Quantifying Consumer Interest and Consumer Valuation from Buy-It-Now Offers

Research-in-Progress

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Abstract

An item offered in the buy-it-now offer (BINO) format is sold to the first consumer who is willing to pay the asked price. The “lifetime” of a BINO, therefore, depends on how many consumers are interested in the item and on how much they value it. In this paper, we model this dependency by combining survival analysis and auction theory. Our model enables sellers to quantify consumer interest and consumer valuation for their items from observing BINO lifetimes only. Further, the influence of covariates (e.g., the item condition) can be investigated. To demonstrate this, we apply our model to a dataset that we have collected from eBay. The dataset consists of 1,821 BINOs of a single product, the iPhone 5S. For this example, we find a new item to attract, on average, 1.26 consumers per day, who have a mean valuation of 384.97 EUR.

Keywords: Consumer interest, Consumer valuation, Buy-it-now offers, Survival analysis

Introduction

During the last two decades, online auctions have become a popular way to sell items over the internet. Sellers often have great freedom when choosing the auction parameters. These include monetary parameters (e.g., the reserve price), design parameters (e.g., the item description), and transaction parameters (e.g., shipping and payment). Obviously, sellers would benefit from knowing how consumers react to a change of these parameters, or, more concretely, how each parameter influences their interest in the item and their valuation for it. However, consumer interest and consumer valuation are latent constructs that cannot be observed. To draw inference on them, one has to relate them to an outcome variable, which for the case of an auction usually is its ending price. This relation is established by consumer behavior, which here means bidding behavior. Unfortunately, bidding behavior is complex because it involves several strategic decisions of each consumer (e.g., when to submit a bid), which depend on the (observed or expected) decisions of her/his competitors at that. A large number of likewise complex models have been developed to describe its numerous aspects. However, such models can only address a few of the latter, and this often only based on strong assumptions (e.g., on consumers’ risk attitudes). Besides, even if they were appropriate, the results may still be biased due to various distortions that auctions are prone to (e.g., sellers bidding on their own items in order to increase ending prices).

On many online auctions platforms such as eBay, auctions are not the only available selling format. An important alternative that we consider in this paper are buy-it-now offers (BINOs). In this format, no auction takes place; instead, the item is offered for a certain time to all consumers at a fixed price set by the seller in the beginning. If a consumer declares to be willing to pay this price, s/he receives the item and the BINO ends successfully. The BINO also ends, but unsuccessfully, if this does not happen until it reaches its maximum duration. In this case, the item remains unsold with the seller. Obviously, consumer behavior in BINOs is much simpler than in auctions because it involves only a single decision of each consumer, which s/he can make without considering her/his competitors at that: whether to buy the item at the asked price or not. This may be one reason why BINOs have drawn much less research attention than auctions, despite they on many platforms make up the largest part of all listings (on eBay, for
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example, roughly 73% (Hasker and Sickles 2010)), which demonstrates their practical relevance. Another reason may be that it is not clear what can be learned from observing BINOS. While the ending prices of auctions have a direct practical meaning, the only outcome of a BINO seems to be whether the item has been sold or not, which is not too informative. However, there is a second, hidden variable that can be regarded as the outcome of a BINO: its “lifetime”. The variation in this variable is obviously much greater than in the aforementioned one, but is seems to lack any practical relevance: Why should sellers care about how long it takes until their items are sold (if they are)? Some will argue that this indeed is important since sellers may exhibit time preference. The actually interesting point, however, is that BINO lifetimes carry information on consumer interest and consumer valuation. This is because the item is sold to the first consumer who is willing to pay the asked price. If it is possible to extract this information, the problems that arise when quantifying these factors on the basis of auctions can be bypassed.

In this work, we develop a model to do so. Our model is based on survival analysis, a set of methods that have been developed in lifetime statistics to analyze duration data (to which BINO lifetimes belong). In information systems research, these methods are still rather uncommon, although more closely related disciplines such as engineering make use of them under various labels. Instead of specifying the probability distribution of BINO lifetimes directly (as it is common in survival analysis), we derive it from standard assumptions of auction theory, observing that the set of consumers on a platform is the same for all selling formats. This way, a natural parameterization is achieved that allows to separate consumer interest and consumer valuation by the variation in the thresholds for the latter, the asked prices.

