DOING THEIR BIDDING: AN EMPIRICAL EXAMINATION OF FACTORS THAT AFFECT A BUYER'S UTILITY IN INTERNET AUCTIONS

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ABSTRACT

What factors make individual bidders pay more or less for the same item in online auctions? We use data on over 55,000 bids over a three-year period collected by a customized Internet software agent. This data is used to perform a *within-bidders* quasi-experiment, testing bidders who bid on the *exact same item* at different times during a 30-day period in online auctions. With theories from information systems and consumer behavior as our theoretical lens, we then examine factors that make individuals pay more for the *exact same item* in online auctions. We find that the same individual will tend to pay more for items sold on a weekend, for items with a picture, and for items sold by experienced sellers. We also find that the same individual is willing to pay more for the same item if others express an interest in that item, exhibiting a type of herd effect. Our results are generalizable to other auctions, and shed light on electronic commerce sales in general, where firms try to sell products for the highest possible price.

KEYWORDS: Auctions, coin collecting, consumer behavior, eBay, economic theory, econometric analysis, electronic commerce, electronic auctions, empirical research, information systems.

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INTRODUCTION

One of the major goals of Information Systems (**IS**) research is to show how information technology changes the way that various kinds of work, decisions and actions can be performed. In electronic commerce, for example, electronic markets differ from traditional markets in that e-commerce transactions are often conducted without personal contact and without specific knowledge about the seller. It is possible for a buyer to make a decision about purchasing a product without being able to examine it, and ascertain the details of its specifications, quality or condition. These differences result in questions regarding the role that product information provided to the buyer plays in Internet-based buying and selling:

- What causes a buyer to be willing to pay higher prices, to the extent they are observed, when making online purchases?
- What is the effect of an Internet seller's online experience on a buyer's decision to purchase items over the Internet?
- How can we empirically investigate consumer buying patterns aggregated from individual bidder observations?

The typical marketing strategy for traditional transactions suggests that a firm may want to obfuscate product details so that existing customers have a hard time comparing them to other products, and, therefore, feel the risks associated with switching to another vendor. Conversely, decision theory shows how people can avoid uncertainty and why they may be willing to pay to have it removed (e.g., Yates, 1990). Uncertainty about e-commerce transactions is increased because of the sight-unseen nature of the product being purchased and the anonymous nature of the seller. In this research, we examine the factors that make the *same bidder* pay more or less for the *same item*. Specifically, we explore what factors a seller can manipulate in an auction to make a bidder's utility for that item increase.

AUCTION LITERATURE

We use theory from marketing science, IS, and economics to describe how price enters into marketing strategy in such electronic market contexts. However, the auction literature from economics has been especially effective in describing how auctions should be viewed, in terms of valuation perspectives, and has developed many models of market microstructure that show how optimal auctions should be formed. IS researchers have added to the findings in the auction literature by examining recent behavior in Internet auctions. In addition, the reference value literature from marketing deals with the price sensitivity of a consumer, and what factors make that consumer pay more or less for the same item.

Auction theory in economics often emphasizes the significance of the *value* of an item for a bidder (e.g., Milgrom, 1989; Riley and Samuelson , 1989; and Vickery, 1961). Economists have advocated that bidders all have either *common values* (**CVs**) (e.g., Athey and Levin, 2001; Bulow, Huang, and Klemperer, 1999), where all bidders share the same valuation of the auctioned item, or *independent private values* (**IPVs**) (e.g., Tschantz,

Crooke, and Froeb, 2000), where each bidder can have a unique valuation of the auctioned item. Milgrom and Weber (1982) go further to examine *affiliated values* (**AVs**), where bidders have valuations commonly influenced not only by outside factors but also by personal factors.

Feldman and Mehra (1993) suggest that with collectors who purchase an item for a collection rather than for resale, the IPV assumption ought to be considered a valid assumption, while resellers who purchase an item for resale at a later date would use both IPV and an estimate of public valuation on the secondary market. Thus, to appropriately study the amounts that an individual bidder is willing to bid for a collectable, as advocated by Feldman and Mehra, IPV and AV need to be examined. Thus, there is a need to study bids *at the bidder level*, not at the auction level, to *evaluate bids from unique bidders whose valuations have a private component*. By studying bids at the bidder/item level, rather than at the item level as in previous studies (e.g., Lucking-Reiley 2000), we can gain more information about factors that cause a bidder to adjust her valuation. This is distinct from studies at the item level, which implicitly assume common valuation, and permits us to study what factors make an item sell for more or less, given a variety of bidders. By contrast, we study bids that have a private valuation component, as is found with both AVs and IPVs. This investigation cannot be accomplished simply by seeing how much each item sold for. Rather, we need to examine how much each individual bidder bids for similar items.

There is an Internet auction literature that has begun to develop as well. Beam and Segev (1998) provide an overview of auction markets on the Internet from 1995, and examine seller characteristics, especially of frequent and infrequent sellers, while Bakos (1998) reviews the characteristics and functions of Internet auctions. In this research, we extend the perspectives offered by Beam and Segev on the one hand, and Bakos on the other, by showing the effects that online auction characteristics have on an individual bidder, in particular those online characteristics that do not play as important role in traditional physical world auctions. Bapna, Goes and Gupta (2001) describe a typology of Internet auctions and how different bidder types are observed to behave in auctions. In this research, we also extend their work to describe factors that motivate change within a single bidder within online auctions. Vakrat and Seidmann (1999) examine how much consumers were willing to pay for identical products offered through online auctions versus online catalogs. They show that bidders prefer shorter auctions and expect larger discounts for expensive items. A second empirical study by these authors (Vakrat and Seidmann, 2000) finds that most bidders arrive during the first half of the online auction, and that high starting bids (especially those set by the seller) result in fewer bidders, while bundling results in more bidders. Our work should be viewed in conjunction with the work of Vakrat and Seidmann in describing the bid-level activity of a single online bidder, rather than with bidders in aggregate.

Lucking-Reiley, et al. (2000), empirically investigated how factors affect final prices for transactional exchange at eBay. In auctions that include bids, the authors conclude that the book value of a coin, the starting bid of an auction, the number of negative comments, and the length of the auction all significantly affect price. In

their study, the authors describe characteristics that sellers can incorporate to affect the final price of an item. The factors they select give rise to similar research, like ours, that can examine similar characteristics. However, our study is different than this study in several ways. We intend to be broader in our coverage. Whereas Lucking-Reiley et al. considered only coins in mint condition in their study, we consider all grades of coins. Our study also expands on this work in that they only consider bids from just July 1999, a period of early, strong growth for online auctions. In contrast, our data consist of observations spread out over three years, from April 1999 to April 2001. Furthermore, the Lucking-Reiley et al. study involved item level observations to determine what item characteristics will command higher prices. Ours employs a *within-subjects* test at the bidder level, showing what makes *individual bidders* pay more. We chose the bidder level instead of the item level so that we could examine what items command a higher price from the market. This also helps us to understand how the technology of the Internet can affect an individual's bidding behavior. Thus, our research extends the Lucking-Reiley et al. study by examining a broader market and investigating how Internet technology and other factors affect *private reactions* and price sensitivity *with IPV*. Lucking-Reiley, et al. examined *public reactions and price sensitivity with CV*. Thus, we show how an individual's valuation is changed, rather than the expected sale price of an auction.

THEORY AND RESEARCH HYPOTHESES

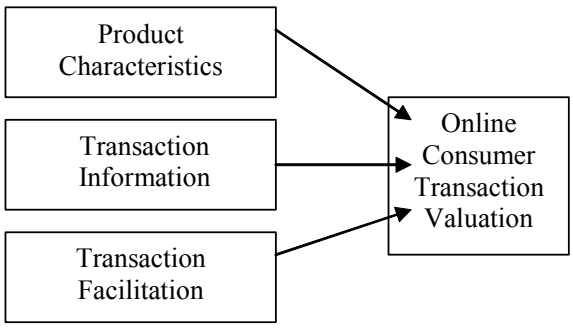
As illustrated by Bakos (1998), in electronic markets switching costs are diminished due to easy comparison of similar or identical products that are concurrently sold by other online sellers. However, online consumers are unable to personally scrutinize the seller or examine the product before purchasing. Information about the seller and about the seller's competence to provide a product may negatively impact the value of completing a transaction to a consumer (e.g., negative comments, uncertainty regarding if the seller is delivering the promised quality, etc.) or positive impact the value of completing a transaction to a consumer (e.g., positive comments, evidence that the seller is delivering the promised quality, etc.). We contend that the online consumer has a higher degree of product and seller uncertainty (which causes negative differentiation to utility) when compared to traditional markets because of the nature of online transactions, which typically allow less seller and product information to be transferred to the consumer before the transaction. This is because traditional markets allow the seller to view both the product and seller before making a purchase, whereas online markets typically do not. So it is natural that consumers might have some different levels of utility for different kinds of online transaction-making capabilities.

