Searching the eBay Market Place

Katharina Sailer[*]

March 2004

VERY PRELIMINARY - DO NOT CITE

Abstract

The paper proposes a dynamic framework for demand estimation with data obtained from eBay auctions when one or more bids of a bidder for similar products offered in consecutive auctions can be observed and bidding is costly. As opposed to standard static auction models, where the bidder either wins or forgoes the product forever, the bidder here values the option to bid again in the next upcoming auction and adjusts her bid accordingly. It is shown that standard panel methods lead to consistent estimates for the common demand parameters, despite of the selection that is introduced by the individual participation decision. The bidding costs can be inferred in a second step from the first order conditions using the individual specific error terms.

1 Introduction

Every day sellers offer millions of items over individual eBay auctions. What once started off as an e-garage sale by now has become a fully developed market place for private and professional resale of new and used goods. eBay claims to be the

[*]Katharina Sailer, Ludwig-Maximilians-Universitaet Muenchen, Center for Information and Network Economics, Institute for Statistics, Akademiestr. 1/I, 80799 Muenchen, Germany. E-mail: ksailer@stat.uni-muenchen.de

most popular shopping address of online buyers worldwide and is highly profitable. Its stunning success story early on triggered researchers' interest. The first papers concentrated on eBays reputation mechanism (e.g. Lucking-Reiley et al. (2000) and Houser and Wooders (2001)). The rich and readily accessible data, however, seems ideal for testing other microeconomic theories, first of all auction models (e.g. Roth and Ockenfels (2002)), and for inferring characteristics of demand (e.g. Bajari and Hortacsu (2003)).

From eBay's bidding histories, not only the transaction price is available but also all non-winning bids can be observed. This allows richer inferences than most other auction data sets. When observing the market for a specific product over time, it is for example possible to trace a bidder's behaviour in this market. This paper offers a dynamic framework which allows to recover common and individual specific demand parameters from bids at eBay.

As opposed to previous work the model stresses the market place characteristics of eBay: not only one but a multitude of objects compete for the attention of a buyer. When a bidder considers buying a relatively standardized product from eBay, she presumably takes account of the different opportunities she has. She might be willing to try in several different auctions before finally obtaining the desired product if this results in paying a lower price in the end. When building her bidding strategy the bidder then does not compare the value of winning the object now or forgoing it forever, as is assumed when a static auction setting is used, but with winning the object now or in future upcoming auctions.

The literature on sequential auctions considers bidders' strategies when the "thin markets"[1] assumption implicit in static auction models is relaxed and a number of identical objects are offered in a series of consecutive auctions. As opposed to static auctions, a bidder in these models is not willing to bid her valuation in the early

[1] "The auction model is a useful description of "thin markets" characterized by a fundamental asymmetry of market position. While the standard model of perfect competition posits buyers and sellers sufficiently numerous that no economic agent has any degree of market power, the bare bones of the auction model involves competition on only one side of the market." (Riley and Samuelson (1981), p. 381)

auctions but takes account of what other bidders would have to pay in the following auctions. A bidder's optimal strategy in a sequential sealed bid second price auction then consists in shading her valuation exactly by her option value, that is by the added value that she receives from the possibility to participate in future upcoming auctions (Weber (2000)). Since there are only a limited number of objects available this option value decreases over time. While the optimal bid of a non-winning bidder hence increases the expected prices that are paid in case of winning are the same and correspond to the highest valuation among the bidders that will not receive a product. Thus, the law of one price for identical objects holds in expectation.

A bidder's "search" for low prices is restricted in these models by the limited availability of objects, that is there are more bidders then products on offer. Assuming a fixed number of auctions offering a specific product does not fit the eBay market very well. When assuming an infinite horizon, instead, the bidder has to be stopped from bidding forever with a bid close to zero by some other device. As in Bajari and Hortacsu (2003) I assume that it is costly for a bidder to take part in an eBay auction. These costs reflect information costs, connection charges, and the time spent in front of the computer when placing a bid. Bidding costs presumably differ between bidders. While some people enjoy bargain hunting others find they could spent their time better elsewhere; while some bidders have access to a fast internet connection or might even be allowed to use their computer at work for this purpose, others rely on a slow modem and bear the connection charges themselves. I will show in the following that when bidding costs are taken into account a bidder still shades her valuation due to future opportunities. The amount of shading now, however, does not only depend on the competitors' valuations but also on the individual bidding costs. Given that there will always be a new product available, that is the horizon is infinite, this option value and hence the optimal bid of a bidder stay constant over time.

If the number of bidders was fixed and everybody was only interested in one object, bidders with high bidding costs would win objects at an earlier stage and prices would decline. Assuming a fixed pool of bidders is, however, not feasible in the infinite horizon model, since exit due to winning would at some point result in a situation where no bidders are left. If ones allows instead for entry, with valuations and bidding costs of entrants being the same in expectation, the expected prices paid by winners do not follow a trend. This result hinges on the assumption that all competitors belief that the draw of the second highest bid comes in every period from the same constant distribution function. Modelling a full fledged dynamic game with entry and exit where each bidder would build in every auction a new expectation of the highest bid of her competitors based on information from past auctions is unfortunately rather complicated. Given the huge amount of bidders that interact in eBay markets for standardized products with an in principle unlimited availability of products it though seems a valid first approximation to assume that dynamic strategies of current bidders and new entrants do not impact on the distribution of second highest bids in a systematic way.

The transaction prices that are observed at eBay show considerable price dispersion. This is still true if different product characteristics are taken into account. The IO literature makes search frictions responsible for why the law of one price often cannot be observed in reality despite of seemingly identical products. I will show that in the auction setting it is also the differing costs of bidders that cause (part of the) price dispersion. The intuition behind this result is that bidders with higher search cost have a lower option value of bidding in future auctions and therefore shade their bids less. (The bidding cost of the current period on the other hand is sunk at the time of bidding, and does not influence the bid.) If bidders bid differently and have a chance of winning the product if they try long enough, observed prices will differ in equilibrium.

Why are search models and eBay auctions similar? Optimal search behaviour follows a stopping (or reservation price) rule: Accept offers that exceed your reservation value and reject all others. The reservation value when searching auctions for low prices corresponds to a "reservation bid" that is placed invariantly in every new auction. If the transaction price, i.e. the second highest bid, is above the bidder's reserve bid, he loses and has to try in a new auction, if it is below it the bidder wins and pays the second highest bid.

Estimating search models has a long history in the labor market literature (e.g. van den Berg and Ridder (1998)). Recent contributions in IO are Sorensen (2001) and Hong and Shum (2003). The search costs that are needed to justify the observed price dispersion are often very high. The advantage of the data from eBay is that the "reserve bid" is observed in every auction, even when a bidder is not winning and that very detailed information on the covariates is available. This allows to distinguish price dispersion caused by search frictions from that induced by product differentiation. The costs that are estimated here are lower then in both Sorensen (2001) and Hong and Shum (2003).

The next section explicates the rules of the eBay game. Section 3 introduces the model. The data is described in section 4. Section 5 discusses identification and presents the estimation strategy. The results are provided in Section 6. Section 7 concludes.

2 The Rules of the eBay Game: Facts and Simplifications

A growing empirical literature uses auction data for demand estimation.[2] Besides being a rich source for observing strategic interaction between individuals, the advantage of auction data as compared to other micro data is that the rules of the game are explicitly stated and common knowledge to all participants at the outset of the game. Additionally many of the auctions for which data is available, e.g. procurement auctions, have been explicitly designed by economists and therefore come close to what is taught in theory. Models for a structural empirical analysis are therefore readily available. Most of this does not hold true for data from eBay. eBay's rules are much less clear cut and many details are left to the discretion of the competing parties. The combination of rules that is used or could potentially be used does not fit any of the textbook examples. A few clarifications and simplifications are therefore in order before starting to develop the model.

