Focusing on Demand: Using eBay data to analyze the demand for telescopes.

Christopher P. Adams
Laura L. Bivins*
Bureau of Economics, Federal Trade Commission
Email: cadams@ftc.gov or lbivins@ftc.gov
Draft

January 17, 2003

Abstract

This paper analyzes the value of using data from on-line auctions to determine product market definitions and competitive effects of mergers. Traditionally this type of demand analysis has been based on retail transaction data, particularly "scanner" data. However, such data is not always readily available and may be difficult to interpret. Auction data, particularly data from on-line auctions like eBay may be easy to access and may be much easier to interpret. The authors analyze data from a series of auctions for 3 different types of telescopes, held over a 8 week period. The results suggest that the demand for telescopes is very elastic and that the two types of telescope designs (the Schmidt-Cassegrain and the Maksutov-Cassegrain designs) are in different product markets, supporting a position taken by the Commission in a recent case.

*The authors would like to thank George Deltas, Dan Hosken, Mike Moiseyev, David Schmidt, Mike Vita, Bill Vogt, two anonymous referees and other FTC colleagues for useful discussions on these issues. However, all errors are our own. Note also that this paper does not necessarily represent the views of the Commission or any individual Commissioners.

1 Introduction

Antitrust economists working at the FTC and the DOJ are routinely asked to determine the answer to two questions when evaluating a potential merger:

- What is the product market?
- What will be the competitive effects of the merger?

Traditionally, evidence from interviews and documents have been complemented by econometric evidence based on retail price and transaction data. Recently, the use of scanner data has become widespread. This data allows for the estimation of cross-price elasticities which are used to determine product market definitions, and own-price elasticities which are used to determine the price effects of a merger.[1] Unfortunately, transaction data is not always available, and even when such data is available the results may not be easy to interpret.[2] On the other hand, on-line auction data may be readily available from sites such as eBay.com. It is possible that auction data is able to provide enough information to identify each bidder's "willingness to pay" for the item and thus the demand curve for the item. Further, it may be possible to determine an individual's willingness to pay for multiple items and thus identify a demand system over multiple products.

This paper presents an analysis of eBay auction data for three types of telescopes, Meade's ETX90EC, ETX125EC and LX200, that retail for between \$500 and \$1,500. This data was collected over an eight week period in April, May and June of 2002, and includes information from over 58 separate auctions with over 200 separate bidders. The data was used to estimate the demand for the three telescopes and calculate own-price and cross-price elasticities. The results suggest that demand for these telescopes is very elastic. This result corresponds with our understanding that these telescopes are

[1]See Hosken et al. (2002) for a discussion of some of the issues involved with using such data.

[2]Such data often suffers from the classic "simultaneity" problem, in that changes in price may be the result of changes in demand rather than changes in supply. See Nevo (2000) for an excellent introduction to one possible solution, the BLP model.

expensive luxury items, generally bought by hobbyists and high end consumers. The results also suggest that the Schmidt-Cassegrain telescopes and the Maksutov-Cassegrain telescopes are in different product markets. This result supports the claim that was made by the Commission in a previous merger case regarding this industry,[3] as well as in the more recent merger case.[4]

EBay and other online auction houses may be a rich source of data for economists analyzing the market structure of certain industries. There exists a number of papers that have used data from online auctions to analyze different aspects of the auction mechanism and the value of information available to buyers and sellers. For example, Lucking-Reiley et al. (2000), Livingston (2002) and Hasker et al. (2001) discuss the importance of seller's ratings, reserve prices and the length of the auction, and Roth and Ockenfels (2000) analyze the effect of the fixed endpoint of eBay auctions as compared to the "going, going, gone" feature of Amazon.com auctions. While it is not the focus of the paper, Hasker et al. (2001) analyze the effect on bids of characteristics of computer monitors sold on eBay (flat screen, dpi, size), the good being sold (like new, refurbished), as well as the auction (secret reserve price). There are also a number of papers that look at the question of whether bids in auctions can be used to infer demand functions. In particular, Haile and Tamer (2002) propose two different methods of bounding demand curves (actually the distribution of private values) from English auction data similar to the data found in eBay auctions. The authors use these methods to make predictions on reserve price policies from timber auction data. The analysis presented below will explicitly look at inferring demand from eBay auction data and discuss some of the concerns relating to this type of inference.