As a consumer becomes more informed, her reference value for the actual product may change. This should occur independent of any influence from the transaction process. The reader should further note that reference value information is subtly different than the value of the information provided by the seller. In this research, we distinguish between the *reference value that a consumer has for owning a given item* and how additional information provided by the market channel adjusts that *reference value for making a given transaction.* For

example, when bidding on a rare coin in an online auction, the consumer feels that the coin itself has a certain value. However, *if the consumer sees other coin collectors willing to bid more for that item, that consumer's reference value may change*, making the consumer place a higher value on owning the product based upon the additional information. Conversely, information about the seller or information that further clarifies the product that the seller is selling (such as a picture), does not change the consumer's reference value, but can act as positive differentiation in that such information makes the consumer feel more comfortable that both the consumer and the seller agree what is to be sold, thus reducing a consumer's product and seller uncertainty. Thus, we differentiate *product information*, which is information the seller provides about a product that describes the product that can change a consumer's expected value from *owning the product*, from *reference value information* provided by sellers or others that can change a consumer's *expected value from making a transaction*. [1] Clearly, the quality of support of the transaction process ought to play a role in establishing customer utility, although, practically speaking, it should be an independent consideration from the consumer's valuation of the product itself. Instead, the bid computation reflects willingness-to-pay, which is more an "all in" assessment of the transactional utility [2]

A consumer's desire for more convenience and for more information in online markets, and the possibility of changes in the reference value and differentiation lead us to several research hypotheses that examine reference value, product uncertainty, seller uncertainty, and convenience. Thus, we propose a new *Online Consumer Transaction Valuation Model*, the framework we use for this research. See Figure 1.

Figure 1. Online Consumer Transaction Valuation Model



[1] The expected value of owning a product comes from the likelihood of receiving a product that matches what the consumer expected. By contrast, the expected value of making a transaction, in this case, adjusts the expected value of owning a product by the probability that the seller will deliver what is expected in a time frame that is stated or assumed.

[2] We thank the special issue editors for their input here. They pointed out that *willingness-to-pay* ought to be a function of the kinds of trans*action facilitation*—different *transaction mechanisms* for mercantile exchange, in effect—that occur in a given transaction-making or exchange environment. As a result, different levels of willingness-to-pay will influence buyers' bid computations, making it possible for a single consumer's valuation of a product to be associated with many different bid levels. Of course, we know this to be true in traditional retail settings as well, e.g., department store shopping vs. bargain basement shopping. The consumer's product valuation is probably identical for identical products, but the willingness-to-pay is dramatically changed.

We define the Online Consumer Transaction Valuation Model to illustrate a consumer's valuation of completing a transaction in an Internet-based market setting. A consumer's valuation for completing a transaction is broken down into product characteristics, transaction information that can increase or decrease consumer valuation, and other meta-information about the transaction (e.g., validation of product information, good seller information, etc.).

This model can be used to test *consumer valuation*, and thus the level of analysis should be a consumer's valuation of a product purchased in a specific transaction-making medium. The base utility in the model is the purchase of a product in a medium without any additional information and with minimal facilitation. When more information and convenience features are provided, the Online Consumer Transaction Valuation Model permits us to test the effects on overall consumer valuation that the additional information creates. In this section, we will develop tests for each of the components in the model in order to examine its effectiveness in an Internet auction setting. This will also allow us to test the explanatory robustness of the model, and examine those areas of information (e.g., product information, previous experience, seller information, etc.) that significantly affect what a customer will pay for an item online.

Hypotheses on How Valuation Results from a Buyer's Own Actions (H1)

Many authors comment about how it is less costly to search online (e.g., Bakos, 1998; Bailey, 1998). A consumer forms an initial impression of how much an item should sell for online based on online searches for similar items and other available information. Product characteristics typically are the main drivers for a consumer's reference value. In this research, we examine how reference value can change based upon actions that occurred in the context of a buyer's previous experience.

We contend that when a bidder loses a previous sale, there will be a tendency to believe that the item is worth more than the bidder previously thought, or that current low bids will no longer be sufficient to win an item. Thus, we contend that *either* a bidder's utility for an item will increase after a learning effect that causes the bidder to increase their private valuation for an item after unsuccessfully bidding on that item *or,* if the bidder is shading and bidding below their true valuation, at least a learning effect that causes the bidder to bid in higher amounts closer to an actual private valuation after unsuccessfully bidding on that item. This leads to our *Bidder Learning Effects Hypothesis*:

- **The Bidder Learning Effects Hypothesis (H1a):** An online bidder will bid more for an item in an auction after that bidder has unsuccessfully bid for that same item in any previous auction.

Economic theory states that substitutes of a product will cause that product's utility to decrease in relative value (e.g., Tirole, 1988, p. 10). In rare coin online auctions, substitutes can be either the same coin purchased by the same buyer at another time, or a similar coin to be added to the buyer's collection. Thus, a bidder may revaluate the reference value of a particular coin if she has purchased the same or a different coin in the past:

- **The Product Substitute Hypothesis (H1b):** An online bidder will have a lower utility for an item in an auction if a substitute product is available.

Hypotheses on How Valuation Results from Others' Actions (H2)

Along with testing to see if a buyer's reference value changes based upon previous actions of that buyer, we also examine how others' actions can change that valuation which a buyer places upon an item. There have been many studies that show a *herd mentality* or *bandwagon effect* in economics (e.g., Biddle, 1991), strategy and information systems (e.g., Wade, 1995), and in marketing (e.g., Muthukrishnan and Kardes, 2001). These studies indicate that a consumer will adjust her utility upward if she observes that other consumers have a higher utility. Thus, a bidder's valuations may be dependent upon the valuation of others. Seeing an elevated interest (or a lack of interest, for that matter) from other consumers a product will force a consumer to question her own valuation. Thus, interest shown by other consumers has an effect of increasing the utility felt by the consumer. In this vein, we examine the effect the number of prior bidders has on the current bidder:

- **The Prior Bidders Hypothesis (H2a):** An online bidder will have a higher utility (i.e., the online bidder will be willing to pay more) for an item in an auction if other buyers show a willingness to purchase that item.

This hypothesis is consistent with a Bayesian view of bidding phenomena in auctions.[3] When bidders base their utility on a prior assessment of common value (instead of independent private values), it will be important for them to track the extent to which their own current common value-driven valuation is in line with the market's common valuation. When the basis for existing beliefs about value that are held in the market change (e.g., through drivers of reduced or increased demand, etc.), the other common-value based bidders will work to adjust their prior beliefs, leading to a different level of utility for a buyer for a given offer price by the seller, resulting in a different level of willingness-to-pay.

To our knowledge, the *Prior Bidders Hypothesis*, and our accompanying Bayesian interpretation of how willingness-to-pay in auctions is updated have <u>not</u> been empirically examined in the online auction literature before. The number of total bidders, however, has been examined to see its effect on the *total price that an item sells for* rather than on an *individual's utility*. In previous studies (e.g., Lucking-Reiley, et al., 2000), other authors convincingly argue that a large number of bidders will result in a higher probability that a single bidder with a large utility will bid on the auction, thus causing the item to be sold at a higher price level. We do not dispute these results. Instead, in this study we examine how *an individual's expected utility* is significantly changed by

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[3] Consider a valuation function, $f(v)$, for an auction sale item, that characterizes willingness-to-pay for bidders who have specific prior distribution of v. Now imagine that some signal, s, is received by the bidder, resulting in a new posterior distribution that is adjusted for the signal. The resulting revision of beliefs kicks off a revision of the bidder's valuation function, according to $f(v|s)$. The *Prior Bidders Hypothesis* is an operationalization of this perspective that permits us to test

the existence of other bidders; we do not examine the final price that an item receives. We argue that a bidder's expected utility for a sale item will increase if other bidders also think the item is valuable, but with only few other bidders, a bidder feels greater uncertainty about her valuation of the item. And so she may be observed to lower her bid for that item, due to a lower level of expected utility.