Different auction models make different assumptions on the valuations of bidders. Pure private (PV) and common values (CV) as well as more general affiliated values

[2] Good overviews are provided in Laffont and Vuong (1996) and Athey and Haile (2002)

have been considered in the theoretical literature. While the general affiliated values model, which includes the two other models as special cases, would be most desirable it does not lend itself easily for empirical analysis. In general the parameters of this model are not identified (see Laffont and Vuong (1996)). Whether authors of empirical papers decide for PVs or CVs normally depends on the characteristics of the goods. The products that I am interested in are off-the-shelf products that are frequently sold outside eBay and that are presumably mainly acquired for personal usage.[3] The PV assumption therefore seems to be more applicable and is taken as a good approximation to the true bidding model.[4]

Assumption 1 *Bidders' valuations for the products are private.*

When a bidder decides for buying a product at eBay and runs a search at eBays homepage she will find a number of auctions that offer more or less equivalent products. And new auctions open every instant featuring again the same product. Bidding in an auction before the earlier ones ended is weakly dominated since bidders can always wait.[5] The auctions can therefore be ordered by their ending dates into a sequence. There are different possibilities how a bidder decides in which of the auctions listed in the search results she will participate. I will assume that she first considers the auction that closes next. When deciding about entry and her bidding strategy she will think of all other following auctions as offering approximately the same average product. This is a very strong assumption. First of all, it does not allow a bidder to jump directly to auctions in the search list that attract her attention most. Secondly, bidders act presumably more forward looking and have a number of auctions in their

[3]Bajari and Hortacsu (2003) quantify the winners curse in the market for coins at eBay. While the winner's curse may also be present in my sample, I assume that it only plays a subordinate role.

[4]There are also tests that try to distinguish from the data which of the models fit the data better. These tests are winner's curse tests, that measure the influence of the number of bidders on the bid of a bidder. The problem with these tests is that competition from future auctions introduces a common component into the PV setting in finite horizon sequential auctions (see below). If this holds also true for the case when an infinite number of products are available, the tests would not distinguish between private and common values.

[5]By bidding in the later auction before the other one closed the bidder precludes herself the option to participate in the auction that closes first. The next paragraph shows that the bidder cannot gain by bidding early in an auction.

choice set when starting to bid in one of them. However, the assumption is necessary to keep the model tractable.

Assumption 2 *Auctions can be sorted by their ending dates into an infinite sequence. Bidders evaluate one auction in the sequence after the other. Meanwhile characteristics of products in future auctions are assumed to be average.*

What about eBay's bidding rules? eBay allows a bidder to either bid incrementally as in an English auction or to submit her maximum willingness to pay to a proxy bidding software at eBay that will then bid for her. Secondly, the rules do not specify when a bidder has to enter an auction. Bidder's are free to abstain from bidding for a while or to only enter in the last seconds of the auction. Thus a bidder never knows how many other bidders are currently competing for the product. Finally, there is a so called "hard close", that is an auction ends at a fixed pre-defined point in time and not when bidding activity ceases. The literature on eBay so far does not provide any evidence how early bidding could benefit a bidder. There are however reasons why a bidder might be reluctant to reveal any private information before the end of an auction. Roth and Ockenfels (2002) show that "sniping", that is bidding in the very last second, is a dominant strategy for a bidder, when he faces other bidders, that bid incrementally. The argument is that by bidding late, bidders avoid price wars. The advantage of this strategy, however, disappears when the competitors decide to tell their maximum willingness to pay to eBays proxy bidding service. Bajari and Hortacsu (2003) look at a common value setting. Bidding early can not be advantageous since it reveals valuable information on the signal that a bidder received. Wang (2003) shows that a common value component is introduced into the private value setting when there is a series of auctions featuring the same product. As was pointed out before, sequential auctions lead to bid shading. The amount of shading depends on expectations about future competitors' bids. Different bidders' expectations though contain a common component. Most data on eBay shows a pronounced increase in bidding activity towards the end of an auction. Following the literature and the data I assume that it is not optimal for a bidder to bid early in an auction and therefore the bidding rules are approximated by a sealed bid Vickery auction. The choice set of a bidder comprises an infinite series of such Vickery auctions.

Assumption 3 *The bidding rules in each auction can be approximated by a Vickery auction.*

Finally, assumptions have to be made on how bidders enter and exit the market and how this behaviour influences the distribution of valuations and costs of participants in an auction. The data shows that only very few bidders continue bidding after winning an auction (see also section 4). I will therefore assume that bidders are only interested in one product and exit after winning. It is further assumed that every winner is replaced by a new entrant who draws his valuation and cost randomly from always the same common distribution functions. Lastly I assume that bidders view their competitors' bids in each new auction as representing a random draw from a constant distribution function. This is probably the most critical assumption of all. It is justified by the huge amount of bidders that interact at eBay and the multitude of products on offer. Both make it unlikely to bid against the same competitor twice if there is some random component to a bidders' entry decision and therefore limit the scope for strategic behaviour. The data confirms that bidders rarely interact twice with the same person.

The fact that bidders in the data do not interact with each other more then once could also be the outcome of bidders' dynamic strategies. To see why go back to the original sequential auction model by Weber (2000). The first auction there provides a complete ranking of valuations, that is every bidder knows who else is in the market. If there are two auctions and bidding is costly, only the second highest bidder in the first auction will find it profitable to enter the second auction. All the others know that they have no chance of winning and are therefore reluctant to incur the bidding costs. The winner in the second auction then pays a price of zero. Since everybody foresees that, bidders will not find it optimal to follow the before mentioned strategies. von der Fehr (1994) shows that in a two-objects-many-bidders model there is room for predation. While the bids in the first auction still provide a complete ranking of bidders' valuations, bids are higher then in Weber (2000). Bidder's might even bid more then their valuation for obtaining the chance of being the only bidder in the highly profitable second auction. The optimality of the predatory strategy hinges on the assumption, that there is a limited number of objects available, that is not every bidder will receive one. The proof does not necessarily carry over to the case where an infinite number of objects are on offer. To see why note that predation is costly, since it includes the danger of winning the object for a price higher then ones valuation. Incurring these costs might not be optimal if bidders could obtain the object at a later instant when the high value bidders exited. Instead of trying to predate entry into future auctions, bidders might also just decide to stay out of some of the auctions but to reveal truthfully when entering (strategic non-participation). If bidders know that they have no chance of winning since there are many high value bidders in the market they might want to stay out until they belief that the high value bidders left the market.[6]

At this stage it seems impossible to model the full fledged dynamic game with entry and exit where the distribution of the participants' valuations is derived endogenously. It will therefore be assumed that bidders' fully dynamic strategies would not influence the optimality of their bidding strategies given entry, that is predation does not exist or is negligible, and that bidders' entry behaviour does not change the distribution of bids in future auctions in a systematic way which could be foreseeable by the competitors. In section 5 I shortly come back to the possibility of strategic non-participation and discuss which problems it causes in the identification.

Assumption 4 *Bidders belief that the draw of the highest bid of her competitors comes in every new auction from the same constant distribution function. The mean of this distribution differs with product characteristics.*

Given these assumptions it is now possible to model the eBay market. Besides some notation it is necessary to make more precise assumptions on the bidders' valuations. The next section deals with these issues and presents bidders' optimal strategies.

