Willingness to Pay and Competition in Online Auctions

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Abstract

The authors 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 (Haile and Tamer 2003). In other words, a "no regret" rule in bidding is proposed. Other than that, no other restrictive assumptions on maximands or behavior of bidders in a competitive auction context are imposed. WTP is modeled 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 measures for 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.

The authors use data of notebook auctions from one of the largest Internet auction sites in Korea. They find that most product characteristics matter in the expected ways. Other primary findings are as follows: (1) 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. (2) More extensive site-surfing and bidding histories lead to lower WTP, implying that search costs and experience matter in bidding. As specific substantive benefits, the authors demonstrate how sellers can calculate changes in WTP, and hence the expected revenue, as the number of concurrently available similar items varies.

Key words: internet auctions, bidder willingness-to-pay, bidder competition, item competition, econometric models.

Auctions on the Internet are a booming enterprise. From a managerial perspective, two recent trends are worth noting. First, the Internet 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. As a recent report indicated, "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). 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.

In measuring consumer valuations from auction data, there are three major issues to be resolved: (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 and 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. For example, the level of competition among items and bidders is likely to matter to WTP over and above a pure product-based intrinsic valuation. Additionally, bidder experience and search costs for bidding and seller reputation are likely to influence WTP in online auction marketplace, given they influence each bidder's expectation of other bidders' and sellers' behavior (see Bajari and Hortacsu 2003

In our model we incorporate how competition among listed items affects the distribution of WTP in two (interrelated) ways. First, we control 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. 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.

The next set of issues in WTP estimation is the assumptions of bidder maximand and equilibrium behavior. 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, though there exists some theoretical work that addresses the issues of "buy it now" (BIN) or a posted price option, theoretical literature regarding BIN with asymmetric bidders and items is very limited to match our empirical model. An additional complication in estimating WTP from bidding data is that 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. 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. We are especially constrained by the pack of theoretical models that take in to account auction market environment variables, making it impossible for us to speculate on the possible relationship between winning bid and second-highest WTP. Our proposed WTP formulation is consistent with a variety of strategic/non-strategic behaviors and maximands used by bidders and sellers, and consistent with bidder utility maximization.

The third and final issue in using auction data to model WTP is how to model heterogeneity of the following type: (1) heterogeneity of bidder preferences for product characteristics; (2) heterogeneity in how bidders are influenced by the market environment (see Rezende 2005 for further discussions). We model this by interacting bidder demographics and experiences, and other variables of auction market environment in the hedonic WTP estimation. Much of the empirical literature so far has focused on building structural models of equilibrium process with symmetric bidders (Hong and Shum (2003) is an exception).

Summarizing, we estimate a model of WTP accounting for auction market environment. The model is robust to assumptions about bidder behavior and equilibrium-generating processes and heterogeneity in bidders and items. We estimate our model on auction data for notebook computers from a leading Internet auction site in Korea. We find that: (1) 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 competition influences WTP. (2) More extensive site-surfing and bidding histories lead to lower WTP, implying that search costs and experience matter in bidding. As specific substantive benefits, we demonstrate how sellers can calculate changes in expected revenue as the auction setting varies.

The rest of the paper is organized as follows. Below, we describe our data, followed by a discussion of the model structure. Next we discuss results, and demonstrate a way to understand the impact of market competition on WTP. We discuss other managerial implications of this research and conclude with directions for future research.

DATA DESCRIPTION

The data are for 21952 bids for 2322 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; the highest bidder wins and pays her bid. This site does not use proxy bidding. There are about 6.5 unique bidders (each of whom can bid multiple times). All bids are in Korean currency (won); at the time of data collection, 1200 won corresponded approximately to $1. The average final selling price is $1077.39.

Sellers have the choice of offering a BIN or posted price. The BIN option at the auction site in our main dataset 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. Winning bidders rate sellers as positive, negative or neutral. Bidder characteristics data include demographics (e.g., age and gender) and behavioral characteristics like cumulative page views, bids and wins, and the cumulative expenditures across all product categories. For all seller and bidder variables, only the cumulative information on these variables at the start of the data period is available.

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 aggregate and group into a category "others", account for 12% of the items. Table 1 reports summary statistics of each of these variables described in this section. We also report in table 1 market competition measures, details of which are in the next section.

----- Insert Tables 1 about here -----

THE MODEL

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.

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. 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.

Turning our attention to an auction designed and exercised with BIN, 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.

Similar to Haile and Tamer (2003), we infer WTP on two behavioral premises that 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.