The rest of the paper proceeds as follows. Section 2 discusses the data and how it was obtained. It also describes the telescopes and provides some background information on the product market. Section 3 analyzes the demand for these telescopes, based on high bids from the eBay auctions. This section will present own-price and cross-price demand elasticities and discuss

[3]FTC v. Harbour Group Investments, 1990 WL 198819 (D.D.C. 1990).

[4]http://www.ftc.gov/opa/2002/05/meadecelestron.htm.

some of the issues and concerns with the estimations. Section 4 concludes.

2 EBay Data on Bids for Cassegrain Telescopes

2.1 Product Market

Telescopes come in three major optical configurations, refractors, reflectors and catadioptric (mirror-lens). The first type of telescope to be invented was a refractor. These telescopes were developed by Galileo and use lenses to magnify the light. The major advantage of refractors is that they can give a sharp image of the object. Refractors are generally used for observing planets, the moon and the sun. The next to be developed was the reflector. This type of telescope was developed by Sir Isaac Newton. This telescope uses a mirror at its base to focus and magnify the light. The major advantage of reflectors is that they can be made at very large apertures very cheaply. This means that they can let in a lot of light, enabling the observer to view very faint objects, such as small galaxies. Newest are the catadioptric optical systems, including the Schmidt-Cassegrain and the Maksutov-Cassegrain designs. These telescopes are also reflectors but they use multiple mirrors to increase the focal distance (the magnification) in a smaller physical space. These are good all-purpose telescopes that tend to have large apertures and large focal lengths for their physical size. The two ETX models are Maksutov-Cassegrain designs, while the LX200 is a Schmidt-Cassegrain design.

The most important characteristic of the telescope is aperture size. Magnification and light gathering ability are both functions of the aperture size. Light gathering ability is a function of the area of the mirror or lens, and thus a function of the square of the telescope's diameter. The greater the light gathering ability the fainter the objects that can be seen. The ETX90EC is the smallest at 90mm (3.5 inches), then the ETX125EC at 125mm (4.9 inches), and largest is the LX200 at 200mm (7.9 inches). Our understanding of the product market suggests, that the actual design difference between the two Maksutov-Cassegrains (ETX90EC and ETX125EC) and the Schmidt-Cassegrain (LX200) is not as important as the difference in aperture (a 3 inch difference between the ETX125EC and the LX200).

In the 1990 case, the Commission argued that the appropriate antitrust market was for 8 inch Schmidt-Cassegrain telescopes (of which the LX200 is one).[5] Only two firms manufactured and sold 8 inch Schmidt-Cassegrain telescopes in the United States, Meade and Celestron, and these two firms were planning to undertake a joint venture. This joint venture was seen by the Commission as being equivalent to a merger. Because of their high quality optics, relatively low prices and relatively compact size, these telescopes were the most popular telescope for the serious amateur astronomer. Due to the Commission's actions, the merger was never consummated. Since 1990, both companies have introduced a line of smaller and cheaper Maksutov-Cassegrain telescopes. Two of Meade's Maksutov-Cassegrain telescopes are the ETX90EC and the ETX125EC. The ETX series is the most popular type of telescope sold by Meade, with sales of around \$70 million dollars annually,[6] although the Schmidt-Cassegrain remains highly prized by the serious hobbyists.[7] Recently the Commission stated, "that the two companies together would monopolize the market for Schmidt-Cassegrain telescopes and would eliminate substantial actual competition between Meade and Celestron in the market for performance telescopes."[8]

2.2 Auctions Methods on EBay

EBay runs a second price English auction for a variety of consumer goods, including telescopes. The auction is "second price" because the winner pays

[5] At the time, the Maksutov-Cassegrain designs were made by very small scale manufacturers and were substantially more expensive than the comparable Schmidt-Cassegrain designs.

[6] This estimate is based on Meade's 2001 10K filing with the SEC and statements by Meade CEO, John Diebel, at the April 2002 Press Conference.

[7] See "astro note" 19 from the Astronomy League (http://www.astroleague.org) for a discussion of the different types of telescopes.

