Consumer Surplus in Online Auctions

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ABSTRACT

Despite the growing research interest in Internet auctions, particularly those on eBay, little is known about the quantifiable consumer welfare accrued from such mechanisms. Using an ongoing novel field experiment, we collect and examine a unique dataset to empirically quantify and understand determinants of consumer surplus in eBay auctions. Our analysis, based on a sample of 5187 eBay auctions, indicates that the median surplus level per auction on eBay auctions is $3.53, which roughly translates to $1.47 billion in accrued consumer surplus for the year 2003 alone. We find that consumer surplus is significantly different across currencies and item categories, negatively influenced by seller experience, auction duration and competition, and positively influenced by bidder experience, bidder aggressiveness and item price. We find that US currency auctions carry higher surpluses relative to Euro and GPB auctions, by a factor of approximately 22%. Surplus levels in Euro and GBP auctions are similar to each other. There appear to be three main groups of surplus categories. The highest surplus is accrued to the group of eBay categories that are antique or collectible in nature. This is followed by a moderate surplus group of items comprised of computers, electronics and books, among others. The lowest surplus is in the group of household items such as toys, health and beauty items and games. We find that sellers with higher feedback ratings, a proxy for experience and trust, tend to yield lower bidder surplus, and that experienced bidders tend to realize higher surplus. We find that the main effects of price, opening bid, and number of bidders have a significant influence on surplus, but so do the interactions of price with opening bid and price with number of bidders. These main effects must therefore be interpreted cautiously. Interestingly, we find that surplus is positively associated with price in auctions with many bidders, but this relationship is moderated by the opening price. We find that surplus is generally positive in auction duration and negative in sniping time, but only for “mainstream auctions” with five to seven day duration and sniping time equal to eight or nine seconds.

JEL: D12 (Consumer Economics: Empirical Analysis), D44 (Auctions), C93 (Field Experiments)

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Introduction and Motivation

Classical microeconomic theory uses the notion of consumer surplus as the welfare measure that quantifies benefits to a consumer from an exchange. Alfred Marshall (1936) defined consumer surplus as “the excess of the price which he (a consumer) would be willing to pay rather than go without the thing, over that which he actually does pay…” Yet, despite its established theoretical standing, little is known empirically about consumer surplus levels in real markets. In this paper we estimate consumer surplus levels in eBay auctions, a vastly popular Internet based electronic market. eBay’s popularity is evident in the reported $23.8 billion in gross merchandise sales for the year 2003, up from $14.9 billion in 2002.

Internet based markets are now mainstream artifacts of today’s economy. Yet, with the exception of Brynjolfsson et al.’s (2003) interesting analysis of how new product introduction in electronic markets can lead to significant consumer welfare gains, very little has been generally said about the quantifiable benefits such markets provide to consumers. One possible reason for the lack of empirical consumer surplus levels, in traditional as well as electronic markets, is that unlike producer surplus, it is not directly observable in posted price markets. In such markets, willingness to pay has to be inferred indirectly through surveys, contingent valuation techniques and price changing experiments such as promotions and discounts. Surveys of willingness to pay have credibility issues and have lead to a stream of research dealing with contingent valuation precision and bias reduction [see Peter A. Diamond and Jerry A. Hausman (1994)].

In this paper we demonstrate the suitability of using direct mechanisms [Roger Myerson (1981)], such as auctions in which it is a dominant strategy for market players to reveal their true valuations, to quantify and understand determinants of consumer surplus. Auction theory is built upon the fact that a consumer with a valuation \( v_i \) for an item, strategizes and formulates a bid \( b_i \) so as to maximize her surplus \((v_i - b_i)\) [R. Preston McAfee and John McMillan (1987)]. Note the similarity here with consumer theory, which evaluates consumer surplus as the value or willingness to pay for a change in price of a good from say \( p_0 \) to \( p^1 \). Thus, the consumer theory notion of the amount the consumer would pay (or would need to be paid) to be just as well off after the price change as she was before the price change, is no different from the auction theory notion that measures the winning bidder’s surplus as how much could the price have gone up, without changing the current allocation\(^1\).

eBay posts almost the complete bid history after the auction closes, with the exception being the value of the highest bid. Since the winner’s bid is not disclosed by eBay, there is no direct measure of the revealed willingness to pay of the winning bidder from the auction that is publicly available. To overcome this limitation, we design an ongoing field experiment that allows real-world bidders to use Cniper.com, our web based bidding agent, to snipe eBay auctions. Internet-based field experiments that deal with real bidders in real markets provide a contrast to the controlled environment of laboratory experiments with student subjects. This is evident in the work of David Lucking-Reiley (1999) and John A. List and Lucking-Reiley (2002). They show how age old questions such as revenue equivalence and the importance of decisions costs respectively, can be practically examined using field experiments with real bidders and without any theoretical assumptions that would be enforced in the laboratory. In the context of the current study, given the lack of published high bids, researchers seeking to model consumer surplus on eBay would have to make distributional assumptions about bidders’ valuation and subsequently use order statistics theory to estimate surplus. Hasker et al. (2001) demonstrate this on a data set of PC monitors. Our field experiment, by virtue of extracting exact revealed measures of consumer surplus for 28 eBay item categories, can serve to validate theoretical assumptions made by researchers, as well as to inform future analytical work aimed at understanding the dynamics and equilibria of eBay auctions.

