**1 Introduction**  
Perhaps the most exciting economic innovation on the Internet is consumer to consumer auctions. In September of 1995 eBay used the power of the Internet to create a marketplace for consumers to auction goods. This combined the power of a “for sale” add with millions of viewers and the price discovery power of auctions. At last a mechanism well understood by economists was used not just for a few expensive items, but for the sale of everyday items to everyday consumers. This market’s success and growth rate have been breathtaking. In 1998 Reiley (2000) estimated that the industry was going to produce over one billion dollars’ worth of sales, in 1999 eBay alone reported $2.82 billion. Last year (in 2002) they had $14.88 billion in sales and this year they can expect $25 billion. Their international membership is currently over 75 million, and will probably surpass the population of the United States next year.

What is known about this market? There have been exploratory papers but there has not been  
a thorough structural analysis. The basic theory of how the market operates is understood since the goods are sold by auction. Since the transactions take place on the Internet it is possible in theory to monitor these transactions and develop data retrieval protocols facilitating in-depth empirical analysis. In fact, data sets of very large sizes can be assembled because of the enormous volume of transactions and their public domain nature. We have collected and processed records of over 10,000 auctions of computer monitors, allowing a thorough structural analysis.

In this paper we estimate structural bidding functions and then test which bidding strategy the  
bidders use. This question is commonly overlooked in empirical research despite the unique insight empirical analysis can give on this question. Many well-specified economic models have multiple equilibria, and only through empirical analysis can we discover which equilibrium people are using. We fail to reject the null hypothesis that they are using competitive bidding strategies instead of the alternative “snipe-or-war” or “jump-call” bidding strategies.

eBay has two different auction formats. The common format is an English auction with a hard  
stop time. This is the type of auction used in 87 percent of our data set and the type of auctions  
on which we focus. Bidding goes on from three to ten days and stops at a preset time. This hard  
stop time does have a significant effect because bidders frequently wait until the last minute to post their bid, and there are reports of bids not getting in on time.

While there are many papers that analyze Internet auctions none use structural techniques on  
such a comprehensive data set. Reiley et al. (2000) did collect a large data set, but limited the  
reduced form analysis to 461 data points. Bajari and Hortaçsu (2003) used parametric structural  
analysis with endogenous entry, but only had 418 observations to base their estimates on and were forced to make some relatively strong assumptions.

A consistent finding in Bajari and Hortaçsu (2003), Houser and Wooders (2001), Reiley et al.  
(2000), and Melnik and Alm (2001) is that the auctioneer’s reputation matters. On eBay reputation is captured in a “feedback rating” for both bidders and sellers. After a sale, sellers and bidders can rate each other as positive (+1), neutral (0), or negative (-1). A participant’s feedback rating is the sum of the evaluations after each auction. The feedback rating can be manipulated by both bidders and auctioneers, but bidders react to it indicating it is valuable information. However, as Melnik and Alm (2001) point out, the economic impact of the feedback rating is not significant. Both Melnik and Alm and Reiley et al. (2000) also analyze how the length of auction affects sales price. Melnik and Alm find that longer auctions do not significantly affect price, while Reiley et al. find they do.

As Melnik and Alm point out this is not surprising since Reiley et al. analyze a rarer good and thus there could be fewer bidders per auction. However, the reduced form methodology prevents this structural issue from being thoroughly understood. What the coefficient measures is the increase in sales price. This could be because many more bidders come to the auction or it could be because there were only a few bidders in the first place. In the latter case even the addition of one more bidder would raise price significantly. Melnik and Alm argue there are fewer bidders in three day auctions Is this true? With our methodology we estimate the number of bidders for all lengths of auction, thus we know both how competitive the market is and how the number of bidders varies with auction length. Bajari and Hortaçsu (2003) do not provide these estimates.