The remainder of this paper is structured as follows: In the next section, we give an overview over previous research related to our work. Afterwards, we present our model and apply it to a dataset collected from eBay. We conclude with discussing its current limitations and how we intend to overcome them as we progress. Furthermore, some directions for future research are given.

Related Previous Research

As mentioned earlier, research on BINOS is sparse compared to research on auctions. However, the related format of buy-it-now auctions (BINAs) has been investigated extensively. In BINAs, sellers offer consumers a buy-it-now option like in BINOS, but, in contrast to these, not as the only way to buy the item but in addition to a concurrent auction. Sellers were shown to have an incentive to do so if they or consumers are impatient (Gallien and Gupta 2007; Mathews 2004) or risk averse (Chen et al. 2013; Mathews and Katzman 2006; Reynolds and Wooders 2009), if consumers form a reference price for the item based on the asked price (Shunda 2009, but see Hernando-Veciana 2012), or if sellers offer multiple identical items simultaneously (Anwar and Zheng 2015). In these situations, the presence of a buy-it-now option affects optimal consumer behavior in such a way that sellers’ revenues increase. Empirical results (Popkowski-Leszczyc et al. 2009; Shahriar and Wooders 2011) are consistent with the theoretical predictions, although it has also been observed that consumers often do not exercise a buy-it-now option even if the asked price is below the prevailing market price of the item (Standifird et al. 2005).

A closely related stream of research has investigated how BINOS compare with auctions and BINAs. A classical result is that auctions dominate any other selling format in terms of maximizing sellers’ revenues under certain conditions (Myerson 1981). However, this may change if these conditions are not met. E.g., if consumers exhibit bounded rationality, no format dominates (Jiang et al. 2013). If the auction is costly for the consumers and/or the seller, the latter may be better off when opting for the BINO format (Sun et al. 2010). Recently, it was even found that sellers would prefer offering their items at a platform where only BINOs are available (Bauner 2015). This is supported by empirical evidence that BINOS achieve higher prices than auctions (Hammond 2010). Using both formats in parallel may still be a better strategy for sellers (Caldentey and Vulcano 2007; Etzion and Moore 2013).

This paper is also related to all studies that investigate consumer interest and/or consumer valuation on an online auction platform. An important result here is that the information contained in bid histories is not sufficient to identify these factors non-parametrically (Athey and Haile 2002). Identification is possible, however, if they are assumed to have no common determinants (Adams 2007) or when consumer interest is endogenized (Nekipelov 2007). The latter can also be canceled out, so that consumer valuation is identified solely (Song 2004). We remark that we are not aware of any study that aims to exploit the information contained in BINO lifetimes for identification purposes.

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The situation is similar apart from identification results. Like our work, most empirical studies related to consumer interest and/or consumer valuation rely on parametric models, given that the influence of covariates is difficult to measure and interpret otherwise. When auctions and their ending prices are considered, the aforementioned problems can arise. An illustrative example is (Lucking-Reiley et al. 2007), who use ending prices without accounting for consumer interest (which, e.g., Bajari and Hortaşçu 2003 do). Therefore, they effectively explain the highest of all consumers’ valuations instead of the average. As mentioned earlier, another approach is to regard whether the item has been sold or not as the dependent variable (Highfill and O’Brien 2009). This approach is actually a trimmed version of ours: In addition to whether the item has been sold, we exploit the (obviously more rich) information of how long it has taken to get to this point. To the best of our knowledge, this is the first study using BINO lifetimes as the dependent variable to draw inference on consumer interest and consumer valuation.

