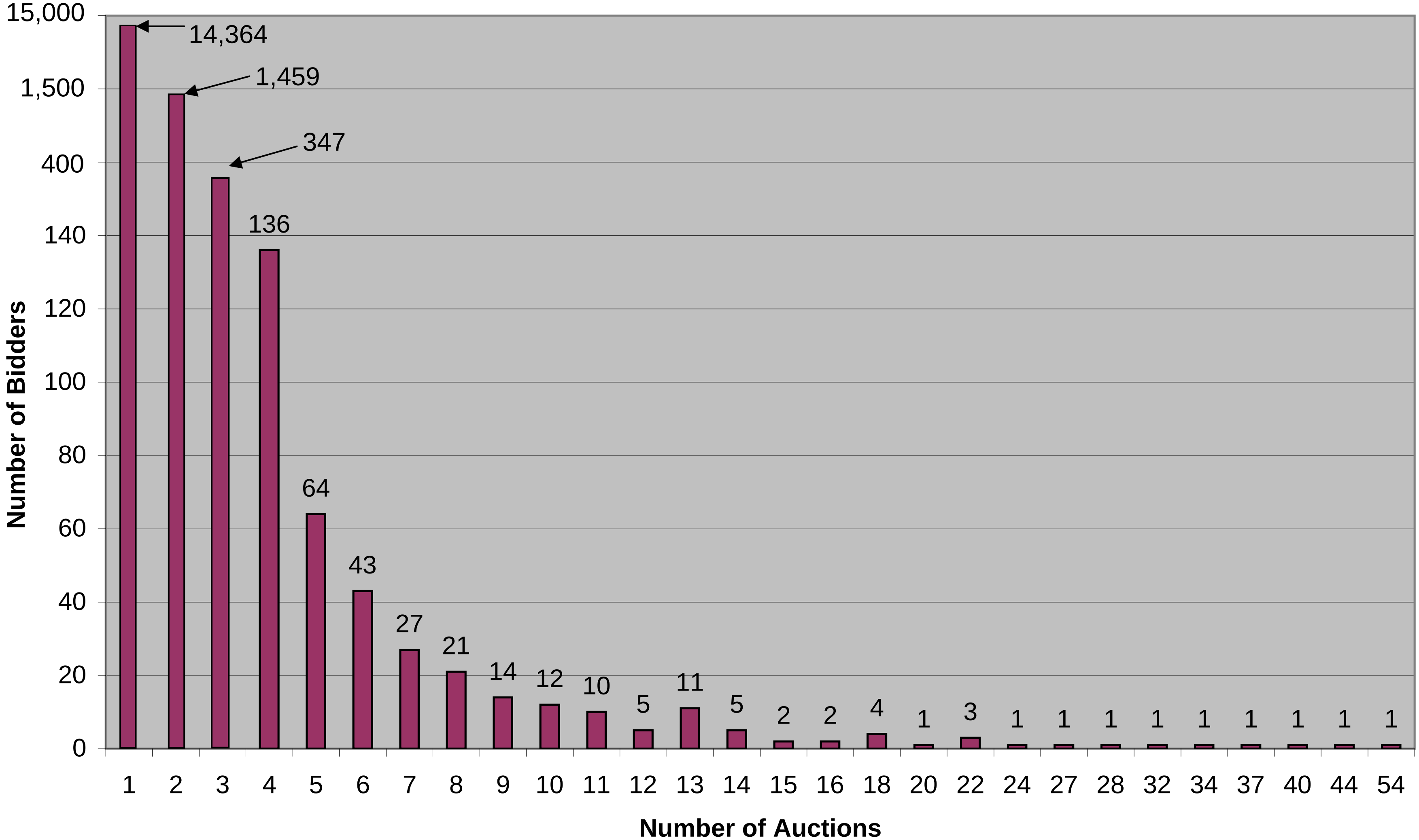
Table A4 (continued)
Marginal Value Distributions

			Adams				Song				Vogt		
Brand	**Model**	**Mean**	**Standard Deviation**	**Min**	**Max**	**Mean**	**Standard Deviation**	**Min**	**Max**	**Mean**	**Standard Deviation**	**Min**	**Max**
NIKON	**COOLPIX700**	146.76	62.56	23.01	874.48	178.10	71.90	32.97	896.06	222.95	355.89	0.84	28136.54
NIKON	**COOLPIX800**	175.13	74.99	32.97	1357.26	245.26	99.44	45.06	1360.59	385.75	577.67	2.10	25572.55
NIKON	**COOLPIX880**	339.89	145.42	52.67	2398.14	446.76	181.94	66.88	2618.61	621.38	1079.02	1.78	57848.88