Bidders using Cniper.com to bid on their behalf reveal their willingness to pay to the agent. Subsequently, to measure surplus, we extract from eBay the actual price paid, for auctions where our agent wins the auction. This yields a unique dataset, based on which we set out to quantify the level and characterize the distribution of consumer surplus in eBay auctions. In addition, with an objective of shedding new light on online bidding strategies, we also identify and examine the determinants of

\(^1\) We hereafter refer to surplus, bidder’s surplus and consumer surplus interchangeably in this paper.
consumer surplus. Do bidder characteristics such as experience, market characteristics such as number of competing bidders, and mechanism design choices made by sellers such as opening bid, have any influence on consumer surplus? From an econometric perspective, particularly challenging is the fact that our data of 5187 auctions consists of 383 auctions with zero-surplus. The “zero-inflated” dependent variable cannot be directly modeled within an ordinary regression model. We therefore use a preliminary step that allows us to integrate the zero and non-zero surplus auctions into a single regression model. Interestingly, our data is diverse, with significant bidding activity in three important currencies (US Dollar, Great Britain Pound (GBP) and the Euro), in all but two eBay item categories. Thus, we are able to shed light on whether there are cross-continental differences in bidding behavior and whether certain groups of categories yield different surplus than others.

I. Description of the Bidding Agent and Data Sample

The prevalence of sniping on eBay has lead to several independent third party sniping agents that help bidders place last second bids on eBay. The interested reader is referred to Roth and Ockenfels (2002) and to Shmueli and Jank (2004) for an analysis of sniping as a bidding strategy on eBay. In addition technical details of of sniping agents can be found at Bapna (2003). This study utilizes data from one such agent, Cniper.com, deployed by us. Cniper’s logo “Snipe bids in your sleep, for free” is all explaining. Cniper is deployed just two hops away from eBay’s server, making bid submissions lightning fast. While most competing eBay sniping agents are fee based, Cniper has always been a free service and has a loyal and steadily growing user base of 2,035 bidders. It relies solely on word of mouth for advertising. In the period beginning July 23, 2003 and ending June 24, 2004, Cniper placed 69,571 bids on eBay on behalf of its users. Cniper is developed using PHP and MySQL and is deployed on an Apache webserver sitting on a Unix box. Thus, Cniper leverages the latest advances in open source software technology to keep its costs low. This helps us provide it as a free service, and provides no incentive for any bid shading to account for bidding agent commissions. The lack of commissions also attracts entry for the tool, which in turn provides us with continuously richer observations of real economic agents acting in real markets. We believe that our approach, a first in the research community, will serve as a model for researchers doing Internet based field experiments and so called action research.

I. A. Description of the Data

The data used in our analysis consist of 5187 eBay auctions that took place between January 9, 2004 and April 21, 2004. In all these auctions the winner was a Cniper.com user. These auctions were carried out in one of three major currencies: US Dollar (USD), Great Britain Pound (GBP), and the Euro. The items auctioned were in a wide variety of categories, spanning most of eBay’s 30 high level categories. To maintain a minimal cardinality level in each category, we grouped the items using eBay call these major categories “metas” internally. Our data did not contain entries from categories “Travel” and “Tickets.”

Roth and Ockenfels (2002) emphasize the probability of bids not getting through in the last seconds.

BidSlammer.com, AuctionSniper.com etc.

This was when the site was significantly redesigned.

A fast growing server-side scripting tool.

The standard open source relational database.

Cniper has zero licensing fees costs. Its only costs are those of hosting and the first author’s time. The latter is bursty and can be significant at times when eBay changes its bid acceptance technology and Cniper has to respond by reprogramming its bid submission protocol.

This corresponds to little more than a three month period, the duration for which eBay posts bid histories of completed auctions.

These two categories “Travel” and “Tickets” were not populated in our dataset.

See http://pages.ebay.com/categorychanges/ for a list of high-level eBay categories. Notice that it includes the category “Everything Else” that contains auctions that do not fit any other classification. Also notice that the category “Automotive” is not contained in this list.