**Modeling the Lifetime of a BINO**

**Structural Model**

Let \( T_j^* \) denote a random variable describing the lifetime of a BINO \( j \). In survival analysis, the probability distribution of \( T_j^* \) is usually characterized by the survival function \( S_j(t) \). For each point in time \( t \), \( S_j(t) \) represents the probability that the event of interest (here the item of \( j \) being sold) does not occur before or in \( t \). We derive this probability by a general consideration: The item of \( j \) is sold only if there exists at least one consumer \( i \) who is interested in it and has a valuation \( V_{j,i} \) for it that exceeds the asked price \( p_j \). Put the other way round, it remains unsold until the end of \( t \) if all \( N_{j,t} \) consumers who have become aware of (have arrived at) \( j \) by then have valuations not exceeding \( p_j \). Thus, \( S_j(t) \) can be formalized rather generally as

\[
S_j(t) := P(T_j^* > t) = \sum_{n=0}^{\infty} P(N_{j,t} = n) \cdot P(V_{j,i} \leq p_j \forall i \in \{1; \ldots; N_{j,t}\}|N_{j,t} = n).
\] (1)

The first part of the right-hand side of (1) is the probability that exactly \( n \) consumers will arrive until the end of \( t \), while summing over all feasible \( n \). In line with literature on auction theory (e.g., Bajari and Hortaşçu 2003), we model the arrival process as a Poisson process with rate \( \lambda_j \); that is,

\[
P(N_{j,t} = n) = \frac{(\lambda_j \cdot t)^n}{n!} \cdot e^{-\lambda_j t}.
\] (2)

Note that because there usually are a large number of consumers on an online auction platform, who are interested in any particular item with only a low probability and independently of each other, this assumption is justified by the Poisson limit theorem (see, e.g., Karr 1993, p. 155).

The second part is the conditional probability that, given that exactly \( n \) consumers have arrived, none of them values the item so much to buy it at the price \( p_j \). We assume that each consumer \( i \) draws her/his valuation \( V_{j,i} \), which is her/his private knowledge, from a probability distribution \( \mathcal{V}_j \), which is common knowledge, independently from her/his competitors. This is referred to as the independent private value paradigm (Vickrey 1961). With \( V_j \) denoting the distribution function of \( \mathcal{V}_j \), this can be formalized as

\[
P(V_{j,i} \leq p_j \forall i \in \{1; \ldots; N_{j,t}\}|N_{j,t} = n) = \prod_{i=1}^{n} V_j(p_j) = V_j(p_j)^n.
\] (3)

Plugging in (2) and (3) into (1), we get

\[
S_j(t) = \sum_{n=0}^{\infty} \frac{(\lambda_j \cdot t)^n}{n!} \cdot e^{-\lambda_j t} \cdot V_j(p_j)^n
\]

\[
= \frac{e^{-\lambda_j t} \cdot \sum_{n=0}^{\infty} \frac{(\lambda_j \cdot t \cdot V_j(p_j))^n}{n!}}{e^{-\lambda_j t \cdot V_j(p_j)}}
\] (4)

\[
= \exp\left(-\lambda_j \cdot \left(1 - V_j(p_j)\right) \cdot t\right)
\]
as the functional form of $S_j(t)$. This means, $T_j^*$ is exponentially distributed with rate $\lambda_j \cdot \left(1 - V_j(p_j)\right)$.

So far, we have implicitly assumed that the realization $t_j^*$ of $T_j^*$ is observable for all BINOs $j$. However, as mentioned earlier, BINOs have a certain maximum duration $d_j$. If the item is sold within this duration (that is, for successful BINOs), $t_j^*$ indeed is observable. Otherwise, one only knows that $t_j^*$ must be greater than $d_j$. Put differently, only $t_j = \min(t_j^*; d_j)$ can be observed for all BINOs. This corresponds to right censoring. Ignoring unsuccessful BINOs would, therefore, bias the results in favor of BINOs with small values of $t_j^*$. Instead, they have to be accounted for by altering the log-likelihood function $LL$ of the model:

While the contribution of uncensored observations (indicated by setting a dummy variable $c_j$ to 0) is the probability density of the event $T_j^* = t_j$, given by $-S_j'(t_j)$, censored observations (indicated by setting $c_j$ to 1) only contribute the probability of $T_j^* > t_j$, given by $S_j(t_j)$. Thus, we have

$$LL(\boldsymbol{\theta}) = \log \left( \prod_{j=1}^{J} \left( -S_j'(t_j) \right)^{1-c_j} \cdot S_j(t_j)^{c_j} \right)$$

$$= \sum_{j=1}^{J} \left[ (1-c_j) \cdot \log \left( \lambda_j \cdot \left(1 - V_j(p_j)\right) \cdot S_j(t_j) \right) + c_j \cdot \log S_j(t_j) \right]$$

$$= \sum_{j=1}^{J} \left[ (1-c_j) \cdot \log \left( \lambda_j \cdot \left(1 - V_j(p_j)\right) \right) - \lambda_j \cdot \left(1 - V_j(p_j)\right) \cdot t_j \right].$$

Note that $\lambda_j$ and $V_j(p_j)$ appear in $LL$ only in the form of their product. This means that they are interchangeable and, thus, cannot be identified. However, the variation in the asked prices $p_j$ can be used to enable identification. For this purpose, a structural assumption on the valuation distribution $V_j$ has to be made. Following previous research (e.g., Bajari and Hortaçsu 2003), we assume it to be normal; that is, $V_j(x) = \Phi \left( \frac{x - \mu_j}{\sigma} \right)$, with $\Phi(x) = \frac{1}{\sqrt{2\pi}} \cdot \int_{-\infty}^{x} e^{-\frac{1}{2}z^2} \, dz$ being the distribution function of a standard normal distribution. The shape of the normal distribution is justified when most consumers have similar valuations for an item and only a few have a significantly lower or higher one, which for many items is a reasonable assumption.

In the specified structural model, $\lambda_j$ describes consumer interest, while the expectation $\mu_j$ and the standard deviation $\sigma$ of $V_j$ describe the mean of and the variation in consumer valuation, respectively.

**Measurement Model**

While we regard $\sigma$ as constant, we allow $\lambda_j$ and $\mu_j$ to vary across BINOs. However, $\lambda_j$ and $\mu_j$ are still essentially interchangeable within a BINO $j$; therefore, this variation has to be modeled for identification.

Consumer interest is likely to vary between items of different condition (new vs. used vs. defect): Used items may have blemishes (e.g., scratches) that make them unattractive for some consumers. Defect items do no longer provide all the functions of new ones. Therefore, they are only of interest to consumers who do not need these functions or can repair them. For similar reasons, consumers may prefer to buy from business sellers than from private sellers because the former usually (have to) give a guarantee for the item. These considerations lead us to the following model for $\lambda_j$:

$$\log \lambda_j = \beta_0 + \beta_1 \cdot \text{Used}_j + \beta_2 \cdot \text{Defect}_j + \beta_3 \cdot \text{BusinessSeller}_j.$$  

We have used an exponential model to account for arrival rates always being positive.

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1 The underbraced term in the second line of (4) is equal to 1 because it can be interpreted as the sum of the probabilities of all possible results $n$ of a Poisson distribution with rate parameter $\lambda_j \cdot t \cdot V_j(p_j)$. 

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The item condition is also likely to influence consumer valuation: Instead of being not interested in used or defect items at all, some consumers may be willing to buy them at a reduced price. This illustrates the need to separate the effects of covariates on consumer interest and consumer valuation.

Consumers in BINOs face information asymmetry (e.g., Ba et al. 2003). This is because it is difficult for them to judge the trustworthiness of the seller on one hand (seller risk) and the quality or exact condition of the item on the other hand (item risk). To compensate for this, they may adjust their valuation for the item (e.g., Zhou et al. 2009). Therefore, all variables relating to information asymmetry may have an effect on consumer valuation. The seller type is such a variable: Business sellers can be assumed to appear more trustworthy than private sellers, reducing seller risk; furthermore, the guarantee they usually give reduces item risk. Consumers can further decrease seller risk by evaluating seller ratings on the platform. Since negative ratings have a much stronger effect than positive ones (Standifird 2001), we consider whether a seller has a poor rating (defined as less than 97% of her/his individual ratings being positive). Item risk can further be decreased by reading the item description. Since its length (after removing HTML tags) tendentially reflects its detailedness, it may have explanatory value.

