THE DETERMINANTS OF SNIPING ON eBay: AN ECONOMETRIC ANALYSIS

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Andrew Haller

Department of Economics
Stanford University
Stanford, CA 94305
andrew.haller@stanford.edu

under the direction of
Prof. Geoffrey Rothwell

ABSTRACT

eBay is the largest and most widely known of many internet auction sites designed to connect buyers and sellers around the world. An eBay auction consists of a set bidding period during which individuals submit “maximum bids” for an item. The winner the auction is the individual with the highest bid, and the price is equal to the second highest bid, plus a small bidding increment. This system is a close approximation to a second-price auction, for which William Vickrey proved in 1961 that a weakly dominant strategy is to bid one’s own private value for an item. A bidding strategy called “sniping,” whereby an individual withholds a bid until the last moment of the bidding period, is widely observed on eBay, but seems to violate rational behavior in the Vickrey model. Bidding late should not have any advantage over bidding early in a second-price auction, so economists have sought ways to rationalize its existence. In this paper, I create a data set from 515 eBay auctions and test several potential determinants of sniping behavior using a standard linear regression model. I incorporate a number of variables from previous literature (a common value indicator for an item, the feedback rating of an individual, and the number of opponents in an auction), as well as a new variable (the number of substitutes for an item), and achieve significant results.

Keywords: game theory, auction theory, second-price auction, internet auction, eBay, sniping

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1) Introduction

*[Sniping] gives your competition no time to respond to your bid. And, because your bid is not revealed until the final seconds of the auction, your knowledge of the item’s value is kept private. Serious collectors and professional dealers know to bid once, late in the auction.* 

–EZ sniper website

The emergence of internet auction websites such as eBay has, over the past decade, created a sudden exposure of a wealth of transparent data to an economic field previously reserved for theorists. Until twelve years ago, theoretical results in auction theory could only be tested using small data sets, making significant results difficult to achieve. Sites such as eBay and Amazon (both founded in 1995) place a heavy emphasis on making detailed records available for research purposes, and economists are now able to support many results from theoretical literature using data. On occasion, peculiar results elicit a second look at a theoretical model. Such is the case with “sniping” on eBay, a strategy whereby an individual withholds her bid until the final seconds of an auction.

Each auction on eBay lasts a predefined length, or bidding period, and the company uses a bid proxy system to determine the outcome. In this system, each individual may submit a “maximum bid” – in theory, equal to the maximum value she is willing to pay for the item – at any time before the bidding period expires. The winner is the individual with the highest reserve bid, and the price is equal to the second highest bid, plus a small bidding increment set by eBay. The bid proxy system closely approximates a standard second-price auction, to which much economic literature can be applied. Specifically, the classic results by William Vickrey (1961) for profit maximization in a second-price auction are quite relevant. In such a setting, it is a weakly dominant strategy to submit a bid equal to one’s own private value for an item,
suggesting that the time at which one submits her bid is irrelevant. In such a model, sniping has no inherent value.

Still, eBay has spawned an entire industry designed to help individuals submit sniping bids. The service is simple: a user specifies the auction she wishes to bid in and the maximum price she is willing to pay for the item, and the company automatically submits a bid seconds before the auction closes. These companies offer a number of reasons why sniping is to a bidder’s advantage. The opening quote from EZ sniper’s website argues for the privacy of late bidding, yet eBay’s online tutorial clearly states about its bid proxy system, “your maximum bid is never disclosed to other bidders or to the seller.” A competitor, PowerSnipe, says sniping “gives you a better chance of winning and helps you to avoid getting into ‘bidding wars’ with other users competing over an item.” Avoiding price escalation seems a profitable pursuit, but if the bid proxy system encourages a single maximum bid for an item, bidding wars should be discouraged naturally. It is true that winning bidders are normally among the last to bid, but this can be attributed to the self-selection of late bidders as those with the greatest value for the item to begin with. A third company called Auction Sniper appeals to the experience of being sniped: “You wait excitedly by your computer expecting to be notified that you've won, but...somehow you've lost…You’ve been sniped.” Perhaps avoiding the suspense and heartbreak of being sniped has some value, but it seems that a more rigorous model is needed.

Economists have offered a number of suggestions as to why bidders choose to snipe online, most having to do with relaxing Vickrey’s assumptions. Malhotra and Murnighan (2000, 2004) suggest that many bidders are naïve regarding the bid proxy system, often leading to an incremental bidding strategy. The authors also introduce the term “auction fever,” suggesting that people get carried away and bid more than their reserve price for an item. Ely and Hossain
argue that with more bidders in an auction, each bidder acts more aggressively, incentivizing late bidding to reduce competition. Each of the above arguments is founded on relaxing Vickrey’s assumption that bidders are rational and profit-maximizing. Wilcox (2000) chooses to relax the assumption that bidders have independent private values for an item. He argues that experienced bidders choose to withhold their bids in a common value setting so as not to surrender value information to competitors. Rasmusen (2006) introduces a model in which a bidder must spend time to estimate her value for an item, leading to late bidding. Wang, Hidvégi, and Whinston (2001) suggest that bidders may be afraid of shill bids – bids by the seller in disguise to raise the price – and thus bid late to avoid showing interest in an item. Roth and Ockenfels (2006) argue that the existence of a bidding increment causes eBay to diverge from the standard second-price model, introducing incentive for late bidding.