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. Let $N_j \geq 1$ be the total number of bidders and n_j be the observed number of bidders in auction j. Without loss of generality, let bidder 1 be the winner. This bidder's WTP is lower-bounded by the winning bid. For all other bidders, had their WTP exceeded the winning bid, they would have outbid the winning bid. Therefore, their WTP has a lower bound of their own bids and an upper bound of the winning bid. A potential issue in this bidding premise is that bidders might run out of time in bidding, even if their WTP is higher than the winning bid (e.g. Roth and Ockenfels 2002). Our auction site uses a "soft ending time" rule that is similar to Yahoo! auctions. Therefore, we are less concerned about this issue.

Formalizing the above two principle, we have

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

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 in equation (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; an appendix demonstrating this is available from us on request. 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. This is because the rules allow any incremental amount in bidding, as long as the valuation exceeds the current outstanding bid plus the increment. Note that this set-up also applies to proxy bidding rules used in eBay where every bidder might bid their true WTP (and the equilibrium is equivalent to a button auction). Our estimation methodology (to be explained below) is inefficient compared to treating final bids as bidders' exact WTP in proxy bidding. Note, however, that even with proxy bidding, it is possible that WTP might lie somewhere between own last bid and next highest bid if proxies can be increased only in certain increments, or if there are costs to participation, especially in the presence of multiple simultaneous auctions. These caveats should be kept in mind when extending our methodology to proxy bidding situations.

Latent bidders

While they are unobserved in the actual data, it appears plausible that latent bidders exist in online auctions. It is also plausible that ignoring latent bidders might lead to biased estimates of WTP if there is self-selection of bidders from latency to active status. However, existing literature does not provide us with adequate definitions of latent bidders or reasons for their

latency. We would like our definition of latent bidders to be theoretically sounds and consistent with industry practices. Also, we would like to be agnostic to reasons for their latency, even if ideally a more comprehensive model of converstion from latency to active status might be desirable when the appropriate theoretical models become available in the literature.

Consider reasons for latency that their WTP are below the lowest observed bid. 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.[1] 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. 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, … , 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 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, WTP for

[1] 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.

latent bidders cannot be specified within a finite range that can be used to identify model parameters.

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

$$\hat{\theta} = \arg\max_{\theta \in \Theta} \left\{ \begin{array}{l} \prod_{j=1}^{J_1} \int 1\left\{ W_{1j} \geq b_{1j};\ b_{ij} \leq W_{ij} \leq b_{1j}, i = 2, \ldots, n_j;\ W_{ij} \leq b_{1j}, i = n_j + 1, \ldots, N_j; \theta, \upsilon \right\} dF_\upsilon \\ \times \prod_{j=J_1+1}^{J} \int 1\left\{ W_{1j} \geq b_{1j};\ W_{ij} \geq b_{ij}, i = 2, \ldots, n_j;\ \theta, \upsilon \right\} dF_\upsilon \end{array} \right\}, \quad (4)$$

where $j = 1, \ldots, J_1$ are the items not designed with BIN options and the items designed with BIN options but not exercised, and $j = J_1+1, \ldots, J$ are those with BIN options exercised. Note that if latent bidders were included in the equation (4) for BIN exercise items, their WTP range is $(-\infty, +\infty)$, which has a probability of one regardless of the values of WTP parameters. Therefore, adding latent bidders in BIN auctions is not informative to the estimation of WTP parameters. The unobservables υ affects the WTP function, and will be explained later.

Turning now to the actual implementation of latent bidders, the definition should include bidders from other auctions who are most likely to participate in the focal auction item but for some reasons 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.

Therefore, to decide the set of latent bidders, we first 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 ±10 percent range; (3) Memory within ±10 percent range; (4) Hard disc capacity within ±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 then 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.

We would like to contrast our incorporation of latent bidders to that of Bajari and Hortaçsu (2003). In their model, anyone who expects to get a positive surplus (i.e., WTP – 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.

While the specifics of the above definition of latent bidders can be debated, a major goal of 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.

The WTP function

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. This formulation of WTP can be derived from utility maximization principles.