Shipping costs effectively increase the (total) price of an item; however, previous research has found consumers to have a biased perception of partitioned prices (e.g., Morwitz et al. 1998), so that it seems more appropriate to model shipping costs as a further determinant of consumer valuation. Shipping may also influence the latter through the mean delivery time. This is because consumers usually exhibit a positive time preference regarding when they receive the item (e.g., Malkoc and Zauberman 2006). For the same reason, the possibility to pay instantly (e.g., using PayPal) should be taken into account. This is because sellers on many platforms often do not ship their items until they have received the payment.

Based on these considerations, we use the following model for $\mu_j$:

$$
\mu_j = \gamma_0 + \gamma_1 \cdot \text{Used}_j + \gamma_2 \cdot \text{Defect}_j + \gamma_3 \cdot \text{BusinessSeller}_j + \gamma_4 \cdot \text{PoorRating}_j + \gamma_5 \cdot \text{DescriptionLength}_j + \gamma_6 \cdot \text{ShippingCosts}_j + \gamma_7 \cdot \text{MeanDeliveryTime}_j + \gamma_8 \cdot \text{InstantPayment}_j.
$$

(8)

$\text{Used}_j, \text{Defect}_j, \text{BusinessSeller}_j, \text{PoorRating}_j, \text{and InstantPayment}_j$ are dummy variables; therefore, all results are to be interpreted in comparison to a new item sold by a private seller with a good rating, without the possibility to pay instantly. All other variables are mean-centered, so that the intercepts $\beta_0$ and $\gamma_0$ reflect the averages of $\log \lambda_j$ and $\mu_j$ across all BINOs, respectively.

Summarizing, the argument vector $\theta$ of $LL$ consists of 14 parameters that are to be estimated: the intercepts $\beta_0$ and $\gamma_0$, the coefficients $\beta_1$-$\beta_3$ and $\gamma_1$-$\gamma_8$, and the standard deviation $\sigma$ of $V_j$. For the latter, the positivity constraint $\sigma > 0$ has to be imposed. Estimation can be done by maximum likelihood, that is, by maximizing $LL$. We omit a proof of our model being identified (that is, of $LL$ having a unique global maximum) due to space requirements. However, as mentioned earlier, identification comes from the variation in the prices $p_j$. This can be easily seen by the fact that $V_j(p_j)$ depends on $p_j$, while $\lambda_j$ does not.

Besides, we have tested our model using simulated data. In these simulations, the true parameters were always accurately recovered, so that identification does not seem to be a problem.

**A First Application**

**Data Collection and Dataset**

We now apply our model to a dataset collected from ebay.de. We focus on eBay because it is the leading online auction platform worldwide. Besides, it is possible on eBay to search for BINOs that have ended during the last 90 days (plus some variation), regardless of whether the item has been sold or not. The data were retrieved in April 2015. Thus, all BINOs considered ended in January 2015 or later.

In this research-in-progress, we restrict ourselves to a single product in order to ensure comparability between BINOs. We have selected the iPhone 5S for this purpose. There were three reasons for this choice: First, it is a product that is offered on eBay very often, so that the sample size is large. Second, it is regularly offered by both private and business sellers in different conditions, so that the influence of these variables can be investigated without worrying about small sample sizes for some of their combinations. Third, it is a very homogeneous product (in contrast to, e.g., paintings), so that there are few varying product characteristics (which we do not investigate). These were further homogenized by restricting our sample to devices with a storage capacity of 16 gigabyte and without a SIM lock.
The data were collected by a self-written crawler. Matching BINOs were identified based on their category and the values of describing attributes (e.g., “brand” and “model”) that sellers are asked to specify when creating the BINO. While this approach may preclude a few BINOs for which the sellers did not specify these attributes, it avoids ambiguities that arise when selecting BINOs by their title. For example, the term “iPhone 5s” may also be contained in the titles of BINOs of iPhone 5S accessories.

On eBay, sellers have the possibility to extend the classical BINO format in two ways: First, by offering identical or similar items multiple times within a single BINO, and second, by allowing consumers to propose a price different from $p_j$ at which they would like to buy the item (“best offer”). Both options alter the basis on which our model has been built, so that we exclude these BINOs from our dataset.