In this paper, I provide support for several claims through a linear probability model. Many of the above hypotheses are difficult to construct a natural experiment for, but my model includes several key variables. With each individual bidder representing a single observation, I define a sniping bid as a bid within the final minute of the defined bidding period, and I use an indicator for snipe as the endogenous variable. As exogenous variables, I include an indicator for common value of the item, a variable to measure bidder experience (based on a user’s eBay feedback rating), an interaction of these first two parameters, and the number of opposing bidders in an auction, all of which have been introduced in previous literature. I also include a new variable to measure the number of substitutes for a given item available to a bidder on eBay. The measurement of this variable is discussed in detail in Section 3, and has two opposing economic interpretations. First, because eBay returns search results in order of nearest auction close, items with more substitutes are more likely to be viewed (and bid upon) later in the
auction period. Second, the existence of substitutes may lower stakes of a single auction, causing an individual to bid less aggressively and lowering the likelihood of a late bid. My regression will provide evidence for the relative significance of these opposing hypotheses.

I run a total of four regressions in this paper on a data set I collected consisting of 515 auctions for 15 types of items. The first regression represents the full extension of the economic theory presented in Section 3. The remaining three regressions represent minor modifications to this model, with the fourth reproducing results from previous literature. On the whole, the regressions return statistically significant results in many cases, and provide a clear empirical extension to previous literature. The data support the following set of hypotheses, discussed in greater detail in Section 5: (1) sniping is a part of the bidding strategy for a subset of the bidding population, (2) in a common value setting, experience raises the likelihood of a sniping bid, (3) the number of opponents has little effect on the likelihood of a sniping bid, and (4) the number of perfect substitutes for an item raises the likelihood of a sniping bid.

The structure of my paper is as follows. In Section 2, I synthesize past economic literature and describe how each paper has contributed to our current understanding of the determinants of sniping. In Section 3, I introduce the theory behind my linear probability model, as well as the data set, and how each variable is constructed from the data collected. In Section 4, I present a number of statistics to assist interpretation of regression results. In Section 5, I summarize the results of the four regressions and the extent to which they support both past literature and the economic model presented in this paper. I also at this time provide several problems that may introduce bias into the data set, and address how these problems can be controlled for in the future. Finally, in Section 6, I summarize the study and results, and provide direction for future research that may extend the results of this paper.
2) Literature Review

Theoretical Origins

The literature on late bidding in online auctions rests on a theoretical article written long before the conception of the internet. William Vickrey is the author of “Counterspeculation, Auctions, and Competitive Sealed Tenders” (1961), an article highlighting the benefits and pitfalls of several auction methods including English (ascending), Dutch (descending), and second-price sealed-bid auctions. For each case, important outcomes include the best response strategy for bidders, the expected revenue of the auction, and whether the final allocation is Pareto-optimal. In these categories, Vickrey finds that the second-price auction is superior to other methods. Here, individuals place bids equal to their exact values for an item (rather than hedging downward in an effort to make profit). The expected final price for an item is equal to that of English and Dutch auctions, but with a lower variance. Finally, and most importantly, in the case of rational bidders with knowledge of their own private values, a Pareto-optimal allocation is always derived.

The key to making a second-price auction more efficient than its first-price ascending and descending bid counterparts is that bidders are incentivized to bid their own private values for an item. Vickrey provides an intuition for this result in his paper. The implicit assumption is \( n \) bidders, each bidder \( i \) with a private value \( v_i \) for an item (which she is aware of). Without loss of generality, the bidder has three options: placing a bid \( b_i \) higher, equal to, or lower than her value for the item. If \( b_i > v_i \), the bidder runs the risk of winning the item and paying more than her value (thus earning negative profit). If \( b_i < v_i \), the bidder runs the risk of losing the item despite having the greatest value (Pareto-dominated). In the case of a first-price auction, this risk may be in the
best interest of the bidder if it means a greater profit \((v_i - b_i)\) in the case of winning. However, in a second-price auction the winner pays the second highest bid, which is unaffected by this hedge. Thus any deviation from bidding one’s private value for an item risks lower profit in certain outcomes without offering greater profits in any outcomes, making bidding one’s value a weakly dominant strategy. Naturally, if each bidder is rational and bids her value for an item, the item will be won by the bidder with the highest value, making the allocation Pareto-optimal. Vickrey also shows that the expected revenue from such an auction (the second-highest value among the bidders) is equivalent to the expected revenue from a first-price English or Dutch.

The benefit of a simple best response strategy (bidding one’s private value) is that a bidder does not have to waste effort predicting the bids of others in order to find her optimal bid, nor does an extended time period need to elapse before bidders arrive at equilibrium. A single bid is required for efficient allocation and revenue. Thus it is not difficult to understand why eBay and most other online auction sites use a second-price system and encourage each bidder to simply bid the maximum value she is willing to pay for an item. The questions arise when online bidders seem to behave irrationally, waiting until the last possible moment to submit a bid when bidding one’s value for an item is a weakly dominant strategy. Such inconsistency causes economists to examine whether bidders are in fact irrational, or operating under a set of assumptions varying from those Vickrey uses in his article.