[6]Caillaud and Mezzetti (2003) and Bremzen (2003) consider two-period models where bidders engage in strategic non-participation since they are reluctant to convey information to the seller respectively to a new entrant.

3 The Model

Consider a mass of homogenous products, that are auctioned off in an infinite sequence of Vickery auctions, one in each period t. There exists a continuum of potential bidders, n of which participate in a specific auction. Each bidder is interested in one product only. v_{it} is the valuation of bidder i for the product, b_{it} her bid. From the bidder's perspective, the highest bid among the competitors in each new auction, b_t^h, represents a random draw from a known distribution function f_t^h with cdf F_t^h and support $[\underline{v}, \overline{v}]$. This distributions are allowed to change with the characteristics of the product in the current auction but do not change with any information on competitors acquired in past auctions or from information on products in future auctions. The indicator function is used to denote that a bidder's bid wins since it is higher than that of all other bidders ($\mathbf{1}_{b_{it} \geq b_t^h} \equiv \mathbf{1}_{it,win} = 1 - \mathbf{1}_{it,lose}$). The bidder may participate in as many auctions as she wishes. Participation however is costly. The cost c_i can be thought of as the time spent in front of the computer, connection charges, etc. Different bidders have different cost. Costs are drawn once upon entry from a common distribution function $h(c)$ with cdf $H(c)$.

Lets first look at a simple example where a bidder's valuation is independently drawn from a common distribution function and stays constant over time. This characterizes a situation with fully homogenous products. Given the other bidders' optimal strategies a bidder chooses a bid that maximizes her expected intertemporal utility. The corresponding Bellman equation is:

$$V_i(v_i) = \max \left\{ \underset{b_i > 0}{max} E \left(\mathbf{1}_{i,win}(v_i - b^h) - c_i + V_i(v_i') \right), V_i(v_i) \right\} \tag{1}$$

$$\text{s.t. } v_i' = \mathbf{1}_{i,lose} v_i.$$

A bidder who wins pays the price determined by the bid of the second highest bidder in the auction. Her valuation then drops to zero. With a valuation of zero she has no interest in winning another object and her option value $V_i(0)$ is zero. Since the single state variable v_i only changes once upon winning the option value in case of losing stays constant. (1) then simplifies to

$$V_i = \max \left\{ \underset{b_i > 0}{max} E \left(\mathbf{1}_{i,win}(v_i - b^h) - c_i + \mathbf{1}_{i,lose} V_i \right), V_i \right\}.$$

A losing bidder has the option to participate in the next upcoming auction. Since the option value depends on the bidder's cost, it is different for different bidders. In any case, whether losing or winning the bidder pays the bidding costs.

The optimal bid directly follows from the first order condition (FOC).[7] Since it is only optimal for a bidder to participate if her value is above zero ($\mathbf{1}_{V_i \geq 0}$), the full bidding strategy is described by:[8]

$$b_i^* = \delta_i^*(v_i - V_i) \qquad \text{with } \delta_i^* = \mathbf{1}_{V_i \geq 0}, \tag{2}$$

where a bid of 0 indicates that a bidder does not participate and is therefore not paying the bidding costs. Since the environment does not change over time a bidder decides only once whether to participate or not. If participation is optimal in the first round it will be so in all following ones until the bidder wins and her valuation drops to zeros. The optimal bid given participation is constant over time.

Substituting the bid back into the Bellman equation gives:

$$c_i = F^h(b_i^*)(b_i^* - E[b^h | b_i^* > b^h]). \tag{3}$$

An optimal policy thus is one that equalizes the cost of bidding with the expected gain from one more trial. The bidder's decision rule here appears as myopic as that of the decision maker in an optimal stopping problem which is at the basis of search models, known for example from the labor market literature (Albrecht and Axell (1984), Burdett and Mortensen (1998)) or the IO literature where a seller faces uncertain demand (Diamond (1971), Rob (1985)). There the decision maker decides on a reservation value which serves as a cutoff value for accepting a price or a wage offer. This reservation value is found by equating the cost form one further search with the expected gain from this search. As long as the environment is constant, that is the state variables do not change over time, there is no added value in deciding sequentially. This holds true for both the auction and the standard search setting. In both cases the state variable only changes once, namely when the decision maker

[7] For a more detailed derivation see the proof of proposition 1.

[8] It is assumed that if entry is profitable today, the bidder prefers to enter today instead of waiting for tomorrow.

succeeds. The distribution of other bidders' bids and the wage or price offer curve stay constant.

The model described so far assumed an infinite sequence of identical products. At eBay there are hardly any two products that are exactly the same. It is therefore necessary to allow for more general valuations, that take account of product heterogeneity. I assume that bidder i's valuation for a product on offer is made up out of the weighted sum of its k=1,...,K product characteristics x_{tk}, with weights common to all bidders, and an individual specific component ϵ_{it}:

$$v_{it} = v(x_t, \epsilon_{it}; \gamma) = \gamma_0 + \gamma_1{}' x_t + \epsilon_{it}$$

with $\gamma = (\gamma_0, \gamma_1) = (\gamma_0, \gamma_{11}, \gamma_{12}, \ldots, \gamma_{1K})$. The weights are known to all participants and stay the same over time. $\epsilon' s$, on the other hand, are drawn in every period anew and independently from a common distribution function $g(0, \iota^2)$. The individual realization is observed by the bidder just before she decides to enter a new auction.

The Bellman equation for bidder i now is:

$$V_i(v_{it}) = \qquad \max \left\{ \underset{b_{it}>0}{max} E \left(\mathbf{1}_{it,win}(v_{it} - b_t^h) - c_i + \mathbf{1}_{it,lose} V_i(v_{i,t+1}) \right), V_i(v) \right\}.$$

x_t is realized before the bidder bids, b_t^h and x_{t+1} afterwards. The bidder's expectation of x_{t+1} is x, her expectation of her future valuation is denoted by $v = v(x, 0; \gamma)$, which is the same for all bidders. Let $V_i(v_{it}) \equiv V_{it}$ and $V_i(v) \equiv V_i$. The bidder's problem then writes as:

$$V_{it} = \max \left\{ \underset{b_{it}>0}{max} \left(\mathbf{1}_{it,win} \left(v_{it} - b_t^h \right) \right) - c_i + \mathbf{1}_{it,lose} V_i \right), V_i \right\} \tag{4}$$

As before the bidder's optimal strategy is derived from the FOC and the participation constraint:

Proposition 1 *Under assumptions 1-4 the equilibrium strategy of a risk neutral bidder i with valuation* $v_{it} = \gamma_0 + \gamma_1{}' x_t + \epsilon_{it}$ *and cost* c_i *is given by*

$$b_{it}^* = v_{it} - V_i$$

and

$$\delta_{it}^* = \begin{cases} 1 & \textit{if } (b_{it} - E_t[b_t^h | b_{it}^* > b_t^h]) F_t^h(b_{it}^*) \geq c_i \\ 0 & \textit{otherwise} \end{cases}$$

A bidder's optimal bidding policy given entry equates:

$$c_i = F^h(b_i^*)(b_i^* - E[b^h | b_i^* > b^h]) \tag{5}$$

with $b_i^* = \gamma_0 + \gamma_1{}'x - V_i$.

Proof. See appendix. □

Note that a bidder still shades her valuation by her option value. Due to different draws of ϵ this bid now, however, changes over time. Additionally, she now might participate in some of the auctions, where her draw of ϵ is high and stay out of others. From equation (5) it can be seen that the analogy to the search setting is still given. The difference to before is that the "reservation bid" now depends on product characteristics and the specific realization of the shock.

