

Willingness to Pay and Competition in Online Auctions

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Abstract

We model how to measure consumer willingness to pay (WTP) from an English or ascending first-price auction based on two general bidding premises: no bidder bids more than her WTP, and no bidder allows a rival bidder to win at a price that she is willing to beat. In other words, we propose a “no regret” rule in bidding. Other than that, we do not impose restrictive assumptions on maximands or behavior of bidders in a competitive auction context. We postulate WTP as having two components: a pure product feature component and one based on the auction market environment. The latter includes bidder experience, seller reputation, and competition among bidders and among items. The proposed model is general enough to include “buy it now” (BIN) (equivalent to a posted price) auction mechanism.

We use data of notebook auctions from one of the largest Internet auction sites in Korea. We find that most product characteristics matter in the expected ways. Our other primary findings are as follows: (1) The difference in WTP of used versus new laptops is consistent with a lack of lemons problem; (2) Compared to neutral seller reputation, positive seller reputation matters more for WTP than negative seller reputation; (3) More extensive site-surfing and bidding histories lead to lower WTP, implying that search costs and experience matter in bidding; (4) WTP declines as more similar items are concurrently listed with the focal item; there is an additional effect if these similar items also belong to the same brand. Therefore, market thickness matters for consumer WTP. As specific substantive benefits, we demonstrate how sellers can calculate changes in WTP, and hence the expected revenue, as the number of concurrently available similar items varies.

1. Introduction

Auctions on the Internet are a booming enterprise. From a managerial perspective, two recent trends are worth noting. First, the auction market appears to have matured enough that managers are beginning to ask whether auction data can be used to estimate consumer valuations for various products. Second, there is a growing interest in understanding the impact of competition among auction items on bidder behavior. These two managerial concerns form the core research questions of our paper.

Turning to the first question of measuring valuations, “For years, eBay Inc. has let its users buy and sell almost anything. Now it wants to become the blue book for just about everything ... Recently, eBay stepped up the program with two deals that show how the San Jose, Calif., company’s data could end up as the basis for guides used to determine fair market prices for items that may never be purchased or sold on the site itself ... eBay is making the push at a time with its site has grown monstrously large, with enough auctions of items across various categories that the company says it can provide representative market prices” (*Wall Street Journal*, December 8, 2003). Therefore, it is important to study whether auction data can be used to infer consumer valuation. We believe there are three major issues to be resolved in answering this question: (1) How to separate out the impact of auction market environment from pure product-based consumer valuation; (2) How to make the estimation of consumer valuation robust to alternative assumptions of bidder maximands, equilibrium-generating processes; (3) How to capture the heterogeneity of bidders and auction items in estimating consumer valuation. We address each of these below.

We measure consumer valuation by estimating consumer willingness to pay (WTP). This is defined as the maximum amount a bidder is willing to bid for an item such that, she is

indifferent between winning the item at this bid and not winning. We emphasize that WTP is not just a consumer's intrinsic value about the product; instead, it cannot be separated from market environment in online auctions. In markets with perfect competition, each producer faces perfectly elastic market demand. As Rosen (1974) pointed out, in such markets "competition prevails because single agents add zero weight to the market and treat prices ... as parametric to their decisions." Given identification conditions such as sufficient heterogeneity of cost function among producers, WTP can be formulated solely as a function of product features. However, online auction markets are unlikely to satisfy the assumptions of perfect competition outlined above if there are few bidders and few sellers, and each of whom can influence the final winning bid by their presence and strategy adopted. That is, each of these players does not "add zero weight" in determining final prices. Therefore, modeling WTP purely based on product features is incomplete; WTP needs to include the impact of the competition among auction items and how that might interact with the evaluation of product features.

Additionally, unlike auction environments typically studied in economics, e.g., forest timber auctions in Haile and Tamer (2003) and highway construction contracts in Jofre-Bonet and Pesendorfer (2003), bidder experience and search costs for bidding and seller reputation are likely to influence WTP in online auction marketplace (see also Hendricks *et al.* 2003). These bidder and seller characteristics matter to each bidder in forming her expectation of other bidders' and sellers' behavior and therefore, her own maximum WTP for any item. Therefore, WTP in online auctions is likely to be a function of the auction market environment defined as including a measure of competition among bidders and items, as well as accounting for bidder and seller characteristics, etc.¹

¹ Behavioral literature in marketing, psychology and economics has documented that contexts influence consumer decision-making (e.g., Ariely and Simonson 2003; Dholakia and Soltysinski 2001; Kamins *et al.* 2004; see also

In our model we incorporate how competition among listed items affects the distribution of WTP in two (interrelated) ways. First, we provide controls for the presence of other bidders in WTP estimation, including both observed bidders in an auction and allowing for the presence of “latent” bidders who might be following the bidding process but do not submit any bid. Second, we model competition among auction items by constructing a set of market thickness measures. These measures are “breadth” (how many items similar to the focal item in product attributes are on sale concurrently) and “depth” (how many of those similar items also of the same brand as the focal items are on sale concurrently). Both these controls for competition among bidders and items are relatively unexplored in the literature. We also provide controls for bidder and seller characteristics that might affect WTP.

A potential benefit of decomposing auction-independent and auction-dependent WTP components is that auction data can be used to obtain WTP among consumers in non-auction markets. In doing so, consider the following view of Sun Microsystems “We suspect ... the customers we’d attract at eBay are not the people attracted by the channel, i.e., the network of independent companies that usually sell Sun equipment” (CNET News.com, Dec 16, 1999). By additionally controlling for possible self-selection of consumers in the auction market, measures of pure product valuation from WTP can be an important step towards addressing more general questions.

The next set of issues in WTP estimation are the assumptions of bidder maximand and equilibrium behavior; the importance of these issues is evident in the emerging literature of estimating WTP from auction data. Almost all existing empirical papers (e.g., Donald and Paarsch 1996; Guerre, Perrigne and Vuong 2000; Laffont, Ossard and Vuong 1995) rely on

references cited therein). The economic constructs of search costs, reputation and market thickness, etc. that we use in the paper to model WTP can easily be interpreted through the lens of context-dependent decisions.

theoretical assumptions of auction behavior and equilibria. As Rezende (2003) argues, these papers characterize carefully how the equilibrium assumptions help econometric identification (e.g., assuming symmetric bidders).

There are several reasons why the task of inferring consumer WTP by imposing equilibrium assumptions on bidding data is not appropriate (see Bajari and Hortaçsu 2004 for a detailed discussion). First, there appears to be no theoretical and/or empirical work that addresses in a fully structural equilibrium model the issue of multiple auctions being open at the same time and of “buy it now” (BIN) or a posted price option, a very important feature of online auctions. BIN price in our setting is the price at which the item can be bought at any time during the auction.² There is a further complication in inferring the WTP from observed bids of English auctions. The highest bid by a bidder does not accurately measure her maximum WTP, but is more likely to reflect the level of competition among bidders and sellers. The bid amount might be seen as providing a lower bound for WTP rather than being equal to maximum WTP. This is a different setting from the “button” auctions where all bidders participate in the auction till the bid price is higher than their WTP, and the winner pays a marginal amount over the second highest WTP (see Milgrom and Weber 1982). Additionally, without making restrictive assumptions of bidding behavior, the winning bid amount of an English auction item may not be equivalent to the second-highest WTP among all bidders.³

To get around the above obstacles, we rely on very general equilibrium-generating assumptions, i.e., our WTP formulation is consistent with a variety of strategic/non-strategic behaviors and maximands used by bidders and sellers. Our model is consistent with the outcome

² The BIN option at the auction site considered here remains in the auction process as long as it is not exercised, which is similar to the Yahoo! version but different from the eBay version. In the latter, the BIN option is no longer available to bidders after the first bid is placed.