**Evidence of Late Bidding**

Roth and Ockenfels (2002) provide the primary literature documenting empirically the disparity between bidding strategies in online auctions and the predictions made by Vickrey in 1961. The authors attempt to determine the frequency with which a bidder places a bid in the final seconds of an auction, depending on (1) whether she is bidding on eBay, featuring a “hard-
close” (set bidding period), or Amazon, featuring a “soft-close” (where the bidding period is extended if a late bid is submitted), (2) the level of experience of the bidder (measured by online feedback systems), and (3) whether an item has a private value (computers) or a common value (antiques). Data are taken from 480 auctions with a total of 2,279 bidders. Information is recorded on the online auction house, the house-adjusted feedback rating of the bidder, and the time before the close of the auction (or hypothetical close, in the case of Amazon) that an individual’s final bid is placed.

The data reveal several patterns of behavior in online auctions. First, late bidding is a very popular strategy online, and significantly more so on eBay, where the bidding period is fixed. Twenty percent of all final bids on eBay are within the final hour of the bidding period, compared to seven percent on Amazon. On eBay, nine percent of all computer bids and 16 percent of all antique bids are placed in the final five minutes of the bidding period. At the auction level, 40 percent of all eBay computers and 59 percent of all eBay antiques are bid on in the final five minutes, compared to three percent in both categories on Amazon. Amazon has only one bid in the last minute, compared to 89 on eBay (29 in the final ten seconds).

Regressions also support the significance of a greater level of late bidding for antiques as opposed to computers (common versus private goods). The authors claim this is consistent with the concept that bidders attempt to wait for signals from “expert” bidders in the case of an auction for a good with a common value, a theory explained in further detail later in this section. Finally, a greater feedback rating has a significantly positive effect on late bidding for eBay, compared to a significantly negative effect for Amazon, suggesting that the more experienced bidders bid late on eBay and early on Amazon. These results are confirmed by a survey sent to
368 auction-winning snipers; of the 20 percent who respond, 91 percent say that sniping is a part of their normal bidding strategy.

**Observed Benefits to Sniping**

Gray and Reiley (2005) are the first economists to attempt a measure of the surplus gained through late bidding. In their paper entitled “Measuring the Benefits to Sniping on eBay: Evidence from a Field Experiment,” the authors bid on 70 pairs of identical items sold by the same seller and ending near the same time. Items have private values and include Playstation 2 games, DVD movies, Xbox games, die cast Hot Wheels cars, and Game Boy Advance Games. For each pair, the authors submit a bid for one item several days before the end of the bidding period and an identical bid for the other just moments before the end of the auction. The data show a 2.54 percent decrease in the price paid for an item won by a late bid; however, the authors find this value to be statistically insignificant. This result cannot reject Vickrey’s prediction that in a second-price auction, the timing of a bid does not matter so long as the bid is equal to the bidder’s value for the item.

Ely and Hossain (2006) follow a similar procedure in their article “Sniping and Squatting in Auction Markets.” Here the authors participate in 566 auctions for 20 newly released DVD titles, bidding on the first day of the auction period for 294 items (squatting) and five seconds before the closing of the auction for the remaining 272 (sniping). In each of the two groups, bids are placed at levels predicted to win 90, 60, 40, and 20 percent of the auctions respectively, and the surplus is calculated by the difference between a winning bid and the cost of the item. The winning percentages in the study are 47.6% for the squatting bids and 52.6% for the sniping bids, with average surpluses of $1.25 and $1.41, respectively. The regression run on these results test
surplus as a dependent variable against a dummy for sniping, the opening bid for the item, and the shipping fee. The results show a $0.18 increase with a snipe, significant at the 95% level.

Ely and Hossain attribute the statistically insignificant results found by Gray and Reiley to a small sample size, and argue that their data more accurately express the surplus enjoyed by bidders employing a sniping bid strategy. Despite this larger sample size, it is impossible to know which of the two articles is more robust without a greater number of studies testing the relationship between late bidding and surplus.

**Theoretical Explanations**

If the theoretical analysis conducted by Vickrey is correct, then there must be some inherent difference between the assumptions made in his paper and the conditions present in online auctions. A number of articles have been written in the past seven years offering theoretical models to describe the set of assumptions under which bidders are made better off by employing a late-bidding strategy. A summary of the articles and the assumptions they relax is given in the table below, followed by a brief discussion of each:

<table>
<thead>
<tr>
<th>Author(s)</th>
<th>Year(s)</th>
<th>Topic of Discussion</th>
<th>Relaxed Assumption(s)</th>
</tr>
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<tbody>
<tr>
<td>Ku, Malhotra, Murnighan</td>
<td>2000, 2004</td>
<td>Auction Fever</td>
<td>Bidder rationality, Profit-maximizing</td>
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<td>Roth, Ockenfels</td>
<td>2002</td>
<td>Naivety, Tacit Collusion</td>
<td>Bidder rationality, Perfect information</td>
</tr>
<tr>
<td>Ely, Hossain</td>
<td>2006</td>
<td>Escalation/Competition Effects</td>
<td>Bidder rationality, Profit-maximizing</td>
</tr>
<tr>
<td>Wilcox</td>
<td>2000</td>
<td>Expert Signals</td>
<td>Independent Private Values</td>
</tr>
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<td>Persico</td>
<td>2000</td>
<td>Value Uncertainty</td>
<td>Perfect Information</td>
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<td>Compte, Jehiel</td>
<td>2005</td>
<td>Value Uncertainty</td>
<td>Perfect Information</td>
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<tr>
<td>Rasmusen</td>
<td>2006</td>
<td>Value Uncertainty</td>
<td>Perfect Information</td>
</tr>
<tr>
<td>Wang, Hidvégi, Whinston</td>
<td>2001</td>
<td>Shill Bidding</td>
<td>Defined Seller/Bidders</td>
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</table>
Naivety and Auction Fever