NIKON	**COOLPIX950**	266.41	114.01	45.70	1357.07	348.05	141.09	63.02	1956.13	468.66	757.30	1.95	31571.74
NIKON	**COOLPIX990**	426.58	182.94	67.76	2102.59	450.12	182.62	67.77	2628.35	776.29	1555.05	1.15	91017.40
OLYMPUS	**C2000**	200.31	129.68	8.55	2788.98	299.36	163.26	20.69	2261.43	387.52	535.25	2.70	20288.70
OLYMPUS	**C2020**	197.44	127.59	14.38	2270.70	295.95	161.63	25.68	2235.76	387.01	540.02	2.67	20527.29
OLYMPUS	**C2040**	198.08	128.25	11.33	2228.34	295.84	160.84	28.27	1950.94	387.01	540.02	2.67	20527.29
OLYMPUS	**C211**	249.13	160.58	17.61	2394.93	395.59	214.84	40.15	3408.64	493.29	802.78	1.57	35393.98
OLYMPUS	**C2500**	244.49	157.81	12.14	2878.83	374.69	204.09	25.51	3000.50	647.25	1193.18	1.85	44348.58
OLYMPUS	**C3000**	289.62	187.09	20.50	3154.31	393.33	214.94	31.29	2626.74	561.76	878.83	2.12	37218.43
OLYMPUS	**C3030**	310.85	200.82	25.01	3570.77	432.37	234.73	47.28	3677.70	640.16	1119.00	1.79	55876.22
OLYMPUS	**D340**	93.08	60.17	5.10	1090.11	147.66	80.78	13.41	1326.76	116.76	137.58	1.17	4997.16
OLYMPUS	**D360**	100.46	65.05	5.64	999.40	164.04	88.85	19.20	1315.68	129.99	168.51	0.84	7077.00
OLYMPUS	**D400**	138.83	89.64	6.85	1674.39	232.00	126.07	20.36	1957.43	292.89	374.04	2.77	11394.27