Roth and Ockenfels (2002) point out an interesting facet of the auctions we will be analyzing. In eBay auctions a large percentage of the bids are submitted in the last minute–over 11 percent in our data set–and most auctions have some bidders bidding more than once–around 77 percent in our data. This last minute bidding happens despite the well documented evidence that these bids sometimes do not get registered. They show that since these bids are not always registered there is an equilibrium where bidders bid seriously only in the last minute. In essence the risk of not getting a bid in allows bidders to “collude” by implicitly agreeing not to bid until this time, resulting in less competition and higher returns for the bidders. Currently this is the only theory which explains both the last minute and multiple bidding behavior on eBay. The theory predicts that in Amazon auctions there should be less last minute bidding, since the auction does not close until ten minutes after the last bid is received and they verify that this does, in fact, occur. We develop a within sample test of their equilibrium and cannot accept that bidders are using this strategy.

Another interesting class of equilibria are strategic jump bids (Avery, 1998). These strategies call for bidders to place high bids early in the auction to intimidate their competitors–much like bluffing in poker. As discussed in Avery (1998) this type of bidding is well documented in auctions, but previously it had not been shown to be equilibrium behavior. Despite the importance of this class of equilibria has not to our knowledge been tested. Due to institutional rules on eBay the strategies Avery specifies are not equilibria. We modify his equilibria for the eBay environment and call the modified strategy jump-call bidding. However, even though we prove that there are equilibria of this type in eBay auctions, we do not verify that bidders are using these strategies.

Our estimation techniques are based on methods developed by Laffont et al. (1995). Their method utilizes the simulated method of moments estimator developed by McFadden (1989) and Pakes and Pollard (1989). It is framed in terms of simulated nonlinear least squares wherein the bidders’ private values are simulated on the basis of an assumed distribution. Distance between these simulated bids and the true bids is minimized. Their techniques were developed for first price auctions but can be modified for our use in English auctions. Two alternative structural methodologies are maximum likelihood and Bayesian estimation with linearly scalable bidding functions. Maximum likelihood estimation (see, for example, Donald and Paarsch, 1993) is problematic for two reasons. First it requires solving a high dimensional integral. Second it must address violations of regularity assumptions used to justify standard maximum likelihood asymptotic since boundary conditions on the random variables are functions of the parameters. Bajari and Hortaçsu (2003) used a Bayesian methodology, but require the bidding functions to be linearly scalable, a restriction unnecessary with our approach and violated by our structural form.

In the next section we briefly introduce the eBay marketplace. In section 3 we describe our data collection methodology. The structural model and estimates are presented in Section 4. In Section 5 we test against the alternative equilibria. Section 6 concludes.  
**2 The eBay Auction Market**  
In September 1995 eBay opened the first Internet based consumer to consumer auction. The  
corporate model was to provide a central market for the sale of goods. Independent sellers use eBay to sell their goods through auctions lasting from three to ten days so that bidders can bid at a convenient time. eBay’s revenues are primarily from the posting and sales of goods. They extract two primary fees, a listing fee and a sales fee. These fees are increasing in the reservation price the auctioneer sets and the final sales price, with a maximum of 5 percent of the final sales price and listing fees under two dollars. The mean listing fee was one dollar for the monitors in our data set, and final sale fee was $2.50, with a median final sales fee of $1.50. For all of eBay at the time our data was collected the average fee per item auctioned–not all of which sell–was $1.41, and 7 cents in fees were generated for every dollar of sales.

eBay is operating two basic types of auctions. If an auctioneer wishes to sell two or more items  
in the same auction she has to use a “Dutch” auction. Bidders enter the number of items they want to buy and the price they were willing to pay for them, and then the good is sold to all bidders at the price offered in the highest losing bid. This type of auction has been studied by Engelbrecht Wiggans and Kahn (1998) and Ausubel and Cramton (1996). The equilibrium is different than in the English auctions we study, thus we drop these observations.

If an auctioneer has one item to sell she uses an “English” auction. An auctioneer interested in  
selling a monitor in an English auction could first look at the monitors currently available and at all auctions that closed in the last thirty days to get a sense of the market. Then the auctioneer had to make three primary decisions at the time our data was collected. First the standard reservation price was set, a publicly visible amount below which the good will not be sold. The auctioneer had the option of setting a secret reservation price. This is a reservation price that is not revealed to the bidders–though they know if there is one and if it has been met. The final decision was how long the auction should run; this could be either three, five, seven, or ten days. If, for example, seven days is selected then the auction will end precisely seven days to the second after it opens on eBay. Note that unlike traditional English auctions the bidding does not continue if someone wants to raise his bid, and that the auctioneer can end the auction early though this is rarely done.