Let Z_j be observed product characteristics, which include CPU type (dummy for Pentium), CPU speed, memory, hard drive size, brand name, screen size and usage of the laptop. We transform the last variable to ln(usage + 1) to account for products that are new (usage = 0). Let X_i be an observed bidder i's characteristics including demographic information of (ln of) age 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 auction-dependent component of WTP comes from the interactions between bidders and sellers. Let Π_{ij} be a vector of these variables. One variable in this is (ln of 1 plus) cumulative page views, which can capture search behavior/costs of the bidder or familiarity with the site, auction procedures, etc. The next variable is (ln of 1 plus) cumulative bids, and could be a descriptor of more purposeful activity than cumulative page views. Third, we include (ln of 1 plus) cumulative wins. 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 (ln of 1 plus) cumulative expenditure of a bidder. 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). Among seller characteristics we include are 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 competition 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. Li (2005) 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.

It is possible that other auction market mechanisms affect WTP. In particular, we include two other variables that capture more details of the competitive structure of the market. First, we include a closing price of similar items as these might capture competition in the previous period and influence both sellers' listing decisions and bidders' price perception and hence WTP. Past price information were not available to bidders in the Korean data at the time this data was collected. In this data, therefore, the impact of past price on WTP is via sellers' decision to sell the item or via a more indirect route of past price influencing the pool of bidders available for later auctions. We calculate a closing price for similar items as the most recent sale price for the

similar auction items as defined in the depth measure. The second additional variable included is whether this item had a BIN option available. The availability of BIN option captures both the seller's assessment of competition in the market and might influence bidders' WTP. For example, it is also possible that sellers who expect similar items to be offered for sale in the near future might want to reduce competition by offering an attractive BIN price now (Kirkegaard and Overgaard 2004). For bidders, BIN might signal quality of product or sellers (Qiu et al. 2005).

To model the impact of these variables on WTP, we assume a parametric function

$$\theta_j^3 = C_j^{'} \cdot \alpha ,$$

where $C_j^{'}$ includes the breadth and depth measures as well as the closing price and BIN indicator, and α their net impact on WTP to be empirically estimated.

Putting the three components together, we assume a ln(WTP) function of bidder *i* for item *j* as

$$\begin{aligned} \ln(W_{ij}) &= \theta_{ij}^1 \cdot \left(1 + \theta_{ij}^2 + \theta_j^3\right) + \varepsilon_{ij} \\ &= \left(Z_j^{'} \cdot \beta_i + \eta_i + \xi_j\right) \cdot \left(1 + \Pi_{ij}^{'} \cdot \gamma + C_j^{'} \cdot \alpha\right) + \varepsilon_{ij}, \end{aligned} \tag{5}$$

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

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

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).

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 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.

Identification conditions

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 unobervables 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. (See also Athey and Haile 2002 who use exogenous variation in the number of bidders and bidder-specific covariates to achieve identification).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. Also we assume no collusion among bidders; collusion would result in winning bid being lower than true WTP of other bidders and our estimation results will be biased. Given our assumptions, 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 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.

RESULTS

Model estimates

Table 2 reports the main results of the WTP model. Model 1 uses data only on actual observed bidders (14051 observations), and Model 2 includes latent bidders (25827 observations).[2] 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. 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. For ease of use, we only report the main effects in this table; interaction effects of equation (5) are not reported but are available from the authors upon request. Elasticities with respect to major variables of interest are also reported in Table 2.

----- Insert Table 2 about here -----

[2] 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 second robustness robustness check was to model the closing price and BIN option in in θ^1 instead of in θ^3. Finally, we also estimated the model with uniform distributions for model error terms The results, available from the authors upon request, are similar in sign and magnitude.

Most product characteristics matter in the expected ways. WTP increases with increase in speed, memory, hard drive, and screen size, and if the CPU is a Pentium. A somewhat surprising finding is the positive impact of usage on WTP (even though the elasticity is much smaller than other product characteristics). A likely explanation is that with a new product, a bidder can reasonably expect more similar products to be offered in the market in the future, but this is not as likely with used products. Therefore, for used products, it is possible that there are expectations of lower offering in the future, and therefore there is additional impact of a thin market for used products over and above current market thickness measures.

As expected, positive reputation increases WTP. Negative reputation does not matter to WTP. Note that since these reputations are compared with neutral reputations, the results imply that negative reputations are viewed as similar to neutral reputations (note that Cabral and Hortaçsu 2005 choose to lump neutral ratings with negative ratings). The magnitude of either effect is not large, which is consistent with the literature (e.g., Melnik and Alm 2002). Consistent with our results, Resnick et al. (2004) find that one or two negative feedbacks for new sellers did not affect WTP, even though these sellers had few positive feedback instances. However, Lucking-Reiley et al. (2005) finds that negative feedback has a larger impact compared to positive feedback. 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 (only 5% of ratings are negative, as table 1 indicates). Therefore, our results on reputations 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. The significance of page views and past bidding indicate that these are not casual, but rather purposeful, activities. 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 four 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 later in this section some further details of this.