OLYMPUS	**D450**	137.35	88.86	8.07	1418.60	227.28	124.15	26.69	1977.56	273.81	347.87	2.76	10591.40
OLYMPUS	**D460**	136.75	88.29	9.28	1407.48	228.00	124.73	17.00	1638.13	273.81	347.87	2.76	10591.40
OLYMPUS	**D490**	203.61	130.71	12.72	1792.76	304.43	164.18	28.69	2329.26	388.30	529.33	2.75	19978.36
OLYMPUS	**D500**	89.11	57.55	4.61	1192.01	149.00	80.78	10.64	1198.30	207.61	213.42	2.52	5949.84
OLYMPUS	**D600**	123.24	79.16	9.44	1235.20	198.19	107.56	17.48	1526.84	283.52	325.45	3.09	11072.62
OLYMPUS	**D620**	132.16	85.49	7.54	1702.94	218.83	119.43	19.64	1764.85	315.38	400.59	3.40	13223.14
OLYMPUS	**E10**	318.01	205.72	17.47	4669.49	452.46	246.75	40.02	3453.29	1109.41	2584.65	1.20	143159.60
OLYMPUS	**E100**	153.86	98.97	11.19	2164.26	285.09	155.89	30.00	3017.97	759.80	1636.36	0.86	70769.36

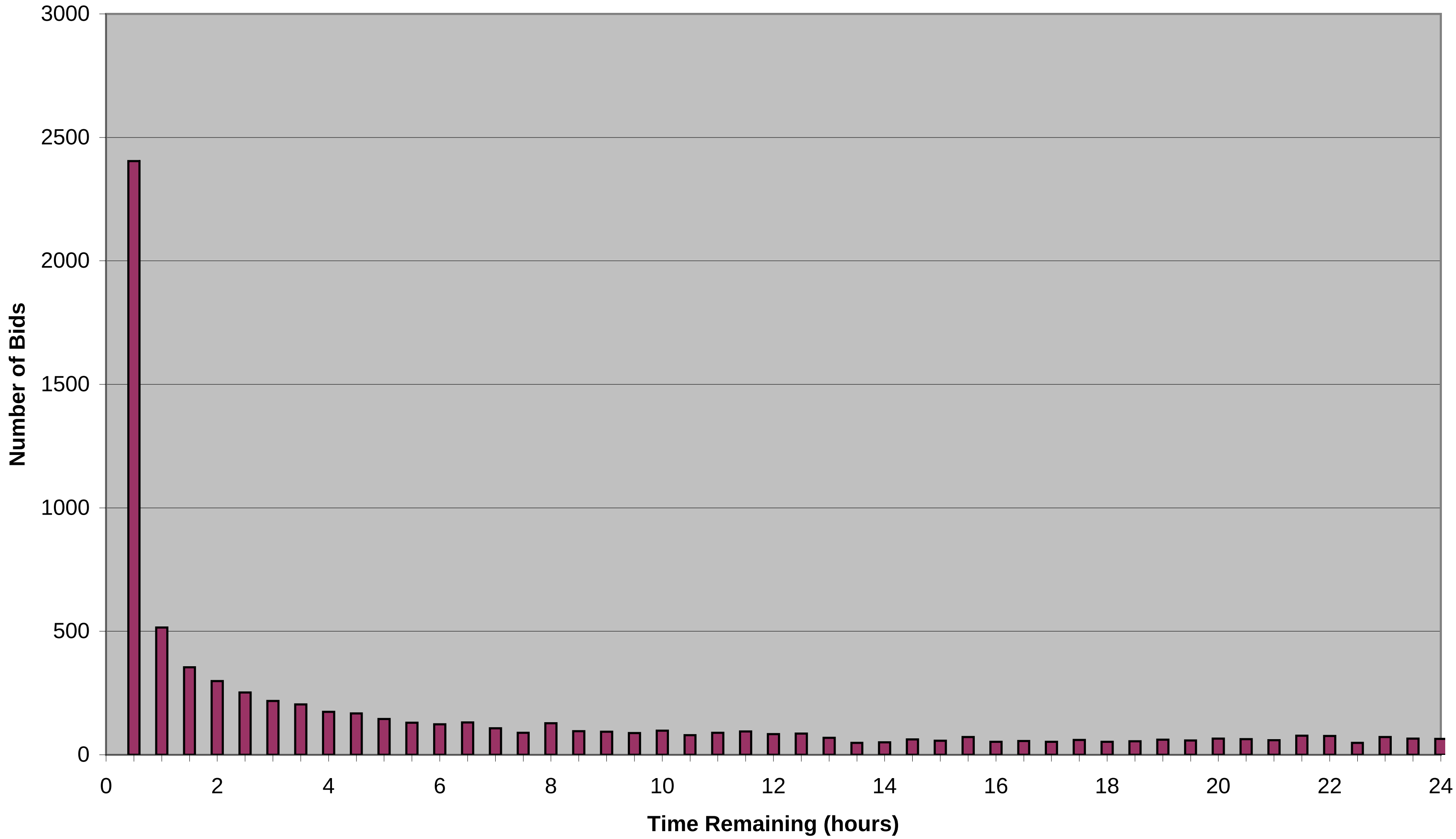
Graph A1
Number of Bidders



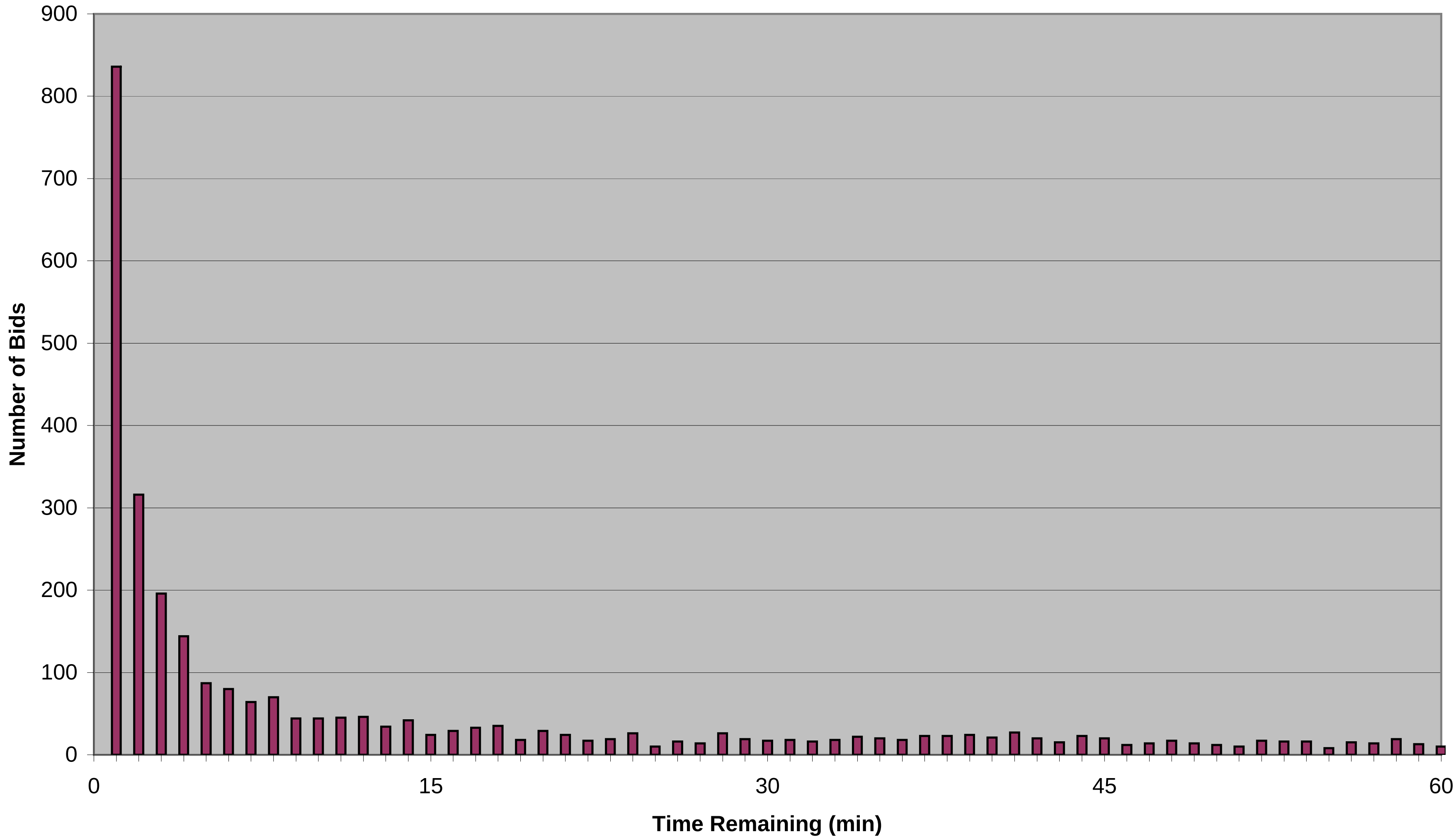
Graph A2
Auctions per Bidder
(note: not to scale)



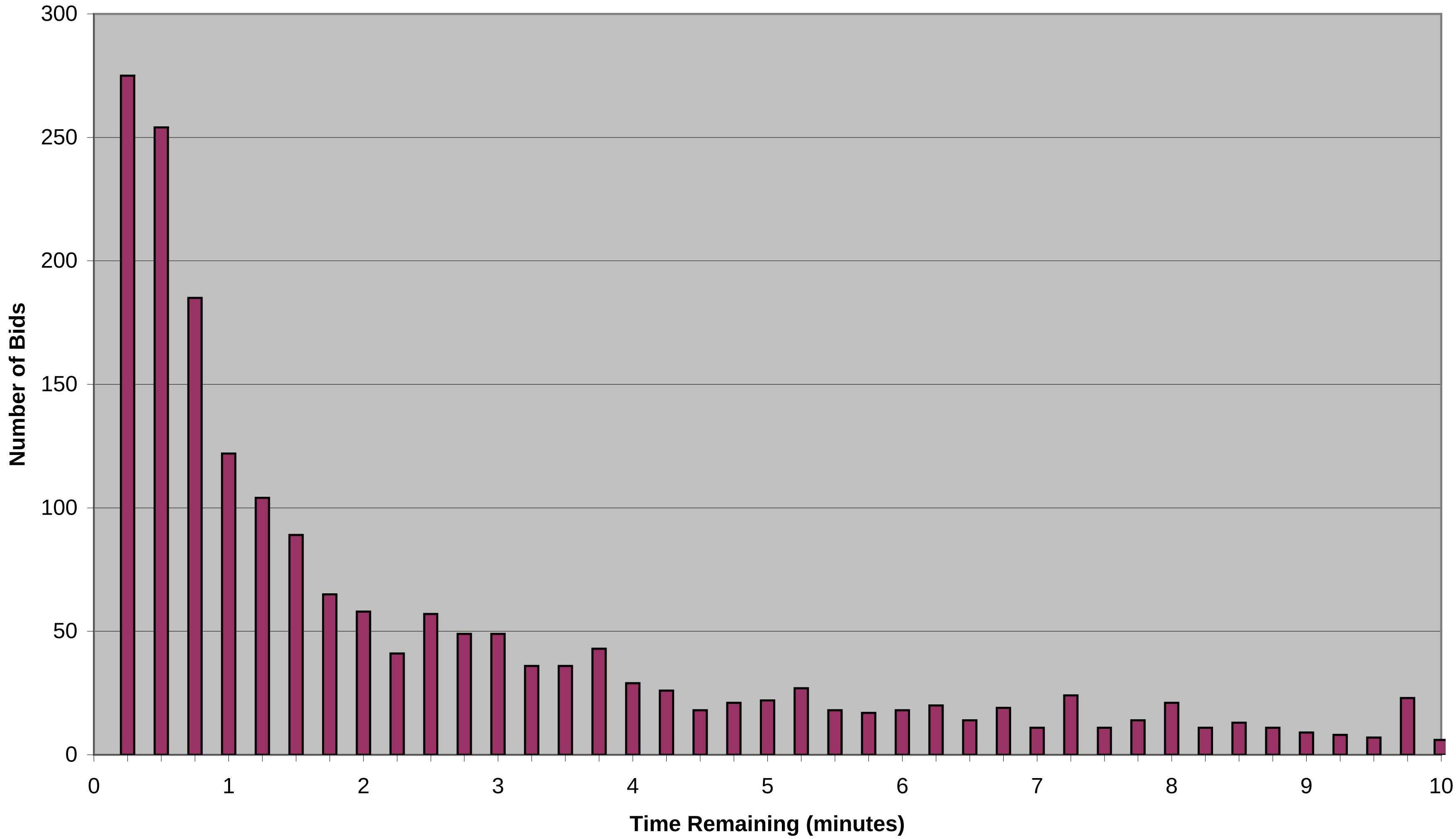
Graph A3
Histogram- Bids in the Final Day



Graph A4
Histogram- Bids in the Final Hour



Graph A5
Histogram- Bids in the Final 10 minutes



Graph A6
Histogram- Bids in Final 5 Minutes