The assumption of perfect bidder information and profit-maximizing rationality is a strong one, and one that can lead to discrepancies in empirical data. Ku, Malhotra, and Murnighan (2000, 2004) choose to relax this Vickrey assumption, looking for evidence of “auction fever,” whereby a bidder will outbid her reserve price for an item in the heat of a bidding war. In their most recent paper, “Towards a Competitive Arousal Model of Decision-Making: A Study of Auction Fever in Live and Internet Auctions,” the authors measure bidding strategies in 21 auctions for Chicago’s famous art cows and similar fiberglass animals in other cities across the United States. They collect data on the amount by which bidders overbid (pass their initial reserve price). The authors assume that if an individual is outbid online and places a new, higher bid, she is exhibiting “auction fever.” This assumption is supported by several surveys sent to bidders in the auctions. It is also appropriate to note that in the surveys sent to successful snipers by Roth and Ockenfels (2002), many bidders described the desire to bid late to avoid “getting carried away.”

The data show that several hypotheses of the competitive arousal model prove statistically significant, namely that a bidder will exceed her reserve price more often (1) when there are fewer opponents remaining in the auction, (2) toward the end of an auction, and (3) when she has invested more time in the auction. These hypotheses do tend to interfere (a bidder has invested more time by the end of the auction), but they are supported in the latter half of the
paper by a controlled experiment on 52 students in a lab. These results support the hypothesis that an individual tends to be better off when bidding late because she is unable to respond to higher bids by irrationally elevating her reserve price for an item.

Roth and Ockenfels (2002), in their article that first documented the prevalence of late bidding, also offer a simple explanation. A naïve bidder entering eBay for the first time may not have an understanding of how the bidding rules work, and may mistake a dynamic second-price auction for a traditional English ascending first-price auction. With this misunderstanding of the rules, a rational bidder will follow the strategy: (1) place a bid slightly above the current price if her value for the item exceeds this price, (2) wait until she is outbid by a competitor, and (3) repeat steps (1) and (2) until the end of the auction. Late bidding is a best response to the possibility of an incremental bidder, since it prevents further bidding from such an individual until it is too late to respond to the sniping bid.

**Escalation Effect vs. Competition Effect**

The concept of auction fever rests on an assumption that a bidder is either irrational or derives utility from the “thrill of the chase.” Roth and Ockenfels (2002) offer another hypothesis through relaxing the rationality assumption. The authors argue that late bidding can be a form of tacit collusion among bidders to capture the seller surplus for the winner of the auction. If all bidders choose to bid late in the auction, many will not get the chance to increase their reserve prices irrationally, and some will not have their bids submitted successfully at all (due to network delays). With competition thus significantly decreased, and the same probability of winning for each bidder (assuming equal internet connections and private value distributions), a greater surplus can be had by the winner of an auction, justifying a collective movement toward sniping.
Ely and Hossain (2006) introduce two exceptions to bidder rationality, the “escalation effect” and the “competition effect.” The former refers to a phenomenon whereby an individual bids more aggressively in the presence of competition – replacing her natural reserve price with a competitive one. This supports late bidding as a method for lowering the aggressiveness of opposing bidders. The latter observes a decrease in opponents’ aggressiveness when an early bid is submitted – perhaps due to the anticipation of stiff competition. This second hypothesis supports early bidding to warn off potential opponents. The authors observe the presence of both effects in the data set. The escalation effect is seen in auctions with more than one bidder; the average opposing bid for a DVD is $11.17, lowered by a statistically significant $1.58 in the case of a sniping bid. In auctions with zero opponents, the price paid by a sniping bidder is actually greater than the price paid by a squatting bidder. The authors claim the “competition effect” keeps potential competitors out of the auctions with early bids, causing a positive correlation with a lower reserve price set by the seller, and thus, a lower price.

**Expert Signals**

One testable hypothesis on the incentive to snipe involves the acquisition and guarding of value-related information for items with common values. This violates an important Vickrey assumption of independent private values for all items. The theory on the effects of common value items begins with a paper by Milgrom and Weber in 1982 entitled “The Theory of Auctions and Competitive Bidding.” The authors show that English auctions will yield greater expected revenue than second-price auctions because bidders can gain information from the bidding behavior of competitors regarding (1) the authenticity of an item, (2) potential resale value, and (3) any “prestige factor” associated with owning the item. This new information leads to higher prices through more aggressive bidding by bidders with new value-related information.
Wilcox (2000) is the first to adopt this concept to the strategy of late bidding in his paper entitled “Experts and Amateurs: The Role of Experience in Internet Auctions.” He introduces four testable hypotheses regarding bid timing in a common value setting:

- **H1**: more experienced bidders will be more likely to place a bid in the final seconds of an auction.
- **H2**: auctions for items with a common value component will be more likely to experience late bids.
- **H3**: more experienced bidders will be less likely to place multiple bids in a single auction.
- **H4**: auctions for items with a common value component will make the effect of experience on multiple bids more pronounced (i.e. experienced bidders will be even less likely to place multiple bids).