See Table 1 for a description of the grouping.
eBay’s categories, into 18 major categories plus an additional 19th category for items in which the category description was missing. To the best of our knowledge, currency and category have not featured in the extant analysis of eBay data.

In addition, we recorded from eBay the following information on each auction: Opening and closing prices in their original currency and their USD equivalent, whether hidden reserve was used, the starting and ending time and date, the number of bids placed in the auction, the number of unique bidders participating in the auction, and seller and winner rating. From Cniper.com we obtained the number of seconds before the auction close that the winning bid was placed, and the winning bid itself. We then calculated the surplus by subtracting the closing price from the winning bid.

II. Analysis of Consumer Surplus

The figure below shows a bar chart of surplus of the USD data; the other two currencies are similar.

Two interesting observations are worth considering. Firstly, we see that the values 0, 0.5, 1.0, 1.5 and so on are especially prevalent. Only a very small proportion of surpluses assume values between these values. For instance, while 75 of the surplus values equal exactly $1, only 10 equal $0.99, only 6 equal $0.98 and only 4 equal $0.97. On the other hand, only 32 values are $1.01. This is surprising, since we would expect surplus to be distributed uniformly in such small intervals.

Thus, our first insight into the distribution of consumer surplus is that the data are apparently semi-continuous. By semi-continuous we mean that while surplus can theoretically assume any value in a given interval, some underlying (and unobserved) data-generating mechanism introduces discretization, causing the data to be concentrated on certain values. We explore the possible causes of this later in this section.

In order to transform surplus from auctions in various currencies into a single scale, we converted all currencies into USD using the conversion rate listed on the auction’s eBay page. The figure below displays a histogram of log(USD surplus+1). The shift of 1 allows us to apply the log transform to the zero surplus data. The figure below reveals that the data are clearly bi-modal, with a large “lump” of zero values (0= log(1)).

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13 While auctions with missing category descriptions could have been assigned to the “Everything Else” category, we decided to keep these auctions separate in order to maintain objectivity.
14 eBay provides approximate conversions on the web page.
15 Always equal.
Given that our research objective is to quantify and understand the determinant of consumer surplus, the above “zero-inflated” data present a challenge, in that we cannot directly model surplus in a regression model (which assumes normal residuals). Our options are to separate the zero-surplus auctions, or at least modify our model to accommodate the “zero-inflated” data. Our solution is to use a novel approach, where we transform the data into a slightly coarser scale. Reasoning that surpluses within a $1 unit range carry the same (or at least similar) information, we transform the original surplus data by applying the ceiling function (which gives the next highest integer). We then take log(integer surplus + 1) to accommodate for the zero surplus data. The new values follow a right-skewed distribution. Further investigation of the probabilistic structure of the data reveals that a 3-parameter Weibull distribution approximates the transformed data fairly well. This can be seen in the figure below which displays a weibull probability plot of the data (left), and in comparison a lognormal probability plot of the same data (right).

The estimated parameters of the fitted Weibull distribution are shape = 1.69, scale = 2.20, and location/threshold = -0.18. Since the surplus distribution is very skewed, the median is a better measure than the mean for the center of the distribution. Although we can compute the median surplus of $3.53 directly from the original values (converted to USD), it is advantageous to have a measure of sampling error. We use the asymptotic normality [Herbert Aron David and Haikady Navada Nagaraja, (2003), page 241] of the sample median and the Weibull distribution to obtain the formula for the median’s standard deviation. After transforming the data back into its original units we obtain a 95% confidence interval of [3.30, 3.71]. Using the median $3.53 value, and multiplying by the estimated 417.5 million transactions on eBay for 2003, we estimate an overall surplus of $1.47 billion accrued to eBay bidders last year.

II.A. Determinants of Consumer Surplus

Prior empirical research dealing with consumer surplus in online auctions has made relative comparisons of groups of bidders in discriminatory multi-unit Yankee auctions [Bapna et al. 2003a, 2003b, Bapna et al. (2004)]. To the best of our knowledge, there has been no other study that has looked at determinants of absolute consumer surplus levels. We believe that the bidders rents’ are potentially influenced by a) Seller’s mechanism design choices –namely the appropriate combination of opening bid level, auction duration and the usage of a hidden reserve price; b) Seller characteristics: eBay’s feedback reputation system has been widely studied [see Chrysanthos Dellarocas (2003)] and studies indicate that sellers with higher reputations engender trust and extract premiums [Sulin Ba and Paul A. Pavlou (2002)]. It can also be argued that sellers with more experience, also proxied by feedback ratings, make better mechanism design choices to maximize expected auction price. Thus, we expect that seller rating to have a negative

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16 The median is asymptotically normal, centered around the population median and with variance \( \frac{4 n f^2(Med)}{f^4(Med)} \), where \( f(Med) \) is the Weibull density at the median [David and Nagaraja (2003), page 241]. We estimate this quantity using the estimated Weibull parameters. This yields a standard deviation of 0.021 for the median of log(integer-surplus). A 95% CI for the population median of log(integer-surplus) is [1.57, 1.65]. Taking an exponent and subtracting 0.5 (the average rounding) yields the 95% CI for median surplus of [3.30, 3.71].