We also believe that seller can try to convey an item's worth by setting the starting bid. Thus, we believe that a higher starting bid can result in a re-evaluation of the reference value of an item. Thus, bidders who believe the seller will re-evaluate their reference value to be more in line with what the seller expects:

- **The Starting Bid Hypothesis (H2b):** An online bidder will have a higher utility for an item in an auction if the seller sets a higher starting bid for that auction.

We contend that the existence and actions of other bidders as well as the starting bid for the item set by the seller can change the bidder's propensity to enter an auction, as suggested by Bapna, Goes and Gupta (2003), as well as change the bidder's willingness-to-pay for the sale item. Our *Starting Bid Hypothesis* differs from traditional *within-item* studies. Since we are doing a *within-bidder/item* study, we are not examining how much an item sells for, as is done in traditional within-item studies. Instead, we are investigating how a high starting bid affects *the same* bidder's final valuation of an item. Intuitively, one may expect the same bidder to bid the same final amount for an item regardless of the selling price mandated by the seller. If a buyer is not willing to bid higher in the other auctions when her bid is surpassed, that same buyer will not be willing to bid higher in an auction where the seller places a high starting bid *unless the buyer's valuation is influenced by the starting bid*.

Product Information Hypotheses (H3)

Unlike what most often occurs in traditional markets, electronic markets seldom, if ever, let the consumer examine a product before the purchase. Koppius and van Heck (2002) make a similar observation in their research on the role of product quality and market state information in the new electronic version of the traditional Dutch flower auction process. They observe that there are multiple changes that have occurred at the same time in the move to electronic auctions, some of which constitute subtle effects that are not very easily decomposed into their individual impacts. Their research setting permitted them to distinguish between the bidding behavior of *internal bidders*, who possessed more information about the state of the market and the quality of the pallets of flowers that were offered for sale, and *external bidders*, who were privy to less market and product information. Interestingly, the authors found that external bidders tended to make higher bids, which runs counter to the expectations that the existing theory would suggest (i.e., less well-informed bidders will bid less). The authors did not abandon the idea that more information regarding a product (providing it is of a given and appropriate quality level) is likely to elicit higher willingness-to-pay. Instead, they suggested that proximity to the market's

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for whether the empirical results are supportive of the Bayesian interpretation. We thank the special issue editors for pointing this out to us.

operations, and an ability to actually observe demand as it materializes in traditional market terms (in this case, based on the flow of potential buyers from flower shops who inspect the pallets of flowers on which they are likely to make bids). Thus, lower bids from informed buyers may be indicative of assessments that are being made about the quality of the market mechanism (e.g., depth of demand, expectations for the trajectory of bids over time, etc.), rather than the product that has been offered for sale.

Bidding on eBay and other online auctions may be observed to be influenced in similar ways. Assuming that there is no "inside information" available to bidders that is not already observable on the eBay Web site for a given auction item, there should be no distinction between internal bidders and external bidders. All of the market's participants are more likely to be characterized in terms of Koppius and van Heck's external bidders. Thus, offering a picture or a more detailed description of a sale item on eBay to a potential buyer ought to be a step in the right direction. So, as a result, a consumer's utility is likely to be higher for an item on sale in an electronic market when the seller of that item provides more product information. The presence of more information and the resulting level of consumer utility should also result in a greater willingness-to-pay, which can be observed indirectly through the bid prices that materialize for the item. These observations leads to our *Picture Hypothesis:*

- **The Picture Hypothesis (H3a):** An online bidder will have a higher utility for an item in an auction if the seller provides a picture of that product.

Another place the seller can convey more information is in the seller description. Of course, it may be difficult to judge the quality of a description. However, we assume that, for the most part, longer descriptions are capable of conveying more product information, thus leading to our *Description Length Hypothesis*:

- **The Description Length Hypothesis (H3b):** An online bidder will have a higher utility for an item in an auction if the seller provides a longer description of that product.

Online Seller Information Hypotheses (H4)

Like the product, the consumer cannot meet or know very much about online sellers before the purchase transaction. Thus, an unscrupulous seller could act anonymously by falsifying name, address, phone, and email address, leaving the consumer vulnerable if any opportunistic behavior should occur. Even if the seller does not hide his identity, the consumer can still be victimized by a seller who typically is far away and, in online auctions, whose business does not depend on satisfied customers. However, sellers who have much experience and history online have more to lose from negative reputation effects than sellers who are inexperienced. Furthermore, we expect that online sellers who have more experience will have learned how to minimize the uncertainty felt by a consumer than those online sellers with little experience. Thus, we put forth the *Experienced Seller Hypothesis*:

- **The Seller Experience Hypothesis (H4a):** An online bidder will have a higher utility for an item in an auction when a more experienced seller hosts that auction.

We also suspect that an online bidder will have less seller uncertainty when dealing with sellers that other consumers have reported to be reputable:

- **The Seller Reputation Hypothesis (H4b):** An online bidder will have a higher utility for an item in an auction when a more reputable dealer hosts that auction.

Note that there is a difference between the *Seller Experience Hypothesis (H4a)* and the *Seller Reputation Hypothesis (H4b)*. In H4a, we are examining the effect that previous seller *experience* has on his ability to elicit higher bids from an individual. Thus, a seller can use lessons learned in previous auctions to give his items more appeal, and the bidder may feel that an experienced seller has shown a dedication to a marketing channel and thus will be less likely to act opportunistically. Conversely, the *Seller Reputation Hypothesis* describes how other bidders have judged the seller's previous actions. Other bidders may react positively or negatively to opinions of other bidders regarding the previous transactions of the seller.

Transaction Facilitation Hypotheses (H5)

We argue that a consumer will pay more for a convenient way to pay for a transaction. First, we examine payment by credit card. Credit card payment allows purchasers to avoid the hassle of mailing, and the wait for the payment to be received before the shipment can occur, leading to our *Way-to-Pay Hypothesis:*

- **The Way-to-Pay Hypothesis (H5a):** An online bidder will have a higher utility for an item in an auction when the seller of that auction accepts credit cards as payment for the merchandise.

In electronic commerce, convenience is increased since ordering can be done electronically from home during hours that are convenient to the buyer, not to the seller. However, in online auctions, many trade journals and online journals advocate "sniping" as a strategy to hide your interest (or level of interest) in an item until the last possible minute (e.g., Hitchcock, 2000; Bapna, forthcoming). Sniping occurs when a potential buyer does not make a bid on a sale item until the very end of the auction cycle. This technique is well known to occur and is often implemented by potential buyers when they are bidding on items. Thus, when adopting this strategy, ending time in an auction becomes an issue because some times are more convenient to the consumer than others. Specifically, we propose that the bids made on items sold in auctions that end on the weekend will command higher bids *from the same individual* than bids on items sold in auctions that do not end on the weekend.

- **The Weekend Hypothesis (H5b):** An online bidder will have a higher utility for an item in an auction when that auction ends on a weekend rather than on a weekday.

Although the *Weekend Hypothesis* appears to violate the long-standing assumptions of economic utility, we propose that buyers' time is less constrained on the weekend, and thus buyers can devote more time, investigation, and consideration to items sold on the weekend than the buyer can during a weekday. We hypothesize, then, that

buyers have more time to consider a purchase on the weekend, and that this further consideration can lead to higher prices because of reduced buyer risk, attributable to the increased ability to consider a transaction.