The hypotheses are then tested empirically against a data set consisting of auctions for pottery, neckties, power drills, and staplers (the first two having common values). The data show that while 1.2% of the least experience bidders place bids late, 8.2% of the most experienced do. There is also an increase in the prevalence of late bidding for common value items (pottery and ties), as predicted by Milgrom and Weber (1982). There is evidence to support **H4** here, but **H3** is found not statistically significant. Altogether the data do support the significant hypotheses regarding late bidding in the case of common goods.

**Value Uncertainty**

The next set of literature argues that even in a private value setting, bidders face a price (in terms of time and effort) to fully understand their values for an item. The argument is founded in the work of Persico (2000) and Compte and Jehiel (2005), and is most thoroughly assessed by Rasmusen (2006). Persico, in his article entitled “Information Acquisition in Auctions,” introduces the concept of “risk-sensitivity” and a model to show that the value of information is greater in more risk-sensitive situations. When there is a greater chance of overbidding with a misestimate of an item’s common value, a bidder will pay a greater price for value information. The article by Compte and Jehiel (2005), “Auctions and Information
Acquisition: Sealed-Bid or Dynamic Format?” extends the Persico literature to a dynamic case where the bidder can choose to acquire value information at any point during the bidding period. The authors show that a dynamic format will outperform a sealed-bid format in terms of revenue since a bidder is incentivized to participate longer in an auction to gain competition signals and learn whether or not to acquire information about her own private value. This offers a gateway to understanding sniping.

Rasmusen (2006) applies the concept of private value information acquisition to late bidding strategies in online auctions. This hypothesis argues that it is in the best interest of a bidder to observe the auction for most of the bidding period before determining whether or not to pay a cost (in terms of time and effort) to acquire a more accurate value approximation and submit a bid. The model analyses two bidders: the “victim” with value \( v \) on a probability distribution \([0,v]\), and the “sniper” with value \( s \) on a probability distribution \([0,s]\). The sniper knows \( s \) but not \( v \), and the victim only knows \( E(v) \) but can pay \( c \) to learn \( v \) in time \( \delta \). There is a \( c_{\text{little}} \) below which the victim chooses to discover her price, and a \( c_{\text{big}} \) above which the victim chooses to approximate her value. Between these two values for \( c \), the bidder places an initial bid and only chooses to discover her true value if another bid comes in above hers. Here it is an obvious best choice for the sniper to snipe, submitting a bid of \( s \) after time \( T-\delta \) so the victim cannot respond (\( T \) marks the end of the auction period). Thus the model supports sniper strategies in dynamic online auctions.

**Shilling and Squeezing**

Several papers analyze potential seller strategies that can induce sniping behavior among bidders. Wang, Hidvégi, and Whinston (2001) introduce the concept of “shill bidding” in internet auctions. Here a seller logs into eBay under a separate registered account, posing as a bidder for
her own auction. Through submitting a bid slightly greater than the current price, she can hope to raise the price the winning bidder must pay for the item without winning the item herself (and thus forgoing the sunk cost of putting the item up for auction). Though shilling is illegal, internet auctions make it easy for a bidder to submit disguised bids from the security of her own home. In their paper with the clever title, “Shill-Proof Fee (SPF) Schedule: The Sunscreen Against Seller Self-Collusion in Online English auctions,” the authors first show that shilling can be profitable in an English auction, and how a seller will determine an optimal shill bid given a certain set of assumptions. This strategy translates directly to second-price auctions, and the best response for an honest bidder is to bid late. Chakraborty and Kosmopoulou (2004) achieve identical results in a common value setting.

Barbaro and Bracht (2005) introduce a variant of the shilling strategy that eliminates the risk of self-purchase, which they call “squeezing.” This technique uses a loophole in the rules of eBay: the seller of an item has the right to cancel any bid for her item at any time. With this in mind, a shilling seller can (1) submit a large bid under an alternate account to identify the largest current value for the item, (2) cancel this bid from the seller’s account, and (3) submit a new bid from the alternate account just below the current high bid, thus squeezing all surplus from the winner of the auction without risking winning the item herself. The authors first prove that squeezing is a rational strategy for the seller, since if there is a bidder with a highest value in the first round, the seller can gain the difference between the first and second highest actual bids in the first round. They then show that sniping is a best response for honest bidders since they ensure no information is gathered by the seller for squeezing purposes.
The Bidding Increment

In their most recent paper entitled “Late and Multiple Bidding in Second Price Internet Auctions: Theory and Evidence Concerning Different Rules for Ending an Auction,” Roth and Ockenfels (2006) offer an explanation for sniping based on the existence of a bidding increment (not present in a classic second-price auction). The authors also assume a non-trivial probability of a sniping bid not being received (due to network delays). The first proof is that because of the bidding increment, there is no dominant strategy in the simple case of rational bidders. The authors then prove that sniping is a rational response to an incremental bidder, since giving no signal to the incremental bidder significantly increases the profit of winning an item. Thus the existence of a weakly dominant strategy that is the strength of Vickrey’s argument is violated in the eBay setting, allowing for sniping to be a rational strategy.