³ Note especially that theoretical models of auctions do not take in to account auction market environment variables. This makes it harder for us to speculate on the possible relationship between winning bid and second-highest WTP.

of utility maximization for bidding behaviors conditional on WTP, but we capture the effects of competition environments, bidders' and sellers' experience, etc. on WTP using reduced-form. Given the lack of theory to guide us, our model's general behavioral assumptions allow the data to infer the distribution of WTP and the impact of various variables on WTP.

The third and final issue in using auction data to model WTP is how to model heterogeneity among bidders and auction items. In modeling WTP, it is logical to use the richness of information available from behavior of various bidders within an auction and across auctions. There are some important requirements for modeling WTP using such data: (1) The estimation needs to allow for heterogeneity of bidder preferences for product characteristics; (2) The estimation also needs to allow for heterogeneity in how bidders are influenced by the market environment (see Rezende 2003 for further discussions). We model this by interacting bidder demographics and experiences, and other variables of auction market environment in the hedonic WTP estimation. As a comparison point, we note that much of the empirical literature so far has focused on building structural models of equilibrium process with symmetric bidders (e.g., Hendricks *et al.* 2003). Hong and Shum (2003) is an exception in that they have asymmetric bidders in a structural equilibrium process model.

Summarizing, we estimate a model of WTP accounting for auction market environment (including modeling latent bidders and market thickness), a model that is robust to assumptions about bidder behavior and equilibrium-generating processes and to concerns of heterogeneity in bidders and items. We estimate our model on auction data for notebook computers from a leading Internet auction site in Korea. To anticipate the major results, we find that most product characteristics matter in the expected ways. Our other primary findings are as follows: (1) The difference in WTP of used versus new laptops is consistent with a lack of lemons problem; (2)

Compared to neutral seller reputation, positive seller reputation matters more for WTP than to negative seller reputation; (3) More extensive site-surfing and bidding histories lead to lower WTP, probably implying that search costs and experience matter in bidding; (4) WTP declines as more similar items are concurrently listed with the focal item; there is an additional effect if these similar items also belong to the same brand. Therefore, market thickness matters for consumer WTP. As specific substantive benefits, we demonstrate how sellers can calculate changes in WTP, and hence the expected revenue as the auction setting varies.

The rest of the paper is organized as follows. Section 2 describes our data of online auctions. In section 3, we present our estimated model. In section 4, we apply the proposed model to notebook auctions and discuss results, demonstrate a way to understand the impact of market thickness on WTP and contrast our model with an alternative model (button auctions of Milgrom and Weber 1982). We discuss other managerial implications of this research and conclude with directions for future research in section 5.

2. Data description

The data are for notebook auctions from one of the largest Internet auction sites in Korea for the time period of July 2001 to October 2001. The site uses an ascending first-price auction or English auction in which the highest bidder wins and pays her bid. The database contains information on the complete history of bids, features of auction design set by the seller, bidder and seller characteristics, and product specifications of auction items. We focus on notebook auctions for the sale of a single item. The total number of notebook auctions considered here is 2322 items and the total number of bids across all the auctions is 21952. On average, there are about 6.5 unique bidders (each of whom can bid multiple times). All bids are in Korean

currency (won), where 1200 won corresponds approximately to \$1. The average final selling price is \$1077.39

In addition, there are five auction design variables: placement (yes or no) of product images or pictures, minimum bid amount (also called a “public” reserve price), BIN option and its price (a posted price which allows bidders to prematurely end an auction by exercising an option to buy the item), and auction duration.

Sellers on this auction site are rated by winning bidders. The rating is in the form of a positive, negative or neutral response after each auction is completed. The database only maintains the cumulative records of these responses at the start of the data time period. We also have information on bidder characteristics. The variables are demographics (e.g., age and gender) and behavioral characteristics including the cumulative page views, bids and wins, and the cumulative expenditures across all product categories. The auction site also keeps only the cumulative information on these variables at the start of the data period. Therefore, these variables are also static in our database, again as of July 2001.

Finally, the data include product characteristics for each auctioned item. These variables are CPU type (Pentium or Celeron), CPU speed, memory, hard disk, screen size, brand name, and the number of months that the auction item has been used by the seller (0 for a brand-new item). There are three American, three Japanese, and three Korean major brands, which account for about 29%, 14%, and 45% of the 2322 items, respectively. All of the rest of the brands, which we aggregated and grouped into a category “others”, account for 12% of the items. Table 1 reports summary statistics of each of these variables described in this section. These variables, along with constructed variables for market thickness to be described, will serve as explanatory variables for estimating WTP.

----- Insert Table 1 about here -----

3. The Model

We infer consumer WTP from bid amounts. We use the maximum bid amount of each bidder because previous bids by bidders carry less information on their maximum willingness to pay. Below, we first explain the relationship between bid amounts and WTP based on the two general bidding premises (Haile and Tamer 2003). We then parameterize WTP function and conclude the section with the discussion of identification conditions.

3.1 The relationship between bids and WTP

In an ascending first-price auction, observed bid amounts need not be equal to the true WTP of bidders. Consider two bidders (bidder 1 and bidder 2) in an auction not designed with the BIN option or an auction designed with BIN but the BIN option not exercised. We observe bidder 2 bids b_2 , and bidder 1 bids b_1 later and wins the auction (see panels A and B in Figure 1). We can infer that bidder 2's WTP (WTP_2) is between b_2 and b_1 . Otherwise, bidder 2 will not allow bidder 1 to win the auction at bidding price b_1 . In addition, bidder 1's WTP (WTP_1) is greater than b_1 . Otherwise bidder 1 will not bid this amount.

----- Insert Figure 1 about here -----

Turning our attention to an auction designed and exercised with BIN (see panel C in Figure 1), we note that bidder 2's WTP could be higher than the BIN price. In particular, bidder 2 might have lost because she did not exercise the BIN option earlier than bidder 1 did, and not because her WTP is inherently lower than the BIN price. In this case we can only infer that bidder 2's WTP is higher than b_2 and bidder 1's WTP is higher than the BIN price.

Finally, the relationship between bid amounts and WTP becomes complicated if we allow the existence of some bidders who follow the bidding process but do not submit any bid for various reasons (to be described later). Specifically, suppose bidder 3 who does not submit for the focal item and let bidder 1 wins the auction at the bidding price b_I (see panel D in Figure 1). Since bidder 3 follows the process and does not submit the bid, we can only infer that her WTP is lower than b_I , but it can be anywhere within the range. We call these bidders as latent bidders described in section 3.2 below.

Similar to Haile and Tamer (2003), we infer WTP on two behavioral premises; these assumptions are able to accommodate latent bidder behavior and the presence of BIN auctions as well. We impose no structural assumptions of maximands or strategies employed by bidders in a competitive auction marketplace. Both behavioral assumptions hold for the observed bidders in any auction.