How does the optimal bid change with the bidding costs? First look at a simple example in which the highest bid among the competitors, given average product characteristics, is distributed uniformly on $[0, \bar{b}]$. From equation (5) it follows that in this case $V_i = v - \sqrt{2c_i\bar{b}}$. The bidder's value hence decreases with the bidding costs. The optimal bid, $b_{it}^* = v_{it} - V_i = \gamma_1{}'(x_t - x) + \epsilon_{it} + \sqrt{2c_i\bar{b}}$, on the other hand increases with c. The corresponding results for an arbitrary distribution are summarized in proposition 2:

Proposition 2 *A bidder's value decreases with her bidding costs:* $\frac{\partial V_i}{\partial c_i} = -\frac{1}{F^h(b_i^*)}$*. The optimal bid increases with c.*

Proof. This follows by applying the implicit function theorem to equation 5. □

The higher the bidding cost of a bidder, the less attractive it is for her to bid in many auctions before winning and hence the lower her option value V_i. To avoid participation in several auctions the bidder will therefore bid more aggressively in the first place.

4 The Data

The dataset was assembled from eBay.de during April to November 2002. During these eight month 1212 auctions of a Personal Digital Assistant (PDA), the Compaq

Ipaq H3850 (Ipaq3850), could be tracked. The product was chosen for several reasons. First of all it is a relatively homogeneous product and frequently sold at eBay. Secondly, substitution towards competing products was limited since the Ipaq3850 was at that period at the top end of the PDA market the product that offered the largest number of new features for the smallest price and was rated best among its competitors by leading German consumer magazines (e.g. Connect). Additionally, consumer electronics tend to be heavily branded products that cater to different target groups. To find out whether substitution was actually limited, additional data on a potentially close competitor was collected. The closest competitor with respect to product characteristics and price at the beginning of the period was the Casio Cassiopeia E-200G. The percentage of Ipaq3850 bidders that also tried in Casio auctions during April to May was less then 5%.

Substitution however did happen towards used Ipaq3850's and those that came with additional accessory or had smaller defects. The dataset therefore includes information on all auctions that where open in the category PDAs and Organizers and included the words "Compaq" and "3850" or "Ipaq" and "3850" in its title. An advantage of the dataset is the detailed information on product characteristics, that was manually retrieved from the descriptions of the sellers. Table 1 lists the variables and provides detailed descriptions. A *product's quality* is assessed by different variables that where build from the sellers description and which include information on the age and the condition of the product as stated by the seller. This category also includes dummies for non German operating systems and different kinds of defects, such as scratches and missing standard accessory. Next, there is a number of *additional accessories* that are frequently bundled with the Ipaq3850. The most typical extras are covers, memory cards, charge and synchronization cables and expansion packs (jackets), plastic casings that enhance the functionality of Ipaqs by for example providing slots for additional memory cards. Most common among the expensive extras are navigation systems and microdrives. Finally, the seller's quality might have an influence on the valuation, a buyer ascribes to the product. This is captured by the seller's eBay reputation and the variable PROFI, that takes the value 1 if the seller gives reference to an own shop outside eBay.

In addition to the information on the auctions, all bids that were placed in each auction, together with the pseudonyms of the bidders and the bidding time are available. In matching the auction and bidder sample the number of auctions decreases to 856, since no bid data is available for auctions, that are not sold (15%) and auctions that have the feature private (bidders' pseudonyms are not revealed; 14.4%). A total of 7630 bids was placed in the remaining auctions. Since it is assumed that it is not optimal for a bidder to reveal any information on her true willingness to pay before the last minutes of an auction, I consider the early bids as not informative and delete them from the panel. By restricting the bids to those that are submitted in the last 10% of the time, the number of bids is reduced to 3202 observations. The 10% mark is found by striking a balance between the informativeness of the bids and the number of remaining observations per bidder. Figure 3 and 4 display the bid distribution in the full and the restricted sample. The full distribution displays a second peak at very low prices. This is due to a number of bids between 1€ and 20€. Bidders will hardly believe that they will win with these bids. One explanation why bidders engage in these bids is that it is an easy way to track an auction.[9] By excluding early bids the two peakedness of the distribution disappears.

Table 3 reports summary statistics of the remaining 788 auctions. Every day around 5 Ipaq3850 auctions closed. 20% of these auctions offered new products, 33% were bundled with additional accessories, 3.5% came with a non-German operating system, and 4% had some other kind of defect such as scratches or missing standard accessory. Winners paid on average 469.93€ for their products (Std: 78.34€, min: 280€, max: 872 Euro) plus an additional 7.2€ for shipping and handling. Figure 1 displays the evolution of prices over time. There is a pronounced decrease in the average transaction price during the sample period. This is probably due to the high tech characteristic of the product. After correcting for this, applying a simple linear

[9] As opposed to eBay.com at eBay.de auctions that are closed cannot be searched for anymore. Alternative ways for obtaining information on the price at which an auction closed are to use eBays tracking service ("observe auctions"), to remember the ID of an auction and construct the URL afterwards manually, or to just participate, since participants receive an email with all the necessary information at the end of the auction.

time trend, the average standard deviation reduces to 52.83€. Figure 2 compares transactions prices at eBay for standard products as sold in the shop, that is new products without any extras, with the corresponding prices from guenstiger.de, a German price comparison machine. From the graphic it appears as if the guenstiger.de prices built an upper bound to the prices at eBay.[10]

To find out whether and which of the variables have explanatory power for the transaction prices a simple OLS regression is run. The results are displayed in table 5. While most of the coefficients have the expected signs many of them do not prove to be significant. This holds first of all true for many of the cheaper extras such as covers, books, or protective slides. For some other more expensive extras there weren't enough observations to allow for efficient estimation of the parameters. The seller characteristics are also insignificant.[11] The results motivate one to restrict attention to a few of the more influential variables. The results for this "parsimonious" specification are listed in column (2). The change in the R^2 due to this selection is small.

The 788 auctions are won buy 744 different bidders. Only around 6 % of the winners thus buy more than 1 item. Bidders that buy more than one item are in the following regarded as different bidders, that is for the purpose of the regression they receive a new identity. Table 3 reports summary statistics of the bids for the full and the restricted sample. The bids that were placed in the last 10% of the time stem from 1869 different bidders. On average a bidder was active on the market for 7 days (average time between first and the last bid placed in any observed auction within the sample period). The modus is with 2.4 hours much lower. During this time a bidder tried on average in 1.7 different auctions. Table 4 shows the number of trials of a bidder in more detail. 53.37% of the bidders received the object when first

[10]Since I have only a few price observations from the beginning and the end of the period, I can not exclude that heavy price drops as they can be observed in the guenstiger.de data towards the end of the sample period are not an exception but the rule.

[11]When plotting the data it appears that the (insignificant) positive effect is mainly due to a few outliers with a very high reputation. The reason why the effects here are insignificant as opposed to previous work might also stem from measurement error. The reputation variables do not capture the seller's feedback at the time of selling the object but at some later date, when the data was collected.

showing up in the data. That means, however, also, that nearly half of the bidders tried twice or more often. Out of those that tried more often (repeat bidders), 60% tried more then twice, 40% more then three times. Simultaneous bidding in two or more auctions as well as switching back to auctions, that had an earlier closing date, once a bidder is outbid in one auction is rarely observed ($< 4\%$ of the bids).