When a bidder enters eBay he firsts come to a summary page listing all the computer monitors  
available–around 580 on an average day in our data set–sorted by the length of time until that  
auction closes. He can then click on an item to see a full description of the monitor, and with a  
few more clicks see the bidding history; information about the auctioneer’s feedback; etcetera. The bidding history shows how many people have bid and their ranking–though not their actual bid amounts. A bid is registered by entering a maximum price into a proxy bidding program. The  
computer program then bids for the bidder as if he was in an English auction–raising this bidder’s bid until either the program hits his maximum or no one else raises their bid. If the price rises above this bidder’s maximum the bidder is notified by e-mail and can raise his maximum price if he so chooses.

A significant problem that eBay faces is moral hazard. If there is no way to differentiate duplicitous from scrupulous auctioneers and bidders, then the usual lemons problem will select the scrupulous ones out of the market. To correct for this, eBay has instituted a “feedback rating”  
mechanism. After a transaction, bidders and auctioneers can rate each other. While such a system may have its drawbacks, it does not seem to be significantly manipulated and eBay members  
do actually pay attention to this. We have observed bidders who have retracted their bids with  
comments like “not a single positive comment on his feedback page,” “too many negatives on his feedback page.” eBay makes it quite clear that an auctioneer can request to have a bidder not bid on their item–with sanction by eBay if the bidder does anyway. Furthermore, many studies have found that this feedback rating does affect price. It would seem that this system has the intended effect.

**3 The Data Set and Our Collection Techniques.**eBay saves all information about closed auctions on their website for a month after the auction  
closes. This allows people who participated in the auction to verify the outcome, and provides  
the source for our data set. Our data was collected using a “spider” program which periodically  
searches eBay for recently closed computer monitor auctions and downloads the pages giving the  
item description and the bid history. Software development was done in Python–a multi-platform, multi-OS, object-oriented programming language. It is divided into three parts. It first goes to eBay’s site and collects the item description page and the bidding history page. It next parses the web pages, and makes a database entry for each closed auction. The final part iterates through the database entries stored, and creates a tab-delimited ASCII file. This method has allowed us to collect information on approximately 9000 English auctions of PC computer monitors.

The original data processing program did not process all of the data. It provided us with the core of the data which was augmented with further processing of the raw html files. Using string searches we have managed to collect extensive descriptive information for the entire data set. With further data processing we have managed to collect all of the bidding histories. This process provided us with information on the 6543 auctions that are used in the estimates.

Our data set consists of PC color computer monitors with a size between 14 and 21 inches which were auctioned between February 23, 2000 and June 11, 2000. All monitors are in working order, and we ignored touch screen monitors, LCD monitors, Apple monitors, and other types of monitors that are bought for different purposes than the monitors in our sample. Also, if there were any bid retractions or cancellations (this happened in 7.4 percent of the auctions) we dropped the observation because the retractions might indicate collusion.

Descriptive variables except for monitor size were constructed using string searches. In Appendix B the strings that were used for each variable are detailed. This allowed us to collect data on whether there was a secret reservation price, whether it was met, monitor resolutions, dot pitch, whether a warranty was offered, several different brand names, whether the monitor was new, Like-New, or refurbished, and whether it was a flat screened monitor. “Brand name” is used for monitors that are from one of the ten largest firms represented in our data set. These firms are Sony, Compaq, NEC, IBM, Hewlett Packard, Dell, Gateway, Viewsonic, Sun, and Hitachi in order of size. Sony has around a 10 percent market share, the smallest are all around 3 percent, in total these 10 firms represent 57 percent of the market. Dot pitch (DPI) and resolution are not reported in all of the auctions. DPI is reported in 35 percent of the auctions, resolution in 58 percent.

In Table 5 the descriptive statistics of variables of interest are presented. Note that some of our auctions last less than three days. The auctioneer has a (rarely exercised) right to end the auction early. It is not uncommon within this group for someone to put up an item and then recall it within ten minutes or so.

In Table 5 we also report the correlation matrix between the variables we use in our structural model, and five subsidiary variables–Number of Bids, Number of Bidders, Secret Reserve Price (Price Met), Secret Reserve Price (Not Met), and Auction Length. Secret reserve price is positively related to a high winning bid. This is consistent with an observation of Bajari and Hortaçsu (2003) that secret reservation prices are used more frequently for valuable goods. Sellers with higher feedback rating (more experience) are more likely to report both resolution and DPI, less likely to use a secret reservation price, and prefer shorter auctions.

One interesting feature of the data is the near independence of the length of auction and most other variables. For example, the most important variable–winning bid–has a very weak correlation with the length, and so does the number of bidders. This seems to suggest that a knowledgeable auctioneer would always prefer short auctions, which is verified by the correlation between seller’s feedback rating and length of auction. Our estimation methodology allows us to find out the number of bidders in the auction (which includes the people who thought about bidding but did not) and we will use this to see whether the true number of bidders also follows this trend.

**4 The Model and Estimates**

In this section we present our model and estimates. We simplify the market environment with several standard assumptions. The nature of the eBay marketplace makes some of these assumptions stronger than in much empirical analysis, but weakens others. For example, since the marketplace is so competitive–we have over 17,000 individual bidders–we do not worry about possible market power effects or widespread collusion. However, since the market is thick–with items being sold at all times of the day and night–we must be more concerned about the effects of entry and exit. Consistent with most of the literature this paper will assume that entry and exit are exogenous, in other words we will study each auction in isolation. Entry is not problematic for our estimation, but exit might be. However, since eBay is a saturated marketplace, with at least 484 monitors for sale on every day for which we have a complete data set, we feel comfortable assuming that the market is in steady state. In this case the approximate effect of exit will be to change the constant term in our regression.

We also assume that computer monitors have a private, or use driven, value. This is a standard simplifying assumption and in this market is easily defensible. The usual reason to assume a common value is that bidders intend to resell the good in the future, and this is falsified both by the data and casual intuition. Due to the rapid rate of technological advance in computer monitors the value of monitors falls precipitously, decreasing the benefit of resell. We also do not see many buyers who buy in large volume, only 1% of our winners buy more than 3 monitors. Thus it seems that the average buyer is using the monitor to fulfill a personal need.

Post estimate tests (described below) also led us to drop some of the auctions. To assure independent observations, we dropped auctions where the price setting bidder has set price in more than one auction. To be certain bidders have unitary demand, we dropped auctions where the price setting bidder had bought more than one monitor.

In the model we have I bidders (which may be a function of the length of the auction) each of  
whom draws an independent private value vi i ∈ {1, 2, 3, ...I} from the same distribution. These  
bidders bid for 3, 5, 7 or 10 days using increasing bidding strategies. Let bi be their final bid. By  
the rules of proxy bidding, the sales price (bw) will be equal to the second highest bid, b(2:1) , plus  
the bidding increment ∆. In our data set ∆ is small, almost always between 1% and 2.5%, and thus  
we assume ∆ = 0. Following Haile and Tamer (2000) we assume that the bidding strategy follows  
two intuitive rules:

1. No bidder ever bids more than he is willing to pay.
2. No bidder allows opponents to win at a price he is willing to pay.

We call a bidding strategy that follows these two rules a competitive bidding strategy. These rules are weakly dominant but there are equilibria that violate these two assumptions, like jump bidding (Avery 1998) and snipe-or-war bidding (Roth and Ockenfels 2002). After developing our estimates under the null of competitive bidding we will test against these alternatives. Haile and Tamer show that these two assumptions imply that if v(2:1) is the second highest value among the I bidders then bw = b(2:1) = v(2:I).  
This is an intentionally incomplete model of bidding. A complete model would also inform us  
about how every bid is calculated, b(k:I) for k ∈ {3, 4, 5, ...I}. Unfortunately the only known model for these bids is falsified by the data–the equilibrium is to have everyone bid their true value or b(k:I) = v(k:I). In this equilibrium everyone must bid only once, and the median number of bids per bidder in our data is 1.6 with a maximum of eleven. To understand why bidders must enter their true value as their first bid consider a bidder who bids $50 for a monitor instead of his true value of $100 when the auction opens. If two other bidders immediately bid more than $100 then the first bidder will not update the $50 bid and his final bid will not be his value. On the other hand, if only one person bids more than $100 then the first bidder will update the $50 bid and bid twice. Thus observing bidders who bid more than once indicates bidders’ final bids might not be their true value.

For auction n there will be a known set of exogenous variables, Xn and we will assume that  
, where ln(ρin) is distributed N (0, σ). Thus in auction n if there is no secret reservation price the equation we estimate will be:  
ln bwn = max( In rn, x!nβ +In ρn(2:1+1))  
If there is a secret reservation price then ln ρn(2: I) will be replaced with ln ρn(2: I+1), or we will use the assumption of Bajari and Hortaçsu (2003) that the secret reservation price is equivalent to having an extra bidder in the auction.

**Timeline**

1979

[Videotex](http://en.wikipedia.org/wiki/Videotex) was being researched since much earlier for supplying the end users with textual information. Much work was done in UK on videotext, it was a two way message service and developed basically for information sending where “many companies” were interested in, but on the backdrop of all that [Michael Aldrich](http://en.wikipedia.org/wiki/Michael_Aldrich) in 1979 gave the “concept of teleshopping” (today online shopping) which revolutionized the way businesses happen. Same happened in the US around that year with services like [The Source](http://en.wikipedia.org/wiki/The_Source_%28service%29) and [CompuServe](http://www.compuserve.com/).

**1982**

**Minitel** succeeded Videotext as online service making online purchases, check share market, search telephone directory and could even chat. This is one of the most successful services before [**WWW**](http://en.wikipedia.org/wiki/World_Wide_Web) using telephone lines, It was launched in **France** successfully but in UK as well but to less success

**1987**

With **[Swreg](http://www.swreg.org/)** (offshoot of CompuServe) the community of software developers and shareware authors got an online market where they could sell their product using “Merchant account”. Thus online shopping started for then software industry people.

**1990**

[**Tim Berners-Lee**](http://www.w3.org/People/Berners-Lee/) wrote the **[WorldWideWeb](http://www.w3.org/People/Berners-Lee/WorldWideWeb.html)** and gave the first browser to view the web which changed most of things; a whole new revolution started, which till date is ON.

**1992**

Revolutionary book by J.H. Snider and Terra Ziporyn namely; Future Shop: How New Technologies Will Change the Way We Shop and What We Buy. St. Martin’s Press.

**1994**

[**Netscape**](http://netscape.aol.com/) released Navigator browser, later introduced [**Secure Sockets Layer (SSL)**](http://en.wikipedia.org/wiki/Secure_Sockets_Layer) encryption for secure transaction. [**Pizza Hut**](http://www.pizzahut.com/) started online ordering on their webpage, cars, bikes and adult content as well started selling on the internet.

**1995**

[**Amazon.com**](http://www.amazon.com/) started selling each and everything online, and along with that Jeff Bezos starts first commercial-free 24 hour, internet-only radio stations. Then Radio HK and NetRadio start broadcasting. Companies like [**Dell**](http://www.dell.com/) and **[Cisco](http://www.cisco.com/)**started using internet in all their transactions. Online auction started by [**eBay**](http://www.ebay.com/).

**1999**

Acquisition of [**Business.com**](http://www.business.com/) by eCompanies in US $7.5 million. [**Napster**](http://www.napster.com/) the peer-to-peer file sharing software launches. Home decorative items started selling on [**ATG Stores**](http://www.atgstores.com/).

**2003**

Online shopping matures showing to the world their confidence **[Amazon.com](http://www.amazon.com/)**posted first yearly profit and thus again making presence on the stock market.

**2007**

Acquisition of [**Business.com**](http://www.business.com/) by [**R.H. Donnelley**](http://www.dexone.com/) for $345 million, making way for bigger players in technology domain.

**2008**

Tremendous growth in US in Ecommerce with sales figures touching $204 billion, a decent 17% rise from the previous year.

**2009**

Online Retailer – Amazon.com has an estimated turnover on a daily basis is over US $2.5 trillion with growth rate of 14% annually. Ebay having sales of US $1.89 billion, these numbers alone speak.