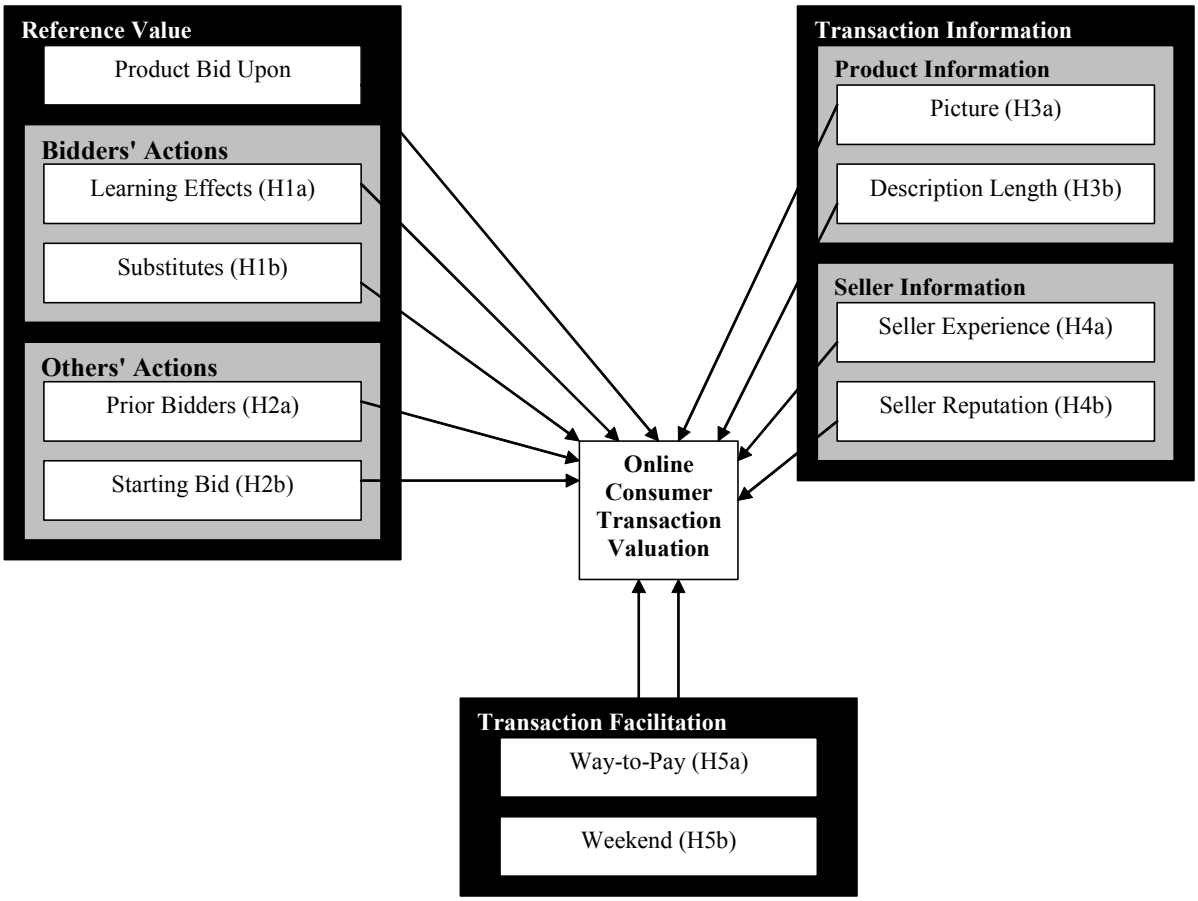
Consider the following background on coin trading on the Internet in this context. *Coin World Magazine* is eBay's supplier of coin information on the latter's coin auction site. We conducted an unstructured interview with *Coin World Magazine* "Contributing Trends" Editor, Stuart Segan in April 2001. We learned that the time of the sale can affect the price at which an item will transact. Specifically, Segan told us that coins sold through eBay on the weekend are more likely to sell at a higher price than coins on the weekday. We note that weekend effects are not absent from the literature. For example, Lucking-Reiley, et al. (2000) echo that conventional wisdom calls for sellers to end their auctions on a weekend, although those authors failed to find significant evidence to assert that this occurs for items sold on eBay. In terms of the Online Consumer Transaction Valuation Model, conventional wisdom indicates that the ending time of an online auction may affect transaction facilitation and thus change a bidder's utility for making a bid upon a given item.

Warner and Barsky (1995) describe a weekend effect where sellers reduce prices at that time of the week. On the face of it, this may seem to be the opposite of what we propose, but our interpretation is that we are seeing something that is quite similar. The authors are concerned with *seller* actions. Lower prices are motivated by sellers who compete to capture consumers' business, since consumers typically are willing to spend more of their money on the weekend due to fewer time constraints, and a desire to make better decisions. In other words, buyers are willing to spend more if a purchase is made to be convenient. We, too, propose that consumers are willing to spend more on the weekend. But we go further. We claim that consumers are willing to pay more for the *same item* when it is sold on a weekend. With fewer time constraints, a bidder's marginal utility of search time is decreased on the weekend, and thus a bidder can make a safer, better-informed bid on the weekend rather than a weekday.

Theoretical Framework for Measuring Utility in Online Auctions

By combining all of the hypotheses, we can operationalize the Online Consumer Transaction Valuation Model, as shown in Figure 2.

Figure 3. Online Consumer Transaction Valuation Model Applied to Online Auctions



Note that in Figure 2, the *Product Bid Upon* does not have a corresponding hypothesis. In this study, we conduct a *within-bidder, within-product quasi- experiment* to <u>*control*</u> for individual utility characteristics as well as product characteristics that are not discernable and yet generate different levels of the utility for each different online consumer. A within-bidder, within-product study is difficult in that it requires much data simply to find multiple bidder and product combinations, where the *same bidder bids in multiple auctions for the same product.* However, in doing so, we control for unobservable product attributes that may appeal to some consumers. We also control for unobservable bidder attributes.

An empirical model enables us to test the validity of our model and to compare various types of information (e.g., seller information, product information, information from others' actions, information from a bidder's own experience, etc.) to see which types of information have the greatest impact.

DATA

To gather data for this project that is both generalizable and realistic, we employed an Internet-based software agent that was written specifically to capture data from eBay. (For additional details, see Kauffman, March, and Wood, 2000.) This agent collected data on *many individuals* that purchased *many different items* from *many*

different sellers. More generally, Internet agents work well for this kind of research because they not only facilitate massive data collection efforts, but (as is necessary in this instance) also allow individual actions (as opposed to reported actions or hypothetical actions) to be captured, thereby contributing to the realism of the research.

Bids on rare U.S. coins, specifically pennies, two-cent pieces, and three-cent pieces, were collected because coins have a grading scale that is commonly used and accepted by almost all coin collectors.[4] With our selection of rare coins, not only can we collect data on year and type of coin, but we can also retrieve the grade reported by the seller. Only coins minted in the U.S. in the 19th century were observed because many 20th century coins were offered in aggregate (e.g., "a bag of wheat pennies, 1909-1959") or were not valid currency, and, therefore, were harder to evaluate (e.g., "amaze your friends with this 1999 $1,000,000 bill, bidding starts at $.50").

Our software agent searched for different U.S. denominations, including rare pennies, one-half-cent pieces, two-cent pieces, three-cent pieces, and twenty-cent pieces. We also sought out mint year and a grade, which were derived from the item name and description based on interpretative algorithms for text-based information. Grades were assigned numerically using ordinal number assignments. These assignments corresponded to the ratings described in a prior footnote that are used by expert coin collectors. Coins that could not be graded or dated by our agent were dropped from the data. Also, multiple coin listings (e.g., "1858 Flying Eagle and a 1868 Indian Head") were dropped from the data. Since we measure demand in this experiment through price, we also dropped the highest bid for an item. This is because the losing bids contained information as to how high the bidder was willing to go. However, the winning bidder may have been willing to bid even more, if she faced any challengers. Information on the data for this study is shown in Table 1.

Table 1. Data Collected from eBay

Date Collected	Number of Bids	Number of Bidders	Number of Coins	Combi-nations Considered	Bids Considered	Bidders in Study
May 1999	15,927	2,852	5,109	111	283	72
January 2000	14,130	3,430	5,982	69	191	37
April 2001	25,295	5,264	10,147	106	276	67
Total	**55,352**	**10,367**	**21,238**	**282**	**750**	**173**

Note: We considered a number of combinations (of bidders, coin, and condition) and bidders in the study, which may each be duplicated across different years. Thus, the total across the years of this study will be somewhat less than the sum of these variables.

[4] Typically-used ratings for collectible coins are as follows from highest quality to the lowest quality levels: Proof, Uncirculated, Almost Uncirculated, Extremely Fine or Extra Fine, Very Fine, Fine, Very Good, Good, Almost Good, Fair, Poor, Unratable. In addition, some ratings use another numeric grading scheme, so MS-64 uncirculated is different than MS-63 uncirculated, and G-4 Good is different than G-6 Good. When numbers were given, they were used to refine our specification of the grade of the coin. For additional information, the interested reader should see Segan (2003).

We considered combinations of bidder / category / year / grade (bidder / product) that were bid on by at least twice (once with a picture, the stimulus—and once without a picture, the control) *and* at least once on the weekend (the stimuli again) and once on a weekday (the control again) *by the same bidder*. We then considered all the high bids in these categories. Thus, we only included bidders who *did not win* and showed a willingness to bid on a specific item both with and without a picture, and bidders who were willing to purchase items both on the weekend and on a weekday. So, by design, we retrieve information on bidders who are relatively experienced by showing a willingness to bid on eBay during multiple periods, and a willingness to bid with and without a picture. As such, results from this study should not be generalized *a priori* to buyers with little experience.

We also only considered the highest bid for each item by each bidder. A bidder can use an agent, provided by eBay, to automatically bid up to her top reservation price for an item in the auction. A bidder can also enter multiple minimum bids until the valuation of the next highest bid is beyond her top reservation price for the item in the auction. We do not investigate bidding behavior within an auction, such as the use of multiple bids or agent bids, as these mechanisms should not affect a bidder's top reservation price for an item in an auction. Rather we investigate the highest value that a bidder is willing to pay for an item in an auction, regardless of how many times that bidder bid in the auction and whether that bidder utilized an agent for bidding.

EMPIRICAL MODEL

To obtain results in this empirical study, we need to examine bidders who each have their own IPVs—*independent private valuations*—as proposed by Feldman and Mehra (1993).

Model Development and Measures

We begin the development of our empirical model by investigating how much each bidder is willing to pay above what that bidder offered for the *exact same item* during the same month. By using a within-subjects design, we can study bids from bidders whose valuations have a private component. Therefore, in this illustration we will not investigate item characteristics that increase or decrease the overall valuation of an item, such as reported book value or the condition of item, as one would when investigating common valuations. Instead, we will investigate what factors motivate a single bidder to paying more (or less) for the *same item* in the *same condition* with the *same book value*. Our data is particularly well-suited to this task. We have access to over 50,000 bids, and with such a large data set, bidders can be identified who entered *multiple losing bids on the same item* (e.g., a coin with the same denomination, the same grade, and the same year) and who have demonstrated *both* the behavior of the stimuli and the behavior of the control (e.g., bid on identical items, at least once with a picture (stimulus) and at least once without a picture (control) *and* at least once on the weekend (stimulus) and at least once on a weekday (control)).

One of the key drivers of a bidder's willingness-to-pay is that person's perceptions about the demeanor of the selling counter-party to the transaction. There are a number of different aspects of the seller's demeanor that most

bidders consider in making bids, however, Internet-based auctions such as eBay have typically boiled these multiple dimensions down to just one: the *reputation score*. There are some difficulties associated with this operationalization, however. Kauffman and Wood (2000) point out that eBay's reputation score, in actuality, behaves as a proxy for experience, not reputation. Because of the mechanics of the eBay's reputation score, the longer a seller has been in the market, the higher the score. Figure 3 below provides an overview of the construction of reputation scores on eBay.

Figure 3. eBay's Construction of Seller's Reputation Score (from 2000)

Overall profile makeup

346 positives. **258** are from unique users and count toward the final rating.

1 neutrals. **0** are from users no longer registered.

3 negatives. **2** are from unique users and count toward the final rating.

ebay ID card wegryn (256)

Member since Wednesday, Feb 16, 2000

me

Summary of Most Recent Comments

	Past 7 days	Past month	Past 6 mo.
Positive	11	79	223
Neutral	0	0	1
Negative	0	0	1
Total	**11**	**79**	**225**
Bid Retractions	0	0	0

In Figure 3 the seller's eBay reputation score is given by the count of comments from unique users less the count of all negative comments from unique users. For example, as of February 16, 2000, "*wegryn*," the seller, received 258 good comments from unique users and 2 negative comments from unique users, resulting in a reputation score of 256 (= 258 - 2).

Kauffman and Wood (2000) also reported some surprising characteristics regarding this reputation score. The number of *positive* characteristics was, as expected, *positively* correlated with the price a seller receives for an item. However, the number of *negative* comments was also *positively* correlated with the price a seller receives for an item. Furthermore, the authors could find no relationship between the *ratio* of positive-to-negative comments and the price a seller received for an item. In unstructured interviews and discussions with eBay sellers and buyers, the authors found that any negative comments tend to be reciprocated, so that if a buyer gives a seller a negative comment, the seller, in turn, makes a negative comment about the buyer. Some sellers even give a discount (5% to 10%) to the winning bidder if that bidder leaves a good comment for the seller. Finally, if a seller merely achieves more good comments than bad comments on a consistent basis, the seller's reputation score will increase even though the percentage of dissatisfied customers remains constant over time. Kauffman and Wood (2000) argue that, since this score only seems to increase *over time* and with *seller activity*, eBay's reputation score is best used as a *proxy for experience* rather than reputation. This research adopts that proxy. Thus, to test the effect of a seller's experience on the price a bidder is willing to pay, we are able to use eBay's seller reputation score to evaluate the *Experienced Seller Hypothesis*. To test for reputation effects, then, we use the ratio of

positive comments to total non-neutral (positive plus negative) comments. This will capture the percentage of commented transactions that have been perceived as beneficial to the buyer, rather than the additive score advocated by eBay.

The empirical model we propose can be used to test these hypotheses. Our test investigates causes of the *variation in an individual bidder's willingness to pay for identical items*. Equation 2 shows the model's general form.

$$\textit{Bid Amount} = f(\textit{Item, Product Information, Seller Information, Convenience}) \quad (2)$$

Equation 2 mirrors the theory shown in our theoretical framework shown in Figure 2. The equation shows that a bid amount is a function of the item for sale as well as product information, seller information, and convenience. We begin with a simple linear regression model shown in Equation 3.

$$\begin{aligned}\textit{\% Above Average High Bid} = {} & \alpha + \beta_{\textit{Number of Prior Bidders}} * \textit{Number of Prior Bidders} \\ & + \beta_{\textit{Minimum Bid}} * \textit{Minimum Bid} + \beta_{\textit{Later Bid}} * \textit{Later Bid} \\ & + \beta_{\textit{Same Coins Purchased}} * \textit{Same Coins Purchased} + \beta_{\textit{Other Coins Purchased}} * \textit{Other Coins Purchased} \\ & + \beta_{\textit{Picture Exists}} * \textit{Picture Exists} + \beta_{\textit{Description Length}} * \textit{Description Length} \\ & + \beta_{\textit{Weekend Bid}} * \textit{Weekend Bid} + \beta_{\textit{Credit Card}} * \textit{Credit Card} \\ & + \beta_{\textit{Reputation Score}} * \textit{Reputation Score} + \beta_{\textit{Reputation Ratio}} * \textit{Reputation Ratio} \\ & + \beta_{\textit{Time Left in Auction}} * \textit{Time Left in Auction} + \varepsilon \end{aligned} \quad (3)$$

In Equation 3, the *Bid Amount* dependent variable is proxied by the amount above the average bid for this item by this bidder in the past. In this way, higher-than-average and lower-than-average can be examined as they relate to other auction characteristics. Item characters are added as control variables to control for item fixed effects. The variables in the model are described in Table 2.

Table 2. Definitions of Variables in the Empirical Model

DEPENDENT VARIABLE	
Variable	**Description**
% Above Average High Bid	The percentage that this bid is above (or below, in the form of a negative number) the average bid made by this same bidder for this same item. The average of the high bids is used in order to center the dependent variable.
INDEPENDENT VARIABLES	
Variable	**Description**
Number of Prior Bidders	Discrete variable measuring the number of bidders in an auction before this bidder makes her final high bid.
Later Bid	Dummy variable indicating whether earlier losing bids for this same item from this same bidder are detected (*Later Bid = 1*) or not (*Later Bid = 0*). We argue that a bidder who is still in the market for a coin will pay more if that bidder has previously lost an auction for the same item.
Minimum Bid	Smallest bid level acceptable by the seller, as a percentage of the book value of the coin. They also are public and are set by the seller.
Same Coins Purchased	Count variable indicating the number of auctions selling this type of coin (excluding condition) that were successfully won by this bidder
Other Coins Purchased	Count variable indicating the number of auctions selling any type of coin that were successfully won by this bidder
Picture Exists	Dummy variable indicating whether this item's description contained a picture (*Picture =1*) or did not contain a picture (*Picture = 0*).
Description Length	Number of bytes contained in the description
Weekend Bid	Dummy variable indicating whether the final bid for this item occurred on a weekend (*Weekend* = 1) or on a weekday (*Weekend = 0*)
Credit Card	Dummy variable indicating whether the seller in this auction accepts credit card payments.
Reputation Score	Continuous variable representing eBay's reputation score for the seller, as proxy for experience rather than to represent "reputation."
Reputation Ratio	Ratio of positive-to-negative comments, as reputation proxy.
Time Left in Auction	Continuous control variable measuring the number of days left in the auction, including fractional portions of a day, when the final bid by this bidder was made.
ε	Regression error term

The reader should note that although we only consider losing bids in the dependent variable, we do control for previous bids (with the *Later Bid* variable), previous winning bids in different auctions selling the same coin (with the *Same Coins Purchased* variable), and previous winning bids in different auctions selling a different coin (with the *Other Coins Purchased* variable). We next perform some preliminary analysis of our data and discuss the rationale for transformations of the data that were required to improve on our naive linear model. We also present what we did to detect possible violations to our regression model's assumptions.

Fixed Effects

We gather data from single-month time periods from three different years in order to alleviate any fixed effects that may show up in the error term of the regression, if they exist, and are not corrected for (Greene, 1999). Fixed effects essentially reflect an omitted variables bias. Such effects include the level of acceptability of technology, the increasing prevalence of online auctions, differing disposable income levels from the rise and fall of the stock market, etc. Thus, we need to include variables that capture the fixed effects of each year. Using 2001 as base year, we can use two dummy variables to capture the 1999 and 2000 fixed effects that cause overall differences between 2001 and the other years. The reader should recognize that although our model acknowledges the fixed effects, it does not discriminate among their multiple potential sources. That issue is beyond the scope of the current research.

Nonlinearity of Independent Variable Relationships

While ordinary least squares models assume that linear relationships exist between each independent variable and the dependent variable, in many cases, the true relationships may be non-linear. This is probably the case with our experience variable and our ratios. With ratios, for example, if the first item that is compared shows less seller experience than the second item that is compared (i.e., the numerator is smaller than the denominator), then the ratio is limited to values between 0 and 1. If the second is larger than the first (i.e., the numerator is larger than the denominator), then the ratios have a lower limit of 1 and an upper limit of infinity. This is resolved by the use of logarithms, which transform ratios and give the same magnitude to differences, whether those differences occur in the numerator or denominator. We define these measures as follows:

Bid Amount Ratio' = ln (Bid Amount Ratio)

Reputation Ratio' = ln(Reputation Ratio)

We assume that the difference of experience and description length indicated by low reputation scores will have a greater impact than differences between high reputation scores. For example, a seller with a reputation score of 20 would be perceived as having much more experience than a seller with a reputation score of 10. However, even though a seller with a reputation score of 2000 shows the same relative increase in experience as a seller with a reputation score of 1000, both sellers would have enough experience to be very proficient at selling since they have sold quite a large number of items. Both are likely to be quite experienced. The amount sellers and buyers learn would be greater in differences at the low end rather than at differences at the high end of the score's distribution. Thus, we believe that a logarithmic transformation is necessary to give more weight to differences in scores at the low end than to differences in scores at the high end:

Reputation Score' = ln(Reputation Score) and *Description Length' = ln(Description Length)*

Interaction Effects

We assume that the *Number of Prior Bidders* interacts with the *Time Left in Auction* and variables interact in that the more time left in an auction, the more likely that auction will attract a higher number of bidders. Neter, et

al. (1996) suggest that, if independent variables interact, an *interaction term* should be introduced that absorbs the interaction in the regression model. This interaction term typically is modeled as a product of the two terms that interact. Thus, we include two interaction terms in our econometric model:

$$NPB*TL = Number\ of\ Prior\ Bidders * Time\ Left\ in\ Auction$$

$$NPB*MB = Number\ of\ Prior\ Bidders * Minimum\ Bid$$

Our final econometric model is presented in Equation 4.

$$\begin{aligned} \%\ Above\ Average\ High\ Bid = \alpha &+ \beta_{Number\ of\ Prior\ Bidders} * Number\ of\ Prior\ Bidders \\ &+ \beta_{Minimum\ Bid} * Minimum\ Bid + \beta_{Later\ Bid} * Later\ Bid \\ &+ \beta_{Same\ Coins\ Purchased} * Same\ Coins\ Purchased + \beta_{Other\ Coins\ Purchased} * Other\ Coins\ Purchased \\ &+ \beta_{Picture\ Exists} * Picture\ Exists + \beta_{Description\ Length} * Description\ Length \\ &+ \beta_{Weekend\ Bid} * Weekend\ Bid + \beta_{Credit\ Card} * Credit\ Card \\ &+ \beta_{Reputation\ Score} * Reputation\ Score + \beta_{Reputation\ Ratio} * Reputation\ Ratio \\ &+ \beta_{Time\ Left\ in\ Auction} * Time\ Left\ in\ Auction \\ &+ \beta_{1999\ Fixed\ Effects} * 1999\ Fixed\ Effects + \beta_{2000\ Fixed\ Effects} * 2000\ Fixed\ Effects \\ &+ \beta_{NPB*TLIA} * NPB*TLIA + \beta_{NPB*MB} * NPB*MB + \varepsilon \end{aligned} \quad (4)$$

The reader should note that we do not have data on a bidder's valuation when the starting bid or current bid are above that bidder's valuation, since a bidder simply will not bid on an item in this case. However, our handling of the dependent variable as *% Above High Bid* allows us to check for effects without having to resolve the usual censored or truncated distribution issues that would require a TOBIT regression or a truncated regression analysis.

Collinearity and Multicollinearity

Kennedy (2000) describes how severe estimation problems can arise when independent variables are highly correlated resulting in collinearity among predictor variables. He points to the instability and large variances among coefficient estimates that occur. This typically causes the parameter estimates for a model to be unstable and the model, as a result, will tend to exhibit low predictive capabilities. Kennedy claims that a high correlation between variables (e.g., 80% or higher) can be indicative of collinearity. Our correlation matrix shows that the highest correlation that appears between our variables is only 45%, and thus we feel comfortable that our model does not exhibit problems with collinearity between any two predictor variables.

Although a correlation matrix can detect collinearity between any two variables, there is still a chance that an independent variable is the product of a *linear combination* of other variables. Because of this possibility, Belsley, Kuh and Welsch (1980) advocate using a *condition number test* that can be examined to detect possible multicollinearity. Greene (1999) says that, as a rule of thumb, any condition number below 20 will indicate that

the variables are safe to use in the same model. Our model's variables have a condition number of 12.6, which is well below the value suggested by Greene. Thus, our model is not affected adversely by multicollinearity.

RESULTS AND DISCUSSION

We next present and interpret the primary findings of our econometrics analysis. We also consider broader implications and discuss the limitations of the applicability of our results and assertions regarding the theoretical underpinnings of willingness-to-pay in eBay auctions for collectible coins.

Econometric Results

Table 3 shows the results of our model in terms of regression statistics, ANOVA analysis, and a list of the estimated coefficients of the model.

INSERT TABLE 3 ABOUT HERE

Model Significance. From Table 3, the F-statistic shows that that the overall model is highly significant. Thus, we show overall support for our Online Consumer Transaction Valuation Model as shown in Figure 1. However, we were not able to statistically validate certain effects that we have hypothesized should be seen to occur within the model for eBay collectible coin auctions. We study *an individual's utility* for each item, measured by the highest amount each bidder was willing to bid, and we exclude winning bids from our study. Thus, the highest bid for each bidder approximates that bidder's private valuation for the item. These bidders expressed an interest in an item, but did not want to spend the money needed to beat the next-highest bid. Therefore, we actually are examining an *individual's variation* in *willingness-to-pay* for *identical items*. With winning bids, the winning bidder may have been willing to pay more for an item, and thus her bid does not reflect that person's true utility of buying a particular item from a particular seller. Note also that the significant negative constant implies that people have lower reference values than their average bids, which supports our interpretation in the Online Consumer Transaction Valuation Model context.

Table 3. Empirical Model Results

MODEL VARIABLES	ESTIMATED COEFFICIENT	STANDARD ERROR	T-STAT	HYPOTHESIS/ SIGNIFICANCE
Constant	-0.147	0.068	-2.165	**
❑ ***Hypotheses on How a Bidder's Own Actions Affect Bidder Valuation (H1)***				
Later Bid	0.024	0.026	0.955	H1a
Number of Same Coins Purchased	-0.005	0.010	-0.494	H1b
Number of Other Coins Purchased	0.000	0.002	-0.094	H1b
❑ ***Hypotheses on How Others' Actions Affect Bidder Valuation (H2)***				
Number of Prior Bidders	0.003	0.001	2.719	H2a***
Minimum Bid	0.306	0.052	5.865	H2b***
❑ ***Hypotheses on How Product Information Affects Bidder Valuation (H3)***				
Picture Exists	0.060	0.023	2.659	H3a***
Description Length'	0.010	0.005	1.981	H3b**
❑ ***Hypotheses on How Seller Information Affects Bidder Valuation (H4)***				
Reputation Score'	-0.006	0.008	-0.753	H4a
Reputation Ratio'	-0.691	1.166	-0.593	H4b
❑ ***Hypotheses on How Transaction Facilitation Affects Bidder Valuation (H5)***				
Weekend Bid	0.062	0.025	2.545	H5a***
Credit Card	-0.036	0.034	-1.055	H5b
❑ ***Control Parameters***				
Time Left in Auction	-0.007	0.005	-1.413	
1999 Fixed Effects	-0.003	0.033	-0.102	
2000 Fixed Effects	0.020	0.033	0.609	
*NOPB*TLIA (Interaction)*	0.000	0.000	0.566	
*NOPB*MB (Interaction)*	0.005	0.009	0.520	
Model: R^2 = 9.4%; adj-R^2 = 7.4%; model standard error = 0.299; observations = 750; F-statistic = 4.767***				
Significance Levels: *** = $p < .01$; ** = $p < .05$.				
Data analysis: Data are analyzed at the bidder/product level in a within-bidder, within-product study that examines 750 bids from 173 unique bidders bidding on 677 unique auctions hosted by 374 unique sellers. Dependent variable is the percentage of a bidder's high bid for an item in an auction above the average high bid that same bidder made for that same item in all auctions during that month.				

Results on Research Hypotheses. Remember that we are measuring factors that change *an individual's willingness-to-pay* for a specific item, not factors that change the final price that an item sells for. All three sets of hypotheses were supported to some extent. Our *Reference Value Hypotheses* (**H1** and **H2**), investigate how a bidder's reference value for an item in an auction is changed based upon actions of others (e.g., other bidders and the seller) and that bidder's own actions. The *Number of Prior Bidders Hypothesis* (**H2a**) was supported ($\beta_{Number\ of\ Prior\ Bidders}$ = 0.003, S.E. = 0.001, t-stat. = 2.719, $p < .01$), showing that other bidders will increase a single bidder's valuation of an item. Note that the number of prior bidders is defined as the number of other bidders observable by a bidder before that bidder makes a final bid. In this research, the effect of competition is minimized since all bidders in this study experienced a sufficient level of competition to cause the bidder to lose the auction. Thus, we are only examining how other bidders change a bidder's valuation, and not the effect that the number of bidders and competition has on the final price of an item. Our *Starting Bid Hypothesis* (**H2b**) also was supported ($\beta_{Minimum\ Bid}$ = 0.306, S.E. = 0.52, t-stat. = 5.865, $p < .01$), indicating that the starting price set by the seller affects what the bidder is willing to pay for an item after that bidder has decided to participate in an auction. Taken together, these two hypotheses (**H2a** and **H2b**) show support for our hypotheses that the actions of others affect a bidder's reference value for an item in an auction, and thus support our *Others' Actions Hypotheses* (**H2**).

Conversely, prior actions by the bidder, such as winning this or other coins in earlier auctions, as in the *Substitution Hypothesis* (**H1b**), do not seem to matter. Two findings provide support, involving observed purchases of the same and other coins: $\beta_{Number\ of\ Same\ Coins\ Purchased}$ = -0.005, S.E. = 0.010, t-stat. = -0.494, not significant; and, $\beta_{Number\ of\ Other\ Coins\ Purchased}$ = 0.000, S.E. = 0.002, t-stat. = -0.094, not significant. Nor does unsuccessfully bidding on the exact same item in earlier auctions, as with the *Learning Effects Hypothesis* (**H1a***)* ($\beta_{Later\ Bid}$ = 0.24, S.E. = 0.26, t-stat. = 0.005, not significant), appear to have driven the observed outcomes. Thus, we are unable to support our *Bidders' Actions Hypotheses* (**H1**). Our analysis implies that a bidder may change her valuations based on the actions of others (e.g., sellers setting a starting bid, other bidders bidding on the same item). By the same token, a bidder's own actions (e.g., bidding unsuccessfully for the same item, winning other items) may fail to change her reference values *to the same extent*, if at all.

Our *Transaction Information Hypotheses* (**H3** and **H4**) investigate information that should not change a bidder's product valuation, but rather should help assure the bidder that the item is being represented properly and that the seller is reputable enough to conduct an honest transaction. In the set of *Product Information Hypotheses*, we show that the existence of a picture, via our *Picture Hypothesis* (**H3a**, significantly increases the price a bidder is willing to bid) ($\beta_{Picture\ Exists}$ = 0.060, S.E. = 0.023, t-stat. = 2.659, $p < .01$). In contrast, the length of description is supported, though not as strongly ($\beta_{Description\ Length}$ = 0.010, S.E. = 0.005, t-stat. = 1.981, $p < .05$), though we asserted the *Description Length Hypothesis* (**H3b**). This conforms to results from the existing marketing literature (e.g., Dahl, Chattopadhyay and Gorn, 1999) that stresses the importance of graphical representation for conveying information to the end user.

Conversely, in our *Seller Information Hypotheses* (**H4**), we assert that bidders probably do not pay much attention to the reputation of any given seller, as it is reported by other bidders, neither as a total score as reported by eBay ($\beta_{Reputation\ Score'}$ = -0.006, S.E. = 0.008, t-stat. = -0.753, not significant), as we hypothesized in our *Seller Experience Hypothesis* (**H4a**), nor as a ratio of positive to negative comments ($\beta_{Reputation\ Ratio'}$ = -0.691, S.E. = 1.116, t-stat. = -0.593, not significant), as we hypothesized in our *Seller Reputation Hypothesis* (**H4b**). We argue that either a bidder will hesitate to change her valuation of a product based on a sellers' reputation, or that eBay's reputation system is inadequate for a bidder to make any informed judgments about a seller's reputation. Our inability to validate the importance of trust in the eBay auction continues to surprise us, based on the work of others whose results indicate otherwise (e.g., Ba and Pavlou, 2002). However, other authors are somewhat more skeptical of the relationship. For example, Dellarocas (2001) points out that although eBay-like reputation mechanisms can work, such mechanisms require that the bidders exhibit an appropriate strictness when judging sellers and that bidders employ the correct "threshold" parameters when judging sellers. Kaufman and Wood (2000) report no evidence to empirically validate the effectiveness of such parameters. They find no significant relationship between the price an item sells for (as the dependent variable) and the reputation score, the number of negative comments, or the ratio between negative and positive comments. It should be noted that although the coefficients of these parameters are negative (and so the opposite of the anticipated relationship), still the coefficients are too close to zero to be considered significant. As a result, more data could change the sign in any direction.

In the set of *Transaction Facilitation Hypotheses* (**H5**), we show that ending an auction on a weekend encourages the bidder to bid more for that item ($\beta_{Weekend\ Bid}$ = 0.062, S.E. = 0.025, t-stat. = 2.545, $p < .01$), as stated in our *Weekend Hypothesis* (**H5b**). The dummy variable indicating whether an item has sold on the weekend is strongly significant, indicating that the same bidder is willing to pay more for the same item in an auction if that auction ends on a weekend. As stated previously, other authors have shown a weekend effect (e.g., Warner and Barsky, 1995), but Lucking-Reiley et al. (2000) did not find this result. To resolve this seeming inconsistency, we suggest that our study may be somewhat broader in its scope, allowing for multiple grades of coins and examining more items, thus allowing us to discover this result that does not appear in the cited work. Furthermore, our study implements a within-bidders and within-products design that permits us to examine individual bidders' utilities and independent private valuations for specific items, whereas the Lucking-Reiley et al. (2000) study examines item selling prices and implying common valuations. Our *Way-to-Pay Hypothesis* (**H5a**) is not supported ($\beta_{Credit\ Card}$ = -0.036, S.E. = 0.034, t-stat. = -1.055, not significant), indicating that once a bidder decides to bid on an item, they are not significantly influenced by the whether the seller takes credit cards as a convenient way to pay. We note that an individual may decide not to participate in an auction if credit cards are not accepted. Such an investigation is beyond the scope of this study.

Interpretation. Taken together, our hypotheses support our assertion that bidders are willing to pay more if more information (e.g., a picture, higher starting bid, actions of other bidders, etc.) is presented or if more bidders participate in the auction. We could not find an effect for sellers' experience or reputation, however. Thus, our findings relative to the *Seller Reputation Hypothesis* were inconclusive. But they hint that bidders may not pay much attention to sellers' reputation score or the comments left by other bidders.

Even more interesting is that on the weekend, bidders are more likely to have higher valuations of products; our evidence shows that they bid accordingly. This result was not found by Lucking-Riley, et al. (2000). We attribute that to the broadness of our study and to the within-bidders (**IPV**) test, as opposed to their item-level (**CV**) test. Our weekend effect is stronger than the prior bidders effect, and thus is not just a function of there being more numerous bids during the weekend. Furthermore, as eBay provides automated agents to bid for you, the time spent in an auction is reduced and the effect of prior bidders on valuation is minimized.

Implications

The implications for this study are far-reaching in several respects. We show in this study that a bidder is more likely to change her reference value for an item based upon input from other sources, but tends to change it very little, if at all, from personal actions or experience. This provides a useful first step towards understanding how Bayesian updating works in the Internet auction context. Thus, an online seller with limited resources should be more motivated to encourage bidders to be interested in his products even if such motivation does not result in a purchase by these bidders. This is because such motivation may make current bidders more willing to pay more for an item. Since other bidders affect a bidder's valuation for an item, as shown in our study, a seller should encourage participation in his auction even if those participating do not bid high enough to win the item.

The implications of our results in Table 3 are important for online auctions and for electronic commerce, in general. We show that reputation scores, both as a total score reported by eBay and as a ratio of positive-to-negative comments from other bidders, have little effect on a consumer's valuation. This result needs to be examined in more detail to see when, if ever, a bidder looks at reputation scores to adjust her valuation.

CONCLUSION

In this research, we investigated factors that change the utility of an e-commerce buyer, based on the high price that the buyer was willing to bid for an item in an online auction using data collected by an Internet agent. Our software agent collected the data during roughly the same time frame in three separate calendar years. The data collection methodology enabled us to collect enough data to investigate a phenomenon that investigates how an electronic auction bidder's utility can be changed based upon information that the bidder receives about the product and the seller, and about other aspects of the environment (e.g., other sale items, other bidders, etc.). In this research, we developed a conceptual model that illustrates this point: the Online Consumer Valuation Model.

We then tested it and found it to provide a highly significant and useful interpretation of the observed behavior of bidders in eBay's Internet-based collectible coin auctions.

Contributions

We make several contributions in this study. By using a broad within-subjects examination of bidding behavior, we are able to shed light on several issues. *First*, our research provides evidence that bidders are willing to pay more for the same item on the weekend that they are during the weekdays. Our interpretation of this result is straightforward. Consumers probably are willing to pay more when they have more time available to think through their purchasing decisions. By implication, weekend purchase decisions among coin collectors may be more well thought out purchases. A similar result, however, has not been found in other studies that did not attempt to investigate the individual bidders' IPVs, independent private valuations. *Second*, our research employs data-collecting agents to investigate phenomena in a quasi-experimental manner. Traditional data collection techniques, such as surveys or experiments, may be too costly or difficult to effectively implement in the real world context that we studied. *Third*, we show that providing more information to buyers can result in the ability of sale items to command higher prices in e-commerce.

Limitations

This study has a number of limitations. *First*, the reader should keep in mind that we only investigated coin auctions, so our results should not be generalized to other areas without care and consideration. The strong condition and type language of coin collectors facilitates examination of rare coins in online auctions. It also enhances transactability for collectors. Nevertheless, we contend that this research yields insights that are relevant for understanding dissimilar auction formats and, and in many respects, for other Internet-based selling environments. However, trade studies show that coin collectors tend to be somewhat older and somewhat more affluent than many other online auction enthusiasts. Thus, if we must narrow the scope of the applicability of our results, then we can say that they probably are most applicable when applied to an affluent adult consumer population that is willing to transact in an Internet-based market setting. Were we to study other types of auctions as various authors have (e.g., rare playing cards, as Lucking-Reiley and his coauthors did) or simpler commodities (e.g., Beanie Babies, baskets or candles), then our results may not apply. Related to this, we remind the reader that our examination of rare coins deals with coins that, for the most part, sell for under $100. Thus, our results may not be applicable to more expensive products sold in online auctions, such as automobiles (Lee, 1998).

Second, we only examine products that an individual is willing to bid upon. In this study, we do not examine the products individuals may disregard altogether. Marketing research (e.g., Wilkie 1994) points out that consumers can use a combination of several decision rules to determine what to buy and how much to pay. Specifically, a *conjunctive rule* is used to exclude items that have a characteristic that makes a product unacceptable to a specific consumer. Conversely, a *compensatory rule* is used to weight each attribute and determine a product's expected utility from the level of each attribute multiplied by the weight of each attribute.

In this research, since the bidder has shown an interest in the product by bidding, the person's observed behavior suggestions that a compensatory rule, instead of a conjunctive rule is in operation. By the time a bidder enters a bid for an item, that bidder is beyond the point of applying the conjunctive rule by making a bid.

Clearly, some consumers apply rules and cognitive heuristics that can cause the consumer to avoid purchasing an item. For example, if a seller sets the minimum starting bid too high in an auction, consumers may not bid at all in that auction. Thus, while we show that a minimum starting bid influences bidders to pay more, that is only for items that have already passed a bidder's conjunctive rules (e.g., that the starting bid not be too high for a specific product). Moreover, a bidder may select a set of sellers that are willing to make a transaction based upon reputation, but then ignore reputation from that point on. Thus, *reputation may be conjunctive rather than compensatory*, too. So, even though reputation may not affect what a bidder is willing to pay for an item, it still may affect whether a bidder transacts at all with a given seller. Accordingly, we recognize that a bidder can apply both conjunctive rules and compensatory rules when making a purchase decision, but we concentrate on compensatory rules after the conjunctive rules have already been applied. So making any strong conclusions about conjunctive rules employed by the online bidder is beyond the scope of this article. Further research is needed to examine a bidder's conjunctive rules and how they interact with her compensatory rules.

Third, we have argued that one strength of our work is the within-bidder analysis approach. However, a related drawback is that our sample contains only experienced and active bidders. So the results do not easily generalize to inexperienced bidders who are new to the auction market channel. Nor are we able to study the aggressiveness of other bidders, and the variance of the distribution of valuations among other bidders. These may also impact their individual valuations and the final price of the auction sale items, respectively. Still, this technique does allow us to examine changes in individual behavior, and as online auctions become more prevalent, this limitation will become less important.

Fourth, it is possible that buyers experience complementarities associated with coin collecting. For example, a complete set of coins is often substantially more valuable to the bidder than an incomplete set. These complementary effects may have a contaminating effect when testing for the effect of available substitute products, as with the *Product Substitute Hypothesis*, **H1b**. Note that, in our study, we used the *Number of Other Coins Purchased* as a proxy for substitute products. However, the test of the *Product Substitute Hypothesis* also evaluates the effect of the *Number of Same Coins Purchased*. But these coins would not be part of a larger set—they represent the exact same coin. But the effect that we tested for was not significant. And so we do not believe that conflicting substitutability or complimentary results explain the lack of significance. Coin collectors who purchase multiple copies of the same coin may be investors or speculators who purchase coins for resale. They are more concerned with the potential value of the coin, regardless of the effect it has upon a collection.

Last, with eBay, there is a possibility of *bid sniping.* Bid sniping occurs when bidders bid at the last possible moment to avoid losing an auction (Bapna, forthcoming). We do not believe this to have been a major issue in

the coin auctions that we tracked for two reasons. The first reason is structural. eBay has features, such as a bidding agent, that allow users to enter the true valuations as the agent automatically bids at the lowest bid increment possible. The second reason is empirical. For the 750 auctions that we analyzed in this study, the average number of days in the auction left when the final bid was entered for a bidder is three days and four hours. As such, we do not feel that sniping significantly impacts whether the bidder actually bid her true valuation.

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