1. Bidders do not bid more than they are willing to pay.
2. Bidders do not allow an opponent to win at a price they are willing to beat.⁴

Let us formalize these ideas. Let W_{ij} be the WTP of bidder i in auction j . First assume the number of bidders is known for each auction, which will be relaxed next. Denote $N_j \geq 1$ be the number of latent bidders and n_j be the observed number of bidders in auction j . Without loss of generality, let bidder 1 be the winner. We know for this bidder that her WTP is lower-bounded by the winning bid. For all other bidders, the WTP has a lower bound of their own bids and an upper bound of the winning bid. That is, if their WTP exceeded the highest bid, they would have come in and bid higher. In other words, based on assumptions 1 and 2, we have

⁴ A potential issue in this bidding premise might be the fact that bidders may run out of time in bidding, and the resulting impact on their strategic behavior (e.g., Ariely *et al.* 2002; Roth and Ockenfels 2002). The auction site considered in this research uses a “soft ending time” rule that is similar to Yahoo! auctions. Therefore, the issue of bidders running out of time and the impact of this on their bidding behavior is less of an issue for us.

$$W_{1j} \geq b_{1j}, \tag{1}$$

for bidder 1, and

$$b_{ij} \leq W_{ij} \leq b_{1j}, \tag{2}$$

for bidders 2, ..., n_j . For auctions where a BIN price is stated and exercised by a bidder (i.e., winner), condition (1) holds. For bidders 2, ..., n_j , we have a less restrictive condition

$$W_{ij} \geq b_{ij}. \tag{2'}$$

The above bidding rules are consistent with utility maximization framework under general conditions.⁵ They are also robust on various bidding behaviors. For example, they are applicable to the “button” model (Milgrom and Weber 1982), or the “alternating recognition” auction (Harstad and Rothkopf 2000). For detailed discussion see Haile and Tamer (2003). They also satisfy the necessary conditions of naïve incremental bidding and the “jump” bidding behavior, where bidders may bid more than the minimum required increment on the current outstanding bid, since the rules allow any incremental amount in bidding, as long as the valuation exceeds the current outstanding bid plus the increment. Note though that despite the flexibility in bidding strategy in our model, behavioral assumptions (1) and (2) above imply “no regret” in biddings. That is, we postulate that a losing bidder should not prefer to win the item at the winning bid (recall that WTP is defined as the amount that leaves a bidder indifferent between winning at that amount versus not winning).⁶

3.2 Latent bidders

While they are unobserved in the actual data, it appears plausible that latent bidders exist in online auctions. A concern with using data only from observed bidders in WTP estimation is

⁵ An appendix that demonstrates the derivation of WTP from utility maximization first-principles is available upon request.

⁶ This is a general assumption in all structural models.

that their WTP might be systematically different from WTP of the latent bidders, leading to a selection bias in estimation results if we ignore the existence of latent bidders. Therefore, we would like our model of WTP estimation to account for latent bidders and our definition to be consistent with economic assumptions about latent bidders. Existing literature does not provide us with adequate definitions of latent bidders. We use a definition that is theoretically sound and consistent with industry practices, even if not unique.

We would like our model to be robust to alternative behaviors of latent bidders. For example, a restrictive assumption would be that their WTP are below the lowest observed bid. But it is possible that latent bidders have valuation above the lowest bid but do not enter active bidding right away, instead, waiting for an opportune moment to enter. There can be a variety of reasons for this waiting behavior. For example, latent bidders might like to strategically enter later in the auction so as to not reveal their preferences or set off a bidding frenzy.⁷ Alternatively, non-strategic reasons for latency include high hassle or search costs of monitoring the auction process or greater surplus available to them in other concurrent auctions. We would like our model to be agnostic to various reasons for latent bidders remaining latent and not bidding for the focal item. Therefore, we choose the least restrictive assumption for latent bidders' WTP, i.e., their WTP is bounded above by the winning bid. That is,

$$W_{ij} \leq b_{1j}, \tag{3}$$

for bidders n_j+1, \dots, N_j .

For an auction with the BIN price exercised, we only know for the actual bidder that her WTP is higher than her bid amount. But we cannot know whether for the latent bidder, the BIN

⁷ In discussing both latent bidders and later in discussing market thickness or competition among various auction items open concurrently, we use a snapshot or static approach to modeling rather than the more appropriate but intractable model of time-varying dynamics of these behaviors. Therefore, our approach should be seen as a reduced-form approach to modeling the underlying dynamics in these behaviors within and across auctions.

price is an upper bound for WTP, unlike the auction not exercised with the BIN price where the winner's bid can define an upper bound for WTP. We also do not know the lower bound for WTP for latent bidders. Therefore, for the auction where the BIN price is exercised, we are unable to specify the range of WTP for latent bidders. Hence, latent bidders for these auctions are not included in the model estimation.

Under the parametric assumption that researchers know WTP up to parameters θ , our estimation model is given by

$$\hat{\theta} = \arg \max_{\theta \in \Theta} \left\{ \prod_{j=1}^{J_1} \int 1\{W_{1j} \geq b_{1j}; b_{ij} \leq W_{ij} \leq b_{1j}, i = 2, \dots, n_j; W_{ij} \leq b_{1j}, i = n_j + 1, \dots, N_j; \theta, \nu\} dF_\nu \right. \\ \left. \times \prod_{j=J_1+1}^J \int 1\{W_{1j} \geq b_{1j}; W_{ij} \geq b_{ij}, i = 2, \dots, n_j; \theta, \nu\} dF_\nu \right\},$$

(4)

where $j = 1, \dots, J_1$ are the items not designed with BIN options and the items designed with BIN options but not exercised, and $j = J_1+1, \dots, J$ are those with BIN options exercised. The unobservables ν affects the WTP function, and will be explained later.

Turning now to the actual implementation of latent bidders, we believe a set of latent bidders needs to satisfy the following criterion: We should include bidders from other auctions who are most likely to want to participate in the focal auction item but for some reason decide to remain dormant. Alternative definitions of latent bidders may include all or random subset of all bidders who are inactive in the focal auction item but active in other items. These alternative selection criteria are likely to produce a diffuse set of latent bidders and are not justifiable by any solid economic rationale. Additionally, our definition needs to be consistent with the strategies of the auction site to attract potential bidders (e.g., email a list of open auction items to losers in auctions of similar items) as well as with the design of the auction site used here. Specifically,

the site is organized to let site visitors/potential bidders surf the auction items by product characteristics (i.e., CPU speed, brand, etc.) and direct them to similar items. Consumer behavior theories suggest that in forming their consideration set, consumers rely on simple heuristics like eliminating alternatives via categorization of items (see Todd and Gigerenzer 2000; see also Fader and McAlister 1990 who use a similar heuristic to build their model of consideration sets).

Therefore, using the route of scanning concurrent and similar auction items for the definition of latent bidders is consistent both with economic/psychology theory and with the auction site's navigation tools for bidders. That said, alternative definitions that are theoretically sound might also exist, e.g., defining latent bidders by looking at budget constraints by focusing on bidders in auctions where the final bid price was less than and closest to the final bid price of the focal item. However, we have picked a definition that is theoretically sound and consistent with industry practices.

Keeping in mind the above two issues (of identifying and bounding WTP) for latent bidders, we first turn to any auction that is open concurrent with the focal auction item. In order to include bidders who are mostly likely to participate in the focal auction item, we next match the characteristics of all concurrently open auction items to the focal item. Specifically, we use the following heuristics: (1) CPU type (Pentium versus Celeron); (2) CPU speed within plus and minus 10 percent range; (3) Memory within plus and minus 10 percent range; (4) Hard disc capacity within plus and minus 10 percent range; (5) Screen size categories (small from 6.1 to 8.9 inches, medium from 10.1 to 13.3 inches, and large from 13.3 to 15 inches); (6) Usage (new versus old); and (7) Origin (American, Japanese and Korean). We pool all bidders who were

active in the items that match all of the above criteria, but not in the focal item, to form the latent bidder set for the focal item.

While the specifics of the above definition of latent bidders can be debated, one of our major purposes incorporating latent bidders is to check whether the estimation results only with observed bidders present any systematic bias. We believe that the broad principles of this definition are intuitive and, as we will demonstrate, our results are quite robust to this definition.