Summary

The prevalence of late bidding in online auctions has been well-documented in economic literature. It is more common among bidders with greater experience, and may heighten bidder surplus, so it seems to be a rational strategy. The literature has produced several hypotheses to explain the incentive for such behavior. Many of these theories use very similar elements or assumptions, yet most have not been (or cannot be) tested in an empirical setting. Thus it seems as though the breadth of theory has been expanded quite far compared to the depth of each analysis, and extension of our understanding of bidder behavior can be greatly improved with the simultaneous testing of several of these hypotheses in an empirical setting.
3) Methodology

Section 2 demonstrates the extent to which economists have sought to reconcile evidence of late bidding with rational behavior. In this section, I will extend the previous literature and introduce a new economic model to be tested through regression analysis. I will explain each variable and the direction of influence the model predicts it will have on the likelihood of sniping. I will then present the data set I have collected from completed eBay auctions, and how I will use it to test the economic model.

Economic Model

The model is an extension of previous literature in several ways: (1) it introduces an interaction variable to test the effect of a common value setting on how experience affects sniping tendencies, (2) it introduces a new measurement of experience based on the log of one’s feedback rating to model a learning curve with decreasing slope, and (3) it introduces a new variable representing the number of perfect substitutes available for a particular item. These three adaptations to previous models will offer new insight into the determinants of sniping behavior. The economic model is given below, followed by the economic theory behind each parameter and a prediction of how each parameter will affect the endogenous variable:

\[ \text{SNIPE}_i = \alpha + \pi \cdot CV_i + \beta \cdot \ln(\text{RATING}+1)_i + \gamma \cdot CV_i \times \ln(\text{RATING}+1)_i + \delta \cdot \text{OPPONENTS}_i + \zeta \cdot \text{SUBS} + \varepsilon_i \]

The SNIPE term is a measurement of the likelihood of a sniping bid (defined as a bid in the final minute of the bidding period), and is a determinant of the remaining parameters in the model. CV is an indicator of common value for the auctioned item, achieving a value of “1” in the case of a common value item and “0” for an item with an independent private value (the
exact items are described later in this section). The \( \ln(\text{RATING} + 1) \) term is a measurement of an individual’s experience on eBay, and consists of the log of the individual’s official eBay feedback rating (plus one, to avoid undefined values). The third exogenous term is an interaction of the first two, used to measure how common value affects experience’s influence on sniping behavior. The OPPONENTS term represents competition in a given auction, and is measured by one less than the number of bidders in the auction. Finally, the \#SUBS term is a measurement of the number of perfect substitutes for a given item, and the measurement of this term is also described in greater detail later in this section. Below is the economic theory behind each of these variables.

**The Constant – \( \alpha \)**

The constant represents the base probability of a late bid associated with a new bidder (with zero feedback rating) competing for an item with zero substitutes and a private value, and in the presence of zero opposing bids. Assuming that all individuals bid immediately upon first viewing an item, this coefficient will be slightly positive. Strategic late bidding due to any of a number of hypotheses – rule confusion, competitive arousal, a fear of shill bids, or value uncertainty – can lead to a greater and more significant coefficient. Thus the model predicts a significantly positive constant, consistent with sniping as a deliberate strategy for those under the base set of assumptions described above.

**Common Value Indicator – \( CV \)**

The presence of a common value indicator stems from the hypothesis that a bidder has greater incentive to withhold her bid in a common value scenario. The argument has been presented in Section 2 (Wilcox, 2000), and will be described rigorously at this time. Consider \( s \) bidders in an auction for a single, unique item with a common value \( v \) such that the \( i^{\text{th}} \) bidder
observes a value estimate $v_i^*$ from the probability distribution $V_i^*$ with mean $\nu$ and standard deviation $\sigma_i^*$. I assume without loss of generality that bidder $m$ is an “expert” and observes a value estimate $v_m^*$ from the distribution $V_m^*$ with standard deviation $\sigma_m^*$, and that bidder $n$ is an “amateur” and observes a value estimate $v_n^*$ from the distribution $V_n^*$ with standard deviation $\sigma_n^*$, where $\sigma_n^* \geq \sigma_m^*$. The argument follows that the expert is necessarily better off than the amateur because her value estimate distribution is weighted closer to the actual value of the item. Having a value far from $\nu$ leads to two sources of suffering: (1) winning the item for a value much too high and earning negative profit, and (2) losing the item with a low bid and forgoing positive profit.

Having established that an expert bidder is necessarily better off than an amateur, I now assume that through observing an expert bid, an amateur can learn the true value of an item. On eBay, a bidder can see the feedback rating of an opponent and her bidding history, both of which can lead to the easy detection of an expert in a certain field. Through following the bid of an expert, an amateur can, in essence, select her value approximation from the expert’s probability distribution function and thus make herself better off. This strategy can only be accomplished if the amateur bidder has not already submitted a bid above the bid of the expert, since bids cannot be reneged. Thus, given that following an expert bidder is a better strategy than using her own distribution, an amateur bidder is incentivized to wait for value signals from an expert, resulting in late bidding. Turning then to the expert bidder’s response, it is in her best interest to bid late to protect her information advantage. Thus, both bidders are incentivized to bid late, and the model predicts a positive coefficient on the common value indicator in the regression.
**Bidder Experience – ln(RATING+1)**

Including an individual’s feedback rating allows for a clear picture of how experience affects bidding strategy. eBay uses a point system for feedback; after a transaction is completed between the seller and the winning bidder, each is given the opportunity to provide the other with either “positive” or “negative” feedback. Receiving positive feedback earns a bidder/seller one rating point, and a negative response causes the individual to lose a point; the sum of all points earned equals the individual’s feedback rating. This rating is a good indicator of one’s experience since less than one percent of all feedbacks are negative (Resnick and Zeckhauser, 2002).