Almost all of the variables we investigate can be retrieved from eBay directly. An exception to this is the item condition. While sellers are required to report it as one of the describing attributes mentioned earlier, we noticed that they have strongly differing perceptions what, e.g., makes the difference between a used and a defect item (often, they even do not comply with eBay’s guidelines on this point). Therefore, we have checked the BINOs manually and, if necessary, harmonized the item condition based on the item description. For example, some sellers have declared devices that work properly but have a broken display as “used”; since consumers are likely to rather make a difference between having any defect or not than between having technical or optical defects, we have changed this to “defect”.

After this preprocessing, 1,821 BINOs remain in our dataset. They are summarized in Tables 1a-1c.

### Table 1a. Number of BINOs by Seller Type and Item Condition

<table>
<thead>
<tr>
<th>Seller Type</th>
<th>New</th>
<th>Used</th>
<th>Defect</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Private</td>
<td>159</td>
<td>344</td>
<td>24</td>
<td>527</td>
</tr>
<tr>
<td>Business</td>
<td>501</td>
<td>763</td>
<td>30</td>
<td>1,294</td>
</tr>
<tr>
<td>Total</td>
<td>660</td>
<td>1,107</td>
<td>54</td>
<td>1,821</td>
</tr>
</tbody>
</table>

### Table 1b. Number of BINOs by Further Dummy Variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Value</th>
<th>1 (Yes)</th>
<th>0 (No)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sold ($1-c_j$)</td>
<td></td>
<td>1,234</td>
<td>587</td>
</tr>
<tr>
<td>PoorRating</td>
<td></td>
<td>35</td>
<td>1,786</td>
</tr>
<tr>
<td>InstantPayment</td>
<td></td>
<td>1,562</td>
<td>259</td>
</tr>
</tbody>
</table>

### Table 1c. Summary Statistics of Cardinal Variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Unit</th>
<th>Item Subset</th>
<th>Min</th>
<th>Mean</th>
<th>Max</th>
<th>Std. Dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Price ($p_j$)</td>
<td>EUR</td>
<td>New Items</td>
<td>300.00</td>
<td>458.2357</td>
<td>779.95</td>
<td>50.8188</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Used Items</td>
<td>100.00</td>
<td>358.6081</td>
<td>530.90</td>
<td>33.0964</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Defect Items</td>
<td>59.95</td>
<td>242.8506</td>
<td>339.80</td>
<td>63.8031</td>
</tr>
<tr>
<td>Duration ($t_j$)</td>
<td>Days</td>
<td>Sold Items</td>
<td>0.0023</td>
<td>4.7153</td>
<td>69.0704</td>
<td>8.8720</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Unsold Items</td>
<td>0.0003</td>
<td>6.9837</td>
<td>93.0418</td>
<td>8.1904</td>
</tr>
<tr>
<td>Description Length</td>
<td>Characters</td>
<td>All Items</td>
<td>10</td>
<td>1,403.2060</td>
<td>19,575</td>
<td>3,052.4110</td>
</tr>
<tr>
<td>Shipping Costs</td>
<td>EUR</td>
<td>All Items</td>
<td>0.00</td>
<td>1.6774</td>
<td>16.00</td>
<td>2.5693</td>
</tr>
<tr>
<td>MeanDeliveryTime</td>
<td>Days</td>
<td>All Items</td>
<td>2</td>
<td>2.6546</td>
<td>12</td>
<td>0.8891</td>
</tr>
</tbody>
</table>

### Estimation and Results

For maximizing $LL$, we employed the BFGS-algorithm (Broydon 1970; Fletcher 1970; Goldfarb 1970; Shanno 1970). To avoid it converging to a local maximum, we repeated the estimation procedure 100 times with different, randomly chosen starting values and regarded the replication that has led to the largest value of $LL$ as the final result (Finch et al. 1989). This value was $-3,688.8840$, compared to a value of $-3,878.3440$ for the null model (with $\beta_0$, $\gamma_0$, and $\sigma$ as parameters only). Using the formula of (Nagelkerke 1991), this corresponds to a pseudo-$R^2$ measure of 19.0553%. Note that unlike the usual $R^2$, values above 20% would already be considered as indicating an “excellent fit” (McFadden 1979, p. 307).
The resulting coefficients of the determinants of consumer interest and consumer valuation are reported in Table 2 (in reverse order for better readability). Their discussion is postponed to the next section.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Consumer Valuation</th>
<th>Consumer Interest</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Intercept)</td>
<td>+384.9727</td>
<td>+0.2285</td>
</tr>
<tr>
<td>Used</td>
<td>-60.7161</td>
<td>-0.5403</td>
</tr>
<tr>
<td>Defect</td>
<td>-85.7710</td>
<td>-0.6639</td>
</tr>
<tr>
<td>BusinessSeller</td>
<td>+134.6030</td>
<td>-2.0576</td>
</tr>
<tr>
<td>PoorRating</td>
<td>-5.4539</td>
<td>-0.20123</td>
</tr>
<tr>
<td>DescriptionLength</td>
<td>-0.0015</td>
<td>0.2870</td>
</tr>
<tr>
<td>ShippingCosts</td>
<td>-4.5329</td>
<td>-0.2307</td>
</tr>
<tr>
<td>MeanDeliveryTime</td>
<td>-3.9358</td>
<td>0.2675</td>
</tr>
<tr>
<td>InstantPayment</td>
<td>+21.0123</td>
<td>1.4883</td>
</tr>
<tr>
<td>(Std. Dev.)</td>
<td>66.2318</td>
<td>0.4454</td>
</tr>
</tbody>
</table>

Significance: *: p < 0.1, **: p < 0.05, ***: p < 0.01

Table 2. Determinants of Consumer Valuation and Consumer Interest

Discussion and Implications

Looking first at the determinants of $\mu_j$, one learns that a new iPhone 5S sold by a private seller is valued at 384.97 EUR on average. Used and defect items are valued at 324.26 EUR (384.9727 – 60.7161) and 299.20 EUR, respectively. While it is as expected that consumer valuation decreases with a worsening item condition, it may come as a surprise that the difference between the latter two conditions is relatively small – just 8%. The reason may be that most defect items are not completely faulty. Often, just one particular function (e.g., the camera) is broken, while all other functions work properly. It is further noteworthy that the valuations for new and used items are lower than the corresponding average prices (see Table 1c), whereas defect items seem to be offered too cheap.

Consumer valuation increases by 134.60 EUR when considering offers by business sellers. For the case of new items, this means that roughly a quarter of the total consumer valuation of 519.58 EUR (384.9727 + 134.6030) comes from the benefits associated with buying from business sellers (such as having a guarantee). This can motivate private sellers to also offer these benefits for an additional fee.

Shipping costs were found to have a negative effect on consumer valuation, as expected. However, it is surprising that the corresponding coefficient is significantly lower than $-1$ ($p < 0.0001$); this means that consumers overcompensate for shipping costs: if the latter increase by 1 EUR, consumer valuation decreases by 4.53 EUR. This result is consistent with the aforementioned finding that consumers have a biased perception of partitioned prices (e.g., Morwitz et al. 1998). On this basis, one would advise sellers to offer free shipping and to compensate for this by asking for a higher price. In fact, this seems to be what actually happens, as sellers with no shipping costs charge, on average, 4.65 EUR more for their items than sellers with shipping costs of 1 EUR (Fritschmann et al. 2012).

Regarding the length of the item description, no significant influence on $\mu_j$ was found. This is probably because an iPhone 5S is a well-known and, as explained earlier, very homogeneous product, so that no detailed description of its functions is necessary – consumers can just google them. Therefore, sellers should not spend too much time working out an in-depth item description for these kinds of products.