We would like to contrast our incorporation of latent bidders to two other approaches adopted in the literature. Li (2002) models the number of latent bidders as being a function of the heterogeneity of the auctioned items and allows it to vary across auctions. His paper focuses on the impact of reserve prices on bidding behavior, and his modeling of latent bidders is that their WTP should be below reserve price and they thus stay out of active bidding. While his method has not been implemented empirically (it is a theory paper), our model differs from his in that WTP of latent bidders need not be bound below by the reserve price, and our definition of latent bidders explicitly uses the richness of cross-auction data. Another approach adopted to model latent bidders is that of Bajari and Hortaçsu (2003). In their model, anyone who expects to get a positive surplus (i.e., $WTP - \text{price paid}$) in an auction is a potential entrant. This surplus decreases as the number of active bidders increases. In the empirical implementation of latent bidders, they make this surplus a function of auction design variables (presence of secret reserve price and minimum bid price), book value of auction item and dummy for blemish in the product. Unlike their approach, we do not model the equilibrium-generating process of conversion of latent bidders to active bidders, and therefore our model is less restrictive in strategies and maximands possibly employed by bidders. For example, in our model, a latent bidder might not become active even if she were to make positive surplus on the focal auction

item; for example, she might be making even larger profits in another concurrent auction.

Moreover, unlike their definition, our definition of latent bidders does not include auction design variables on the grounds that these variables might cause potential endogeneity in estimation, and accounts explicitly for all items that might be in the choice set of latent bidders.

3.3 The WTP function

As mentioned previously, the WTP function can be derived from utility maximization under very general conditions. To understand how data from auctions can be used to infer WTP, we make WTP a function of auction-independent or pure product valuation variables (product characteristics), auction-dependent variables (buyer and seller characteristics, and market environment variables), and an interaction between auction-independent and auction-dependent variables.

Let Z_j be observed product characteristics, which include CPU speed, memory, and hard drive size of the laptop. We also have information on whether the laptop is used and for how many months. This last variable enters in the log-linear form but the variable is defined as $(\text{usage} + 1)$ of product to account for products that are new ($\text{usage} = 0$). We also use information on brand name, CPU type (Pentium or not) and screen size. Brand and CPU type are discrete variables and therefore are postulated to have linear effects on WTP.

Next, let X_i be an observed bidder i 's characteristics including demographic information of age (log-linear) and gender. We assume a parametric function that will affect the WTP as

$$\theta_{ij}^1 = Z_j' \cdot \beta_i + \eta_i + \xi_j,$$

where η_i represents unobserved bidder-specific characteristics affecting the WTP that are *i.i.d.* across bidders, ξ_j unobserved product- and auction-specific characteristics that are *i.i.d.* across

auction items, and $\beta_i = \beta \cdot X_i$, where β is a parameter matrix to be estimated. We can interpret θ_{ij}^1 as bidder i 's intrinsic valuation of product j .

The second component, which is the auction-dependent WTP, comes from the interactions between bidders and sellers. Let Π_{ij} be a vector of variables including bidder experiences and seller reputation. Specifically, we include in Π_{ij} the cumulative page views, which can capture search behavior/costs of the bidder or familiarity with the site, auction procedures, etc. Another explanatory variable is cumulative bids, and could be a descriptor of more purposeful activity than cumulative page views. We also include cumulative wins. We use the logarithm of cumulative page views, bids and wins, plus one to avoid taking the logarithm of zero. The difference between cumulative bids and cumulative wins can be a rough measure for various things: the bidder's desire to win in the focal auction item, the bidder's experience at formulating a strategy to win an auction item, the bidder's risk aversion to bidding too high, etc. We also include cumulative expenditure of a bidder (in log-linear form). This variable could capture a budget constraint faced by an individual bidder and thus have a negative impact on WTP. Alternatively, it could capture a bidder's income level (over and above the number of wins in the past).

We include fractions of positive and negative reputation in seller characteristics. We also include a parameter for inexperienced sellers. Their coefficients should be interpreted as compared to the base neutral reputation. These variables will capture any risk aversion on part of bidders and provide a possible control for mitigating lemons problems. Managerially, understanding the impact of reputation on WTP is a highly relevant issue as sellers try to understand the value of going the extra mile just to obtain a favorable rating from a buyer.

To model the impact of bidder experience and seller reputation variables, we assume the following parametric function

$$\theta_{ij}^2 = \Pi_{ij}' \cdot \gamma,$$

where γ is a vector of parameters to be estimated.

The final component of the auction-dependent WTP function captures the competition among auction items listed concurrently. Bidders' WTP for any specific item may decline if several similar items are available. This might happen either because bidders with higher WTP have won previous auctions and left the market, or bidders use strategic waiting to avoid bidding aggressively for those similar items, etc. It is difficult, if not impossible, to structurally model the optimal bidding behavior when multiple similar items exist in the auction setting.

We use a reduced-form approach to model the impact of market thickness as follows. We first pool all items being auctioned during the time interval that the focal item is being auctioned. We calculate the mean CPU speed, memory, hard drive size, and screen size of these items. We next select items that are within one standard deviation of the focal item's speed, memory, hard drive, and screen size. We define these items as comprising the "similar item superset." We see if the focal item is new or has a Pentium chip. If so, "similar items set" is deemed to be the subset of the previous set that are also new or have a Pentium. If the focal item is used or does not have a Pentium microprocessor, it is compared to items that are used or do not have a Pentium.

Having once created this set of similar items, we define market thickness on two dimensions. First, we define a breadth measure as how many items with product attributes except for brand name are similar to the focal item. Second, from the pool of auction items with similar product attributes, we define a depth measure as how many items are also of the same

brand as the focal item. Note that by this definition, the impact of depth is additional to that of breadth. Managerially, a useful question is how much will WTP be reduced due to either of the competition effects. We also create additional breadth measure for the “high-end products,” which include those new, Pentium laptops with CPU speed of one standard deviation higher than the average from the whole sample.

To provide a benchmark, existing literature has alluded to the importance of market thickness, while the impact of this variable on WTP has not been studied formally. For example, Dholakia and Soltysinski (2001) provide evidence on how bidders gravitate towards and bid for auction items that have more active bidders and often ignore comparable or more attractive items being auctioned concurrently. Ariely and Simonson (2003) find in their field studies that minimum bids leads to higher winning bids but only when comparable items are not available. Unlike these papers, we model directly the impact of market thickness on WTP to account for the information across auctions. As mentioned previously, Li (2002) models latent bidders as being a function of the heterogeneity of auctioned items, which is intuitively similar to the breadth measure, but does not explicitly model for breadth and certainly not for depth. We have argued previously that it is important to account for cross-auction information more rigorously and systematically.

To model the impact of market thickness on WTP, we assume a parametric function

$$\theta_j^3 = U_j' \cdot \alpha ,$$

where U_j' represents the breadth and depth measures (or a measure of the “uniqueness” of the item), and α the net impact on WTP as the number of auction items increases and will be empirically estimated.

Putting the three components together, we assume a $\ln(\text{WTP})$ function of bidder i for item j as

$$\begin{aligned}\ln(W_{ij}) &= \theta_{ij}^1 \cdot (1 + \theta_{ij}^2 + \theta_j^3) + \varepsilon_{ij} \\ &= (\mathbf{Z}'_j \cdot \beta_i + \eta_i + \xi_j) \cdot (1 + \Pi'_{ij} \cdot \gamma + U'_j \cdot \alpha) + \varepsilon_{ij},\end{aligned}\tag{5}$$

where ε_{ij} represents the unobservable that affects the WTP and is *i.i.d.* across bidders and auctions. The unobservables in the WTP function are specified as

$$\eta_i \sim N(0, \sigma_\eta^2); \xi_j \sim N(0, \sigma_\xi^2); \varepsilon_{ij} \sim N(0, \sigma_\varepsilon^2).^8$$

We argue that consumers evaluate product characteristics, but their overall WTP is also a function of the auction market environment. That is, a valuation for a product in a thin market might be higher than that in a thicker market. A more experienced bidder is likely to have a different WTP compared to a less experienced one. To capture these interactions between product characteristics and auction market environment, we use the multiplicative form as shown in equation (5).⁹

As mentioned in the introduction, we note that θ^1 , the intrinsic valuation of the product, is the most important factor in deciding “representative market prices.” It is crucial to separate effects of auction market environment from intrinsic valuation for the purpose of inferring representative market prices from auction data. For example, scarcity in supply of other items of the same brand in online auction markets might lead to over-estimation of the brand preference in a context where supply is plenty. Also bear in mind that we need to understand how different

⁸ We also estimated the model with uniform distributions for these error terms. Results, available from the authors upon request, are similar in sign and magnitude.

⁹ It is plausible that the market environment variables such as bidder experience, seller reputation, and market thickness, influence not only the level of WTP but also the precision with which bidding data identify the WTP. We choose to not model this for two reasons. First, it is possible that not only market environment variables but also other variables (e.g., what specific maximands are adopted by bidders and sellers) influence the precision of bounds of WTP. Therefore, making the precision of WTP a function of market environment variables would introduce restrictive assumptions. Second, there appear to be some identification issues with modeling precision and level of WTP estimates as functions of the market environment variables.

types of consumers select the channels to purchase products. We can infer the distribution of WTP in outside market only after we understand the population distribution of consumers as compared to the sample within auctions. Done correctly, auction data can be managerially valuable, especially in the new product context where auction data can become an alternative for laboratory-based conjoint study data.

One remaining issue in modeling preference heterogeneity via including measures of auction market environment is that there should be no product characteristics and auction market environment characteristics that are observed by the bidders but not by the econometrician. This is to ensure that there is no endogeneity bias if these unobserved characteristics influence the WTP function systematically. Our data are detailed in terms of information available on the product being auctioned, and bidder and seller characteristics that might affect WTP over and above the product characteristics, thus minimizing concerns about resulting endogeneity from omitted variables.

3.4 Identification conditions

As with any econometric model, we need to check the identifiability of our model parameters. That is, what variation in our data allows us to estimate the parameters? As Haile and Tamer (2003) argue, without an equilibrium model, there is no one-to-one correspondence between WTP and bids, and therefore only bounds for WTP can be identified rather than point estimates. Hence, they only estimate the upper and lower bounds.

In our model, two assumptions help to generate the asymptotic identification. First, we impose parametric assumptions for distributions of unobservables in the WTP and we argue that these explanatory variables critically determine the point estimate of WTP. Second, we assume

that there is enough randomness in the strategy of bidding behavior. For example, consider equation (2), specifically for bidder 2 for item j :

$$b_{2j} \leq W_{2j} \leq b_{1j}.$$

For the second-highest bidder, how much below WTP is her bid? There is likely to be a significant variance in the bidding behavior of the second-highest bidder across auctions. For example, if a bidder is impatient and wants to win this auction, she might bid her WTP. Contrast this to a more patient bidder who might bid below her WTP because she is strategically waiting instead of revealing her WTP. Therefore, the difference between bid and WTP varies as a function of bidder type. Additionally the very identity of the second-highest bidder might vary across auctions. For example, in one auction, bidder 2 might be the bidder with the second-highest WTP. It is equally possible that in another auction, a more aggressive bidder with a lower WTP might bid more and become the observed second-highest bidder even if she was not the actual second-highest WTP.¹⁰ The behavior described above will not bias our results because our model does not specify who the bidder with the second-highest WTP is.

Going beyond the intuitive explanation above, all we need for identification is that there exists positive probability that bidder 2 will bid in each round as long as the bid amount is below her WTP. For example, we do not allow the case that, in every auction, the bidder with the highest WTP always bids first at an amount higher than the WTP of bidder 2 and win immediately.¹¹ Once W_{2j} can be identified asymptotically, the distribution of WTP among bidders and hence the parameters will also be identified asymptotically under our distributional assumptions. To conclude, if there exists a positive probability that the final bid amount of some

¹⁰ See also Athey and Haile (2002) who use exogenous variation in the number of bidders and bidder-specific covariates to achieve identification.

¹¹ Another example is the collusion among bidders. In this case the winning amount may be lower than the true WTP of other bidders, and our estimation results will be biased.

bidders is equal to the true WTP and a positive probability that they will bid in each round, the model is asymptotically identifiable based on our distributional assumptions of unobservables.

4. Results

4.1 Model results

Table 2 reports the main results of the WTP model. Model 1 uses data only on actual observed bidders (15149 observations). And Model 2 includes latent bidders (26312 observations).¹² As shown in Table 2, comparing Models 1 and 2, we find that adding latent bidders induces mostly moderate changes in parameter estimates at best and there are no directional changes in results. For most part, though, the parameter estimates seem lower for Model 2. In other words, the mean WTP is lower when accounting for latent bidders. This is expected considering our behavioral assumption where a latent bidder's WTP is bound above by the winning bid. We cannot directly compare Models 1 and 2 given they are estimated on different data. Given the theoretical completeness of Model 2 for having accounted for latent bidders, we will focus on results of Model 2 hereon. Moreover, Model 2 with latent bidders is useful for simulation exercises in section 4.4 where we cannot identify actual bidders and instead pick a pool of latent bidders. For ease of use, we only report the main effects in this table; interaction effects of product characteristics and buyer characteristics, and brand and buyer characteristics are not reported but are available from the authors upon request. Elasticities with respect to major variables of interest are reported in Table 3.

----- Insert Tables 2 and 3 about here -----

¹² Given the large variance in final prices (minimum = 50.83, maximum = 5916.67), we also estimated Model 2 on a subset of the data with price in the \$500-\$2000 range. This comprises about 90 percent of the auction items of the whole sample. The results, available from the authors upon request, were similar in sign and magnitude.

Most product characteristics matter in the expected ways. The more used the laptop, the lower the WTP. WTP is much more sensitive to CPU type, CPU speed, memory, hard drive, and screen size relative to the impact of usage on WTP. This is a somewhat surprising finding, especially given the average usage level of auction items is 9.59 months. Let us explore whether either seller or buyer characteristics explain the low usage elasticity. We first note that, compared with neutral rating, the fraction of positive seller reputation has a ten times larger elasticity (positive impact on WTP) than does the negative seller reputation (negative impact on WTP). One potential explanation for this lack of lemons problem is that the used items are sold mostly by reputed sellers; however, correlations between usage and sellers' reputations are very small. We also note that all the variables of bidder experience have small elasticities too. Hence, there might not be a very serious lemons problem in this category, despite less-than-perfect information about sellers or less-than-major impact of buyer history. Another possible explanation is that there is enough market depth to offer consumers choices (note at any given time there are 16.21 similar items up for auction). Other explanations that cannot be corroborated in the data are that lemons are inherently less of a problem in this category (e.g., laptops come with warranties) or that the auction site is very committed to stopping fraud/lemons (see Dewally and Ederington 2003 for a comparison of these explanations).

As expected, positive reputation increases WTP and negative reputation decreases WTP (see Houser and Wooder 2003 for similar results based on eBay Pentium microprocessor auctions). The magnitude of either effect is not large, which is consistent with the literature (e.g., Melnik and Alm 2002). More insightful is the asymmetry in the magnitude of seller positive and negative reputation, which is very stark in our results. Since they are compared with neutral seller reputation, these results imply that bidders perceive a neutral reputation more

similar to a negative reputation than a positive one (note that Cabral and Hortaçsu 2004 choose to lump neutral ratings with negative ratings). To benchmark against existing research, Lucking-Reiley *et al.* (2000) finds that negative feedback has a larger impact compared to positive feedback. Consistent with our results, Resnick *et al.* (2003) find that one or two negative feedbacks for new sellers did not affect WTP, even though these sellers had few positive feedback instances. Thus, it appears possible that there are threshold effects in the impact of negative reputation. It is also possible that sellers change their online identity when they get negative ratings, and therefore we rarely observe any seller with a substantial negative rating.¹³ Therefore, our results of the greater impact of positive ratings should be interpreted with care.

The results on bidder history are as follows. Cumulative expenditure has a positive impact on WTP. This estimate is inconsistent with the explanation of a budget constraint, but is consistent with the explanation of a disposable income and propensity to bid. Bidders who have viewed more pages on this auction site prior to our data period, and who have bid and won previous auctions have lower WTP. All these elasticities are consistent with an experience and learning explanation. Our findings are also consistent with Jin and Kato (2004) who find that uninformed bidders are more likely to be misled by non-credible claims of quality and are likely to pay a higher price for items. List and Lucking-Reiley (2002) find that bidders are more likely to bid strategically and in line with principles of economic rationality in high-stakes bidding. Given the high price of laptops, bidder history variables are expectedly important to WTP. An alternative view of the cumulative viewing/bidding/winning elasticities is that the former two reflect casual bidding behavior, whereas the cumulative winning elasticity is more representative of serious bidding. If it were the case that page views and past bidding were indeed casual, they

¹³ In our data, only 40% of items are sold by experienced sellers, and the fraction of positive ratings are 57%, in contrast to 5% negative.

would not be significant explanatory variables for WTP. This is not what we find in our estimation. Therefore, it must be the case that past viewing and bidding represent search costs/experience which are likely to affect WTP.

The elasticities for breadth and depth are also informative. Increase in breadth reduces WTP about 3.5 times as much as increase in depth. This is after controlling for brand effects (and other brand interactions effects) in the WTP estimates. Therefore, consumers may value breadth in selection as it helps them better determine WTP by reducing search and comparison shopping costs (especially if multiple listings of the same brand are from a common seller). This explanation is consistent with literature in psychology and marketing in terms of consumer consideration and choice set formation and decision-making. We explore in section 4.3 some further details of this.

4.2 Estimated revenue

We want to check how good our estimation results fit with the data, and how sellers can use the model to predict final winning bids conditional on the pool of bidders and competition environments. It will not be valid to compare the estimated WTP of each bidder with the observed bids in data, given that various bidding strategies including jump bidding and waiting sidelines are allowed (we will further explore this issue later). Instead, we estimate the following model using OLS:

$$Y_j = \rho \cdot \hat{W}_{2j} + \zeta_j, \quad (6)$$

where Y_j is observed bid, \hat{W}_{2j} is estimated second-highest WTP for item j , and ζ_j is error term.

Under our assumptions, the parameter ρ should be close to but larger than 1 and the model should have a high fitted value. We use only those items for which BIN price was not exercised, given there is no second-highest bid for such items with BIN options exercised. For these items,

we simulate the second-highest bid from the model under the distribution assumptions of unobservables (1000 random draws for each item and each bidder). The estimated ρ is 1.007 (standard error = 3.69e-008) and the R^2 for the regression is 0.72. In other words, the final winning bid is higher than the estimated second-highest WTP by 0.7%. The significance of the estimate and the high R^2 for the regression indicates that there is a good fit between our results and the data. Further, sellers may simulate the estimated second-highest WTP, based on their expectations of the pool of potential bidders and other market environments, then multiplied by 0.7 percent to obtain the expected revenue amounts.

4.3 Impact of market thickness on WTP: Further exploration

To understand better the role of market thickness in WTP, especially as it might vary across brands, we conduct simulations based on the estimated parameters of Model 2. Table 4 shows the impact of market thickness on WTP of a particular brand, Toshiba.¹⁴

----- Insert Table 4 about here -----

Table 4 is to be read as follows: any cell (x,y) is read as when there are x similar items up for auction concurrently, of which y belong to the same brand. We assume that the number of bidders is fixed at 12 latent bidders.¹⁵ We randomly draw 1000 times from the pool of actual and latent bidders and use that to calculate the estimated WTP for each of them. Based on the behavioral assumptions in the model, the final winning bid is bounded below by the second highest WTP, but the exact amount depends on the bidding strategy of the highest WTP bidder, which we do not attempt to model. Instead, we use our result in the previous section that the winning bid is likely to be 0.7% higher than the second-highest WTP as an approximation of the

¹⁴ Similar results hold true for other brands, given there is no interaction between brand intercepts and market thickness variables.

¹⁵ This is the average number of latent bidders in our data. Note that bidders' entry decisions are not modeled in this paper. Instead, we treat the number of bidders as exogenous.

winning bid. While each specific bidder's bidding strategy and other auction designs including BIN may affect the final winning bid, we believe that the above is a good approximation given the high R^2 (0.72) for the regression. The number in a cell indicates the second-highest WTP for the first of the similar items being auctioned concurrently. Given that we do not have an explicit model for entry of new bidders (other than calculating latent bidders), we are unable to provide estimates of the second-highest WTP for the rest of similar items.

The results of the simulation are as follows. We find that the increase in depth and breadth both have a damaging impact on WTP. For Toshiba, an additional laptop under different brand name but with similar attributes will on average decrease the second-highest WTP by 2.60%. For example, WTP decreases from \$1726.36 to \$1547.86 when going from 1 to 2 items, and \$1421.89 to \$1418.45 when going from 9 to 10 items, when depth is fixed at 1. If the additional laptop is also a Toshiba, the second-highest WTP will decrease by 4.22%. For example, WTP decreases from \$1726.36 to \$1437.31 when two Toshiba laptops are available for auction concurrently (breadth *and* depth go from 1 to 2. Note that when depth increases by one, breadth automatically increases by one too given there is one more product in the competitive "similar item" set; this is why our Table 4 is upper triangular). The same decrease when going from 9 items to 10 items is from \$1421.89 to \$1317.14, when depth increases from 1 to 2. The decrease is largest initially, and drops later. For example, the first increase in breadth decreases WTP by 13.54%, the next one by 5.52%, the third by 3.10 %, etc. Similar results hold for an increase in depth with breadth constant (8.84%, 3.22%, 1.71%, etc). This evidence seems to suggest that the bidders in the category care about product characteristics a lot when bidding; that is, an item with similar characteristics is seen as being much closer a competitor to the focal item than one with the same brand but different characteristics.

These simulations provide a first-cut in-depth look at the problem described in the introduction, “offering many identical items undercuts price for sellers” (*Wall Street Journal*, February 26, 2004). Table 4 shows how much of a drop off in winning bid will occur, which can be considered as a valuable tool for sellers to think about the appropriate timing of sales of similar products. For example, it would be straightforward to generate similar tables for a larger or smaller set of potential bidders and see the sensitivity of results. Given the current technologies available to track potential bidders (e.g., losers in auctions of similar items in the last week), managers at auction sites have the ability to send customized invitations to these bidders and in effect increase the pool of potential bidders. It would be worth knowing how much of an increase in winning bid would occur as a result of this, and weigh the benefits and costs of such actions in an environment of non-unique products.

4.4 The empirical distribution of WTP and bids

As mentioned previously, the theoretical and empirical literature of auctions in economics has been focused on equilibrium models of auction outcomes, whereas we have chosen to model not the process of equilibrium but rather the outcome of it. It would be interesting to see how our results compare with some predictions from theory in terms of equilibrium outcomes.

A classic model of auctions is so-called “button” auctions of Milgrom and Weber (1982). In this model of ascending second-price auctions, the last bid of each bidder (except the winner) can be treated as the “exit” price, which is equivalent to her WTP.¹⁶ In our Internet auction world, we have argued that there is no obvious way to know who is active in which auction (e.g., latent bidders could well be following the auction closely and reveal themselves as active bidders

¹⁶ An alternative is to assume that the WTP of the n -th highest WTP bidder is equal to the final bid amount of the $(n-1)$ -th highest bidder in the data for every auction.

at any time). Also, depending on the level of competition and bidding strategies, the final bid for each bidder might or might not be close to her WTP. So how do our results compare with the button-auction prediction?

We construct a variable $\frac{b_{1j} - b_{kj}}{b_{1j}}$ representing the ratio between the observed winning bid

and the k -th highest bid for auction j in data. We also construct another variable

$\frac{\hat{w}_{2j} - \hat{w}_{kj}}{\hat{w}_{2j}}$ representing the ratio of the simulated second-highest WTP and the k -th highest WTP

for auction j . Figure 2 compares the distributions of the two variables. As expected, the ratio in bid has a far tighter distribution compared with the ratio in WTP (probability mass is virtually zero for ratio greater than 0.3).¹⁷ Considering that bidders already self-select into the items they are interested, and that auction market prices are generally available for bidders, the fact that more than 20% of bidders bid lower than 50% of the final winning bid (shown from the distribution of the ratio in bid) could likely not represent the real differences in WTP. Simple assumption of the equivalence between WTP and observed bids, as implied by the “button” auction model, will lead to very biased estimation results. This demonstrates the importance of using our “bounds” approach in inferring the distribution of WTP from observed bids.

----- Insert Figure 2 about here -----

In Table 5, we list the percentage difference between WTP and bid amounts for the second highest bidder onwards (per the rules of the button auction, the highest bidder gets the item at the WTP of the second highest bidder when the second-highest bidder drops out, and therefore gets to keep the difference between her own WTP and the second-highest WTP). As

¹⁷ We only use the observed bidders (and hence the estimation results from Model 1) for comparison. In theory latent bidders should have lower WTP than the observed ones. If we take latent bidders into account, the distribution will skew further rightwards.

Table 5 shows, as we go down the list of bidders, the difference between their WTP and maximum bid is quite substantial, and by no means can the results be explained by a simple button auction mechanism. This could be for various reasons. Some of these reasons are bidders leaving to go to more attractive auctions, or facing high search or monitoring costs hence are unlikely to submit bids frequently, or getting disheartened by fierce bidding, or that they are savvy enough to know that the other bidders have higher WTP than them and that they will eventually not win the item. Our model is unable to distinguish between these alternative explanations, but we offer the results above as a useful comparison with a well-accepted alternative model of auction behavior, as well as flagging this as an issue to be possibly explored in more depth in future studies.

----- Insert Table 5 about here -----

5. Conclusions

We model how auction data can be used to recover consumer WTP under very general assumptions of bidding behavior. Our model is agnostic to a variety of bidding strategies and maximands used by bidders and is consistent with utility maximization. We argue that WTP has the two components, a pure product-feature component and a component based on auction market environment. The latter includes bidder- and seller-specific variables and variables that capture competition among items up for auction concurrently. Using the data of notebook auctions directly obtained from an auction site in Korea, we present such a modeling framework. Once built, the conclusions on the impact of various variables on WTP are not surprising. As we had stated in the introduction, auction sites including eBay are excited about the possibility of selling their auction data to companies who in turn can use the data to evaluate consumer WTP.

Our results from WTP can be useful for this effort because we can separate out auction-invariant, especially product-feature elasticities from auction data. We demonstrate how our model can be used as a valuable tool for managers or sellers of auction sites to predict revenue generated from auction items conditional on market environments, and to determine the impact of market thickness on the WTP or expected revenue from an auction. While we acknowledge that more complex, and albeit realistic, behavioral models could be built, our proposed model is parsimonious and is consistent with key behavioral aspects of bidding behavior established in the existing literature on Internet auctions.

As is to be expected, there are a number of caveats and limitations in the proposed approach that should be acknowledged and perhaps addressed in future research. First, while we report interesting findings (e.g., lack of lemons problem), we are unable to speculate further why this happens in online auctions which leads to transaction risks such as identity uncertainty of online trading parties and product quality uncertainty (e.g., Ba and Pavlou 2002). Second, we have estimated our model for notebook auctions in which our results could be reflective of the nature of the product category (e.g., private value, multiple similar items, etc.). We hope our model provides a framework for further empirical exploration in other product categories (e.g., collectibles). Third, as noted in section 2, the data considered here is from ascending first-price auctions. The contrast of this auction design to the proxy bidding used at eBay has been under much discussion in the auction literature (e.g., Lucking-Reiley 1999). It is important to bring our model to the eBay data, given that eBay is dominant in the online auction market in the U.S. However, the proxy bidding rule used in eBay brings a flavor of second-price auctions, which should be addressed more carefully in our model. Also the BIN option at eBay works differently from that at Yahoo! and the auction site considered in this research. Finally, our auction site

(and Yahoo!) has a soft ending time rule, in contrast to eBay. As a result, our model approach cannot be directly applied to the eBay data. Nevertheless, we believe that our research provides a useful first step into inferring WTP from bids on Internet auctions and can be extended in a number of ways.

While the model proposed in this paper is robust to the usual traps in the literature of translating bidding data to WTP functions, there are several possible extensions to this work. First, while we have modeled competition among bidders via latent bidders and competition among auction items via market thickness measures, we have not explicitly modeled competition among sellers. An instructive extension of this work would be to examine the latter by modeling latent sellers as a first step of modeling seller entry behavior. Second, it would be interesting to model to impact of auction design mechanism, such as BIN pricing, on the final selling price of the product.

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Table 1: Summary statistics

<u>Variables</u>	<u>Average</u>	<u>Std. Dev.</u>
<u>Bidder characteristics</u>		
Age	31.14	8.23
Gender (Male = 1, Female = 0)	0.84	
Cumulative page views	502.65	1154.48
Cumulative bids	13.21	29.03
Cumulative wins	10.52	24.02
Cumulative expenditure (dollars)	1693.84	4449.67
<u>Seller characteristics</u>		
Inexperienced seller (% in data)	0.59	
Fraction of positive seller reputation	0.57	0.34
Fraction of negative seller reputation	0.05	0.12
<u>Product characteristics</u>		
CPU type (Pentium = 1, Celeron = 0)	0.80	
CPU speed (mhz)	532.45	221.50
Memory (megabytes)	117.78	60.29
Hard drive size (gigabytes)	11.78	7.16
Screen size (inches)	12.91	1.24
Usage (months)	9.59	10.00
<u>Auction designs</u>		
Number of bidders per auction	6.52	7.00
Auction price (dollars)	1077.39	555.54
Auctions with minimum price	1.00	
Minimum price (dollars)	662.28	636.54
Auctions with BIN price	0.89	
BIN price (dollars)	1183.31	596.19
Auctions with BIN exercised	0.41	
<u>Market thickness measures</u>		
Number of similar items per auction item (breadth)	16.21	15.16
Number of same-brand items per auction item (depth)	3.83	4.14

Table 2: Regression of ln(WTP)

	Observed bidders only	Latent bidders included
Variables	Model 1	Model 2
Constant (base: others)	10.678 *	10.096 *
<u>Bidder characteristics effects</u>		
ln(Age)	-0.435 *	-0.336 **
Gender	-0.004	-0.009
ln(Cumulative page views + 1)	0.0004 *	0.0003 *
ln(Cumulative bids + 1)	-0.004 *	-0.003 *
ln(Cumulative wins + 1)	0.0005 **	0.0004 **
ln(Cumulative expenditure + 1)	0.001 *	0.001 *
<u>Seller characteristics effects</u>		
Fraction of positive seller reputation	0.007 *	0.004 *
Fraction of negative seller reputation	-0.004 **	-0.004 **
Inexperienced seller	0.004 *	0.000
<u>Pure product characteristics effects</u>		
Pentium	0.310 *	0.424 *
ln(CPU speed)	0.653 *	0.658 *
ln(Memory)	0.087	0.117 **
ln(Hard drive)	0.405 *	0.372 *
Screen size	-0.232 *	-0.213 *
ln(Usage + 1)	0.017	0.021
<u>Pure brand effects</u>		
Compaq	0.446 *	0.438 *
Dell	0.161	0.089
IBM	0.143	0.265 **
Fujitsu	0.021	0.000
Sony	-0.002	-0.002
Toshiba	0.285	0.709 *
Daewoo	0.198	0.164
Sambo	0.091	0.219 **
Samsung	0.304 *	0.240 *
<u>Market thickness measures</u>		
1/Breadth (high-end products)	0.00002	0.0001
1/Breadth (all products)	0.006 *	0.011 *
1/Depth (brand name)	0.003 *	0.016 *
<u>Estimated error variances</u>		
σ_{η} (item-specific)	0.0001	0.0004
σ_{ξ} (bidder-specific)	0.001	0.0003
σ_{ε} (item- and bidder- specific)	0.220 *	0.243 *
Likelihood Value	-22477.3	-26875.7

* = 99% significance, ** = 95% significance; main effects only reported.

Table 3: Elasticity estimates of WTP (Model 4)*

Variables	Elasticity
<u>Bidder characteristics</u>	
Age	0.50
Gender	0.03
Cumulative page views	-0.12
Cumulative bids	-0.99
Cumulative wins	-0.13
Cumulative expenditure	0.27
<u>Seller characteristics</u>	
Inexperienced seller without any reputation	Not significant
Fraction of positive seller reputation	0.67
Fraction of negative seller reputation	-0.06
<u>Product characteristics</u>	
CPU type	0.56
CPU speed	1.39
Memory	0.11
Hard drive	0.31
Screen size	-0.52
Usage	-0.10
<u>Market thickness</u>	
1/Breadth	0.22
1/Depth	1.37

* As an illustration, usage elasticity is calculated as follows. From equation (5), we have

$$\text{Usage Elasticity} = \frac{\partial(W_{ij}) \cdot \text{Usage}}{\partial(\text{Usage}) \cdot W_{ij}}.$$

Note that usage is parameterized as $(\text{usage} + 1)$. Thus,

$$\frac{\partial(\ln W_{ij})}{\partial \ln(\text{Usage} + 1)} = \frac{\partial(W_{ij}) \cdot (\text{Usage} + 1)}{\partial \ln(\text{Usage} + 1) \cdot W_{ij}}.$$

Therefore, usage elasticity can be rewritten as follows:

$$\text{Usage Elasticity} = \frac{\partial(\ln W_{ij})}{\partial(\text{Usage} + 1)} \cdot \frac{\text{Usage}}{(\text{Usage} + 1)}.$$

We note that usage has a main effect, interaction effects with each bidder characteristics including brand, and each of these is then interacted with the variables of seller reputations, buyer bidding experiences, and market thickness measures. In calculating the effects, we take the average value of each of these variables from Table 1 and include only those effects that are statistically significant at Table 2.

Table 4: WTP as a function of market thickness (columns: breadth, rows: depth)

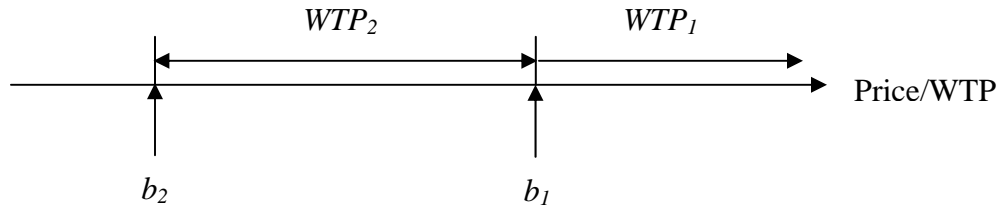
Toshiba: Expected second-highest WTP										
	1	2	3	4	5	6	7	8	9	10
1	1726.36	1547.86	1492.56	1465.66	1449.75	1439.24	1431.78	1426.21	1421.89	1418.45
2		1437.31	1385.96	1360.98	1346.21	1336.45	1329.52	1324.35	1320.34	1317.14
3			1352.15	1327.78	1313.36	1303.84	1297.08	1292.04	1288.13	1285.01
4				1311.48	1297.24	1287.84	1281.16	1276.18	1272.32	1269.24
5					1287.67	1278.33	1271.71	1266.76	1262.92	1259.86
6						1272.03	1265.44	1260.52	1256.70	1253.66
7							1260.98	1256.08	1252.27	1249.24
8								1252.76	1248.96	1245.94
9									1246.40	1243.38
10										1241.33

Table 5: Percentage difference between a bidder's WTP and bid

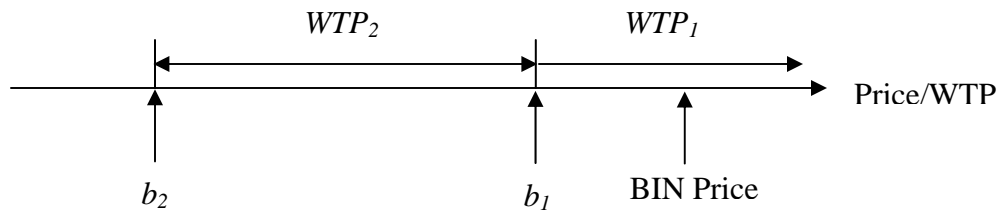
Bidder Number	Percentage difference between estimated WTP and final bid by this bidder
2	2.95
3	5.17
4	8.98
5	13.93
6	18.09
7	23.05
8	29.18
9	33.91
10	38.71

Figure 1: Bidding prices and WTP under various auction settings

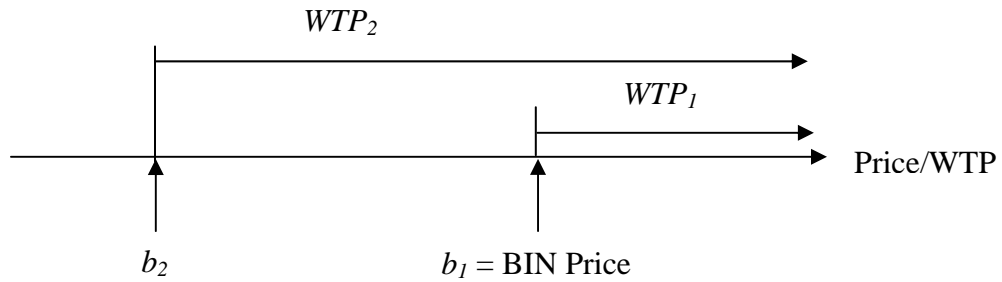
A. Auctions without BIN



B. Auctions with BIN but not exercised



C. Auctions with BIN exercised



D. Auctions with Latent Bidders (bidder 3)

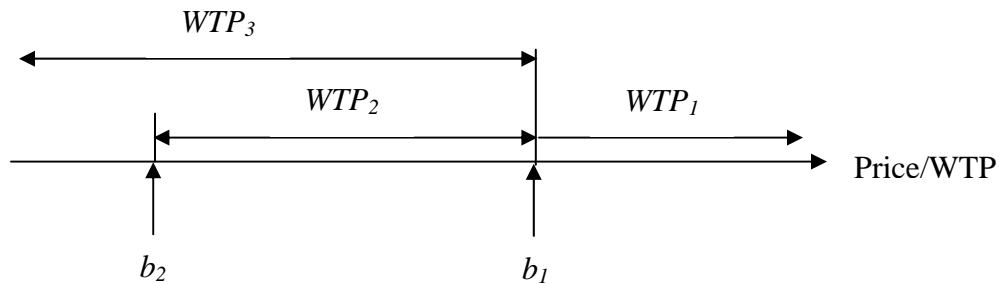


Figure 2: Distributions of Ratios of Observed Bid and WTP