[8] http://www.ftc.gov/opa/2002/05/meadecelestron.htm

the next highest bid, and they are "English auctions" because bids are ascending. A typical eBay auction lasts for 7 days, although the seller can decide to have an auction last for 3, 5, or 10 days. When a potential bidder views a current auction on eBay, they see a description of the item for sale. This description is up to the seller's discretion, but is usually fairly detailed and may include a picture of the item. The bidder can also review the recent history of the seller and ratings by previous customers. Most importantly, the bidder observes the current high bid for the item. They also observe information on other bidders for that auction including when they bid, but not what their bid was.[9] Lastly, all bidders know the exact time remaining before the close of the auction.[10]

After observing this information, the bidder may decide to bid on the item. The amount entered by the bidder is actually a "proxy" bid. That is, eBay will take that bid and automatically bid slightly above the next highest bidder up to the amount entered. For example, lets assume the bidding increment is $1 and say that the current high bidder is "bidmaniac" and the current high bid is $47. Then "scopeme" enters the auction with a bid of $300. What happens next depends on the actual bid entered by bidmaniac. If it is $50, then scopeme becomes the high bidder and $51 becomes the current high bid. If, however, bidmaniac entered a bid of $302, then bidmaniac remains the highest bidder and the current high bid is $301. This system allows the bidder to leave the auction, without having to worry about being outbid, as the proxy system will keep on bidding automatically. If however, a bidder is outbid, then eBay can notify them by email. The winner of the auction, is the highest bidder (at the earliest time if there is a tie), at the end of the auction. The winner pays an amount slightly above the next highest bid.

[9] The bidder's ID is clickable and provides a recent history of that bidder's transactions, as well as ratings from sellers or buyers involved in those transactions.

[10] An important difference between eBay auctions and Amazon.com auctions is that eBay auctions have a precise end point. Roth and Ockenfels (2000) discuss the effect of this difference in detail.

2.3 EBay Auction Data

At the close of each auction, eBay provides the following information: a description of the product, including photos and other information at the seller's discretion, the date and time of each bid, the identification name for each bid (their eBay account name), and the amount of each bid, except for the highest bid.[11] We collected data from 31 auctions for the ETX90EC, 20 auctions for the ETX125EC and 7 auctions for the LX200 during April, May and June of 2002. Table 1 presents some summary statistics for the auctions that we observed. These figures clearly show that the ETX90 is the most popular of the three telescopes, with greater numbers of both buyers and sellers. Note that the retail prices are for the basic units which don't come with tripods or the "go to" system in the case of the ETX products (both are included in the price of the LX200). Winning bids are greater than the retail prices because many of the telescope auctioned come with accessories. Note also that the retail price for the LX200 is actually the retail price for the equivalent Celestron telescope, as the current version of the LX200 includes GPS tracking hardware and is significantly more expensive.

Table 2 presents summary statistics of important characteristics of the actual telescopes sold. Note that we did not include auctions with very small number of bidders. The telescopes themselves are second hand, while the sellers may be individual owners or stores. The product itself may be fairly new or even "in the box." For example, one seller stated that their ETX90EC was

> "...a great piece of glass for viewing your cosmic neighbors from your backyard. The package includes the ETX-90 telescope, a hard carrying case made to fit, a tripod, t-adaptor to connect to your SLR camera, a hand controller, an upgraded lens, and a right-angle viewfinder. I've used it only twice over the past year

[11] The exact information on the high bid depends on how much greater it is than the second highest bid. If the difference between the two high bids is less than the increment, then the high bid is observed. Otherwise, the amount listed for the high bid is equal to the second highest bid plus the increment.

	ETX90	ETX125	LX200
Number of Auctions	31	20	7
Number of Bidders	157	98	44
Average Bidders	6.7	6.9	7.9
Average Bid	$394.68	$785.19	$1166.39
Average High Bid	$506.47	$966.68	$1555.07
Highest High Bid	$830	$1349.01	$1750
Lowest High Bid	$270	$680	$1331.50
Retail Price (Basic)	$495	$895	$1,499

Table 1: Summary Statistics of Telescope Auctions

> to catch a glimpse of Saturn's rings and Jupiter's moons. It is in excellent condition."