The remaining determinants of $\mu_j$ are mainly of interest because of their magnitude (when compared to the reference case). While our results confirm that consumers value an iPhone 5S less if it is sold by a seller with a poor rating, the difference is very small: just 5.45 EUR. The same applies to the mean delivery time: additional days to delivery are indeed penalized by consumers – but just by 3.94 EUR each. Contrarily, the possibility to pay fast is rewarded by an increase of 21.01 EUR in $\mu_j$. This may indicate that consumers overestimate the time until the seller receives their money when not paying via an instant payment service (but, e.g., via a traditional bank transfer) compared to the delivery time.
Switching now to the determinants of \( \lambda_j \), we first note that, on average, only 1.26 \((e^{0.2285})\) consumers arrive at a BINO of a new iPhone 5S per day. This reflects that this product is sold on eBay very often, as mentioned earlier, so that consumer interest in any particular item is not very large. For used and defect items, the rates are even lower: 0.73 \((e^{0.2285-0.5409})\) and 0.65, respectively. This suggests that almost half of all arriving consumers look for new items, while about a quarter each look for used and defect ones.

Interestingly, the arrival rates decrease strongly when considering offers by business sellers – for new items by 87\% to 0.16 consumers per day \((e^{0.2285-2.0676})\). This may be puzzling at first glance, especially against the background that we have found consumers to value items offered by a business seller much higher than those offered by a private seller. However, this also hints at a possible explanation: Consumers may intend to make a snatch on eBay. Therefore, they look foremost for items that they expect to be cheap, assuming that sellers set low prices rather for items valued low by consumers.

**Conclusion, Limitations, and Further Research**

In this paper, we have presented an approach to quantify consumer interest and consumer valuation based on the observed lifetimes of BINOs. Being still in progress, this research currently has some restrictions, which we intend to overcome as we advance:

First, we have investigated only a single product. This has an immediate practical benefit: Sellers can proceed analogously and apply our model to any product that they offer in order to learn about consumer interest and consumer valuation for their items. As mentioned earlier, this knowledge can be useful when deciding on price setting, BINO design (e.g., regarding the item description), and transaction parameters (e.g., shipping). However, scientific interest is usually not focused on particular products but aims for more general findings. Therefore, our next step will be to extend our model in such a way that it can be used to analyze different products from potentially different categories. This is not a trivial matter, though, since it is not clear how dissimilar products can be made comparable. A step towards a solution may be the introduction of product- or product category-specific fixed effects in (7) and (8).

Second, we have regarded the price of a BINO as an exogenous variable. However, with it being set by the seller, it is potentially endogenous. Sellers may decide on it with respect to (possibly unconsidered) variables that also influence consumer valuation. After this endogeneity is accounted for, one can also aim to investigate whether the distribution of asked prices matches the consumer valuation distribution for an item, that is, whether (or when) items are sold too cheap or too expensive. Thinking this to the end, the optimal price setting of sellers may be studied and compared to the observed price setting, as previous research has done based on different available information (e.g., Adams 2007).

Third, while our abstract model (1) is relatively broad, its concretizations are somewhat narrow due to the specification of the consumer arrival process in (2) and the consumer valuation distribution in (6). E.g., previous research suggests that consumer arrival processes may be inhomogeneous (Shmueli et al. 2007). That is, the consumer arrival rate \( \lambda_j \), which we here have regarded as being constant over time, may in fact vary with time. Accounting for this, one can also investigate the presence of potential time-specific effects (such as, for example, less consumers searching for items during the night). Regarding consumer valuation, distributions other than the normal distribution can be used and compared with each other. Besides, it would be interesting to see whether the information contained in BINO lifetimes can complement other information from, e.g., bid histories, in such a way that the non-parametrical identification of consumer interest and consumer valuation becomes possible.

With our work, we hope to raise interest not only in auctions and BINOs but also in the methods of survival analysis, which can be useful in many unexpected ways, as demonstrated in this paper. Their usage is advisable whenever duration data are available and censoring events can occur. This is common in the domain of electronic business. For example, most websites log the behavior of their users. Based on these log files, website owners can analyze (the determinants of) the time it takes users to perform a certain action (e.g., to buy a product) in order to, e.g., simplify navigation. Observations for users who leave the website without doing so are censored. Another possibility is to generate duration data somewhat artificially by defining an event of interest and observing the time until it occurs. Such an event can be, for example, the costs of an advertising campaign exceeding a certain limit. Censoring here takes place when the defined event has not occurred up to the time of analysis or cannot occur anymore (e.g., because the advertising campaign has been stopped before becoming too expensive).
References