17 eBay’s feedback rating, which indicate the difference between positive and negative ratings, have been viewed as indicators of experience as they are generally reflective of the number of transactions conducted by the seller. Paul Resnick and Richard Zeckhauser (2001) report that only 0.6% of feedback comments left on eBay by buyers about sellers was negative or neutral.
influence on bidder surplus; c) **Product characteristics**: In contrast to the prior empirical studies on eBay that controlled for product heterogeneity, our dataset is diverse, covering all but two of eBay’s 30 major item categories, with prices ranging from 1 cent to $7600. This allows us to test the implications of stakes and product attributes on bidding behavior in a far more generalizable setting. Smith and Walker (1993) have predicted that individuals’ behavior will more closely match the predictions of rational behavior as the stakes of the decision increase (2000); d) **Bidder characteristics**: We expect more experienced bidders to have more confidence in their valuations and bids and hence we expect them to derive higher surplus. In addition, we also measure aggressiveness of the bidder by looking at how many seconds prior to the close of the auction they snipe; e) **Market characteristics**: We are fortunate to have significant data in three prominent currencies, namely USD, GBP and the EURO. Given that eBay was founded in the US and subsequently expanded to UK and Europe, it is reasonable to expect that the US market and its bidders have greater experience with bidding and strategizing.

**II.B Modeling Approach**

Our main challenge with surplus data such as ours, is the extremely large number of auctions resulting in zero-surplus. Although “zero-inflated” models exist for discrete data (e.g., “zero-inflated Poisson”, Lambert, 1982), we are not aware of such models for continuous data. As described in the Section II, the rounding of surplus values and taking a log transform yields a distribution that is suitable for regression modeling. Using the transformed data, we applied stepwise regression (with all pairwise interaction terms) for model selection\(^{18}\). The best model is given in the Table below.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>SE</th>
<th>Pvalue</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>2.51</td>
<td>0.52</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>Categories*</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Antique/Art</td>
<td>0.41</td>
<td>0.10</td>
<td>&lt;.0001</td>
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<tr>
<td>Pottery/Glass</td>
<td>0.28</td>
<td>0.07</td>
<td>0.00</td>
</tr>
<tr>
<td>Collectibles</td>
<td>0.41</td>
<td>0.05</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>EverythingElse</td>
<td>0.38</td>
<td>0.09</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>Toys/Hobbies</td>
<td>0.33</td>
<td>0.08</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>Music/Movie/Games</td>
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<td>0.15</td>
<td>0.03</td>
</tr>
<tr>
<td>Jewelry</td>
<td>-0.30</td>
<td>0.12</td>
<td>0.00</td>
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<td>0.06</td>
<td>0.00</td>
</tr>
<tr>
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<td>0.05</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>Health/Beauty</td>
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<td>0.06</td>
<td>0.00</td>
</tr>
<tr>
<td>US Dollars**</td>
<td>0.20</td>
<td>0.04</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>NUM DAYS</td>
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</tr>
<tr>
<td>SNIPED TIME</td>
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<td>0.00</td>
</tr>
<tr>
<td>NUM BIDDERS***</td>
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<td>0.05</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>PRICE***</td>
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<td>&lt;.0001</td>
</tr>
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<td>S_RATING***</td>
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<td>0.00</td>
</tr>
<tr>
<td>W_RATING***</td>
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<td>0.01</td>
<td>0.02</td>
</tr>
<tr>
<td>OPENING_BID***</td>
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<td>&lt;.0001</td>
</tr>
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<td>0.02</td>
<td>&lt;.0001</td>
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<tr>
<td>PRICE x NUM_BIDDERS</td>
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<td>0.02</td>
<td>&lt;.0001</td>
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<tr>
<td>NUM DAYS x SNIPED_TIME</td>
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<td>0.01</td>
<td>0.01</td>
</tr>
</tbody>
</table>

** Base category: Euros and GBP
*** The variables surplus, price, opening bid, winner rating, seller rating and number of bidders were transformed to the log-scale

While we have summarized the main findings from the above table in the abstract, we expect to elaborate on these results at WISE 2004.

For references and generalizability of our results please visit
http://www.sba.uconn.edu/users/rbapna/wise04

\(^{18}\) For the regression model, all of the quantitative variables (integer surplus, price, opening bid, winner rating, seller rating and number of bidders) were transformed to the log-scale.