Digital Demand: Demand for digital cameras on eBay

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March 29, 2004

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 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.

*Thanks to Laura Bivins, George Deltas, Mike Sandfort, Unjy Song, Steve Tenn, and other FTC colleagues for helpful discussions. Thanks also to Hao Xu for providing the data. Finally, thanks to Peter Newberry, Jorge Roberts and Jeanne Schoenfelder for excellent research assistance. Note that this paper does not necessarily represent the views of the Commission or any individual Commissioners. All remaining errors are our own.

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. 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)).[1] 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 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

[1] Our colleague, Laura Bivins, even bought her wedding dress on eBay!

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 considers two new models for estimating demand from eBay auction data. The first model is based on Song (2003) and uses the second highest and the third highest bids to estimate the value distribution. The second model is based on Adams (2004) and uses the second highest bid and a distributional assumption on the number of bidders to estimate the value distribution.

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.

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 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.[2] 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 under an additional distributional assumption on a potential bidder's entry probability, the distribution of values is identified. Both models are estimated below.

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 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

[2]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)).

same data to analyze the effect of option values on bidding behavior.

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,[3] and a bidder ID. Attached to this information is data collected from web sites like znet.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 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 Number of Bidders shows

[3] 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.

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} 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 ($B_{t^ij}^i = V_j^i$), 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 Song (2003). The author shows that

$$\Pr(v_2|v_3) = \frac{2(1 - F(v_2))f(v_2)}{(1 - F(v_3))^2)} \tag{2}$$

where v_2 is the second highest bid in the auction and v_3 is the third highest bid in the auction. Note that the highest and second highest potential bidders do not have their bids censored. That is, the second highest potential bidder always has the opportunity to bid at her "last opportunity". If in addition we assume that the third highest potential bidder has the opportunity to bid at her "last opportunity". Then v_2 and v_3 are the values of the second highest and third highest potential bidders respectively. Song (2003) shows that as the time of the latest of the two highest bids approaches the end of the auction, the probability that the third highest potential bidder has the opportunity to bid at her last opportunity approaches 1. While Song (2003) shows that the underlying value distribution is non-parametrically identified, here it is assumed that each potential bidder's value is from the following distribution.

$$V_j^i = X_j^{\beta}\epsilon_{ij} \tag{3}$$

where $Log(\epsilon_{ij})$ is distributed $N(\mu_j, \sigma_j^2)$. The concern with this approach is that third highest potential bidder may not be the third highest observed bidder giving biased estimates (Song (2003)). Another concern is that auctions with only two bidders are excluded. This has an effect of reducing the sample size, it also may lead to some difference in the sample of auctions that is analyzed.[4]

Adams (2004) presents an alternative model to account for the censoring problem in the eBay data. Assume that the probability distribution over the number of potential bidders in the auction is given by $p_{nj} = (1 - p_j)p_j^n$. Given this assumption Adams (2004) shows that

$$\Pr(v_2 | v_2 > c) = \frac{2(1 - p_j)(1 - F(c))f(v_2)(1 - F(v_2))}{(1 - (1 - p_j)F(c) - p_j F(v_2))^3} \tag{4}$$

where c is the minimum bid amount. Adams (2004) shows that $f(v_2)$ is non-parametrically identified. Here V_j^i is assumed to be distributed as above and

$$p_j = \frac{\exp\{X_j \gamma\}}{1 + \exp\{X_j \gamma\}} \tag{5}$$

where γ is the vector of coefficients that determine the number of likely potential bidders. The concern with this estimator is that it makes parametric assumptions on the entry probability which may not be correct.[5] The value of the distributional assumption is that it leads to a simple formula for the probability function. The concern is that the resulting distribution puts most of the weight on there being a small number of potential bidders in the auction.[6] Graph A1 Number of Bidders shows that the number of *observed* bidders is at least consistent with this distributional assumption on the number of *potential* bidders.

Another important difference between the random coefficients model and the two order statistics models is that the observation in the random coeffi-

[4]There may be some unobserved heterogeneity between auctions that is observable to a bidder and affects the likelihood that she bids in the auction. See **?**) for a discussion of this issue in first price auctions, or Livingston (2002) for a discussion related to eBay auctions.

[5]Adams (2004) presents some Monte Carlo comparisons between the models presented in Song (2003) and Adams (2004).

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

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			
-2 Log Likelihood	56958.7			

Table 1: Random Coefficients (standard error)

cients model is a bid, while the observation in the two order statistics models 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.

Given some important differences between the brands and the difficulties of estimating the order statistics models we choose to assume that coefficients were *not* randomly distributed but we do allow differences across brands by estimating a separate model on each brand. Table 2 presents the results of the two order statistics models (labelled Adams and Song, respectively) for the Canon and Kodak cameras. The two models are basically estimated on the same data with the same explanatory variables. There are two differences. First the Song model uses fewer auctions because of the requirement that there must be three bidders in the auction. Second the Adams model has an additional coefficient, the γ coefficient. Remember from above that the probability of entry is $\frac{\exp \gamma}{1+\exp \gamma}$. For the Canon camera this probability is .91. In theory both models should present identical results. The results are not identical which may suggest a misspecification error. However, closer inspections shows that there are only two cases where the estimate from the Song model is statistically different from the point estimate in the Adams model. These are the coefficient on Log(Megapixel) and Log(Memory) for the Canon brand. Consistent with the random effects model the Canon brand is considered more valuable than the Kodak brand. Also the models with more megapixels and greater optical zoom are considered more valuable, although the coefficient on optical zoom is not statistically significant from 0 in the Song model. The results on weight and memory are a little strange. Results from the Adams model suggest that bidders prefer heavier cameras with less memory which contradicts both the results from the random coefficients model and common sense. The results from the Song model aren't quite as strange, but neither are any of the coefficients significantly different from 0.

Table 3 presents the estimated coefficient results for the Fuji, Nikon and Olympus brands. In general the estimated coefficients make sense and are consistent with each other and the estimates from the random coefficients

		Adams		*Song*	
	Variable	β		β	
Canon	Log(Megapixel)	1.03	(.07)	.34	(.29)
	Log(Optical Zoom)	.58	(.08)	.06	(.36)
	No Optical Zoom	-		-	
	Log(Weight)	.31	(.07)	-.13	(.39)
	Log(Memory)	-.27	(.07)	.39	(.24)
	Const.	4.51	(.17)	4.83	(.91)
	Residual	.16	(.01)	.20	(.01)
	γ	2.32	(.35)	-	
	Number of Observations	472		450	
	Log Likelihood	423.91		1052.62	
Kodak	Log(Megapixel)	.81	(.10)	.67	(.17)
	Log(Optical Zoom)	.29	(.10)	.04	(.18)
	No Optical Zoom	.06	(.11)	.06	(.20)
	Log(Weight)	.26	(.13)	.03	(.24)
	Log(Memory)	-.04	(.06)	.11	(.11)
	Const.	3.54	(.29)	4.55	(.52)
	Residual	.57	(.01)	.48	(.02)
	γ	2.54	(.18)	-	
	Number of Observations	796		657	
	Log Likelihood	-296.23		441.67	

Table 2: Estimates for Canon and Kodak Cameras (standard error)

		Adams		*Song*	
Fuji	Log(Megapixel)	.84	(.13)	1.18	(.22)
	Log(Optical Zoom)	1.04	(.15)	1.05	(.27)
	No Optical Zoom	.59	(.14)	.79	(.24)
	Log(Weight)	-.85	(.21)	-.59	(.36)
	Log(Memory)	.10	(.08)	-.04	(.12)
	Const.	5.16	(.47)	5.15	(.77)
	Residual	.49	(.02)	.34	(.02)
	γ	3.37	(.24)	-	
	Number and Ln Likelihood	414	-94.85	349	388.00
Nikon	Log(Megapixel)	.95	(.10)	.89	(.21)
	Log(Optical Zoom)	1.02	(.14)	.85	(.28)
	No Optical Zoom	.53	(.19)	.27	(.38)
	Log(Weight)	-		-	
	Log(Memory)	.05	(.07)	-.22	(.16)
	Const.	3.55	(.14)	4.63	(.30)
	Residual	.41	(.02)	.39	(.02)
	γ	2.67	.24	-	
	Number and Ln Likelihood	375	-18.37	323	340.95
Olympus	Log(Megapixel)	.83	(.05)	.61	(.09)
	Log(Optical Zoom)	.01	(.18)	.07	(.34)
	No Optical Zoom	-.32	(.20)	-.27	(.37)
	Log(Weight)	-.21	(.08)	-.19	(.14)
	Log(Memory)	.10	(.04)	.14	(.07)
	Const.	4.83	(.18)	5.24	(.30)
	Residual	.58	(.01)	.51	(.02)
	γ	2.75	(.16)	-	
	Number and Ln Likelihood	990	-404.35	811	533.37

Table 3: Estimates for Fuji, Nikon and Olympus Cameras (standard error)

model. One difference is that these models suggest that the brand Nikon is not as valuable as the random coefficients model suggests. The cases where the coefficient estimates from the Song model are statistically different from the point estimates from the Adams model are the constant for the Nikon brand and the Log(Megapixel) coefficient for the Olympus brand.

Table A4 presents the marginal value distributions for each camera model. These distributions highlight the fact that the Adams model suggests that the mean value is lower than is suggested by both the Song model and the random coefficients model. The other difference is that the random coefficients model puts much larger weight on very high valuations relative to the two order statistics models.

Table 4 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 5% 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. While the results for the order models are similar, the results for the random coefficients model are quite different. 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 than what is suggested by the order statistics models.[7] Considering the results from the order statistics models, the demand for the major Canon cameras is very elastic with a 5% decrease in price leading to a 70% to 100% increase in demand. For the other major cameras, the changes are less dramatic but still a 5% decrease in price leads to between a 15% and a 30% increase in demand. For some reason the Olympus E10 is almost always the bridesmaid in the order statistics models. In general the cross elasticities estimates are between 2 and 0.3 for the best substitutes and between 1.4 and 0.17 for the 2nd best substitutes.

[7]Note that the order statistic models are estimated separately on each brand.

	Camera Model	Own	Best Sub.	Cross	2nd	Cross
Random	Canon S10	10.71	C. S20	-4.47	C. A50	-2.24
	Olympus D360	9.00	O. E10	-4.00	K. DC3200	-1.00
	Nikon CP950	9.25	N. CP800	-2.48	N. CP880	-2.04
	Canon G1	3.20	C. S20	-1.28	N. CP990	-0.09
	Olympus D460	-	-	-	-	-
	Kodak DC215	12.98	K. DC210	-4.31	O. E10	-0.77
	Fuji FP1400	8.91	O. E10	-1.04	F. FP2400	-0.93
	Kodak DC4800	2.33	O. E10	-0.34	K. DC3400	-0.29
	Nikon CP990	2.42	N. CP880	-0.80	O. E10	-0.20
	Kodak DC280	-	-	-	-	-
Adams	Canon S10	14.17	O. E10	-1.18	C. G1	-0.78
	Olympus D360	3.96	O. E10	-0.84	C. G1	-0.45
	Nikon CP950	5.23	O. E10	-0.49	C. G1	-0.34
	Canon G1	14.72	O. E10	-0.77	C. S20	-0.40
	Olympus D460	4.21	O. E10	-0.62	C. G1	-0.51
	Kodak DC215	3.72	C. G1	-0.58	C. S20	-0.52
	Fuji FP1400	4.44	C. G1	-0.84	O. E10	-0.68
	Kodak DC4800	3.77	O. E10	-0.37	C. G1	-0.24
	Nikon CP990	5.72	O. E10	-0.53	C. G1	-0.28
	Kodak DC280	3.81	O. E10	-0.42	C. G1	-0.26
Song	Canon S10	7.14	O. E10	-2.86	C. A50	-1.43
	Olympus D360	2.94	O. E10	-0.53	O. C211	-0.32
	Nikon CP950	4.38	O. E10	-0.62	F. FP4900	-0.17
	Canon G1	20.00	-	-	-	-
	Olympus D460	2.75	O. E10	-0.54	0. C3000	-0.17
	Kodak DC215	2.89	O. E10	-0.64	0. C211	-0.35
	Fuji FP1400	6.53	O. E10	-1.45	K. DC4800	-0.41
	Kodak DC4800	3.18	O. E10	-0.36	Fuji FP4900	-0.16
	Nikon CP990	6.14	O. E10	-0.28	0. C2500	-0.17
	Kodak DC280	2.73	O. E10	-0.46	0. C11	-0.21

Table 4: Elasticity Estimates for Top 10 Models

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. Unfortunately, there a number of concerns with interpreting bids in this way. 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.)		Megapixels		Optical Zoom		Memory (MB)		Models with SLR (%)	Models with TIFF Format (%)	Models with Digital Zoom (%)
	Mean	Variance	Mean	Variance	Mean	Variance	Mean	Variance			
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%

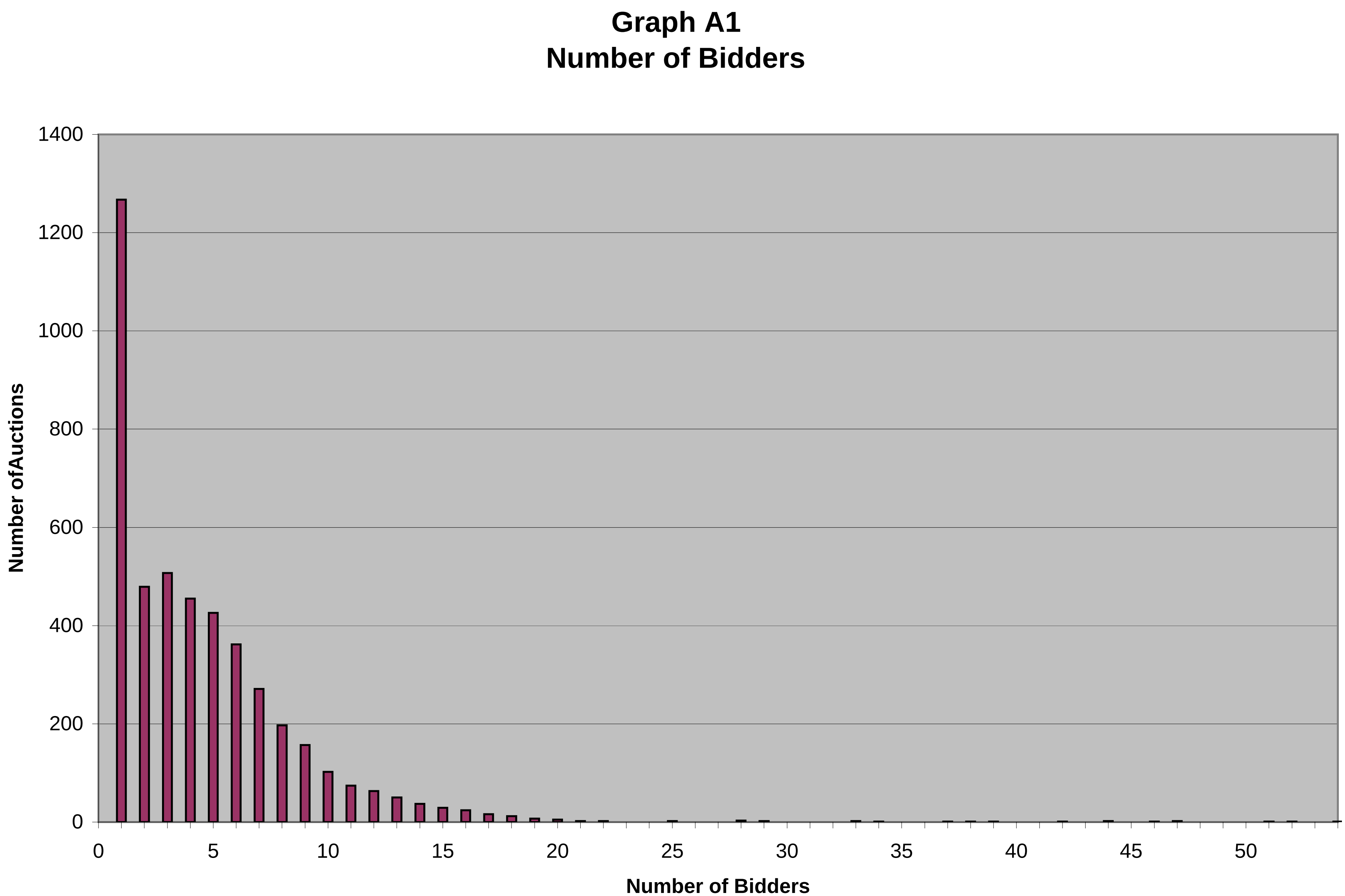
*Only bidders that bid in 2 or more auctions.
**Pr(X|Y) is defined as the percentage of the total bids on a given model by a bidder who bids on two or more auctions. For example, of the bidders who bid on the Canon S10 and bid in 2 or more auctions, 80% of their total bids were on the Canon S10, 4% of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

Table A4
Marginal Value Distributions

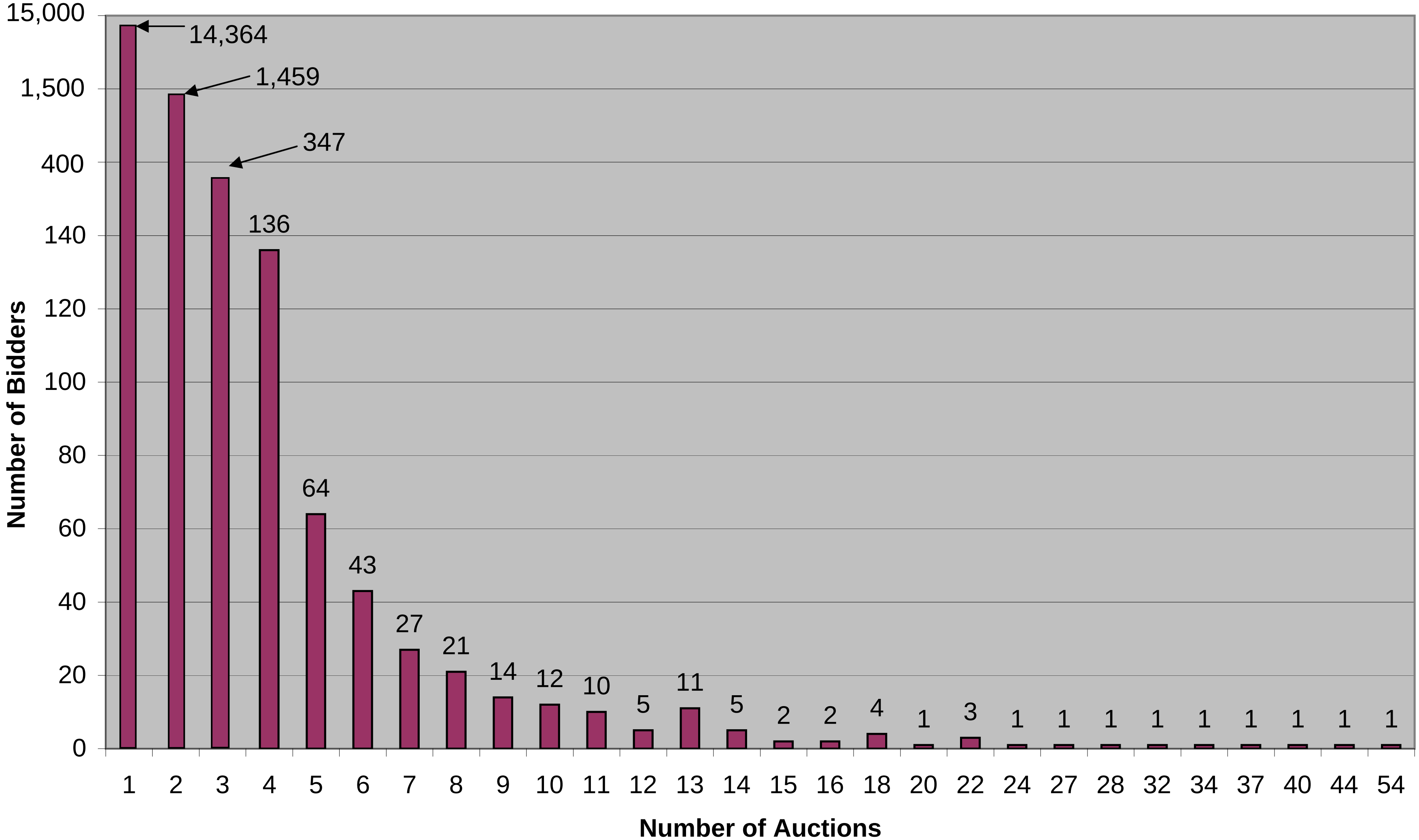
			Adams				Song				Vogt		
Brand	**Model**	**Mean**	**Standard Deviation**	**Min**	**Max**	**Mean**	**Standard Deviation**	**Min**	**Max**	**Mean**	**Standard Deviation**	**Min**	**Max**
CANON	**A50**	239.99	38.71	114.90	482.44	245.99	49.61	103.30	596.25	307.80	400.89	2.28	11966.83
CANON	**G1**	656.50	105.68	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

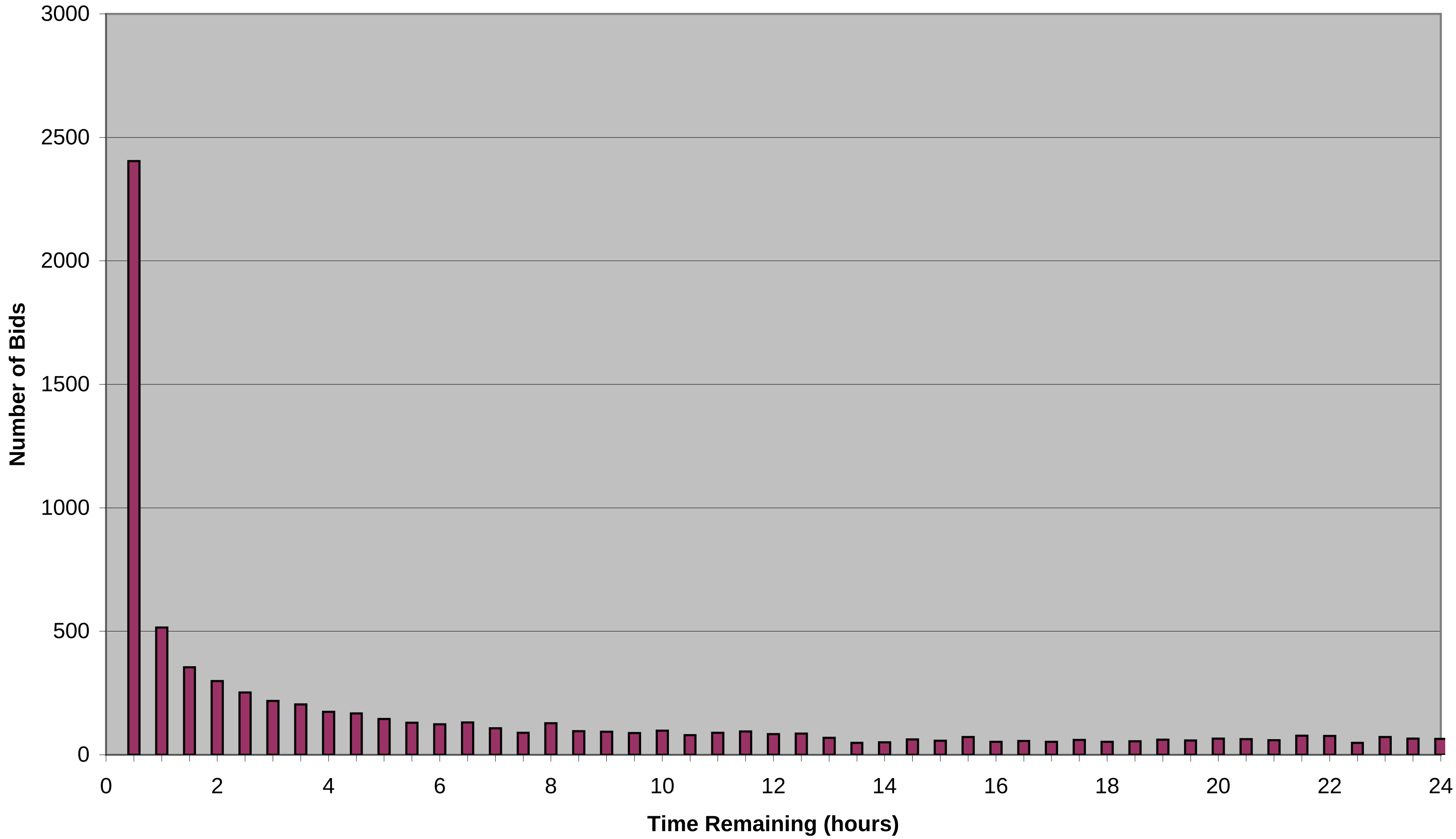
			Adams				Song				Vogt		
Brand	Model	Mean	Standard Deviation	Min	Max	Mean	Standard Deviation	Min	Max	Mean	Standard Deviation	Min	Max
NIKON	COOLPIX700	146.76	62.56	23.01	874.48	178.10	71.90	32.97	896.06	222.95	355.89	0.84	28136.54
NIKON	COOLPIX800	175.13	74.99	32.97	1357.26	245.26	99.44	45.06	1360.59	385.75	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
Number of Auctions
0
200
400
600
800
1000
1200
1400
0
5
10
15
20
25
30
35
40
45
50
Number of Bidders

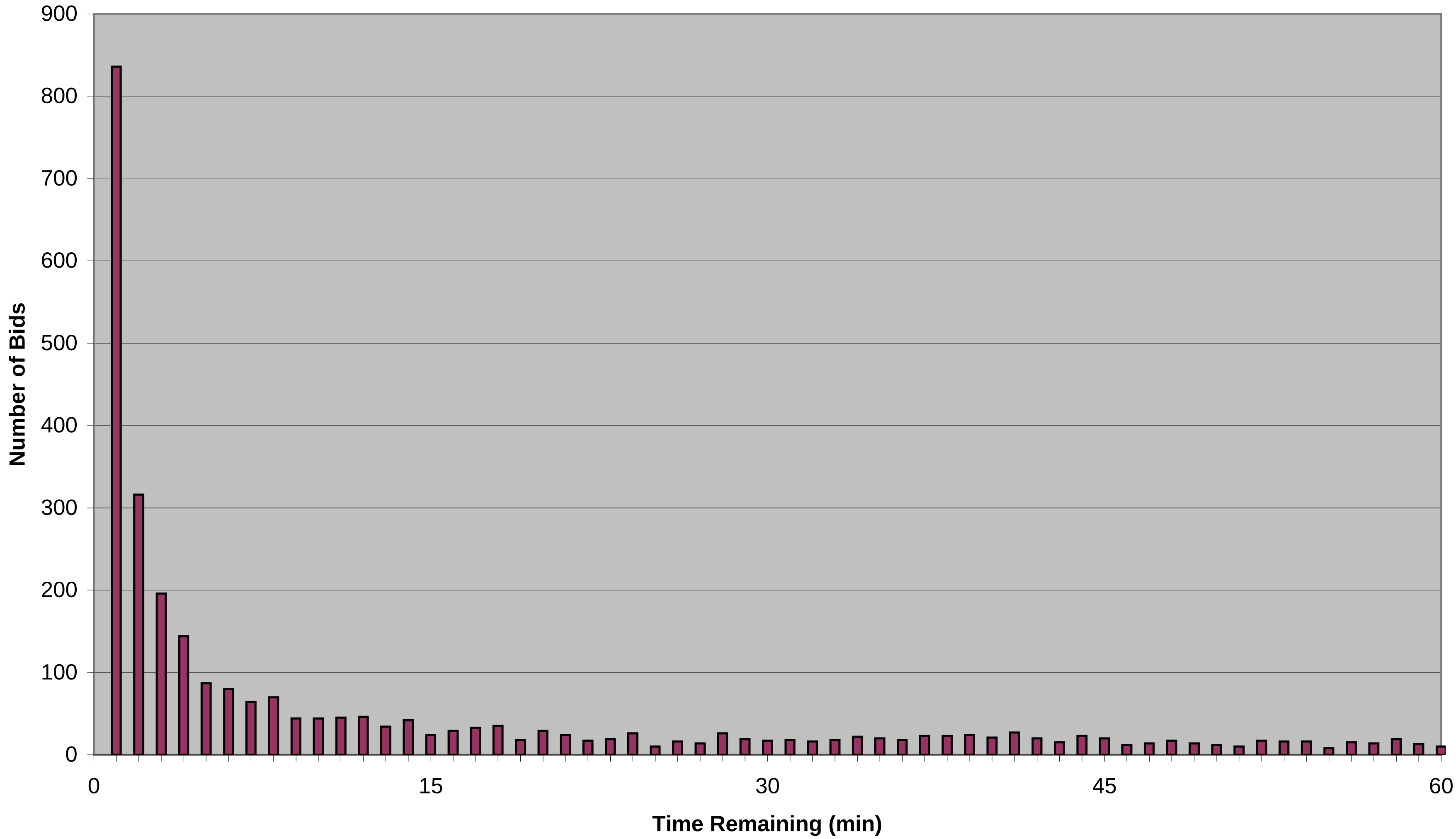
Graph A2
Auctions per Bidder
(note: not to scale)



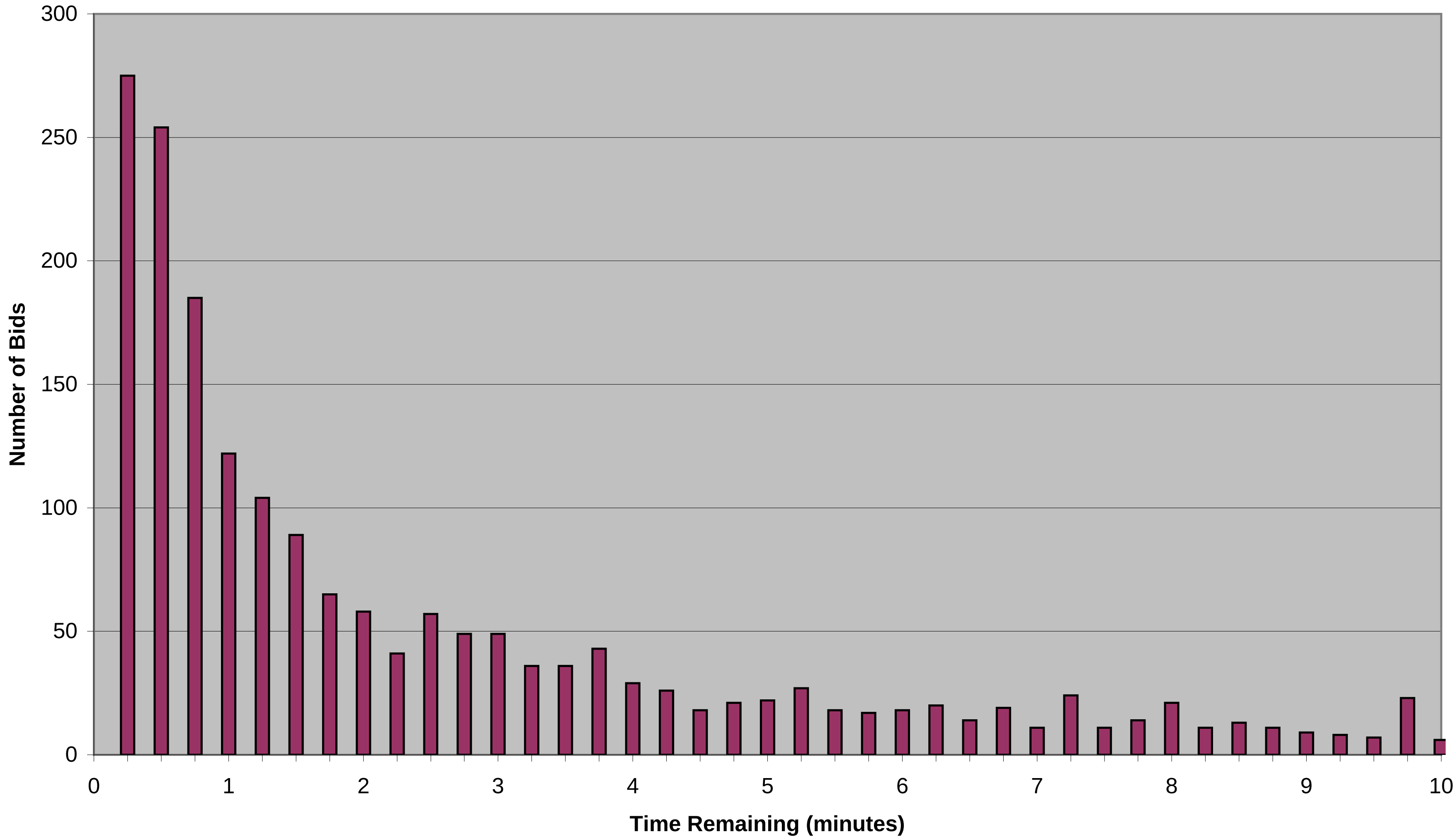
Graph A3
Histogram- Bids in the Final Day

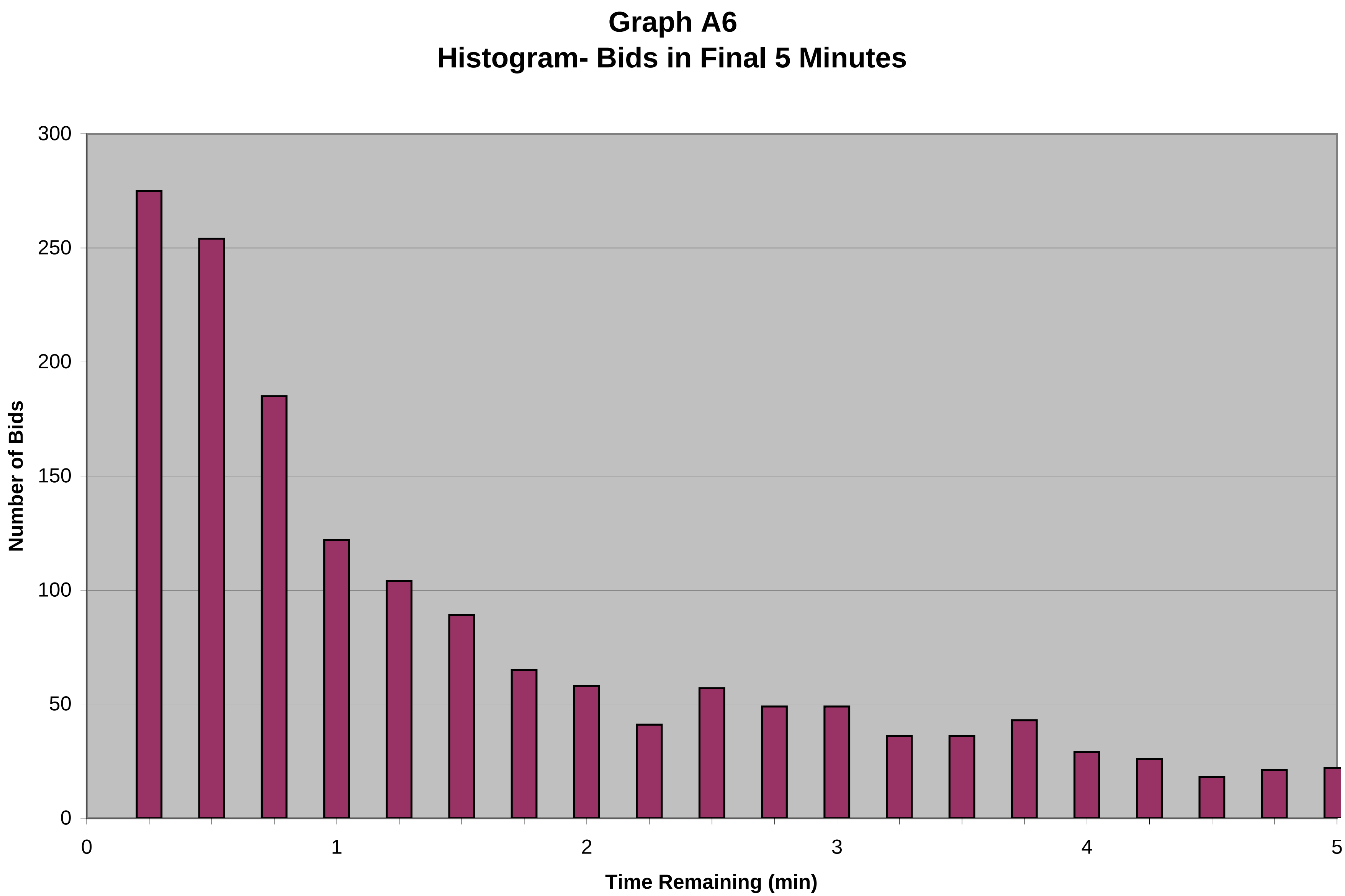


Graph A4
Histogram- Bids in the Final Hour



Graph A5
Histogram- Bids in the Final 10 minutes




Graph A6
Histogram- Bids in Final 5 Minutes
Number of Bids
300
250
200
150
100
50
0
0
1
2
3
4
5
Time Remaining (min)