Sellers often describe their telescope as being "like new" or "as if new". Hasker et al. (2001) shows that this type of statement is an important determinant of computer monitor prices. Another important characteristic of the Meade telescopes is the inclusion of the "go to" or Autostar computer controller. All of Meade's telescopes come with a computer located in the mount of the telescope. Once the telescope is aligned, this computer can point the telescope at any of the thousands of celestial objects that are programmed into the computer's database.[12] The Autostar controller allows the user to access the computer. The other vital accessory is the tripod, especially for the larger telescopes. The camera adapter (T-adapter) allows a 35mm SLR camera to be attached to the telescope for celestial photography.

Table 3 presents information on the 85 bidders who bid in more than one auction for one of the three products during the time in which the data was being collected. The first row states that for bidders who bid multiple times and bid on the ETX90, 56 % bid only on the ETX90, 39 % also bid on the ETX125, and 11 % also bid on the LX200. Of the 85 bidders who

[12]This system is also fairly simple to align. The process involves setting the telescope level and pointing north, entering time and location (unnecessary with GPS), and correcting the alignment against two prominent stars.

	ETX90	ETX125	LX200
"Like New"	20 %	56 %	42 %
"Go to"	53 %	86 %	58 %
Tripod	64 %	71 %	100 %
Camera Adapter	18 %	12 %	27 %

Table 2: Summary Statistics of Telescope Characteristics

	ETX90	ETX125	LX200	N
ETX90	.56	.39	.11	54
ETX125	.53	.45	.10	40
LX200	.32	.21	.63	19

Table 3: Tracking Bidders Across Products (85 Bidders)

bid multiple times, 54 bid on the ETX90. Note that the choices are not exclusive and so the percentages add to more than 100%. The numbers suggest an important characteristic of the telescope market. That is, bidders on the Schmidt-Cassegrain (LX200) are more likely to only bid on that telescope and not on the Maksutov-Cassegrain (ETX90 and ETX125) telescopes, while bidders for the Maksutov-Cassegrain telescopes are unlikely to bid on the Schmidt-Cassegrain. These statistics support the Commission's position that the two telescope designs are not in the same antitrust product market. This table also highlights an important characteristic of eBay data, which is that it is possible to follow people across a series of auctions for related products providing the Commission with information on how customer's perceive differentiated products.

3 Inferring Demand for Telescopes from EBay Data

3.1 Estimation Techniques

We use bids from these auctions to estimate the demand for the ETX90, the ETX125 and the LX200. If in the population, we know each person's value or "willingness to pay" for each particular telescope, then we can calculate the demand for each telescope. At each price, all those people with values greater than the price will buy a telescope and choose the telescope with the highest consumer surplus, giving the quantity demanded at that price. By changing the prices and recalculating demand for the three telescopes at the new prices, we can calculated own and cross-price elasticities. If however, we have valuations for a random sample of the population then we can estimate the demand. The eBay data gives a sample of the population, although not a random sample of the population. The sample is a self-selected group willing to bid on telescopes on eBay. This sample is also not a sample of each person's valuation, but rather a sample of each person's bid for a particular telescope. The following is a list of assumptions necessary to use this data to estimate demand.

Assumption 1 *The sample represents buyers for new telescopes.*

Assumption 1 captures three issues. First, it assumes that eBay bidders for telescopes are representative of the general population of telescope buyers. Unfortunately, we are not aware of any demographic information on either eBay bidders or telescope buyers. However, in 2002 there were over 50 million registered eBay users, and there is no reason to expect an substantial difference between the two groups. Second, it assumes that eBay bidders are randomly selected out of the population of telescope buyers. Due to the low cost of searching and bidding on-line, such buyers may have a greater elasticity of demand than off-line buyers. Therefore, our estimates may be biased to the high side. Third, it is based on people buying second-hand telescopes. It is not clear how this affect the interpretation of our elasticity estimates.