The largest elasticity is the one related to the presence of BIN option. The positive sign is consistent both the explanation of BIN being a signal of quality and therefore raising WTP. The impact of previous closing price on WTP is negative. Given that in this site, previous closing price is not available to bidders to view, the impact has to be other than via a simple

search-and-compare bidder behavior. A possible explanation is that given most bidders are likely to buy a single laptop, a high closing price for a previous item means from the pool of bidders, the highest WTP bidder has been eliminated and therefore WTP is lower for the pool of remaining bidders.[3]

Estimated revenue

We want to check how well 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.[4] Instead, we estimate the following model using OLS:

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

where Y_j is observed bid, $\hat{W}_{2j}$ is estimated second-highest WTP for item j, and ζ_j is error term. We expect 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 1.005 (standard error = 5.27E-

[3] As another robustness check, we also estimate our model on eBay data for 387 notebooks sold during a two week period in August 2005. The estimation comprises far fewer parameters given these data do not have extensive information on bidder demographic and behavioral characteristics. Note that in eBay past prices are available to bidders, unlike in the Korean dataset. We find that even in a market as thick as eBay, the more the similar items listed, the lower the WTP. Also, the higher the past prices, the higher the WTP, supporting the reference price theory. Further details of these results can be obtained from the authors upon request.

[4] We did however compare the difference between highest bid and other bids and second-highest WTP and other WTPs and compared the distribution of these two variables for the following reason. If we believe in the "button auction" model of auctions where bidders bid close to WTP, the distribution of these variables should not be different from each other. We find that more than 20% of bidders bid lower than 50% of the final winning bid. Considering bidders already self-select in to items they are interested in, these large differences could not likely represent real differences in WTP. Therefore, it appears that the button auction model is not appropriate for our context. Further details of this exercise are available from the authors upon request.

08) and the R^2 for the regression is 0.78. In other words, the final winning bid is higher than the estimated second-highest WTP by 0.5%. This 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 1.005 to obtain the expected revenue amounts.

Impact of market competition on WTP: Further exploration

To understand better the role of market competition on WTP, especially as it might vary across brands, we conduct simulations based on the estimated parameters of Model 2. Table 3 shows the impact of market thickness on WTP of a particular brand, Toshiba; these results are generalizable to other brands given our model does not include an interaction between brand intercepts and market thickness variables.

----- Insert Table 3 about here -----

Table 3 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, the average number of latent bidders in our data and treated as exogenous in our model. 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. The number in a cell indicates the second-highest WTP for the first of the similar items being auctioned concurrently.

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 1.37%. For example, WTP decreases from $1383.73 to $1290.40 (6.74%) when going from one to two items, and $1222.18 to $1220.27 (.16%) when going from nine to ten items, when depth is

fixed at one (i.e., reading across the first row). If the additional laptop is also a Toshiba, the second-highest WTP will decrease by an average of 2.07%. For example, WTP decreases from $1383.73 to $1159.28 (10.2%) when two Toshiba laptops are available for auction concurrently (breadth *and* depth go from one to two. 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 nine items to ten items is from $1010.20 to $1006.23 (.24%), when depth increases from one to two. The decrease is largest initially, and drops later. For example, the first increase in breadth decreases WTP by 6.74%, the next one by 2.3%, the third by 1.16 %, etc. Similar results hold for an increase in depth (10.2%, 3.51%, 1.77%, etc).

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). 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), it would be worth knowing how much of an increase in winning bid would occur if these potential bidders could be converted to participating bidders, and weigh the benefits and costs of such actions in an environment of non-unique products.

CONCLUSIONS

We model how bidding data can be used to recover consumer WTP under very general assumptions of bidder strategies, maximands and behavior. We model WTP as having 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. Our results from WTP can be useful for to get to auction-environment invariant WTP because we can separate out auction-invariant, especially product-feature elasticities from auction data. 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 a more complex and realistic behavioral models can 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.