The data thus shows that repeat bidding plays an important role in this market. This, however, does not mean that it also has an impact on the market outcome. To provide a first answer to this question the transaction price in each auction is regressed on the product and auction characteristics and an indicator for the bidding strategy followed by the winner in that auction. The indicator takes the values 1-9 according to the number of previous trials of a bidder. Regression (2) in Table 5 provides the results. The parameter estimate for the indicator is significantly negative, stating that bidders that try more often pay lower prices.

5 Identification and Estimation Strategy

Proposition 1 builds the basis for estimation:

$$b_{it} = \delta_{it} b_{it}^{+} = \delta_{it}(\gamma_0 + {x_{it}^{+}}' \gamma_1 + \epsilon_{it}^{+} - V_i(v)^{+}) = \gamma_0 + x_{it}' \gamma_1 + \epsilon_{it} - V_i(v)$$
$$\text{with} \quad \delta_{it} = \mathbf{1}_{[c_i - (b_{it} - E_t[b_t^h | b_{it} > b_t^h]) F_t^h(b_{it}) \leq 0]}$$

where a $^{+}$ denotes the corresponding latent variable.

The optimal bid of an entrant is a strictly increasing function of the valuation of a bidder for the product characteristics. The bid distribution therefore identifies these valuations.[12] In order to exploit the panel structure of the data a one-way error component model with $V_i^0 = V_i - \overline{V}$ as the fixed individual specific error part is specified:

$$b_{it} = (\gamma_0 - \overline{V}) + x_{it}' \gamma_1 - V_i^0 + \epsilon_{it}$$

[12]It is not possible to identify the constant parameter γ_0 separately from the part of V that is constant over all individuals ($\overline{V}$).

Proposition 3 *The $\gamma_1 s$ can consistently be estimated by OLS from the within transformed model:*

$$b_{it} - b_{i.} = (x_{it} - x_{i.})'\gamma_1 + e_{it} - e_{i.} \tag{6}$$

with $e_{it} = \epsilon_{it} - E[\epsilon_{it}|\delta_{it} = 1, \delta_{i.} = 1]$.

Proof: Formal proof [TO BE COMPLETED]. Sketch of proof: The selection introduced by the entry decision of bidders does not affect the consistency of the estimators in this model. The first term, that might cause problems is $\delta_{it} V_i(v)^+ = V_i(v)$. However, since $\delta_{it} = 1$ for all entrants this term clearly falls out in the within transformation. When differencing equation 6 and building expectations one obtains:

$$E[b_{it} - b_{i.}] = (x_{it} - x_{i.})'\gamma_1 + E[\epsilon_{it} - \epsilon_{i.}|\delta_{it} = 1, \delta_{i.} = 1]$$

The second term falls out when either $E[\epsilon_{it}|\delta_{it} = 1, \delta_{i.} = 1] = 0$ or $E[\epsilon_{i1}|\delta_{it} = 1, \delta_{i.} = 1] = E[\epsilon_{i.}|\delta_{it} = 1, \delta_{i.} = 1]$ (see Kyriazidou (1997)). The latter is the case here. The intuition is, that the cutoff value for an individual above which she decides to enter an auction is independent of the product characteristics, i.e. the time varying part in the selection equation. The expected return (and the winning probability) only depend on the realization of $u_{it} = \epsilon_{it} - V_i^0$. $\square$

So far it is assumed that all bids are observable. The problem with using data from second price auctions is that the true bid of the winner is not observable, but only a lower bound to it. Usually this lower bound, which is the transaction price and equals the bid of the second highest bidder, is the only observation one has. In order to identify the correct distribution underlying the data generation process, the empirical auctions literature exploits the fact that the observed bids constitute draws from the distribution of the second highest order statistic. Knowledge of the distribution of an order statistic however allows to infer the underlying parent distribution. This approach requires the number of interested bidders n as an input. Since entry into an eBay auction is assumed to be costly not all bidders will enter, and therefore this number is not available. A nice identification result is due to Song (2004). She shows that a parent distribution is (nonparametrically) identified from two order statistics without needing to know n.[13]

The problem with this approach is that it ignores the dependency that exists between different bids of the same bidder. The likelihood contribution of an auction in Song (2004) is given by the conditional distribution of the second and the third order statistic conditional on the third order statistic. The full likelihood is the product of the auction specific likelihoods and therefore does not take account of individual specific effects. This generates an inefficiency. At this stage it seems impossible to jointly take care of individual specific effects and the dependency between the order statistics in one auction. The problem is that the likelihood requires computation of an integral whose dimension is the number of bidders in the panel. An alternative correction for the winning bid is, however, possible. In the data description it could be seen that the prices from guenstiger.de build an upper bound to the prices at eBay. If one assumes that a bidder always prefers to buy at guenstiger.de when the prices are equal, the guenstiger.de prices can be used as an upper bound to the unobserved winning bids. By this imputation method it is possible to find bounds for the parameter values. While the specification that uses transaction prices for the unobserved winning bids builds a lower bound, the one that uses the guenstiger.de prices builds an upper bound.

Another reason why one might be reluctant to exploit information from the ordering of the bids is due to another kind of selection that has been shortly addressed before. If a bidder's strategy was only guided by the behaviour described in section 3, she would stay out of those auctions in which her draw of ϵ is low. Therefore the bidders with the k highest draws of u_{it} would enter. The order of the entrants would not be affected by this kind of selection, that is the econometrician would be sure which order statistics he observes. If bidders on the other hand stay out of some of the auctions because they know from past auctions that they have no chance of winning, given that there are other bidders with presumably very high search costs currently in the market, the observed ordering does not necessarily reflect the true

[13] This result is easily extended to allow for the inclusion of more order statistics, since any conditional distribution of k order statistics conditional on the lowest of the k order statistics is independent of n. Including more observations should increase the efficiency of the estimates.

ordering. To see why, take the example of three bidders, that compete in an auction in t. While one of them wins and exits, the other two face the decision whether to participate in the next auction in t+1. Let bidder 2 be the bidder with the second highest bid, bidder 3 the one with the third highest bid. Assume that bidder 3 stays out because he thinks his chances of winning are too low to justify the costs, given that bidder 2 is in the market. Bidder 2 enters and bids against the two new entrants (bidder 4 and 5).[14] Assume bidder 5 has the highest draw of u and wins. If the bid of bidder 4 is above that of 2 the observed ordering is equal to the true ordering. If it is lower, it might however be that bidder 3, who stayed out of the auction has a higher draw of u_{it}. The econometrician then would observe the 2nd and 4th highest draws. The data shows that bidders do not participate in every auction in a row. Additionally their decision to enter is influenced by the position of their bid in the last lost auction. The more others had higher bids the longer they wait before re-entering a new auction. Estimating from the wrong order statistics increases the variance of the estimated parent distribution and biases its mean.

Given parameter estimates for product characteristics, the search costs can be estimated in a second step from equation (5) using the estimates obtained in the first step to construct the average expected bid. The average product characteristics are obtained from their sample means. By weighting the average characteristics with the before estimated coefficients and subtracting the bidder specific mean an estimate of the expected optimal bid is obtained for each bidder. Note, that with this method the costs of the participants and not those in the full population of interested bidders are estimated. [TO BE COMPLETED]

6 Results

Table 6 reports the results from the different panel specifications. Column (1) lists the parameter estimates when the winning bid is approximated by the transaction

[14]It does not matter whether these two are fully new bidders or some that decided to re-enter after abstaining from bidding for a while. The important point is, that they do not know who is in the market and therefore base their entry decision on expected values.

price. This represents a lower bound to the true bid. The specification in column (2) uses the corresponding guenstiger.de prices instead. these represent an upper bound to the true bids.