Assumption 2 *Each bidder's highest bid in each auction is equal to that bidders value for the product being auctioned.*

We assume that the highest bid that a person makes in a particular auction is equal to that person's valuation for the product sold in that auction. There are two characteristics of eBay auctions that justify this assumption. First, as discussed above, eBay uses a "proxy" bidding system. That is, it asks the bidder to enter their "maximum" bid for the item, and then it automatically bids the lowest amount such that the bidder with the highest maximum is the highest bidder. In a sealed bid second-price auction, the weakly dominant strategy is for the bidder to bid their valuation for the product. In fact, eBay states that this is what each person should do (Roth and Ockenfels (2000)). Second, eBay is an English (ascending price auction), and in the "button model" of such an auction, each bidder holds down a button up until their valuation is reached. The last person holding down her button wins the auction. Therefore, even if people don't understand the proxy bidding system, they should remain in the auction and keep bidding until their valuation is reached.[13] However, there are good reasons to think that people do not bid their valuations, and these are discussed at the end of this section.

Assumption 3 *Bidder i's high bid in auction j is*

$$\log(B_{ij}) = \log(v_{ij}) = X_j\beta + \log(\epsilon_{ij}) \tag{1}$$

Where B_{ij} is bidder i's highest bid in auction j, v_{ij} is bidder i's value for the item sold in auction j, X_j is the observable characteristics of the item, and ϵ_{ij} is the error term. This assumption allows the estimation of a "hedonic" bid model using OLS. It states that bids vary linearly with respect to characteristics of the product that is being auctioned. We can

[13] EBay offers the option of emailing the bidder once they have been outbid.

interpret $X_j\beta$ as representing the "common value" for the telescope and ϵ_{ij} as representing the "private value" for the telescope. In the results section, β and ϵ_{ij} are estimated using OLS.

Assumption 4 *Each B_{ij} represents a distinct buyer, k.*

Assumption 5 *Each buyer, k, has a value v_{kl} for each of the three telescopes, denoted $l \in \{ETX90, ETX125, LX200\}$.*

Assumptions 4 and 5 form the basis for the demand estimation. Even though one bidder may bid in multiple auctions, their bids in the different auctions are assumed to represent distinct bidders. These is mainly done for simplicity. The fact that bids are not independent can be accounted for by bootstrapping the standard errors. The distribution of errors (private values) across the three telescopes is accounted for by Assumption 6. This method allows the own and cross-elasticities to be calculated without making unreasonable assumptions on the distribution of errors. The distribution of errors is drawn from the actual residuals, with correlation across telescopes based on the actual probability that different bidders bid across different types of telescopes.

Assumption 6

$$v_{kl} = \begin{cases} \exp(X_l\beta + log(\epsilon_k)) & \textit{if } j = l \\ \exp(X_l\beta + log(\epsilon_k)) & \textit{w/prob } p \textit{ if } j \neq l \\ 0 & \textit{w/prob } 1-p \textit{ if } j \neq l \end{cases} \tag{2}$$

Where p is calculated from Table 3. For example, for a buyer k whose bid comes from an ETX90, their value for the ETX90 is $\exp(X_{ETX90}\beta + log(\epsilon_k))$. While, buyer k's value for the ETX125 is either 0 or $\exp(X_{ETX125}\beta + log(\epsilon_k))$. Which, depends on the probability that a bidder on the ETX90 will also bid on the ETX125. In this case, $p = .39$. Setting the buyer's value to 0 is somewhat arbitrary. The important point is that the buyer's value is "low enough" so as not be included in the cross-elasticity calculation.

Demand is estimated in three steps. Step 1 estimates $\hat{\beta}$ using OLS and Equation (1), where the X_j variables include dummies for the ETX90, the ETX125, a dummy for "like new", a dummy for the "go to" system, a dummy for a tripod, and a dummy for a camera adapter.

Step 2 calculates the "new" value of each of the three types of telescopes for every observation (that is for every bidder's high bid in every auction). This is done using $\hat{\beta}$, the estimated residual (ϵ_{ij}), and the probabilities of bidding across products calculated from Table 3, where each telescope is assumed to be "like new" and have no camera adapter. Additionally, in the case of the LX200, the telescope is assumed to have a tripod and "go to". In the case of the ETX90 and the ETX125, the telescope is assumed to have neither. Therefore, for bidder i who bid in auction j, where auction j is for an ETX90 telescope, their value for the ETX90, $v_{ij}(ETX90)$, that is "like new" and doesn't have any accessories is given by,

$$v_{ij}(ETX90) = \exp(X_{ETX90}\hat{\beta}_{ETX90} + X_{likenew}\hat{\beta}_{likenew} + \hat{\beta}_{constant} + log(\epsilon_{ij})) \quad (3)$$

Next we need to determine what the "like new" value is for products that were not bid upon by an individual bidder. Here we use the probabilities of bidding across products to give us our estimates. For example, if the bidder is from an auction for the ETX125, the probability *a priori* that bidder has a positive value for the ETX90 is 53 % which, from our data, is the proportion of ETX125 bidders who bid multiple times and bid on the ETX90. Thus, for bidder i who bid in auction j, where auction j is for an ETX125, their value for the ETX90 that is "like new" and doesn't have any accessories is given by

$$v_{ij}(ETX90) = \begin{cases} \exp(X\hat{\beta}_{ETX90} + \log(\epsilon_{ij})) \text{ with probability } .53 \\ 0 \text{ with prob } (1 - .53). \end{cases} \quad (4)$$

To summarize, for each observation (ij) we calculate $v_{ij}(ETX90)$, $v_{ij}(ETX125)$ and $v_{ij}(LX200)$. If ij is from an ETX90 auction, then $v_{ij}(ETX90)$ is defined by Equation (3). While $v_{ij}(ETX125)$ and $v_{ij}(LX200)$ could be either positive (using the OLS estimates and the residual (ϵ_{ij})) or 0. The proportion that are 0, is determined by the probabilities from Table 3, and the observations are assigned 0 at random.[14]

Step 3 uses these valuations and the prices to determine whether each bidder i for auction j will purchase an ETX90, an ETX125, a LX200 or nothing. An ETX90 is purchased if

1. $v_{ij}(ETX90) > P_{ETX90}$, and
2. $v_{ij}(ETX90) - P_{ETX90} > v_{ij}(ETX125) - P_{ETX125}$, and
3. $v_{ij}(ETX90) - P_{ETX90} > v_{ij}(LX200) - P_{LX200}$,

where P_j is the retail price of product sold in auction j.

3.2 Results

Table 4 presents the results for the OLS estimates.[15] The assumption that bidders bid their values for each telescope is of major concern. One argument is that higher bidders or "later" bidders are going to bid much closer to their value than lower bidders or earlier bidders. The results are estimated on four different samples. The first column shows the estimates for a sample restricted to the top 8 bidders in each auction, the second column estimates the regression on a sample restricted to the top 4 bidders in each auction, the third column is for the bidders who bid on the last day of the auction, and the fourth column is for bidders who bid in the last 4 hours of the auction. A concern with these estimates is sample selection bias. A possible alternative is to use quantile regression (Koenker and Hallock (2001)). These results don't seem to depend crucially on the sample that is used, however it is necessary to look at the elasticity estimates for each sample. Step 2 calculates the log residuals using the estimated coefficients for Equation (1). Table 5 presents the mean value for the telescopes, assuming that every buyer has a positive

[14] An alternative is to just use the people who bid across products, but the sample is very small, given the variation in the characteristics in the telescopes.

[15] The standard errors are from the OLS estimates, however the bootstrap standard errors were similar.

	Top 8 Bidders	Top 4 Bidders	Last Day	Last 4 Hours
ETX90	-.97	-1.03	-.93	-.98
	(.06)	(.04)	(.04)	(.05)
ETX125	-.34	-.45	-.41	- .43
	(.07)	(.04)	(.04)	(.05)
"Like New"	.12	.07	.08	.06
	(.04)	(.03)	(.03)	(.03)
"Go to"	.15	.22	.21	.24
	(.05)	(.03)	(.03)	(.04)
Tripod	.21	.22	.21	.24
	(.05)	(.03)	(.03)	(.03)
Adapter	.22	.12	.06	.06
	(.05)	(.03)	(.03)	(.04)
Constant	6.59	6.84	6.82	6.87
	(.07)	(.05)	(.05)	(.06)
N	400	226	178	113
R^2	.60	.86	.86	.89

Table 4: OLS estimates (Standard Errors)

	Top 8	Top 4	Last 24 hours	Last 4 hours
ETX90	328.00	336.26	400.00	387.69
	(99.40)	(65.77)	(66.77)	(59.47)
ETX125	618.45	654.04	671.46	669.99
	(187.42)	(117.45)	(112.08)	(102.78)
LX200	1241.20	1585.17	1541.94	1651.40
	(376.14)	(284.67)	(257.38)	(253.33)

Table 5: Mean Value by Telescope Type (Standard Deviation)

value for every telescope. Step 3 uses the values for each type of telescope for each bidder in each auction to calculate the demand system for the three telescopes. The assumption is that each bidder in each auction is a distinct individual demander of telescopes.

Table 6 presents the own-price and cross-price elasticities for the three types of telescopes, calculated at retail prices for the basic telescope (presented in Table 1) using the sample of the top 8 bidders for each auction. The numbers presented are the absolute value of the ratio of a percentage change in the demand for the telescope named at the top of each column over a 10 % *increase* in the price of the telescope named in the left hand column. This table shows that the own-price elasticity of demand for the three types of telescopes is very high, confirming our intuition that these are expensive luxury items. It also shows that while there is a lot of movement between the ETX models (the Maksutov-Cassegrain design), especially down from the ETX125 to the cheaper ETX90, there is no movement between either ETX model and the LX200 (the 8 inch Schmidt-Cassegrain). Table 7 presents the own-price and cross-price elasticity measures calculated at retail prices for the sample of bidders who bid in the last day. The results show that the demand elasticities are higher for this population. However, there is still no movement between the two telescope designs.

	ETX90	ETX125	LX200
ETX90	3.33	0	0
ETX125	13.33	5	0
LX200	0	0	5

Table 6: Demand Elasticities at Retail Prices (Basic) - Top 8

	ETX90	ETX125	LX200
ETX90	5.56	10	0
ETX125	0	10	0
LX200	0	0	4.83

Table 7: Demand Elasticities at Retail Prices (Basic) - Last Day

3.3 Issues and Concerns

There are three major concerns with using data from eBay auctions to infer demand for new telescopes. First, in many cases the telescopes sold on eBay are second-hand. Second, we do not have a random sample of potential telescope buyers. Third, bidders may not actually bid their valuation (or willingness-to-pay) for the telescope.

In regards to the first concern, there does not seem to be a major lemons problem with the market and the telescopes seem to hold their value well. We see from Table 1 that the retail price for the ETX90, ETX125 and the LX200 is $495, $895, and $1,499 respectively. The average sale price on eBay is higher because these auctions include accessories. For example, the retail price for the ETX90 does not include the "go to" system or a tripod, while a high proportion of ETX90s sold on eBay come with these accessories. The overall success of eBay suggests that it has been able to resolve the lemons problem in a great number of markets (Cohen (2002); Livingston (2002)). While the estimated coefficients are calculated using all of the telescope auctions, the demand elasticities are calculated at the value for "like new" telescopes.

The second concern is a concern with any data used to infer demand for the whole population. It is likely that data from different supply channels (speciality telescope retailers, camera shops, department stores) will each give different estimates of elasticity. The value of the data collected from a particular channel, depends on how important that channel is. The telescopes analyzed in this paper are sold on Amazon.com, Ritz Camera (Wolfe Camera), Scope City (a major speciality telescope retailer), the Discovery Store and Astronomics (another major speciality telescope retailer). It seems reasonable to suspect that data collected from eBay is going to give higher elasticities of demand than data collected from a speciality telescope retailer like Scope City.[16] Another issue is that eBay bidders on telescopes may not be representative of buyers of telescopes. However, it is not obvious why there would be a substantial difference between the two groups. EBay users are likely to have higher incomes than the general population, however telescope buyers are also likely to have higher incomes than the general population.

The third concern with these estimates is the assumption that each person bids their valuation. A more reasonable assumption would be that each person bids *below* their valuation for the telescope.[17] Unfortunately, knowing that bidders are bidding under their valuation and that the demand curve may be biased in this way, does not tell us whether the estimate for the elasticity is too high or too low. Haile and Tamer (2002) discuss this issue in detail and present two methods for "bounding" the demand curve, by making two assumptions. First, that each bidder bids below their valuation. Second, that the final auction price is above each losing participants valuation for the item. The authors show that with a large number of auctions (around 200), it is possible to get very tight bounds with just these two assumptions by using general characteristics of order statistics. Hasker et al. (2001) makes the assumption that last minute bids (literally) are equal to the bidder's valuation for the item. Their argument is that in the last minute of an

[16]Speciality stores are more likely to have customers with a high interest in buying a telescope. It would be good to test this hypothesis, however the data for such a comparison is not currently available.