In the model, I use the log function to adjust the linear feedback rating in my measurement of experience. This modification is consistent with the assumption of decreasing marginal experience in sequential transactions, or a flattening learning curve. Intuition says that the fourth transaction will provide an individual with more experience than the 4,000th. Because the model also includes an interaction term between common value and experience (described below), RATING describes the effect of experience only in a private value setting. If late bidding is in fact a profitable strategy (as Ely and Hossain, 2006, suggest), the experienced bidder will be more aware of this fact and will employ the strategy with greater frequency, so the model predicts a positive value on this coefficient.

**CV/Experience Interaction – CV ln(RATING+1)**

Wilcox (2000) proposes that a greater feedback rating (more experience) heightens the effect of a common value setting on a bidder’s tendency to bid multiple times (reducing multiple bids even more). The model in this paper argues that a feedback rating affects the way that common value affects late bidding (or interpreted differently, a common value setting affects the
way experience affects late bidding). In the common value case described above, an expert bidder bids late to hide her value signal, while the amateur bids late to attempt to react to any signals. However, the assumption that an expert bidder is rational and has full understanding of her best strategy is less likely to be violated than for a novice. Thus experience is expected to have a positive effect on the amount of extra incentive to snipe brought about by a common value item, and this coefficient should be positive.

**Opposing Bidders – OPPONENTS**

The primary hypothesis for the OPPONENTS parameter stems from the escalation effect introduced by Ely and Hossain (2006). The authors argue that an individual will bid more aggressively in the presence of increased competition. The “aggression” with which an individual bids can be defined in both private and common value settings without violating bidder rationality. In a private value setting, a bidder may have uncertainty regarding her value for an item (Rasmusen, 2006), and may spend more effort accurately predicting this value in a more aggressive state – leading to a sniping bid more often. In a common value setting, the presence of many opponents creates a strong signal of a high value for an item, which can lead to bidding wars late in the auction. Thus in either setting, a bidder has an incentive to bid late when a greater number of opponents are present, suggesting a positive coefficient.

There is a question regarding the exogeneity of the OPPONENTS parameter. First, the number of bidders in an auction may depend on the timing of various bids, which also determines the presence of a sniping bid. Second, there is a difference between the actual number of bidders in an auction and the potential number of bidders (which includes individuals who view the item but do not bid). To address the first issue, any endogeneity is likely to be minimal at most, because the range for a sniping bid (one minute) is so small. For SNIPE to affect
OPPONENTS, one must assume that an individual can react to a sniping bid by choosing to enter or not enter an auction, which is unlikely to be true. In response to the second issue, the model is attempting to measure the “perceived” level of competition, which more accurately follows the number of actual bidders rather than the number of potential bidders. Neither of these issues should pose a significant threat to the model, and the coefficient on this variable should accurately detect any escalation effect.

**Perfect Substitutes – #SUBS**

The parameter #SUBS measures the average number of perfect substitute items available on eBay simultaneously to a given auction. I assume that all common value items are unique (zero substitutes) and all DVD movies of the same title are perfect substitutes. I do not address the issue of varying levels of substitutability in this paper (a potential source of bias). There are two major economic reasons why this parameter is relevant to sniping behavior. The first theory argues that the existence of many perfect substitutes will have a positive effect on the likelihood of sniping, while the second argues for the opposite. Including this variable in the regression will allow for a determination of which of these two effects is greater, if in fact either is significant.

The first hypothesis is that a greater number of substitutes will affect sniping tendencies in a positive way. The reasoning is twofold: (1) a strategic bidder will tend to enter auctions with less time remaining in order to minimize the opportunity cost of waiting for the results of an auction, and (2) a non-strategic bidder will tend to enter auctions with less time remaining because eBay returns search results in the order of soonest closing. An individual who enters an auction close to the end of a bidding period has a greater chance of submitting a sniping bid, and thus, the more substitutes an item has, the greater the likelihood of a sniping bid for a given individual. Consider items $a$ and $b$ being auctioned on eBay simultaneously and for the same
bidding period length $T$, except that $a$ is a unique item with no substitutes and $b$ is a common good with an identical item being posted to eBay every minute. Since item $a$ is unique, a potential bidder will on average first view the auction with $T/2$ time remaining in the bidding period. Item $b$ may only make it to the first page of the average search result list in the final 40 minutes of the bidding period, and from that point a potential bidder will on average first view the auction with 20 minutes remaining in the bidding period.

The second, and opposing, hypothesis argues that the number of substitutes for a given item has a negative effect on sniping behavior. The argument is similar to the escalation effect proposed by Ely and Hossain (2006), originally describing the effect of increased competition through additional bidders on sniping. Here the presence of substitute items has the opposite influence on bidders, “lowering the stakes” of an individual auction because there are many more items that can be won. As a result, a bidder will bid less aggressively, and there will be a lower probability of a sniping bid for each individual. Given the strong assumptions above, the coefficient will help to analyze the relative weights of these two opposing hypotheses.