In both specifications the parameters have the expected signs. Additionally the relative importance of the different characteristics is in line with what would be expected. While the parameters of the second specification are higher, as expected, it cannot be said that they are statistically different from those in the 1st specification. [TO BE COMPLETED]

Figure 5 shows the distribution of bidding costs for specification (1). The mean costs are 11.84€. The 25 50 and 75% quantiles are: 3.79, 8.46 and 16.76€. [TO BE COMPLETED]

7 Conclusion

The paper presented a dynamic framework for the eBay market place, similar to a search model. It was shown that standard panel methods can be used to consistently estimate demand from bidding data.

A number of issues remains for future research. First of all, the seller side is so far not modelled explicitly. Further, the theoretical model assumed that in every instant a new auction opens and bidders do not care whether the time difference between the auctions is smaller or bigger. Including parameters for the degree of competition from other auctions into the theoretical model would be desirable.

Secondly, when deriving the theoretic model it was assumed that the distribution of second highest bids is exogenously given. Relaxing this assumption could lead to more sophisticated dynamic strategies, which include predation and strategic non-participation.

Finally, the error terms obtained from the panel estimation display autocorrelation. This lets to assume that there is some more complicated story behind the data generation process. While here it was assumed, that bidders exactly know the distribution of second highest bids, Sailer (2004) allows for the possibility of learning about a parameter of the distribution.

References

Albrecht, James W. and Bo Axell, "An Equilibrium Model of Search Unemployment," *Journal of Political Economy*, October 1984, *92* (5), 824–40.

Athey, Susan and Philip A. Haile, "Identification of Standard Auction Models," *Econometrica*, November 2002, *70* (6), 2107–40.

Bajari, Patrick and Ali Hortacsu, "The Winner's Curse, Reserve Prices, and Endogenous Entry: Empirical Insights from eBay Auctions," *RAND Journal of Economics*, Summer 2003, *34* (2), 329–55.

Bremzen, Andrei, "Sequential Auctions with Entry Deterrence," *mimeo*, 2003, (November).

Burdett, Kenneth and Dale T. Mortensen, "Wage Differentials, Employer Size, and Unemployment," *International Economic Review*, May 1998, *39* (2), 257–73.

Caillaud, Bernard and Claudio Mezzetti, "Equilibrium Reserve Prices in Sequential Ascending Auctions," *mimeo*, 2003, (May).

Diamond, Peter, "A Model of Price Adjustment," *Journal of Economic Theory*, 1971, *3*, 156–168.

Hong, Han and Matthew Shum, "Can Search Costs Rationalize Equilibrium Price Dispersion in Online Markets?," *mimeo*, 2003, (May).

Houser, Dan and John Wooders, "Reputation in Auctions: Theory, and Evidence from eBay," *University of Arizona Working Paper*, 2001, (00-01).

Kyriazidou, Ekaterini, "Estimation of a Panel Data Sample Selection Model," *Econometrica*, November 1997, *65* (6), 1335–64.

Laffont, Jean Jacques and Quang Vuong, "Structural Analysis of Auction Data," *American Economic Review*, May 1996, *86* (2), 414–20.

Lucking-Reiley, David, Doug Bryan, Naghi Prasad, and Daniel Reeves, "Pennies from eBay: the Determinants of Price in Online Auctions," *mimeo*, 2000, (January).

Riley, John G. and William F. Samuelson, "Optimal Auctions," *American Economic Review*, June 1981, *71* (3), 381–92.

Rob, Rafael, "Equilibrium Price Distributions," *Review of Economic Studies*, July 1985, *52* (3), 487–504.

Roth, Alvin E. and Axel Ockenfels, "Last-Minute Bidding and the Rules for Ending Second-Price Auctions: Evidence from eBay and Amazon Auctions on the Internet," *American Economic Review*, September 2002, *92* (4), 1093–1103.

Sailer, Katharina, "Searching and Learning at eBay," *mimeo*, 2004, (February).

Song, Unjy, "Nonparametric Estiamtion of an eBay Auction Model with an Unknown Number of Bidders," *mimeo*, 2004, (January).

Sorensen, Alan T., "An Empirical Model of Heterogeneous Consumer Search for Retail Prescription Drugs," *NBER Working Paper*, October 2001, *8548.*

van den Berg, Gerard J. and Geert Ridder, "An Empirical Equilibrium Search Model of the Labor Market," *Econometrica*, September 1998, *66* (5), 1183–1221.

von der Fehr, Nils Henrik Morch, "Predatory Bidding in Sequential Auctions," *Oxford Economic Papers*, July 1994, *46* (3), 345–56.

Weber, Robert J., "Multiple-Object Auctions," in Paul Klemperer, ed., *The economic theory of auctions*, VOL 2, Cheltenham, UK and Northampton, MA: Elgar, 2000, pp. 240–66.

yi Wang, Joseph Tao, "Is Last Minute Bidding Bad?," *mimeo*, 2003, (September).

8 Appendix

Proof of Proposition 1:

Participation Constraint: A bidder enters an auction when the expected return form participating is higher then the return from waiting to the next auction:

$$E[\mathbf{1}^*_{it,win}\left(v_{it} - b^h_t\right)) - c_i + \mathbf{1}^*_{it,lose} V_i] \geq V_i$$

Rearranging and taking expectations gives:

$$(b^*_{it} - E_t[b^h_t | b^*_{it} > b^h_t]) F^h_t(b^*_{it}) \geq c_i.$$

Optimal Bid: The decision problem of an entering bidder, given other bidders' optimal strategies follows from equation (4):

$$V_{it} = \underset{b_{it}>0}{max} E\left[\mathbf{1}_{it,win}\left(v_{it} - b^h_t\right) - c_i + \mathbf{1}_{it,lose} V_i\right]$$

Rearranging and taking expectations gives:

$$V_{it} = \underset{b_{it}>0}{max}\left(\int_{\underline{v}}^{b_{it}} \left(v_{it} - V_i - b^h_t\right) dF^h_t - c_i + V_i\right)$$

The FOC is derived by applying Leibniz's rule.

$$\frac{\partial V_{it}}{\partial b_{it}} = (v_{it} - V_i - b_{it}) f^h_t(b_{it}) = 0$$

$$\Leftrightarrow b_{it} = v_{it} - V_i.$$

Optimality Condition: Substituting the optimal bid $b^*_{it} = v_{it} - V_i$ back into the Bellman equation gives:

$$c_i = F^h_t(b^*_{it})(b^*_{it} - E_t[b^h_t | b^*_{it} > b^h_t]) - V_{it} + V_i.$$

Since $V_{it} - V_i$ is equal to $F^h_t(b^*_{it})(b^*_{it} - E_t[b^h_t | b^*_{it} > b^h_t]) - F^h(b^*_i)(b^{0*}_i - E[b^h | b^*_i > b^h])$, (8) can also be expressed as a function of the expected optimal bid in the future, b^*_i, which is constant over time:

$$c_i = F^h(b^*_i)(b^*_i - E[b^h | b^*_i > b^h]).$$

$\square$

Figure 1: Distribution of Transaction Prices over Time

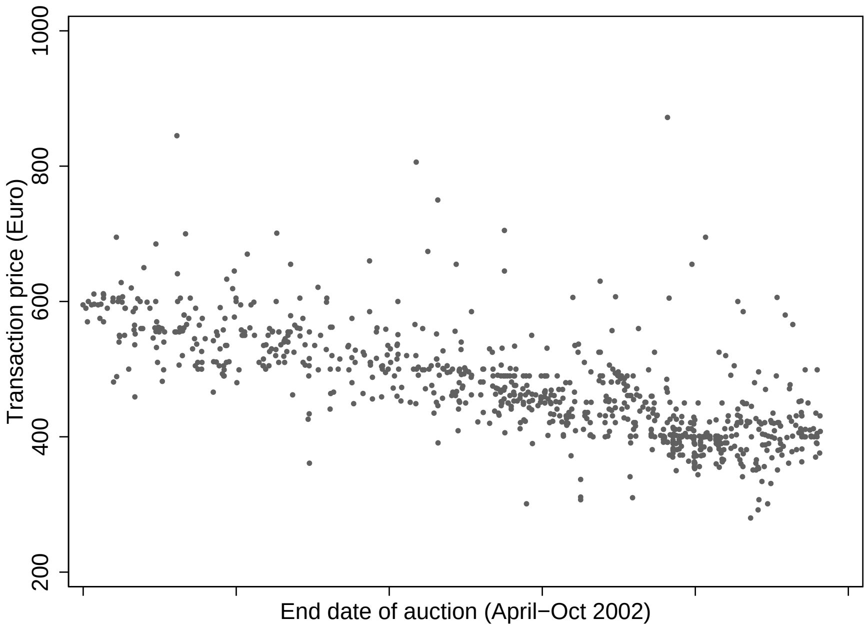
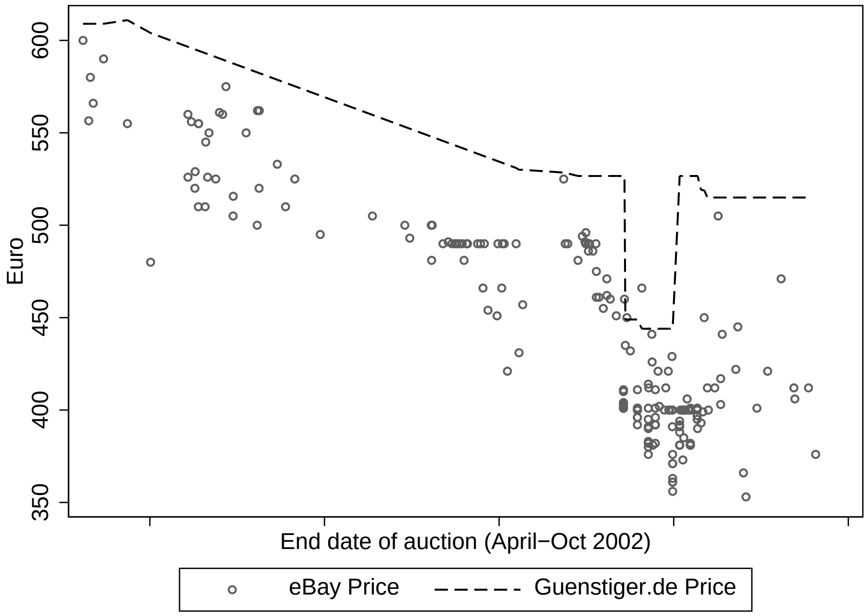


Figure 2: Distribution of Transaction Prices for New Products*



* The data from guenstiger.de comprises 11 different observations for April and May and 12 observations from September to November 2002, two of which are considerably lower then the others.

Figure 3: Frequency Distribution of Bids: All Bids

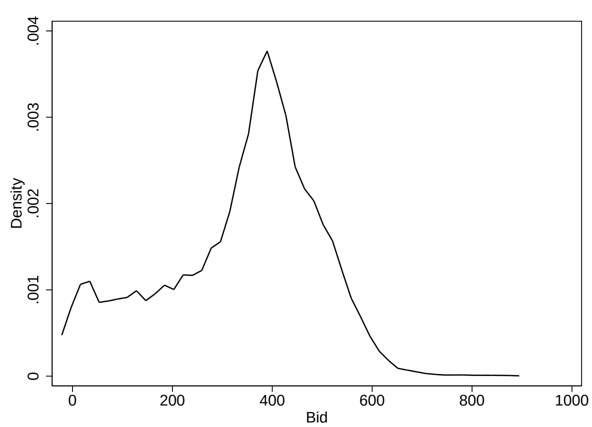
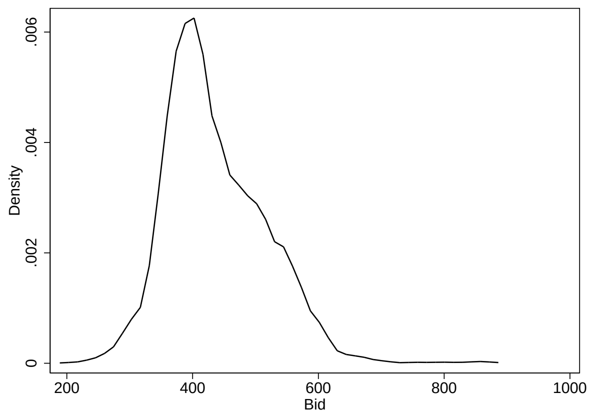


Figure 4: Frequency Distribution of Bids Submitted in the last 10% of an Auction.*



*Kernel density.

Figure 5: Distribution of Bidding Costs

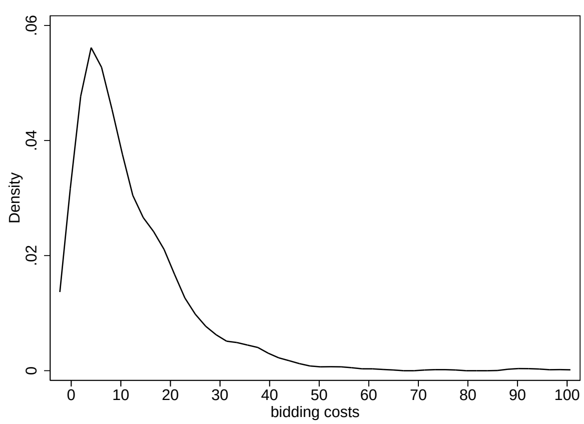


Table 1: Variables Used in Regression

Category	Variable	Description
Product Quality	OVP	1 if in original packing (unopened) .
	AGE/AGE_NS	Age in days as stated by the seller/1 if the age is not mentioned in the description.
	COND_NEW/ COND_USED	Condition is said to be new/used (as opposed to average condition)
	OS_ENGL/OS_FRENCH	1 if english/french operating system.
	DEFECT1-4	1 if product comes without bill (1), lacks standard accessory (2), has scratches on the display (3) or other defects (4).
Additional Accessories	EXTRAS	1 if the product comes with any additional extra.
	JACKET1-5	1 if with PC Card Jacket (1), CF Card Jacket (2), Dual Slot Jacket (3), Bluetooth Jacket (4), GSM/GPRS Jacket (5).
	HARDDISK	1 if with external memory in form of Toshiba 1GB harddisk.
	NAVIGATION	0, 1, or 2 depending on the scope of the included navigation system.
	MEMORY	Amount in MB of external memory in form of CF, SD, or MMC card(s).
	CAREPAQ	0, 1, 2, or 3 depending on the scope of the additional producer warranty.
	Other extras: Dummies for book, cover, earplugs, keyboard, modem, protective slides, software, synchronization and charge cable.	
Seller Characteristics	PROFI	1 if the seller gave a link to an own shop outside eBay.
	REP_POS_REL	Percentage of positive eBay feedback scores.
Other	TREND	Linear time trend
	SHIPPING/ SHIPPING_NS	Shipping costs as stated by the seller/ 1 if shipping costs are not specified.

Table 2: Summary Statistics of Auctions

	Full sample	**Restricted sample**
No. of auctions	1212	788
No. of unsuccessful auctions	182	
No. of private auctions	174	
No. of auctions with last bidding activity earlier then 10% before end of auction	68	
Mean transaction price	476.9€	469.93€
Min-max	280€ - 999€	280€ - 872€
Standard dev.	79.07€	78.34€
Average shipping costs	7.2€	7.2€
Used products	59.08%	79.32%
Products with add. accessories	25.91%	32.49%
Products with defects	9.49%	4.06%
Products with foreign operating system	3.22%	3.43%
Auctions sold by professional sellers (PROFI=1)	10.73%	1.27%
Average no. of parallel auctions	42	37
Average distance between auctions	4.5 hours	4.8 hours
Average number of bidders per auction	6.86	9

Table 3: Summary Statistics of Bidders

	Full sample	**Restricted sample**
Number of bids	7630	3202
Number of individual bidders	3829	1869
Av. number of auctions a bidder participated in	2	1.7
Rel. importance of ”switching back”*.	9.72 %	3.1 %
Rel. importance of ”simultaneous bidding”.**	10.13 % (12.6 %)	3.6 % (4.9 %)
Time a bidder is observed in the sample:		
Mean	5.65 days	7.15 days
Quantiles (25 50 75)	0min 5.6min 1.89 days	0min 2.44hrs 3.98 days
Bids:		
Mean/max-min/std. dev	334.35€ /1€ -827€ /155.39€	437.9€ /203€ - 872€ /78.73€
Av. std. dev. per bidder	52.21€	27.13€

* Percentage of bids, that were placed by a bidder in an auction t after she was outbid in auction t+1. **Percentage of bids, that were placed by a bidder while she had still a standing bid in another auction.

Table 4: Frequency of Trials

	Full Sample			Restricted Sample		
# of trial	Freq.	Percent	Cum.	Freq.	Percent	Cum.
1	2,505	65.44	65.44	966	53.37	53.37
2	603	15.75	81.19	318	17.57	70.94
3	285	7.45	88.64	196	10.83	81.77
4	152	3.97	92.61	110	6.08	87.85
5	92	2.4	95.01	66	3.65	91.49
6	49	1.28	96.29	38	2.1	93.59
7	36	0.94	97.23	28	1.55	95.14
8	19	0.5	97.73	13	0.72	95.86
9	15	0.39	98.12	12	0.66	96.52
10	12	0.31	98.43	10	0.55	97.07
11	9	0.24	98.67	8	0.44	97.51
12	6	0.16	98.82	6	0.33	97.85
13	7	0.18	99.01	7	0.39	98.23
14	3	0.08	99.09	2	0.11	98.34
15	9	0.24	99.32	8	0.44	98.78
>16	26	0.74	100.00	23	1.25	100.00
Total	3,828	100.00		1,810	100.00	

Table 5: OLS Estimates*

	(1)	(2)	(3)
TREND	-.869 (.021)***	-.871 (.021)***	-.866 (.021)***
#TRIAL			-3.116 (.643)***
OVP	4.229 (2.986)		
AGE	-.088 (.024)***	-.083 (.022)***	-.076 (.021)***
AGE_NS	-23.946 (3.514)***	-24.621 (3.435)***	-22.758 (3.414)***
COND_NEW	10.838 (3.721)***	12.649 (3.245)***	13.33 (3.276)***
COND_USED	-11.206 (3.647)***	-12.413 (3.527)***	-12.288 (3.514)***
OS_ENGL	-15.892 (9.646)*	-19.31 (9.31)**	-15.202 (8.96)*
OS_FRENCH	-81.218 (24.916)***	-78.768 (20.276)***	-81.293 (19.863)***
DEFECT1	-19.115 (6.037)***	-17.579 (6.158)***	-18.878 (6.07)***
DEFECT2	-41.72 (12.115)***	-47.549 (12.606)***	-48.661 (12.509)***
DEFECT3	-12.575 (8.219)		
DEFECT4	-46.348 (11.761)***	-52.917 (11.286)***	-46.439 (21.057)**
SHIPPING	-1.604 (.574)***	-1.193 (.63)*	-1.263 (.635)**
SHIPPING_NS	-9.357 (4.935)*	-9.776 (5.294)*	-11.105 (5.253)**
EXTRAS	2.181 (4.491)	8.158 (3.391)**	8.031 (3.369)**
JACKET1	50.486 (18.484)***	50.312 (17.543)***	51.346 (19.516)***
JACKET2	.261 (9.788)		
JACKET3	97.133 (26.099)***	90.227 (27.387)***	91.755 (29.791)***
JACKET4	14.192 (13.79)		
JACKET5	158.819 (33.052)***	178.129 (21.457)***	177.899 (20.909)***
MEMORY_ALL	.499 (.082)***	.478 (.075)***	.484 (.074)***
HARDDISK	93.242 (11.744)***	93.444 (10.406)***	96.566 (13.46)***
NAVIGATION_NS	141.599 (20.853)***	144.2 (19.482)***	141.239 (19.666)***
CAREPAQ	16.515 (4.729)***	20.102 (8.217)**	19.973 (7.952)**
MODEM	38.001 (56.563)		
KEYBOARD	23.531 (14.904)		
EARPLUGS	3.549 (11.696)		
PROTECT	.383 (.86)		
COVER	1.352 (1.72)		
BOOK	-11.706 (14.439)		
SOFTWARE	8.152 (5.19)		
CABLE_ETAL	-8.9 (9.45)		
REP_POS_REL	8.957 (23.487)		
URL	23.294 (16.159)		
OBS	745	787	787
R^2	.811	.798	.8
adj R^2	.801	.793	.795

* White heteroscedasticity robust estimation.
Standard errors in parenthesis (marked confidence levels: 90, 95, 99).

Table 6: Panel Estimates

	(1)	(2)
TREND	-.499 (.067)***	-.274 (.091)***
AGE	-.065 (.013)***	-.069 (.018)***
AGE_NS	-14.188 (2.857)***	-13.459 (3.849)***
COND_NEW	15.154 (2.364)***	15.394 (3.186)***
COND_USED	-5.188 (2.185)**	-5.922 (2.945)**
OS_ENGL	-15.106 (5.096)***	-5.113 (6.867)
OS_FRENCH	-84.502 (13.159)***	-71.142 (17.73)***
DEFECT1	-13.557 (6.25)**	-20.389 (8.421)**
DEFECT2	-31.524 (7.293)***	-33.587 (9.827)***
DEFECT4	-22.739 (14.285)	-37.668 (19.248)*
SHIPPING	-.505 (.468)	-.568 (.631)
SHIPPING_NS	-4.808 (3.657)	-7.711 (4.928)
EXTRAS	5.179 (2.117)**	4.291 (2.852)
JACKET1	38.881 (7.042)***	50.005 (9.488)***
JACKET3	114.604 (17.287)***	81.097 (23.292)***
JACKET5	127.888 (12.952)***	130.943 (17.452)***
MEMORY	.255 (.027)***	.24 (.036)***
HARDDISK	97.203 (7.324)***	105.875 (9.869)***
NAVIGATION	163.582 (16.264)***	138.283 (21.914)***
CAREPAQ	13.975 (3.675)***	17.568 (4.951)***
CONSTANT	444.106 (4.134)***	457.369 (5.57)***
OBS	3202	3202
R^2	.6694	.4865
σ_{V^0}	50.304	61.162
σ_ϵ	28.854	38.878