An important tradeoff made in our paper, and in model estimation in general, is the following. Modelers can provide more structure to various agents' decision making processes; in our case this might include modeling entry and exit of active bidders and items, differentiating between active and latent bidders' reasons for activity and latency, and perhaps even differentiating between active and latent sellers' reasons for activity and latency. Such an approach provides clarity to the equilibrium generating process. However, the estimates are very dependent on the validity and robustness of exact assumptions made on these processes. The alternative approach, the one we use in this paper, is to use less restrictive assumptions about equilibrium generating processes. While these estimates are more robust and agnostic to, and compatible with alternative mechanisms, the researcher is unable to provide direct insights in to the exact strategy adopted by various players in the industry. We have chosen the latter approach for reasons of robustness, tractability and in the absence of theoretical and empirical structural models that match our empirical setting.

Going forward, there are at least two important directions for future research. First, we await theoretical developments to be able to structurally model details of competition among items and bidders, and entry and exit of bidders and items. Second, it would be interesting to explore in more detail some auction design variables (like the existence and level of BIN pricing), and especially to understand the impact of competition on these choices made by sellers. In pursuing both these research directions, two caveats, of the intricacies of equilibrium formation and behavioral aspects of internet auctions, must be kept in mind.

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Table 1: Summary statistics

Variables	Average	Std. Dev.
Bidder characteristics		
Age	31.14	8.23
Gender (Male = 1, Female = 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
Seller characteristics		
Inexperienced seller (% in data)	.59	
Fraction of positive seller reputation	.57	.34
Fraction of negative seller reputation	.05	.12
Product characteristics		
CPU type (Pentium = 1, Celeron = 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
Auction designs		
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	.89	
BIN price (dollars)	1183.31	596.19
Auctions with BIN exercised	.41	
Market competition measures		
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
Closing price of similar items	1038.94	507.15

Table 2: Regression of ln(WTP)

Variables	Model 1: Observed bidders only	Model 2: Latent bidders included	Elasticity
Constant (base: others)	10.589 *	10.107 *	
Bidder characteristics			
ln(Age)	-.338 **	-.329 **	.252
Gender	-.013	-.062	.225
ln(Cumulative page views + 1)	.0004 *	.0004 *	-.148
ln(Cumulative bids + 1)	-.004 *	-.003 *	-.975
ln(Cumulative wins + 1)	.0004 **	.0004 **	-.119
ln(Cumulative expenditure + 1)	.001 *	.001 *	.282
Seller characteristics			
Inexperienced seller	.002	.000	n.s.
Positive reputation fraction	.004 *	.003 *	.610
Negative reputation fraction	-.007	-.003	n.s.
Pure product characteristics			
Pentium	.492 *	.300 *	.148
ln(CPU speed)	.704 *	.680 *	.680
ln(Memory)	.098	.152 **	.087
ln(Hard drive)	.334 *	.353 *	.152
Screen size	-.212 *	-.208 *	.201
ln(Usage + 1)	.041	.112 *	.028
Pure brand effects			
Compaq	.503 *	.523 *	
Dell	.117	.176	
IBM	.152 **	.312 *	
Fujitsu	.000	.000	
Sony	-.007	.039	
Toshiba	.498	.594 *	
Daewoo	.149	.245	
Sambo	-.028 *	-.034 *	
Samsung	.195 *	.367 *	
Market competition measures			
1/Breadth (high-end products)	.000 *	.005 **	
1/Breadth (all products)	.005 *	.010 *	.216
1/Depth	.003 *	.015 *	1.398
BIN option	.007 *	.004 *	1.302
ln(Closing price of similar items)	-.003 *	-.002 *	-.618
Estimated error variances			
σ_η (item-specific)	.0002	.0015	
σ_ξ (bidder-specific)	.001	.001	
σ_ε (item- and bidder- specific)	.221 *	.242 *	
Likelihood	-20785	-26299	

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

Table 3: WTP as a function of market competition (columns: breadth, rows: depth)

Toshiba: Expected second-highest WTP

	1	2	3	4	5	6	7	8	9	10
1	1383.73	1290.40	1260.71	1246.12	1237.45	1231.70	1227.61	1224.55	1222.18	1220.29
2		1159.28	1132.61	1119.50	1111.71	1106.55	1102.87	1100.13	1097.99	1096.29
3			1092.87	1080.22	1072.70	1067.72	1064.18	1061.53	1059.47	1057.83
4				1061.10	1053.72	1048.82	1045.34	1042.74	1040.72	1039.10
5					1042.49	1037.65	1034.20	1031.62	1029.63	1028.03
6						1030.26	1026.84	1024.28	1022.30	1020.71
7							1021.61	1019.07	1017.09	1015.52
8								1015.18	1013.21	1011.64
9									1010.20	1008.63
10										1006.23