**Error Term – $\varepsilon$**

The error term includes exogenous variables not considered in the above model, divided into two categories: (1) variables introduced in previous literature but untestable and (2) other idiosyncratic behavior/circumstances. The first category may introduce omitted variable bias, depending on the variables that are unable to be tested. Other idiosyncratic behavior or circumstances may include the following examples. A bidder may learn new information or re-read the description of an item midway through the bidding period. She may drop out of the auction early, or network delays may cause her bid not to be received by the computer. One bidder may have an extreme desire for a particular item, or may experience a change of heart...
midway through the bidding period. There are many other situations that can cause error in the above model, as ultimately humans are not wired the same nor do they have a controlled experience from their respective homes at different times of day and times in their lives.

The Data Set

The data set constructed for the purpose of testing the above model consists of the results of 515 eBay auctions. A total of 2,563 individuals submit 4,326 bids for 15 types of items. The auctions come from a larger set of 945 auctions I “watched” online until expiration. The primary reason for an auction being excluded from the final data set is the absence of any bidding activity. Without any bids there is certainly no sniping behavior to observe. I also dismiss auctions where the identities and feedback ratings of the bidders are kept private by the seller, and auctions that have ended early with a “Buy Now” selection.

For each of the remaining auctions, I record: (1) the type of item, (2) whether it is a common or private value item, (3) the number of bidders in the auction, (4) the number of bids placed, (5) the length of the bidding period, (6) the date and time of the hard close, (7) the number of sniping bids submitted, (8) the price paid by the winner, (9) the shipping cost to my house in Chicago, and (10) the number of substitutes for the item. For each individual, I record: (1) the auction the individual bids in, (2) the account name of the individual, (3) the feedback rating of the individual, (4) the number of bids the individual submits, (5) the date and time of the individual’s final bid, (6) whether or not the individual submits a sniping bid, and (7) whether or not the individual wins the auction.

Several exceptions arise during the recording of these data, and at this point I will describe my methods for dealing with certain circumstances. First, for many common value items that achieve a certain price level, the seller chooses to withhold some information about the
bidders. As mentioned above, I dismiss an auction when all bidder information is withheld. In most cases, however, the seller does not release the account names of the bidders, and displays their feedback ratings in levels, rather than exact values. The levels are 0-9, 10-49, 50-99, 100-499, 500-999, and 1,000-4,999, and there are no bidders with ratings above 4,999 in the data set. In this case, I enter the midpoint of the feedback rating level (5, 30, 75, 300, 750, and 3,000, respectively) for each individual. Though not as specific, this assumption does not create a bias in the results assuming ratings are distributed uniformly throughout each level.

There are also several individuals who have negative feedback ratings, who apparently have negative feedback from more transactions than positive. Because the log function is defined only on the set of positive real numbers, I create an artificial lower bound of zero for all feedback ratings. The bias created by this assumption is quite small because of the infrequency of a negative feedback rating. Occasionally there will be a bid submitted by an individual who is no longer a registered user. Such an individual will still have a feedback rating, but her account has become inactive – perhaps due to a violation of eBay rules. I make no distinction in the data set between a registered and an unregistered user, and assume the model holds equally for both. Finally, there are several individuals in the data set who have chosen to keep their own feedback ratings private. The rating shows up as private in the bidding history, but there is a hyperlink to see the rating. Again I make no distinction between these users and users with public ratings.

Specific items are chosen to be watched for the data set based on: (1) having a common or private value, and (2) having a different number of perfect substitutes. For items with independent private values, I select 11 DVD movie titles. In doing so, I assume that one’s value for such a movie is derived from personal enjoyment, and is independent of any other individual’s value. There are four items assumed to have common values: (1) antique chairs, (2)
pre-1900 antique rugs, (3) pre-1900 original paintings, and (4) silver items. I assume that an individual’s value for these items is derived in part by resale value and a sense of authenticity of the item, and is thus dependent on the value of others. For each private value item, a “0” is recorded in the “CV” column, and a “1” is recorded for each common value item. The use of an indicator variable allows for a single coefficient in the regression to describe any change in behavior due to a common value setting.

Among the private value items, each movie title is associated with a number of perfect substitutes. I do not include any near substitutes in the model. This value is derived from the average number of copies of a particular movie are available on eBay over the course of a two-day test period. This value is subtracted by one, to create a value for the number of substitutes for an individual item, and the resulting value is recorded in the “#SUBS” column. In the case of a common value item (chairs, rugs, paintings, and silver), I assume that each item is unique, and thus there are no perfect substitutes. While neither assumption – all DVDs are perfect substitutes and common value items are unique – is likely to be perceived by all bidders, the two allow for the construction of a variable to approximate the availability of substitutes. A violation of either assumption should not, in theory, create a bias in the results, and the coefficient on this variable should describe the relative weights of the two hypotheses regarding substitutes.

The next three sections of this paper are based on the empirical results captured by the data set. In Section 4, I note a number of statistical findings including averages, distributions, and covariances, which will help to put the results of the regression analysis into an economic context. In Section 5, I describe the results of several regressions, and the degree to which the coefficients are consistent with the economic model and with existing literature. Finally, in Section 6, I summarize the study and ways the literature can be extended in future studies.
4) Descriptive Statistics

The data set offers many interesting results that are worth noting before the regression analysis. The set consists of observations from 515 eBay auctions for 15 different types of items, in which 2,563 individuals participate by submitting a total of 4,326 bids and spending a total of nearly $150,000. In this section I will present these statistics in two categories: (1) by auction and (2) by individual. