The Buy-it-now Option, Risk Aversion, and Impatience in an Empirical Model of eBay Bidding

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Abstract

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In 2000, eBay introduced its "buy-it-now" feature, allowing sellers to post a buy price at which a bidder can end the auction early. Theory suggests that a buy price can increase the seller's expected revenue if bidders are risk-averse or impatient. The linkage between risk-aversion, impatience, and the buy-it-now feature also suggests that data from these auctions may be informative about risk aversion and time preference parameters, which are typically difficult or impossible to identify in conventional auction data. In this paper, we develop a structural model for bidding in auctions with eBay's buy-it-now feature, and apply this to data collected from eBay auctions of Pentium laptops. Because the buy-it-now feature disappears after the first active bidder rejects the buy price, it is important to capture the temporal structure of eBay auctions. We model arrival of potential bidders as a Poisson process, and specify how bidders choose to enter the auction based on information available when they arrive. In eBay, bidders are often observed to raise their bids later in the auction, which is difficult to explain using conventional theory for second-price auctions. To allow for bidders to raise their bids without making assumptions on why or how this rebidding occurs, we follow Haile and Tamer (2003) and Canals-Cerda and Pearcy (2004), and use an "incomplete" specification for bidder behavior. We develop a novel estimation technique for our model, based on partial likelihood arguments combined with moment simulation.

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1 Introduction

In 2000, the online auction site eBay introduced its "buy-it-now" (BIN) feature, which allows sellers to use hybrid auctions with a fixed price component. In a BIN auction, the seller lists a "buy price" for the good. A bidder may purchase the item immediately at the buy price and end the auction, or she may place a bid below the buy price, in which case the BIN option disappears and the auction proceeds as a standard (oral ascending bid) eBay auction. The BIN feature has become very popular; in 2005, fixed price sales (in BIN auctions and sales through Half.com) totaled $13.8 billion, comprising 33.1% of eBay's total sales.[1]

Theory suggests that a buy price may increase seller revenue if bidders are risk averse or impatient. Reynolds and Wooders (2006) show that, in an independent private values (IPV) setting, risk averse bidders will pay a premium to obtain the good with certainty. Thus, an appropriately chosen buy price can raise seller revenue. Mathews (2003) considers auctions with impatient bidders and shows that a similar effect holds.[2] These models, however, abstract signficantly from the form of eBay auctions, by assuming that the number of bidders is fixed and known to all participants, and that all bidders choose simultaneously whether to accept the buy price. In actual eBay auctions, bidders arrive over time and the number of bidders is not known in advance. In addition, the buy price disappears as soon as any bidder makes a bid, so bidders who arrive later in the auction may not have the opportunity to accept the good at the buy price. One of our goals in this paper is to construct a detailed empirical model that captures both the effects described by Reynolds and Wooders (2006) and Mathews (2003), and these specific features of eBay auctions.

We construct an empirical model of bidding behavior in auctions for laptops, both with and without a BIN feature. Since buy prices affect bidder behavior through risk aversion and impatience, our structural model of bidder behavior allows us to recover risk aversion and time preference parameters from the data. As Athey and Haile (2005) note, risk aversion is important for substantive questions such as the determination of optimal auction format and reserve prices, but it is difficult to identify risk aversion in standard auction data. For example, in standard ascending auctions with independent private values, bidders will bid their valuations, hence risk aversion cannot be detected. In first-price auctions, risk aversion causes aggressive bidding. The actual identification and estimation of the index of risk aversion is, however, a challenging task. Campo, Guerre, Perrigne and Vuong (2002) start with a general utility function in an IPV setting and show

[1] BIN auctions in eBay can take three forms: (a) a BIN auction where bidding is possible; (b) a BIN auction without bidding, which amounts to a posted-price offer; and (c) a BIN auction where bidders can place their best offers. In "best-offer" auctions, the bidder whose offer is accepted by the seller wins the item at the bidder's offered price. In this paper, we only focus on the first type of BIN auction, where bidding can follow rejection of the BIN price, and we refer to such auctions as BIN auctions.

[2] In addition, Mathews and Katzman (2006) find that risk averse *sellers* may find buy prices advantageous, because they reduce the variance of revenue when buyers are risk-neutral. We focus on identifying risk aversion and time preferences in buyers in this application, but note that our empirical results could then be used to calculate the value to the seller of using a well chosen buy price.

that the model is non-identified even when constant relative risk aversion (CRRA) is assumed, and that the same bid data can be rationalized by risk neutrality and many different specifications of risk aversion. Identification is only achieved using a parametric CRRA utility function and the assumption that the distribution of value conditional on the item characteristics satisfies a parametric quantile restriction. Perrigne (2003) makes similar assumptions for identification and extends the study by Campo, Guerre, Perrigne and Vuong (2002) to auctions with random reserve prices. Our paper extends this literature by proposing an alternative approach to identifying risk aversion (and impatience), by examining bidder behavior in BIN auctions.[3]

In our model, bidders arrive in continuous time according to a Poisson point process, with a time-varying arrival rate.[4] Bidders' valuations are assumed to be independent draws from a distribution (the distribution being common knowledge among bidders). If the BIN option is available, a bidder who has arrived may choose to buy the good immediate at the buy price, or start bidding. This decision will depend on the distribution of valuations, the arrival rate function, and the amount of time remaining in the auction. Bidders can be risk averse and/or impatient, which may make the BIN option attractive.

Empirical data from eBay exhibits some characteristics that are difficult to capture in standard models of bidding. Bidders enter their "maximum" bid to a proxy (making the auction similar to theoretical models of "button" or "clock" auctions). Thus, bidding one's true valuation is a weakly dominant strategy. However, in practice we observe many bidders raising the "maximum" amount they are willing to pay later in the auction, in some cases multiple times within the same auction. It is not clear why this rebidding happens, and standard theoretical models do not predict such rebidding. Rather than fully specify a particular model for rebidding, we set up an incomplete model of bidding, following Haile and Tamer (2003) and Canals-Cerda and Pearcy (2004). This allows us to estimate our main structural parameters without making any strong assumptions on why the rebidding occurs.

Although we make parametric assumptions about the arrival process and the distribution of valuations, our model is incomplete because we do not specify the rebidding process. As a consequence, the model does not possess a likelihood function in the usual sense. (Alternatively, it can be viewed as a semiparametric model with an infinite-dimensional nuisance component.) We show, however, that a partial likelihood can be constructed based on a portion of the data, by considering a subset of the data vector as a marked point process. Additional information about model parameters can also be obtained using simulated moment equalities and inequalities.[5] Our

[3]Our continuous-time model of eBay BIN auctions is complicated to analyze using formal semiparametric methods, as in Campo, Guerre, Perrigne, and Vuong (2002). However, we provide below an intuitive discussion of how bidder reaction to the BIN option should identify risk aversion and impatience.

[4]In our current structural estimates, we assume a constant arrival rate, but we plan to estimate versions of the model with time-varying arrival rates in future work.

[5]Currently, we only simulate some basic moment equality restrictions and use these in our estimation scheme. We plan to extend this method in future versions of the paper.

estimator combines a marked point process partial likelihood component and simulated moment conditions.

The next section briefly describes earlier literature on eBay auctions and the buy-it-now option. Section 3 describes the data set we have collected and provides some preliminary evidence on the role of buy prices on bidder behavior. Section 4 describes our basic theoretical model for bidding in eBay, sets up our structural model and estimation technique, and discusses our preliminary estimates of the structural parameters.

2 Previous Literature

Several studies on eBay auctions look at the relationship between seller and auction characteristics, and sale prices. McDonald and Slawson (2002) and Lucking-Reiley et al (2000) find that auctions with high minimum bids have fewer bidders. Evidence is mixed on whether longer auctions attract more bidders. Lucking-Reiley et al (2000) find that the number of observed bidders is higher in longer auctions, while McDonald and Slawson (2002) find no significant difference. Houser and Wooders (2006) and McDonald and Slawson (2002) did not find any evidence of a relationship between auction length and sale price. However, both Lucking-Reiley et al. (2000) and Dewally and Ederington (2006) find that longer auctions are associated with higher sale prices. Studies have found that sellers' reputation measures are strongly related to sale price: positive reputations are associate with higher prices (Houser and Wooders (2006) and Lucking-Reiley et al (2000)). Melnik and Alm (2005) suggest that the reputation measures are more important when the items being auctioned are heterogeneous and the bidders are uncertain about the quality of the items.

A few studies take a structural approach to analyze eBay auctions. Bajari and Hortacsu (2004) analyzes bidder and seller behavior in eBay coin auctions. They find that an additional bidder reduces the average bid by 3.2%, and argue that these auctions should therefore be viewed as common value auctions. Song (2004) proposes a nonparametric identification method for the valuation distribution which does not requires that the number of potential bidders be known or constant across auctions. The identification result requires that we observe two order statistics from the valuation distribution, which may be difficult if we do not assume that bids correspond exactly to underlying values.

Both Gonzalez, Hasker, and Sickles (2004) and Canals-Cerda and Pearcy (2004) develop incomplete econometric models of standard eBay auctions (without the BIN option) within the IPV framework based on the assumptions of Haile and Tamer (2003). In both of these studies the sale price is determined by the second highest valuation among the potential bidders, which plays an important role in the identification of underlying valuation distribution. In the former, entry is exogenous and the number of potential bidders is assumed constant across auctions of the same length, while in the later, entry is endogenous and the number of potential bidders is stochastic which is an outcome of a Poisson process. The former study uses a data set of 6543 auctions of computer monitors and utilizes only the winning bid. The later one uses a data set of 4518 auctions of art works (e.g. paitings, collages, sculptures, etc.) and utilizes all the bids.

To our knowledge, there are two empirical studies of eBay's BIN auctions. Anderson et al. (2004) uses a data set of 722 auctions of Palm Vx handheld computers. They use instrumental variables methods to examine the effect of offering the BIN option on seller revenue, conditional on the number of bids. They instrument for the number of bids, but their results are difficult to interpret because the number of bids is an intermediate outcome, which could be directly affected by the BIN option. Thus, even after instrumenting, the coefficient on the BIN option does not have a clear causal interpretation. In addition, many of the auctions in their data had a BIN price equal to the reserve price, making the auctions effectively posted-price offers. In our analysis below, we do not consider posted-price offers. Also, we focus on estimating a detailed model of behavior and recovering underlying behavioral parameters, such as parameters related to risk aversion and underlying valuations.

Wang, Montgomery and Srinivasan (2004) model BIN auctions where bidders incur participation costs by bidding in the standard eBay auctions. Their model show that BIN options can increase the expected profits from an auction when bidder participation costs are high. Their theory predicts that the sellers are more likely to post BIN options when the number of potential bidders are low, and the bidders are more likely to accept BIN options when their participation costs are higher and there are secret reserve prices for the products. The paper tests the predictions in reduced-form settings using some data collected from eBay.

3 Data from eBay

Using a set of Perl scripts, we collected data on 3245 auctions of twelve different models of used Pentium-3 Dell Latitude laptops, between 22 July to 10 August 2005. We restricted our data to auctions satisfying the following characteristics: (1) each auction was for a single laptop; (2) the auction either had no buy price (a WBIN auction) or had a buy price with the option to bid (a BIN auction); (3) the auction had a public reserve price; (4) bidder identities were not secret; (5) the laptops being sold were fully functional; and (6) the buy prices were higher than the reserve price.[6]

Since the BIN option disappears as soon as any bidder places a bid, we collected pre-auction data as soon as the laptop was listed on eBay. This included characteristics of the laptop (processor speed, hard drive size, RAM, etc.) and auction design features (length of auction, reserve price, buy price). We also collected information on the descriptions of the laptop given by the seller,

[6] A buy price equal to the reserve price makes the auction a posted-price offer. We did not include posted-price offers in our data set.

such as cosmetic appearance and functionality, as well as seller characteristics such as their eBay rating. One month later, we revisited every laptop auction and collected data on the bidding in that auction.

3.1 Summary Statistics

Table 1 shows the number of BIN and WBIN auctions in our data, along with buy prices, reserve prices, and sale prices. Of the 3245 auctions, 2243 are WBIN auctions, and the remaining 1002 are BIN auctions. (Tables and figures appear at the end of the paper.) Figure 1 in Appendix B shows the distribution of buy prices in BIN auctions. 95% of the buy prices are between $225 and $645, with an average buy price of $396.

The reserve price ("starting bid" in eBay terminology) is an important auction design parameter. The number of active bidders tends to be lower for auctions with higher reserve prices (Lucking-Reiley, Bryan, Prasa, and Reeves, 2000). The average reserve price in our sample is $165.9 (including shipping costs), but there are 1306 auctions (1247 WBIN and 59 BIN) with a reserve price (without shipping costs) of $0.99, which is the minimum allowed by eBay. Table 1 shows that BIN auctions have an average reserve price of $326, which is more than three times the average reserve price in WBIN auctions of $94.4. Figure 2 in Appendix B shows the distribution of reserve prices among all auctions in our sample.

80% of all auctions ended in a sale of the laptop to some bidder. Of the BIN auctions, about 57% ended in a sale (either through the buy price being accepted, or through the ascending bid phase of the auction). About 22% of BIN auctions ended with a trade at the buy price. The average sale price (including shipping costs) for WBIN and BIN auctions is $355.9 and $355.3, respectively. However, in auctions where the buy price was accepted, the average sale price is $375.4. Below, we explore further the relationship between sale price and various characteristics of the laptop and the auction design. Figure 3 shows a histogram of the sale prices for all auctions ending in a trade (including trades at a BIN price) in our sample.

In addition to auction outcomes, we also collected detailed descriptions of the laptops being auctioned, from the information shown to bidders on eBay. We summarize some of the laptop characteristics in Table 2. On average, laptops sold in BIN auctions have lower specifications (processor speed, hard drive size and memory) then laptops sold in WBIN auctions. In addition to these basic laptop characteristics, we also collected variables such as: whether or not an operating system was installed; whether a wireless card was included; whether there was additional software or other hardware such as a printer; whether the laptop was under warranty; removable media drives; and other variables.

On eBay, sellers can choose between auctions of 1,3,5,7, or 10 days. Table 3 shows the distribution of auction lengths among different types of auctions. In addition, Table 4 shows average auction length by type of auction. The average length of BIN auctions is higher than in WBIN auctions in our data. Among BIN auctions, the proportion of auctions that traded at the buy price is higher for auctions with higher lengths.

At the end of each auction, we revisited the auction web page and collected the entire available bid history for these auctions. Figure 4 shows a typical bid history page for an eBay auction that ended with a trade. Since each bidder has a unique eBay ID number, it was possible to determine the number of bidders who placed bids and exact time when each bid was placed, including any bid revisions. In addition, by noting the price at which bidders dropped out, we could determine the amount of each bid with the exception of the winning bid. Table 4 indicates that BIN auctions (excluding those where the BIN price was accepted) have fewer bidders and a lower number of total bids than WBIN auctions.

Following each transaction on eBay, the winning bidder and the seller can leave feedback on the other party, and bidders and sellers accumulate feedback scores over time. Previous studies of eBay have shown that these reputation measures are strongly related to auction outcomes (Lucking-Reiley et al (2000), Bajari and Hortacsu (2003), and Houser and Wooders (2006)). We visited each seller's web page, and collected a number of reputation measures: the feedback score (number of positive comments from other parties); the sum of positive and negative feedbacks, and the percent of negative feedback. We also collected information on how long the seller had been an eBay member. Table 5 gives some summaries of these data. We see that sellers in BIN auctions on average have a smaller number of transactions, but longer length of membership, and a higher fraction of positive feedback.

3.2 Regression Analysis

Next, we examine the relationship between auction characteristics, including the BIN price, and auction outcomes. From the seller's perspective, the reserve price, the auction length, and the use of the BIN feature are all choices variables, and theory suggests that in some cases, using a positive reserve price and a BIN price could increase expected revenue.

We first consider the choice of whether to offer a BIN price. Table 6 shows ML estimates of a probit model for the existence of a BIN price, given seller and laptop characteristics. We find that "power sellers" are less likely to use the BIN option, as are sellers with an eBay store. The BIN option is used more when the laptop is bundled with a printer, laptop bag, or other item. Table 7 shows least squares estimates in a linear regression of the buy price on seller and laptop characteristics, for auctions with a BIN option. Sellers with an eBay store post a higher buy price, by about $32. The buy price tends to be higher when the laptop has better features, as one would expect.

Tables 10-12 show regressions of seller revenue on auction, seller, and laptop characteristics. The regressions use all the auctions in our data set, with revenue equal to 0 in auctions where the good did not sell, and differ only the auction characteristics included in the specifications. In

Table 10, we use an indicator for the BIN option, but do not control for the specific buy price. We find that having the BIN option is associated with about \$29 higher expected revenue to the seller, which would appear to be consistent with the argument that the BIN option can increase seller revenue. In Table 11, we include the BIN price as a regressor, in addition to the indicator for the existence of the BIN option. To interpret these results, it is useful to consider the effect of offering the average BIN price of \$420.60. At this price, the expected revenue to the seller would be higher by $\$5.50 + [0.07 \cdot \$420.6] \approx \$35$. The positive coefficient of 0.07 on the BIN price suggests that revenues are roughly increasing in the BIN price, and the coefficient of -.60 on the reserve price suggests that higher reserve price leads to lower revenues.

It seems plausible that both reserve price and BIN price have a nonlinear relationship with seller revenue, with some "optimal" level of both prices maximizing revenue. We tried estimating a regression with quadratic terms in both reserve price and BIN price. Table 12 shows the results. However, the coefficients are difficult to interpret. The relationship between BIN price and revenue appears to be convex, and increasing over most of the observed range for the BIN price. To explore this in slightly more detail, we show in Figure 5 a scatterplot of the residuals from a regression of revenue on all the variables *except* the BIN variables, against the BIN price. (The residuals were generated from a regression using all auctions.) The graph also shows a nonparametric regression curve, generated using the `loess` function in R. There is some weak evidence that the seller revenue is increasing in BIN price over most of the range of the data, and certainly little to indicate a value of BIN price beyond which revenue starts to decline. We may not be conditioning sufficiently finely on the laptop and seller characterisics to be able to make useful policy prescriptions about the auction design. We intend to explore this further in future versions of the paper.

4 Structural Empirical Model

In this section, we set up our primary model for bidder behavior in eBay auctions, and take this model to the data we have collected. We will refer to auctions with a buy price B as buy-it-now (BIN) auctions, and auctions without a buy price as without-buy-it-now (WBIN) auctions. A WBIN auction is a standard eBay auction.

The auction takes place from time 0 to a prespecified ending time T. In the time interval $[0, T]$, potential bidders arrive according to a nonhomogeneous Poisson process with intensity function (arrival rate) $\lambda(t)$, for $t \in [0, T]$. We assume that this function is bounded away from 0 and ∞. Thus, the number of bidders is stochastic. We allow the arrival rate to change with time, because bidders appear to arrive more frequently near the end of auctions. At any time $t \in [0, T]$, the probability that exactly n potential bidders will arrive in the remaining time $[t, T]$ is

$$\frac{(\gamma_t)^n e^{-\gamma_t}}{n!}, \quad n = 0, 1, 2, \ldots,$$

where

$$\gamma_t := \int_t^T \lambda(t)dt.$$

A bidder who arrives at time t, and who wins the object at time $\tilde{t} \in [t, T]$ at price p, obtains a utility of $u(v-p, \tilde{t}-t)$.[7] The utility has a constant absolute risk aversion form:

$$u(v-p, \tilde{t}-t) = \delta^{\tilde{t}-t} \frac{1-e^{-\alpha(v-p)}}{\alpha}.$$

Here $\delta \in (0, 1]$ is a discounting factor, v is a "valuation" of the ojbect to the bidder, and α is the bidder's level of risk aversion. When $\alpha = 0$, we set $u(v-p, \tilde{t}-t) = \delta^{\tilde{t}-t}(v-p)$. Currently, we set $\delta = 1$ in our empirical analysis. We plan to estimate δ in future versions of the paper. The risk-aversion parameter α is assumed to be the same across individuals.

The value v is distributed independently and identically across bidders, according to a continuous distribution F with support $[\underline{v}, \bar{v}]$. Let f denote the density of F with respect to Lebesgue measure. Below, we will specify a parametric model for the valuation distribution conditional on observed characteristics of the object being auctioned, and seller characteristics.

4.1 WBIN Auctions

We first describe bidder behavior in our model of standard eBay auctions without a buy-it-now price. Our model is essentially the same as that of Canals-Cerda and Pearcy (2004). In the next subsection, we then extend our model to BIN auctions.

In a WBIN auction, the seller sets a starting or reserve price r, assumed to be in $[\underline{v}, \bar{v})$, and the length of the auction T. At any point in time t, there is a current standing bid $s(t)$, which is the second highest of the bids placed up to that time. If fewer than two bids have been received, then $s(t) = r$, the reserve price.

When a bidder arrives at some time t, (according to the Poisson process introduced above), we call her a *potential bidder*. Upon arrival, she decides whether or not to enter the auction. If she exits the auction, she does not enter again at a later time. If she enters the auction, she becomes an *active bidder*. She must place a bid immediately, and the bid must be greater than the standing bid $s(t)$. Active bidders can later raise their bids as many times as they like. At the end of the auction at time T, the highest bidder wins and pays the amount of the second highest bid. Since the auction ends at T, we have $\tilde{t} = T$ and the winner's payoff is discounted by δ^{T-t}.

We assume that any potential bidder with valuation greater than or equal to the current standing bid enters the auction (i.e. places a bid):

[7] In practice, $\tilde{t}$ will either be equal to t (in the case that the BIN option is exercised and the auction ends immediately) or T (when there is no BIN option or the option is not exercised, and a standard eBay auction ensues).

Assumption 1 *In BIN auctions, a potential bidder with valuation v enters the auction if $v \geq s(t)$; otherwise, she exits the auction.*

In eBay auctions, bidders enter their "maximum" bid amount, and a computer proxy raises bids as long as the standing bid is below the bidder's maximum bid. Thus, it would seem natural to consider the auction as a standard English or oral ascending bid auction, and assume that bidders bid up to their valuation. However, we observe many bidders raising their "maximum" bids later in the auction. This suggests that bids may not necessarily correspond to valuations. We follow Haile and Tamer (2003) and make a weaker assumption on bidder behavior.

Assumption 2 *a bidder's bids are less than or equal to her valuation v.*

Assumption 3 *a bidder does not allow an opponent to win at a price they are willing to beat.*

Assumption 3 ensures that the bidder with the highest valuation wins the auction. In general, bids are not necessarily equal to valuations (although this is not ruled out), and the relationship between bids and valuations is not fully specified. In addition, bidders are allowed to raise their bids as many or as few times as they like.

Because eBay uses proxy bidding, Assumption 3 implies that the bidder with the second highest vauation will (at some point) keep bidding against the bidder with the highest valuation, until eventually she has bid her true valuation. At that point, $s(t)$ will be equal to the second highest valuation and no other bidder will be able to place any more bids. As a result, the sale price at the end of the auction will be equal to the second highest valuation, whenever there are at least two active bidders.[8] This argument, due to Canals-Cerda and Pearcy (2004), means that in these auctions, the second highest bidder's valuation is observed, providing an additional source of information beyond the inequalities which follow directly from Haile and Tamer's assumptions.

4.2 BIN Auctions

In a BIN auction, the seller sets a reserve price $r \in [\underline{v}, \bar{v})$, auction length T, and a buy price $P_B > r$. The BIN feature is available at the start of the auction. It remains available until a bidder arrives and either accepts the buy price (thus ending the auction and winning the item at price P_B), or places a bid b where $r < b < P_B$. If a bidder places a bid below the buy price, the buy-it-now option disappears, and the auction becomes a standard ascending bid auction, with the same rules as in the WBIN auction. Thus, the buy-it-now feature allows a bidder to obtain the item with certainty, and obtain the item earlier than time T.

[8]This argument ignores the fact that eBay has minimum bid increments. Because of these increments, it is possible that the sale price could be higher than the second highest valuation by an amount up to the increment. Since these increments are generally very small, we ignore them in the empirical analysis, but note that it could cause a very small upward bias in our estimated valuation distributions.

We assume that when a potential bidder arrives at time t, she decides to enter the auction as long as $v \geq s(t)$. If she does not enter, she disappears from the auction and cannot enter at a later date. If she does enter the auction, she must either buy the item at the buy price P_B (if the buy option is still available), or place a bid immediately.[9] The bid must be greater than the standing bid $s(t)$, and if a buy price is available, must be less than the buy price. In the ascending bid phase that follows, active bidders can revise their bids. Once again, Assumptions 2 and 3 restrict bidding behavior in the ascending auction.

There are two benefits for a bidder taking the BIN option First, the bidder gets the item with certainty, rather than potentially being outbid (or paying more) later in the auction. Second, the bidder gets the item earlier, at $\tilde{t} = t$ rathen than $\tilde{t} = T$. On the other hand, the cost of taking the BIN option is that it is possible that the bidder could win the item at a lower price by waiting. For bidders who face a choice between the buy price and placing a bid below the buy price, we can characterize the decision whether or not to accept the buy price. Consider a bidder who arrives at time t with value $v > r$ and finds the BIN option available. A strategy for this bidder maps her value into her decision of accepting or rejecting P_B, and conditional on rejecting P_B, the value of her bid b. We will focus on "cutoff strategies" for the bidder. A cutoff strategy at time t is defined by a constant $c_t \in [P_B, \bar{v}]$, such that the bidder accepts the BIN price P_B if $v > c_t$, and she rejects P_B and places a bid if $v < c_t$.

When the bidder accepts P_B she gets a certain payoff. However, if she rejects P_B and places a bid, her payoff is uncertain. In this case, she will win only if she has the highest value among the bidders who arrive in the remaining time. The expected payoffs from accepting and rejecting P_B, denote $U^A(v,t)$ and $U^R(v,t)$, are

$$U^A(v,t) = u(v - P_B, 0),$$

$$U^R(v,t) = \sum_{n=0}^{\infty} E[u(v - \max\{r, y\}, T - t)|y \leq v] G_n(v) \frac{\gamma_t^n e^{-\gamma_t}}{n!},$$

where $G_n(\cdot) = F(\cdot)^n$ is the distribution function of y, and $\gamma_t = \int_t^T \lambda(t)dt$. In the last expression, n is interpreted as the number of potential bidders who arrive after t, and y is the highest among n draws from the distribution F.

A cutoff c_t^* is an equilibrium cutoff if $U^A(v,t) > U^R(v,t)$ for all $v > c_t^*$, and $U^A(v,t) < U^R(v,t)$ for all $v < c_t^*$. It is useful to define $\bar{P}_{Bt}$ as the buy price that makes a bidder with $v = \bar{v}$ indifferent beween accepting and rejecting at time $t \in [0, T)$. This solves:

$$u(\bar{v} - \bar{P}_{Bt}, 0) = \sum_{n=0}^{\infty} E[u(\bar{v} - \max r, y, T - t)] \frac{\gamma_t^n e^{-\gamma_t}}{n!}.$$

[9] While the assumption that a bidder must make a decision immediately upon arrival might appear strong, we could interpret the arrival as the time of the bidder's first decision to take an action.

Now, the following proposition characterizes the equilibrium cutoff c_t^*:

Proposition 1 *Consider a BIN auction with a reserve price $r \in [\underline{v}, \bar{v}]$, a buy price P_B, and time length T. Suppose that a bidder with risk aversion index α and discount factor δ arrives at time $t \in [0, T)$, and that P_B is available at time t. Then*

1. *If $P_B \geq \bar{P}_{Bt}$, she does not accept P_B in equilbrium; that is, $c_t^* = \bar{v}$.*
2. *If $P_B < \bar{P}_{Bt}$, there exists a unique equilibrium cutoff $c_t^* \in (P_B, \bar{v})$. This cutoff is implicitly defined by*
$$U^A(c_t^*, t) = U^R(c_t^*, t).$$
The cutoff is c_t^* is decreasing in α and r, and increasing in P_B, t, and δ.

Note that $\lambda(t) < \infty$ ensures that it is not always better for a bidder to accept P_B, while $\lambda(t) > 0$ ensures that it is not always better to reject the buy price.

An important aspect of this result is that we can compute the equilibrium cutoff c_t^* using only assumptions 1-3, without specifying the rebidding process. The reason this is possible is that the expected utility of rejecting the BIN option depends only on the distribution of the winning price. Assumptions 1-3 are sufficient to define this distribution, without fully specifying the complete distribution of bids and rebids.

4.3 Parametric Specification

For auction i, let X_i be a vector of laptop characteristics, and let W_i be a vector of seller reputation measures. Then we assume that the valuation distribution in auction i is lognormal, where the log valuation has mean
$$\mu_i = \beta_0 + X_i'\beta_x + W_i'\beta_w.$$
and variance σ^2.

In our initial results reported below, the arrival rate is assumed to be constant over time, and with respect to auction characteristics: $\lambda(t; X_i, W_i) = \lambda$. We currently assume that the discount factor $\delta = 1$, so that there is no impatience. The risk aversion parameter α is constant across auctions, and is a parameter to be estimated within our setup. We will denote the entire parameter vector by θ:
$$\theta := (\beta_0, \beta_x, \beta_w, \sigma, \lambda, \alpha).$$
We will write the distribution of valuations in auction i as $F_\theta(v|X_i, W_i)$, and the associated density as $f_\theta(v|X_i, W_i)$. The cutoff function $c(t)$ also depends on the parameter θ, so we will use $c_\theta(t)$ to make this explicit.

In our analysis, we treat the auction design variables (reserve price, auction length BIN option, BIN price) as exogenous. Implicitly, we are assuming that the auction design variables are not related to the valuation distribution or the other behavioral parameters, after conditioning on the laptop and seller characteristics.

4.4 Partial Likelihood based on Arrivals of Bidders and the BIN option

Consider a single auction i with K observed bidders. For now, we drop the "i" subscript and the conditioning on (X_i, W_i) for notational simplicity. We first consider the statistical information contained in the observations on initial arrival times $t_1, \ldots, t_K$, along with the time of acceptance of a buy price (if the BIN option is available). The arrival-time observations can be viewed as a counting process (see Andersen, Borgan, Gill, and Keiding, 1993), and, augmented with the information about acceptance of a buy price, can be viewed as a marked point process (a point process with additional random variables observed at each point). However, the appropriate conditioning set for this process at any point in time t should include the standing bid process $s(t)$ and other observed variables up to time t. Thus, the appropriate filtration for this process is larger than the filtration generated by the marked point process itself (the process is "non-self-exciting"). Cox (1975) noted that one can often construct pseudo-likelihoods by conditioning arguments, and pointed out that such "partial" likelihoods behave like ordinary likelihoods from the point of view of statistical inference. Here, we use this insight to construct a partial likelihood for this component of our data.

To give a heuristic explanation of the partial likelihood, it is useful to (a) normalize $T = 1$ (this can always be done by redefining the arrival rate $\lambda(t)$ appropriately), and (b) discretize the time interval into n periods $1/n, 2/n, \ldots, n/n$. For $j = 1, \ldots, n$, let $\delta_j = 1$ if there is a new arrival (of an active bidder) at time j/n, and 0 otherwise. In addition, let $\tau_j = 1$ if the buy price P_B is accepted at time j/n, and 0 otherwise. (If the BIN option is not available, or has already been rejected at an earlier time period, $\tau_j = 0$.) Collect these two observations at time j/n into

$$\psi_j = (\delta_j, \tau_j),$$

and for any j, also define the sequence of observations up to time j/n as:

$$\Psi_j = (\psi_1, \psi_2, \ldots, \psi_j).$$

There is other information available at any time j/n. Let B_j denote the history of bids up to time j. Then, for an auction with reserve r and buy price P_B, the complete history of the auction before time j/n is

$$\Omega_{j-1} = (\Psi_{j-1}, B_{j-1}, r, P_B),$$

with obvious modification for WBIN auctions. Let $s_j = s(j/n)$ denote the standing bid at time j/n, and let $c_j = c_\theta(j/n)$ denote the cutoff value at time j/n. In addition, let BIN_j be an indicator for whether the BIN option is available at time j. Clearly, s_j, c_j, and BIN_j are all functions of

Ω_{j-1}.

In order the derive the distribution of ψ_j, it is useful to define latent variables w_j and v_j, where w_j as an indicator for whether a potential bidder arrives in period j, distributed Bernoulli with probability $\lambda(j/n)/n$, and v_j is an independent draw from the valuation distribution $F(v)$. Then we can define

$$\delta_j := w_j \cdot 1(v_j > s_j),$$

and

$$\tau_j = w_j \cdot 1(v_j > c_j) \cdot \text{BIN}_j.$$

We now focus on obtaining the conditional distribution of ψ_j given Ω_{j-1}. The expressions will be slightly different depending on whether the BIN option is available or not available at time j/n:

BIN Option Not Available at j/n:
In this case, $P_\theta(\tau_j = 0|\Omega_{j-1}, \theta) = 1$, and simple calculations lead to:

$$\begin{aligned} P_\theta(\psi_j = (0,0)|\Omega_{j-1}) &= 1 - \frac{\lambda(j/n)}{n}\left(1 - F_\theta\left(s_j\right)\right); \\ P_\theta(\psi_j = (1,0)|\Omega_{j-1}) &= \frac{\lambda(j/n)}{n}\left(1 - F_\theta\left(s_j\right)\right). \end{aligned}$$

Intuitively, this says that the probability of observing an active bidder enter at period j is equal to the probability of a potential bidder arriving, times the probability that the bidder's valuation is higher than the current standing bid.

BIN Option Available at j/n:
Again, using the latent variable representation of the model, we can derive:

$$\begin{aligned} P_\theta(\psi_j = (0,0)|\Omega_{j-1}) &= = 1 - \frac{\lambda(j/n)}{n}\left(1 - F_\theta(s_j)\right); \\ P_\theta(\psi_j = (1,0)|\Omega_{j-1}) &= \frac{\lambda(j/n)}{n}\left[F_\theta(c_j) - F_\theta(s_j)\right]; \\ P_\theta(\psi_j = (1,1)|\Omega_{j-1}) &= \frac{\lambda(j/n)}{n}\left(1 - F_\theta(c_j)\right). \end{aligned}$$

Here, there are three possibilities. The probability of the BIN option being taken in period j is equal to the probability that a potential bidder arrives, times the probability that the bidder's valuation is above the BIN cutoff c_j. The probability of a standard bid in period j is equal to the probability of a bidder arriving, times the probability that the bidder's valuation is between the current standing bid and the BIN cutoff.

Having calculated these conditional probabilities, we can then define, for a given auction, a partial likelihood composed of the product of these conditional densities:

$$PL_n(\theta) = \prod_{j=1}^{n} P_\theta(\psi_j|\Omega_{j-1}).$$

Notice that $PL_n(\theta)$ is not a sequential decomposition of the joint density of $\psi_1, \ldots, \psi_n$, because the conditioning set Ω_{j-1} at each period includes additional variables beyond the lagged ψ_j. In the terminology of stochastic processes, the process $\{\psi_j\}$ is not self-exciting, because the sequence of conditioning sets (the filtration) is larger than the conditioning sets implied by the lagged values of the process. This is therefore not a standard likelihood, because it is not a joint density for the observed data.

We can take $n \to \infty$ and use standard results on product integration to get the continuous-time version of the partial likelihood. (See Andersen et al, 1993, for a formal derivation of continuous time partial likelihoods of counting processes.) In the case of a WBIN auction with K arrivals at time $t_1, t_2, \ldots, t_K$, that ends in a trade, we have

$$\begin{aligned}
PL_n(\theta) &= \prod_{j=1}^{n} \left[\frac{\lambda(j/n)}{n}(1 - F_\theta(s_j))\right]^{\delta_j} \left[1 - \frac{\lambda(j/n)}{n}\left(1 - F_\theta\left(s_j\right)\right)\right]^{1-\delta_j} \\
&= \prod_{j:\delta_j=1} \frac{\lambda(j/n)}{n}(1 - F_\theta(s_j)) \times \prod_{j:\delta_j=0} \left[1 - \frac{\lambda(j/n)}{n}\left(1 - F_\theta\left(s_j\right)\right)\right] \\
&\propto \prod_{j:\delta_j=1} \lambda(j/n)(1 - F_\theta(s_j)) \times \prod_{j:\delta_j=0} \left[1 - \frac{\lambda(j/n)}{n}\left(1 - F_\theta\left(s_j\right)\right)\right] \\
&\longrightarrow \left[\prod_{k=1}^{K} \lambda(t_k)(1 - F_\theta(s(t_k)))\right] \cdot \exp\left(-\int_0^1 \lambda(t)[1 - F(s(t))]dt\right) \\
&=: PL(\theta).
\end{aligned}$$

Hence the continuous-time partial log-likelihood (up to an additive constant C) is:

$$\log PL(\theta) = C + \sum_{k=1}^{K} \log[\lambda(t_k)(1 - F_\theta(s(t_k)))] - \int_0^1 \lambda(t)(1 - F_\theta(s(t)))dt.$$

Similarly, for a BIN auction that ends with the buy-it-now price P_B accepted at time t_1, we have

$$PL(\theta) \propto \lambda(t_1)(1 - F_\theta(c_\theta(t_1))) \exp\left(-\int_0^{t_1} \lambda(t)(1 - F_\theta(s(t)))dt\right).$$

For a BIN auction that ends with a sale through bidding, the partial likelihood reflects the fact that the buy-it-now price was rejected at time t_1:

$$PL(\theta) \propto \lambda(t_1)\left[F_\theta(c_\theta(t_1)) - F_\theta(s(t_1))\right]\left[\prod_{k=2}^{K} \lambda(t_k)(1 - F_\theta(s(t_k)))\right] \exp\left(-\int_0^1 \lambda(t)(1 - F_\theta(s(t)))dt\right).$$

When an auction (either BIN or WBIN) ends without a trade, the likelihood is:

$$PL(\theta) \propto \exp\left(-\int_0^1 \lambda(t)(1 - F_\theta(s(t)))dt\right).$$

Having constructed the partial likelihood, we can use it like a standard likelihood. In particular, by the argument of Cox (1975), a version of the information equality holds: the expected log partial likelihood

$$E[\log PL(\theta)]$$

is maximized at the true value of θ, and therefore we have the moment equation

$$E\left[\frac{\partial \log PL(\theta)}{\partial \theta}\right] = 0.$$

4.5 Moment Conditions Based on Bids

The previous partial likelihood function uses information in the arrival times of bidders and in their decisions of whether to take the BIN option. This is particularly informative about the Poisson arrival process parameter and the risk aversion parameter (which enters the partial likelihood through the cutoff function). However, the partial likelihood does not use any information in the actual bid amounts, which should be quite informative about the distribution of valuations F. To utilize this information, we augment the moment conditions from the partial likelihood approach above witha set of simulated moments related to bid amounts.

The Haile-Tamer assumptions imply various moment inequalities relating observed bids to valuations. In our eBay context, they also imply some moment equalities, because of the fact that they imply that we observe the second highest valuation in every auction with 2 or more bidders. For now we focus on these simpler moment equalities, but we plan to incorporate additional information in moment inequalities in future work.

The key to our current moment equalities is that Assumptions 1-3 imply that the sale price will equal the second highest valuation if there are two or more bidders, and will equal the reserve price if there is only one bidder. Conceptually, this means that given parameters and a particular auction (i.e. item and seller characteristics), we can very easily simulate possible sale prices. We can then form moments by matching these simulated sale prices to actual sale prices.

More specifically, we simulate sale prices as follows. Consider a particular auction in the data with a given set of item and seller characteristics and auction length. First, given the arrival rate, reserve price, and auction length, we simulate the number of bidder arrivals for the auction by drawing from a Poisson process. Next, given the mean and variance of the valuation distribution for the auction, we take a draw from the valuation distribution for each of these arrivals. Now find the first simulated valuation that is higher than the observed reserve price. This is the first observed bidder. If none of the valuations are higher than the reserve price, the auction ends with no sale. If the first observed bidder has a valuation higher than the BIN threshold, the auction ends with a sale at the BIN price.[10] If the valuation is less than the BIN threshold, the first bidder bids and the auction reverts to standard format. In this case, the auction ends with a sale at either the second highest of the simulated valuations (if at least two are higher than the reserve price) or a sale at the reserve price (if not).

At any given set of parameters, we can simulate these sale prices for each auction NS times. We then construct

$$\begin{aligned} EP_i &= \frac{1}{NS}\sum_{ns} P_{ns} \\ EP_i^2 &= \frac{1}{NS}\sum_{ns} P_{ns}P_{ns} \\ ED_i &= \frac{1}{NS}\sum_{ns} D_{ns} \end{aligned}$$

where P_{ns} is the simulated price in the nsth simulation, and D_{ns} is a dummy variable indicating that the item was sold in the nsth simulation. Thus, EP_i is the simulated price for the ith auction, and ED_i is the simulated probability of sale. EP_i^2 is the simulated second moment of sale price, which should be useful for identifying the variance of bidder valuations.

Given the above simulated values, our additional moment conditions are:

$$\begin{gathered} \frac{1}{N}\sum_i [P_i - EP_i] \\ \frac{1}{N}\sum_i [P_i - EP_i]x_{1i} \\ \frac{1}{N}\sum_i [P_i - EP_i]x_{2i} \\ \vdots \end{gathered}$$

[10]Right now, we are using the BIN cutoff from the observed first bidder's arrival time rather than the simulated first bidder's arrival time. This is because of the computational burden involved in recomputing the cutoffs multiple time. We are working on an alternative conditional moment approach that avoids this problem.

$$\frac{1}{N}\sum_i [P_i - EP_i]x_{ji}$$
$$\frac{1}{N}\sum_i [P_i^2 - EP_i^2]$$
$$\frac{1}{N}\sum_i [D_i - ED_i]$$

where P_i is the observed sale price in auction i (0 if no sale), and D_i is an indicator that auction i ended in a sale. By construction, all these moments should equal zero when the simulated values are computed at the true parameter values. We combine these moments with the score-type moments implied by the partial likelihood function to form one large set of moment conditions. We use a two step GMM procedure for estimation based on these moments. In the second step we weight our moments optimally given consistent estimates from the first stage. Standard errors of our estimates are computed in the usual way. We ignore variance in our estimates due to simulation error, but this should be extremely small. This is because simulation error will only increase the variance of the above subset of the moments by $1/NS$ (McFadden (1989), Pakes and Pollard (1989)) and we are setting NS=300.

Lastly, we briefly discuss identification. As noted above, the patterns of observed arrivals should well identify the parameters of the Poisson process through the partial likelihood function. The parameters of the distribution of valuations should similarly be well identified by the observed sale prices. This leaves us with the critical risk aversion and discounting parameters. If there were no discounting, then the propensity of consumers to take the BIN option (as captured by the partial likelihood function) should identify the risk aversion parameter. The intution here comes from Proposition 1, which says that as the risk aversion parameter increases, the BIN cutoff decreases. Intuitively, the more risk averse buyers are, the more likely they are to favor the certainty of the BIN option. Of course, BIN behavior will also depend on the arrival rates and distribution of valuations, since these impact the amount of risk one faces in not taking the BIN option. But as mentioned above, these should be pinned down by the observed rate of arrivals and the observed sale prices.

When we add discounting, things become a little more complicated. The reason is that the discount factor can also very clearly impact BIN behavior. Again, as pointed out in Proposition 1, as consumers discount the future more, they will be more likely to take the BIN option, as it gets them the item sooner. Fortunately, as noted above, we have data on auctions of various lengths, from 1 day to 10 days. This is the key to separately identifying the discount factor and the level of risk aversion, as the length of the auction should directly impact the effect of discounting (the longer the auction, the more important is discounting), but not directly impact the effect of risk aversion. Of course, there is an indirect impact on the effect of risk aversion because longer auctions will likely have more potential bidders, but this effect can be measured by the Poisson parameters (which are identified from the rate of arrivals), and will be implicitly controlled for in the partial likelihood function. Intuitively, we will identify the discount factor by looking at BIN behavior across auctions of different lengths. If there is no discounting, changes in the number of potential arrivals across these different length auctions should affect BIN behavior in a very specific way (as pinned down by the Poisson parameters). Increased propensity of BIN behavior as auction length increases over and above this specific effect will suggest discounting, and the extent will suggest the level of discounting.

4.6 Results and Discussion

Our preliminary GMM structural estimation results are given in Table 13. The estimated Poisson arrival rate (λ) is 2.96. This implies an estimated value of 2.96 for the expected number of potential arrivals in an 1-day auction. Excluding the BIN auctions where BIN options were accepted, the average number of active bidders per day in our data set is 2.27 which is less than our estimated expected potential arrivals. This makes sense - not all arriving bidders will actually place bids because their valuations may be lower than the standing bid.

The estimates for β_0 and σ, the mean-intercept and standard deviation of $\log(v)$, along with the estimates of the characteristic coefficients, imply that for an auction with the average computer and seller attributes, the median of the valuation distribution is \$352.52. This includes shipping costs (the average shipping cost in our data is \$28.70). The estimated median is slightly lower, as we would expect, than the average sale price of \$355.90 in WBIN auctions. Given our estimate of σ, the standard deviation of $\log(v)$, the 9 decile range of the valuation distribution is from \$262.96 to \$472.57.

Examining the estimates of the effects of item and seller covariates, most appear sensible. Processor speed and more memory significantly increase valuations, as does inclusion of an operating system, wireless, and extra software. Our processor speed and memory variables are normalized to have mean 0 and unit variance, so the estimates imply that a one standard deviation increase in processing power increases the mean valuation by 15% while one standard deviation increase in memory in laptops increases the mean valuation by 1%. The three other item covariates mentioned above are dummy variables, so the coefficients imply that an operating system increases the mean valuation by 25%, a wireless card adds 3% and additional software adds 20%. These laptop characteristics also had positive effects on the sale prices (Tables 10-12) in our OLS regressions. Hard drive size comes up the wrong sign, but it is insignificant. Examining the three seller covariates, the results are more difficult to interpret. While the proportion of negative feedback significantly decreases valuations, the total number of negative feedback entries significantly increases valuations. Total feedback score is positive but insignificant. It could be that negative feedback is actually picking up a non-linear positive effect of seller experience. Another is that our model is not yet flexible enough to get accurate estimates of these parameters. Right now, both observed arrival rates and observed bids are identifying these parameters. One can easily tell stories how this could generate these results. For example, if sellers with more negative feedback advertise their listings more and hence get more bidder arrivals, it will suggest a positive coefficient in our current model. As noted above, in future work we will allow the arrival rate to vary across both time and item/seller characteristics. In that model, arrival rates and observed bids will be identifying different parameters.

Our estimates suggest that bidders are risk averse. The estimated CARA index (α) is 0.29 which is significantly different from 0. This allows us to reject the null hypothesis of risk neutrality against an alternative hypothesis of risk aversion. The implications of this risk aversion parameter on BIN decisions by bidders is easiest to explain in an example. Consider an item with mean seller and item characteristics. Consider a 5-day auction with the sample average reserve price of $326.00 and the sample average buy price of $420.60. The estimates in Table 13 imply that a buyer arriving at the halfway point of the auction will have BIN cutoff of $421.77. This means that if the buy price is available at this time, the bidder accepts it if his valuation is higher than $421.77, otherwise she rejects the buy price and places a bid if his valuation is greater than $326.00. If his valuation is less than $326.00, she exits the auction. The small interval between the BIN price and the cutoff suggests that bidders are fairly risk averse—virtually any buyer with a valuation higher than the BIN price takes it. This difference increases though, as the BIN price increases. In addition, note that we are assuming a discount factor of 1 currently, which if anything will bias our estimate of the risk aversion parameter upwards.

5 Conclusion

[to be added]

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Appendix A: Proofs

Proposition 1
Proof:

We consider a buy price $P_B \in (r, \overline{P}_{Bt})$, and a bidder arriving at time t with a value $v \geq P_B$. Let n denote the number of bidders who arrive after time t. Now, define $U^A(v,t)$ and $U^R(v,t)$ as

$$U^A(v,t) = u(v - P_B, 0), \tag{1}$$

and

$$U^R(v,t) = \sum_{n=0}^{\infty} E\left[u\left(v - \max\{r, y\}, T - t\right)|y \leq v\right] G(v) \frac{(\gamma_t)^n e^{-\gamma_t}}{n!}, \tag{2}$$

where y is the highest among n value draws, and $G(.) = F(.)^n$ is the distribution function of y. For $n = 0$, $\max\{r, y\} = r$. Whenever (a) and/or (b) do not hold we have $U^R(v,t) = 0$. Notice that $\lambda(t) = 0$ implies $P_0(t) = 1$ and $P_n(t) = 0$ for $n > 0$, which in turn implies that $U^R(v,t) = u(v - r, T - t)$. On the other hand, $U^R(v,t) \to 0$ as $\lambda(t) \to \infty$.

$\overline{P}_{Bt}$, the buy price that makes a bidder with $v = \overline{v}$ indifferent between accepting and rejecting at time $t \in [0, T)$, solves the following equation:

$$u(\overline{v} - \overline{P}_{Bt}, 0) = \sum_{n=0}^{\infty} E\left[u\left(\overline{v} - \max\{r, y\}, T - t\right)\right] \frac{(\gamma_t)^n e^{-\gamma_t}}{n!}. \tag{3}$$

Now, we first prove part (2) and then part (1).

Part (2): We start by showing the existence of some value $c_t^* \in (P_B, \overline{v})$ such that the indifference condition in Proposition 1 holds for a bidder with $v = c_t^*$. This is a necessary condition for c_t^* to be in equilibrium. To show this, it is sufficient to show that $U^A(v,t)$ and $U^R(v,t)$ intersect at some $v \in (P_B, \overline{v})$. Then we can set c_t^* equal to this v.

Clearly, $U^A(P_B, t) = 0$, and $v > r$ implies that $U^R(P_B, t) > 0$. So, $U^R(P_B, t) > U^A(P_B, t)$. On the other hand, $P_B < \overline{P}_{Bt}$ implies that

$$\begin{aligned} u(\overline{v} - P_B, T - t) &> u(\overline{v} - \overline{P}_{Bt}, T - t) = U^R(\overline{v}, t); \\ U^A(\overline{v}, t) &> U^R(\overline{v}, t). \end{aligned}$$

Then, since $U^A(v,t)$ and $U^R(v,t)$ are continuous, it must be the case that there is some value $v \in (P_B, \overline{v})$ such that $U^A(v,t) = U^R(v,t)$. We set c_t^* equal to this value.

Now, we show that the value c_t^* satisfying $U^A(c_t^*, t) = U^R(c_t^*, t)$ is unique and actually an equilibrium cutoff. We accomplish both by showing that $U^A(v,t)$ is steeper than $U^R(v,t)$ at any v

where $U^A(v,t) = U^R(v,t)$. Lets start by deriving the slope equations for $U^A(v,t)$ and $U^R(v,t)$ as follows:

$$\begin{aligned}
\frac{\partial U^A(v,t)}{\partial v} &= u_1(v-P_B,0) \\
&= \delta^0 - \alpha u(v-P_B,0) \\
&= 1-\alpha U^A(v,t)
\end{aligned}$$

where the second line utilizes the relationship $u_1(.,x) = \delta^x - \alpha u(.,x)$ which holds for CARA utility function, and using Leibniz's rule,

$$\begin{aligned}
&\frac{\partial U^R(v,t)}{\partial v} \\
&= \frac{\partial}{\partial v}\left[u(v-r,T-t)e^{-\gamma_t} + \sum_{n=1}^{\infty}\left[u(v-r,T-t)G(r) + \int_r^v u(v-y,T-t)dG(y)\right]\frac{(\gamma_t)^n e^{-\gamma_t}}{n!}\right] \\
&= u_1(v-r,T-t)e^{-\gamma_t} + \sum_{n=1}^{\infty}\left[u_1(v-r,T-t)G(r)\frac{(\gamma_t)^n e^{-\gamma_t}}{n!}\right. \\
&\quad \left. + \frac{(\gamma_t)^n e^{-\gamma_t}}{n!}\left[\int_r^v u_1(v-y,T-t)dG(y) + u(v-v,T-t)\right]\right] \\
&= \left[\delta^{T-t} - \alpha u(v-r,T-t)\right]e^{-\gamma_t} + \sum_{n=1}^{\infty}\left[\left(\delta^{T-t} - \alpha u(v-r,T-t)\right)G(r)\frac{(\gamma_t)^n e^{-\gamma_t}}{n!}\right. \\
&\quad \left. + \frac{(\gamma_t)^n e^{-\gamma_t}}{n!}\left[\int_r^v \left(\delta^{T-t} - \alpha u(v-y,T-t)\right)dG(y)\right]\right] \\
&= \delta^{T-t}e^{-\gamma_t} + \delta^{T-t}\sum_{n=1}^{\infty}\left[G(r) + G(v) - G(r)\right]\frac{(\gamma_t)^n e^{-\gamma_t}}{n!} \\
&\quad -\alpha\left[u(v-r,T-t)e^{-\gamma_t} + \sum_{n=1}^{\infty}\left[u(v-r,T-t)G(r) + \int_r^v u(v-y,T-t)dG(y)\right]\frac{(\gamma_t)^n e^{-\gamma_t}}{n!}\right] \\
&= \delta^{T-t}\left[e^{-\gamma_t} + \sum_{n=1}^{\infty}G(v)\frac{(\gamma_t)^n e^{-\gamma_t}}{n!}\right] - \alpha U^R(v,t)
\end{aligned}$$

where the second line utilizes the relationship $u_1(.,x) = \delta^x - \alpha u(.,x)$. Notice that for $v < \overline{v}$,

$$e^{-\gamma_t} + \sum_{n=1}^{\infty}G(v)\frac{(\gamma_t)^n e^{-\gamma_t}}{n!} \quad < \quad e^{-\gamma_t} + \sum_{n=1}^{\infty}\frac{(\gamma_t)^n e^{-\gamma_t}}{n!}$$

$$= \sum_{n=0}^{\infty} \frac{(\gamma_t)^n e^{-\gamma_t}}{n!}$$
$$= 1.$$

The above inequality implies that,

$$\frac{\partial U^A(v,t)}{\partial v} > \frac{\partial U^R(v,t)}{\partial v} \text{ when } U^A(v,t) = U^R(v,t). \tag{4}$$

As a result, $U^A(v,t)$ is steeper than $U^R(v,t)$ at $v = c_t^*$. So, $U^A(v,t)$ lies below $U^R(v,t)$ for $v \in [\underline{v}, c_t^*)$ and $U^A(v,t)$ lies above $U^R(v,t)$ for $v \in (c_t^*, \overline{v}]$. This completes the proof that c_t^* is an equilibrium cutoff and is unique.

Now we prove part 1 of Proposition 2.

Part (1): We have two cases to consider.

(1) When $P_B = \overline{P}_{Bt}$: By definition of $\overline{P}_{Bt}$ in equation (3), when $P_B = \overline{P}_{Bt}$, $U^A(\overline{v},t) = U^R(\overline{v},t)$. Since, from (4)

$$\left.\frac{\partial U^R(v,t)}{\partial v}\right|_{v=\overline{v}} = \delta^{T-t}\sum_{n=0}^{\infty} \frac{(\gamma_t)^n e^{-\gamma_t}}{n!} - \alpha U^R(\overline{v},t) = \delta^{T-t} - \alpha U^R(\overline{v},t)$$

it is the case that, when $\delta = 1$,

$$\left.\frac{\partial U^A(v,t)}{\partial v}\right|_{v=\overline{v}} = \left.\frac{\partial U^R(v,t)}{\partial v}\right|_{v=\overline{v}}.$$

Then it has to be that $U^A(v,t)$ lies completely below $U^R(v,t)$ over $[\underline{v}, \overline{v})$, and $U^A(v,t) = U^R(v,t)$ at $v = \overline{v}$. Otherwise, for $P_B < \overline{P}_{Bt}$ or $P_B > \overline{P}_{Bt}$, $U^A(\overline{v},t)$ and $U^R(\overline{v},t)$ would intersect twice over $[\underline{v}, \overline{v})$ which we know cannot happen (from part 2 above). This is because $U^A(\overline{v},t)$ is steeper than $U^R(\overline{v},t)$ at any such intersection. So, $c_t^* = \overline{v}$ when $P_B = \overline{P}_{Bt}$.

Now, when $\delta \in (0,1)$

$$\left.\frac{\partial U^A(v,t)}{\partial v}\right|_{v=\overline{v}} > \left.\frac{\partial U^R(v,t)}{\partial v}\right|_{v=\overline{v}}.$$

As a result, $U^A(v,t)$ will lie completely below $U^R(v,t)$ over $[\underline{v}, \overline{v})$, and $U^A(v,t) = U^R(v,t)$ at $v = \overline{v}$. Otherwise, if they intersect at some $v \in (\underline{v}, \overline{v})$, it will imply that $U^R(v,t)$ is steeper than $U^A(v,t)$ which we know cannot happen (from part 2 above).

(2) When $P_B > \overline{P}_{Bt}$: Given what we found above, for $P_B > \overline{P}_{Bt}$, it will be the case that $U^A(v,t)$ lies completely below $U^R(v,t)$ over $[\underline{v}, \overline{v}]$ which is consistent with $c_t^* = \overline{v}$.

Now we show that c_t^*, the solution to $U^A(c_t^*,t) = U^R(c_t^*,t)$, would be decreasing in α and r, and increasing in P_B, t and δ. We start with the relation between c_t^* and α. To explicitly show the dependence of $U^A(v,t)$ and $U^R(v,t)$ on α we write them as $U^A_\alpha(v,t)$ and $U^R_\alpha(v,t)$. Now, define κ_α which solves

$$U^R_\alpha(v,t) = u(v-\kappa_\alpha, T-t)\sum_{n=0}^{\infty} G(v)\frac{(\gamma_t)^n e^{-\gamma_t}}{n!}.$$

Since κ_α is a certainty equivalent payment, κ_α will be increasing in α. A more risk averse bidder prefers accepting the certain payoff on the RHS of the above equation than rejecting P_B and participate in the auction where the payoff is uncertain.

Lets consider two risk aversion levels, α' and α'' where $\alpha' < \alpha''$. Let $c_t^{*\prime}$ and $c_t^{*\prime\prime}$ be the cutoffs corresponding to α' and α'' which solve the indifference condition in Proposition 1. We want to show that $c_t^{*\prime} > c_t^{*\prime\prime}$. From the indifference condition we get

$$\begin{aligned}
& U^A_{\alpha'}(c_t^{*\prime}, t) = U^R_{\alpha'}(c_t^{*\prime}, t) \\
\Rightarrow\quad & \frac{1-e^{-\alpha'(c_t^{*\prime}-P_B)}}{\alpha'} = \delta^{T-t}\frac{1-e^{-\alpha'(c_t^{*\prime}-\kappa_{\alpha'}(c_t^{*\prime}))}}{\alpha'}\sum_{n=0}^{\infty} G(v)\frac{(\gamma_t)^n e^{-\gamma_t}}{n!} \\
\Rightarrow\quad & \frac{1-e^{-\alpha'(c_t^{*\prime}-P_B)}}{1-e^{-\alpha'(c_t^{*\prime}-\kappa_{\alpha'}(c_t^{*\prime}))}} = \delta^{T-t}\sum_{n=0}^{\infty} G(v)\frac{(\gamma_t)^n e^{-\gamma_t}}{n!}.
\end{aligned}$$

Since $\sum_{n=0}^{\infty} G(v)\frac{(\gamma_t)^n e^{-\gamma_t}}{n!} < 1$, we have $c_t^{*\prime} - P_B < c_t^{*\prime} - \kappa_{\alpha'}(c_t^{*\prime})$. For some fixed x and y and $x < y$, we can show that $\frac{1-e^{-\alpha x}}{1-e^{-\alpha y}}$ is increasing in α. So, if we let $x = c_t^{*\prime} - P_B$ and $y = c_t^{*\prime} - \kappa_{\alpha'}(c_t^{*\prime})$, we have

$$\begin{aligned}
& \frac{1-e^{-\alpha''(c_t^{*\prime}-P_B)}}{1-e^{-\alpha''(c_t^{*\prime}-\kappa_{\alpha'}(c_t^{*\prime}))}} > \frac{1-e^{-\alpha'(c_t^{*\prime}-P_B)}}{1-e^{-\alpha'(c_t^{*\prime}-\kappa_{\alpha'}(c_t^{*\prime}))}} = \delta^{T-t}\sum_{n=0}^{\infty} G(v)\frac{(\gamma_t)^n e^{-\gamma_t}}{n!} \\
\Rightarrow\quad & \frac{1-e^{-\alpha''(c_t^{*\prime}-P_B)}}{1-e^{-\alpha''(c_t^{*\prime}-\kappa_{\alpha'}(c_t^{*\prime}))}} > \delta^{T-t}\sum_{n=0}^{\infty} G(v)\frac{(\gamma_t)^n e^{-\gamma_t}}{n!} \\
\Rightarrow\quad & \frac{1-e^{-\alpha''(c_t^{*\prime}-P_B)}}{\alpha''} > \delta^{T-t}\frac{1-e^{-\alpha''(c_t^{*\prime}-\kappa_{\alpha'}(c_t^{*\prime}))}}{\alpha''}\sum_{n=0}^{\infty} G(v)\frac{(\gamma_t)^n e^{-\gamma_t}}{n!}.
\end{aligned}$$

As κ_α is increasing in α, we get

$$\begin{aligned}
& \frac{1-e^{-\alpha''(c_t^{*\prime}-P_B)}}{\alpha''} > \delta^{T-t}\frac{1-e^{-\alpha''(c_t^{*\prime}-\kappa_{\alpha''}(c_t^{*\prime}))}}{\alpha''}\sum_{n=0}^{\infty} G(v)\frac{(\gamma_t)^n e^{-\gamma_t}}{n!} \\
\Rightarrow\quad & U^A_{\alpha''}(c_t^{*\prime}, t) > U^R_{\alpha''}(c_t^{*\prime}, t).
\end{aligned}$$

Since $U^A_{\alpha''}(c_t^{*\prime\prime}, t) = U^R_{\alpha''}(c_t^{*\prime\prime}, t)$, $U^A_{\alpha''}(v,t)$ lies above $U^R_{\alpha''}(v,t)$ for $v \in (c_t^{*\prime\prime}, \overline{v}]$, and $U^A_{\alpha''}(v,t)$ lies below $U^R_{\alpha''}(v,t)$ for $v \in [\underline{v}, c_t^{*\prime\prime})$, the above inequality implies that $c_t^{*\prime} \in (c_t^{*\prime\prime}, \overline{v})$. So, c_t^* is decreasing in α.

Since $U^A(v,t)$ is steeper than $U^R(v,t)$ at $v = c_t^*$, and $U^R(v,t)$ is decreasing in r as $\max\{r, y\}$ is increasing in r, the solution to the indifference condition in Proposition 1 is decreasing in r. Similarly, since $U^A(v,t)$ is decreasing in P_B, the solution to the indifference condition in Proposition 1 is increasing in P_B. Again, since $U^R(v,t)$ is increasing in t, the solution to the indifference condition is increasing in t. To see this, notice that $U^R(v,t)$ in (2) is decreasing in γ_t, while γ_t is decreasing t. Finally, since $U^R(v,t)$ is increasing in δ, the solution to the indifference condition is increasing in δ.

□

Appendix B: Tables and Figures

Table 1: Number of Listings, Trades, and Prices

	Total Listings	Average Buy Price (SD)	Average Reserve Price (SD)	Successful Trade (%)	Average Sale Price (SD)
All	3245	–	165.9	2610	355.7
			(164.1)	(80.4%)	(92.2)
WBIN	2243	–	94.4	2036	355.9
			(114.6)	(90.8%)	(90.2)
BIN	1002	420.6	326.0	574	355.3
		(102.1)	(143.6)	(57.3%)	(99.1)
Buy Price	219	377.8	311.1	219	375.4
Accepted		(106.2)	(129.7)	–	(104.7)

Average sale price computed using only auctions ending in a trade. All prices are in dollars and include shipping costs. Average shipping cost in our data was $28.7.

Table 2: Laptop Characteristics

	All Total	Traded	WBIN Total	Traded	BIN Total	Traded	BIN Accepted
Hard Drive (GB)	19.2	19.4	19.6	19.6	18.4	18.7	18.1
	[2-100]	[2-100]	[2-60]	[2-60]	[2-100]	[2-100]	[2-60]
Processor (MHZ)	908.1	919.6	937.0	942.4	843.0	838.5	812.6
	[400-2000]	[400-2000]	[400-2000]	[400-2000]	[400-1300]	[400-1300]	[400-1300]
Memory (MB)	268.5	272.6	272.0	273.7	260.6	268.8	266.2
	[64-1024]	[64-1024]	[64-1024]	[64-1024]	[64-1024]	[64-1024]	[64-512]

Minimum and maximum values given in square brackets.

Table 3: Length of Auctions

		All	WBIN	BIN	Buy Price Accepted
1 Day	Total	1300	1182	118	-
	Traded	1140	1057	83	14
3 Days	Total	972	576	396	-
	Traded	753	543	210	96
5 Days	Total	346	215	131	-
	Traded	288	202	86	35
7 Days	Total	602	251	351	-
	Traded	409	216	193	72
10 Days	Total	25	19	6	-
	Traded	20	18	2	2

Table 4: Average Length of Auctions and Number of Bidders and Bids

		All	WBIN	BIN	Buy Price Accepted
Average Length	Total	3.2	2.7	4.5	-
	Traded	3.0	2.7	4.4	4.6*
Average No. Bidders		7.1	8.8	2.2	-
Average No. Bids**		15.1	18.8	4.5	-

** Average time until buy price accepted: 1.9 days.
** Excludes auctions where buy price was accepted.

Table 5: Seller Characteristics

	Feedback Score		Sum of Positive and Negative Feedback		Negative Feedback as % of Total		Months of Membership to June 2005	
	Total	Traded	Total	Traded	Total	Traded	Total	Traded
All	4019.9	3909.3	4130.5	4024.4	1.3	1.3	44.4	43.1
WBIN	4412.5	4268.3	4547.5	4405.1	1.4	1.4	41.8	41.2
BIN	3141.1	2636.1	3197.1	2674.0	0.8	0.7	50.3	49.8
Buy Price Accepted	-	2519.1	-	2563.3	-	0.9	-	47.4

Table 6: Probit Regression of Sellers' Decision to Offer BIN Price

	Mar. Prob.	SE	$P > \|z\|$
Seller Characteristics			
Power Seller	-0.05	0.02	0.02
eBay Store	-0.06	0.02	0.00
Feedback Score	0.00	0.00	0.01
% Negative Feedback	-0.01	0.00	0.08
Months of Membership	0.00	0.00	0.00
Laptop Characteristics			
Hard Drive (GB)	0.00	0.00	0.16
Processor (MHZ)	0.00	0.00	0.01
Memory (MB)	0.00	0.00	0.72
Operating System	-0.04	0.03	0.12
Wireless Card	0.00	0.02	0.85
Additional Software	-0.13	0.02	0.00
Printer/Laptop Bag/Gifts	0.30	0.03	0.00
Warranty	-0.07	0.02	0.00
Battery_missing	-0.27	0.01	0.00
Powercord_missing	0.27	0.06	0.00
Minor Problem	-0.11	0.02	0.00
CD-Rom	0.04	0.03	0.19
CD-RW	0.38	0.05	0.00
DVD-Rom	0.27	0.04	0.00
CD-DVD Combo	0.38	0.05	0.00
No. of Observations	3211		
Pseudo R^2	0.32		

Marginal Probabilities at covariate sample means. Regressions also included indicator variables for laptop models.

Table 7: OLS Regression of BIN Price

	Coefficient	SE	$P > \|z\|$
Seller Characteristics			
Power Seller	7.04	7.48	0.35
eBay Store	32.29	6.92	0.00
Feedback Score	0.00	0.00	0.00
% Negative Feedback	3.63	2.89	0.21
Months of Membership	0.14	0.18	0.43
Laptop Characteristics			
Hard Drive (GB)	0.65	0.34	0.06
Processor (MHZ)	0.22	0.03	0.00
Memory (MB)	0.03	0.02	0.17
Operating System	-5.91	7.01	0.40
Wireless Card	9.78	5.98	0.10
Additional Software	33.50	7.18	0.00
Printer/Laptop Bag/Gifts	17.71	4.87	0.00
Warranty	25.06	5.31	0.00
Battery_missing	-62.06	19.36	0.00
Powercord_missing	-7.74	12.92	0.55
Minor Problem	-31.21	7.73	0.00
CD Rom	3.60	10.50	0.73
CD RW	25.91	10.94	0.02
DVD Rom	19.23	10.64	0.07
CD-DVD Combo	59.45	11.09	0.00
Intercept	132.23	30.02	0.00
No. of Observations	998		
R^2	0.62		

Regressions also included indicator variables for laptop models. Heteroskedasticity-consistent standard errors reported under "SE."

Table 8: Regression of Number of Bidders (excluding BIN auctions with trades at buy price)

	Coefficient	SE	$P > \|t\|$
Auction Characteristics			
Reserve Price	-0.03	0.00	0.00
3 Day	0.13	0.16	0.40
5 Day	0.37	0.19	0.06
7 Day	0.59	0.20	0.00
10 Day	1.98	0.65	0.00
BIN	-0.73	0.16	0.00
Seller Characteristics			
Power Seller	0.32	0.14	0.02
eBay Store	0.40	0.16	0.01
Feedback Score	-0.00	0.00	0.03
% Negative Feedback	-0.11	0.03	0.00
Months of Membership	0.01	0.00	0.04
Laptop Characteristics			
Hard Drive (GB)	0.02	0.01	0.04
Processor (MHZ)	0.00	0.00	0.00
Memory (MB)	0.00	0.00	0.02
Operating System	1.23	0.15	0.00
Wireless Card	0.24	0.11	0.03
Additional Software	0.59	0.15	0.00
Printer/Laptop Bag/Gifts	-0.21	0.14	0.14
Warranty	0.91	0.12	0.00
Battery_missing	-1.92	0.22	0.00
Powercord_missing	-0.44	0.19	0.02
Minor Problem	-0.55	0.14	0.00
CD-Rom	0.17	0.20	0.39
CD-RW	0.87	0.26	0.00
DVD-Rom	1.05	0.23	0.00
CD-DVD Combo	0.89	0.30	0.00
Intercept	6.12	0.52	0.00
No. of Observations	2992		
R^2	0.77		

Regressions also included indicator variables for laptop models. Heteroskedasticity-consistent standard errors reported under "SE."

Table 9: Probit Regression of Bidder Decision to Accept BIN Price

	Mar. Prob.	SE	$P > \|z\|$
Auction Characteristics			
Reserve Price	0.00	0.00	0.00
3 Day	0.04	0.05	0.41
5 Day	0.10	0.07	0.12
7 Day	0.05	0.06	0.34
10 Day	0.16	0.22	0.39
BIN Price	0.00	0.00	0.00
Seller Characteristics			
Power Seller	-0.09	0.05	0.06
eBay Store	0.03	0.04	0.48
Feedback Score	0.00	0.00	0.30
% Negative Feedback	0.00	0.01	0.58
Months of Membership	0.00	0.00	1.00
Laptop Characteristics			
Hard Drive (GB)	0.00	0.00	0.97
Processor (MHZ)	0.00	0.00	0.15
Memory (MB)	0.00	0.00	0.07
Operating System	0.05	0.03	0.15
Wireless Card	0.00	0.03	0.98
Additional Software	0.11	0.05	0.01
Printer/Laptop Bag/Gifts	0.01	0.03	0.84
Warranty	-0.11	0.03	0.00
Battery_missing	-0.11	0.06	0.26
Powercord_missing	-0.14	0.04	0.02
Minor Problem	-0.05	0.04	0.20
CD-Rom	-0.03	0.05	0.60
CD-RW	0.00	0.06	1.00
DVD-Rom	0.01	0.06	0.85
CD-DVD Combo	0.18	0.09	0.02
No. of Observations	998		
Pseudo R^2	0.18		

Coefficients reported are estimated marginal probabilities (at covariate sample mean). Regressions also included indicator variables for laptop models.

Table 10: OLS Regression of Revenue to Seller

	Coefficient	SE	$P > \|z\|$
Auction Characteristics			
Reserve Price	-0.59	0.02	0.00
3 Day	-8.54	5.47	0.12
5 Day	-14.58	7.25	0.04
7 Day	-30.81	7.44	0.00
10 Day	-4.65	23.36	0.84
BIN	29.48	7.20	0.00
Seller Characteristics			
Power Seller	-4.21	4.75	0.38
eBay Store	15.95	5.19	0.00
Feedback Score	0.00	0.00	0.25
% Negative Feedback	-4.58	1.92	0.02
Months of Membership	0.12	0.11	0.25
Laptop Characteristics			
Hard Drive (GB)	1.17	0.32	0.00
Processor (MHZ)	0.16	0.02	0.00
Memory (MB)	0.12	0.02	0.00
Operating System	27.56	6.20	0.00
Wireless Card	1.44	4.33	0.74
Additional Software	39.45	5.91	0.00
Printer/Laptop Bag/Gifts	-0.67	7.21	0.93
Warranty	-3.86	4.85	0.43
Battery_missing	-53.73	10.36	0.00
Powercord_missing	-25.42	9.13	0.01
Minor Problem	-8.52	4.50	0.06
CD-Rom	-3.28	6.75	0.63
CD-RW	4.74	13.76	0.73
DVD Rom	28.98	9.39	0.00
CD-DVD Combo	49.23	15.93	0.00
Intercept	151.27	20.11	0.00
No. of Observations	3211		
R^2	0.52		

Regressions also included indicator variables for laptop models. Heteroskedasticity-consistent standard errors reported under "SE."

Table 11: OLS Regression of Revenue to Seller

	Coefficient	SE	$P > \|z\|$
Auction Characteristics			
Reserve Price	-0.60	0.02	0.00
3 Day	-8.33	5.48	0.13
5 Day	-15.09	7.28	0.04
7 Day	-30.45	7.40	0.00
10 Day	-6.23	23.70	0.79
BIN	5.50	31.34	0.86
BIN*BIN Price	0.07	0.09	0.44
Seller Characteristics			
Power Seller	-3.95	4.83	0.41
eBay Store	15.14	5.25	0.00
Feedback Score	0.00	0.00	0.22
% Negative Feedback	-4.64	1.84	0.01
Months of Membership	0.12	0.11	0.27
Laptop Characteristics			
Hard Drive (GB)	1.17	0.31	0.00
Processor (MHZ)	0.16	0.02	0.00
Memory (MB)	0.12	0.02	0.00
Operating System	27.57	6.22	0.00
Wireless Card	1.30	4.37	0.77
Additional Software	38.21	6.00	0.00
Printer/Laptop Bag/Gifts	-0.67	7.21	0.93
Warranty	-4.20	4.92	0.39
Battery_missing	-52.64	10.42	0.00
Powercord_missing	-25.98	9.06	0.00
Minor Problem	-8.06	4.59	0.08
CD-Rom	-3.24	6.75	0.63
CD-RW	3.98	13.90	0.77
DVD Rom	28.48	9.46	0.00
CD-DVD Combo	47.42	15.49	0.00
Intercept	155.64	18.87	0.00
No. of Observations	3211		
R^2	0.52		

Regressions also included indicator variables for laptop models. Heteroskedasticity-consistent standard errors reported under "SE."

Table 12: OLS Regression of Revenue to Seller

	Coefficient	SE	$P > \|z\|$
Auction Characteristics			
Reserve Price	-0.03	0.09	0.74
Reserve Price^2	0.00	0.00	0.00
3 Day	-1.20	5.70	0.83
5 Day	-13.21	7.26	0.07
7 Day	-23.47	7.41	0.00
10 Day	7.94	22.29	0.72
BIN	182.71	80.46	0.02
BIN*BIN Price	-1.06	0.46	0.02
(BIN*BIN Price)^2	0.00	0.00	0.01
Seller Characteristics			
Power Seller	-3.62	4.68	0.44
eBay Store	19.83	5.18	0.00
Feedback Score	0.00	0.00	0.18
% Negative Feedback	-6.65	1.27	0.00
Months of Membership	0.05	0.11	0.62
Laptop Characteristics			
Hard Drive (GB)	1.35	0.30	0.00
Processor (MHZ)	0.17	0.02	0.00
Memory (MB)	0.12	0.02	0.00
Operating System	34.75	6.15	0.00
Wireless Card	4.14	4.19	0.32
Additional Software	38.16	5.85	0.00
Printer/Laptop Bag/Gifts	-1.84	7.12	0.80
Warranty	1.24	4.83	0.80
Battery_missing	-73.09	10.71	0.00
Powercord_missing	-25.10	9.00	0.01
Minor Problem	-15.14	4.46	0.00
CD-Rom	0.93	6.85	0.89
CD-RW	14.59	14.02	0.30
DVD-Rom	36.47	9.46	0.00
CD-DVD Combo	55.36	15.20	0.00
Intercept	109.98	19.32	0.00
No. of Observations	3211		
R^2	0.54		

Regressions also included indicator variables for laptop models. Heteroskedasticity-consistent standard errors reported under "SE."

Table 13: Structural Estimates.

	Estimates	SE	$P > \|z\|$
λ	2.96	0.03	0.00
α	0.29	0.10	0.00
β_0	5.56	0.01	0.00
σ	0.18	0.01	0.00
Negative Feedback	0.08	0.01	0.00
Negative Feedback/(Total Feedback+1)	-0.01	0.01	0.07
ln(Feedback Score+1)	0.00	0.00	0.86
Processor	0.15	0.01	0.00
Memory	0.01	0.01	0.06
Hard Drive	-0.01	0.01	0.18
Operating System	0.25	0.01	0.00
Wireless Card	0.03	0.01	0.01
Additional Software	0.20	0.01	0.00

Note: Seller characteristics and Processor, Memory, and Hard Drive are standardized to have mean 0 and standard deviation 1.

Figure 1: Histogram of buy prices (including shipping costs) in BIN auctions.

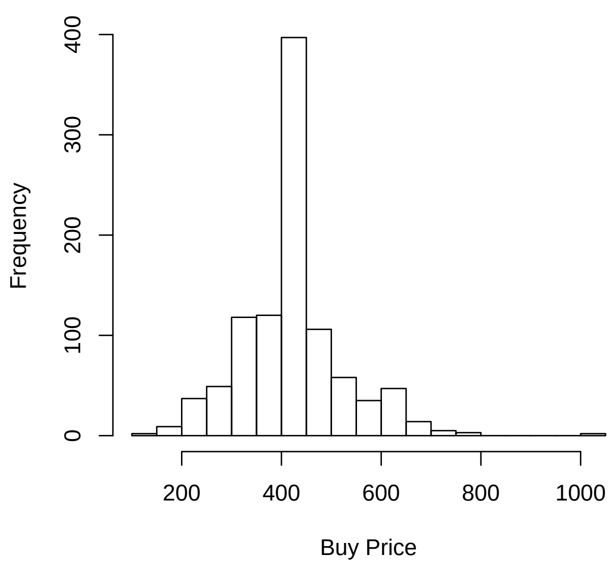


Figure 2: Histogram of reserve prices (including shipping costs) in all auctions.

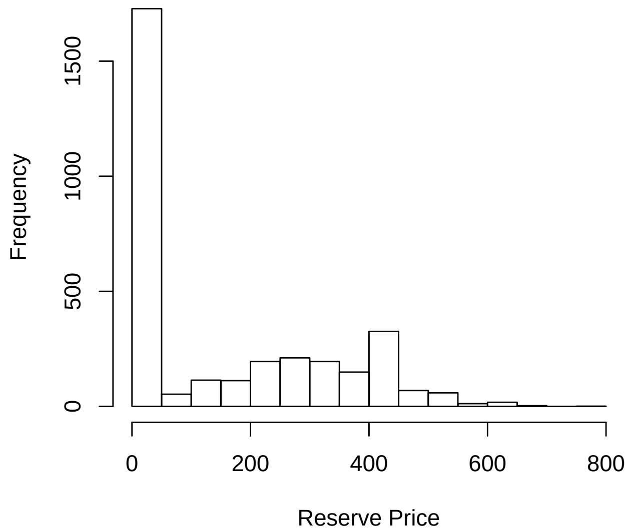


Figure 3: Histogram of sale prices (including shipping costs) in all auctions ending in a trade.

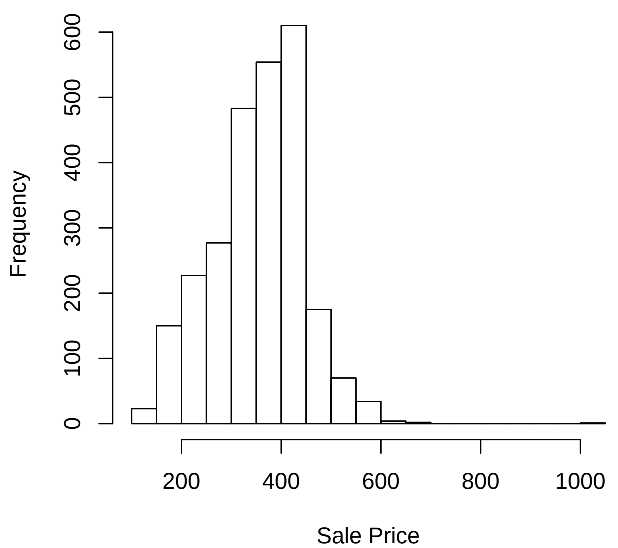
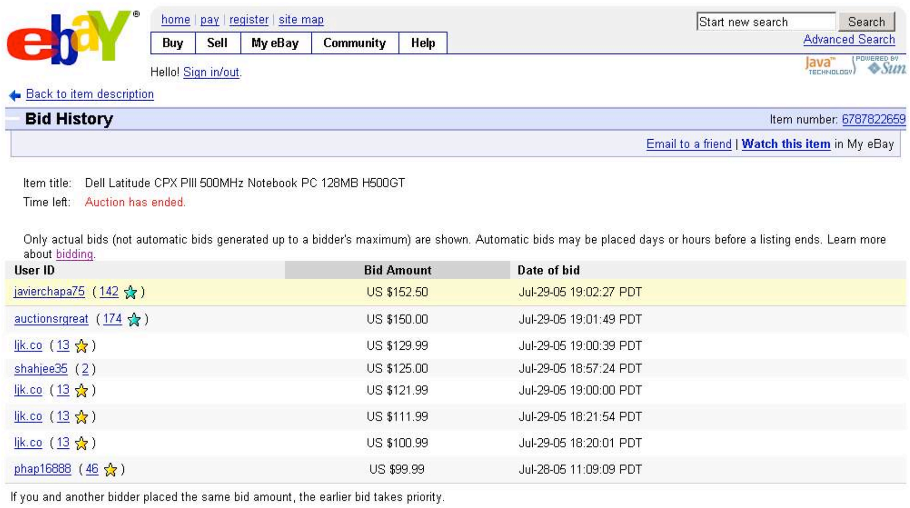


Figure 4: Typical Bid History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Bid History Item number: 6787822659

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Item title: Dell Latitude CPX PIII 500MHz Notebook PC 128MB H500GT

Time left: Auction has ended.

Only actual bids (not automatic bids generated up to a bidder's maximum) are shown. Automatic bids may be placed days or hours before a listing ends. Learn more about bidding.

User ID	Bid Amount	Date of bid
javierchapa75 (142)	US $152.50	Jul-29-05 19:02:27 PDT
auctionsrgreat (174)	US $150.00	Jul-29-05 19:01:49 PDT
ljk.co (13)	US $129.99	Jul-29-05 19:00:39 PDT
shahjee35 (2)	US $125.00	Jul-29-05 18:57:24 PDT
ljk.co (13)	US $121.99	Jul-29-05 19:00:00 PDT
ljk.co (13)	US $111.99	Jul-29-05 18:21:54 PDT
ljk.co (13)	US $100.99	Jul-29-05 18:20:01 PDT
phap16888 (46)	US $99.99	Jul-28-05 11:09:09 PDT

If you and another bidder placed the same bid amount, the earlier bid takes priority.

Figure 5: Seller Revenue Residuals and BIN price