[17]See Arora et al. (2002) for an estimate of how eBay bidders discount their bids to account for the "option" value of future auctions for the same good.

auction on eBay, it is "as if" the auction is a sealed bid second price auction and therefore Vickery's result applies.[18]

Two other issues are that the data may be censored and that arbitrage may affect the demand estimates. Censoring may occur because when a potential bidder arrives at an eBay auction, the current price may already be above their willingness to pay.[19] Censoring is a major problem for estimating the whole demand curve using this kind of data. However in this case it is not a major concern because we do not estimate the whole demand curve, just the elasticities at retail prices. Arbitrage is likely to be a problem in many markets, particularly those with low transaction costs. Arbitragers may introduce supply shocks into the data reducing the accuracy of the demand estimates. However, telescopes have substantial transaction costs because they are difficult and expensive to ship. The telescopes analyzed in this paper are quite large, fairly heavy and quite fragile.

4 Conclusion

EBay data may provide a solution to a number of problems faced by economists analyzing demand in particular industries. The data has a number of important characteristics, including the fact that it is based on bids in second price auctions, and thus may allow the economist to directly estimate demand characteristics. This paper analyzes the demand for three types of telescopes ranging in price from \$500 to \$1,500. The results suggest that the demand for telescopes is highly elastic, and that the smaller Maksutov-Cassegrain designs are not a close substitutes for the larger more expensive Schmidt-Cassegrain designs. There are, however, a number of concerns about the assumptions necessary to generate these results. The authors believe that much more research needs to be done before an accurate conclusion can be drawn about

[18] Note, such bidders may still discount in order to account for future auctions (Arora et al. (2002)).

[19] See Zhang et al. (2002) for a discussion of how to account for this problem. Note however that a disproportionate number of bidders bid at the end of the auction. In our data, 38% of bidders bid in the last day, and over 25% of those bid in the last 20 minutes.

the overall value of using data from on-line auctions for antitrust purposes.

References

Arora, Ashish, Hao Xu, Rema Padman, and William Vogt, "Optimal Bidding in Sequential Online Auctions," 2002. Heinz School of Public Policy, Carnegie Mellon University.

Cohen, Adam, *The Perfect Store: Inside eBay*, first ed., Little, Brown and Company, 2002.

Haile, Philip A. and Elie T. Tamer, "Inference with Incomplete Model of English Auctions," *Journal of Political Economy*, 2002. Forthcoming.

Hasker, Kevin, Raul Gonzalez, and Robin Sickles, "An Analysis of Strategic Behavior and Consumer Surplus in eBay Auctions," October 2001. Rice University.

Hosken, Daniel, Daniel O'Brien, David Scheffman, and Michael Vita, "Demand System Estimation and its Application to Horizontal Merger Analysis," FTC Working Paper April 2002.

Koenker, Roger and Kevin F. Hallock, "Quantile Regression," *Journal of Economic Perspectives*, 2001, *15* (4), 143–156.

Livingston, Jeffrey, "How Valuable is a Good Reputation? A Sample Selection Model of Internet Auctions," September 2002. University of Maryland.

Lucking-Reiley, David, Doug Bryan, Naghi Prasad, and Daniel Reeves, "Pennies from EBay: the Determinants of Price in Online Auctions," January 2000. Vanderbilt University.

Nevo, Aviv, "A Practicioner's Guide to Estimation of Random-Coefficients Logit Models of Demand," *Journal of Economics and Management Strategy*, 2000, *9* (4), 513–548.

Roth, Al and Axel Ockenfels, "Last Minute Bidding and the Rules of Ending Second-Price Auctions: Theory and Evidence from a Natural Experiment on the Internet," 2000. Department of Economics, Harvard.

Zhang, Alex, Dirk Beyer, Julie Ward, Tongwei Liu, Alan Karp, Kemal Guler, Shailendra Jain, and Hsiu-Khuern Tang, "Modeling the Price-Demand Relationship Using Auction Bid Data," July 2002. Hewlett-Packard.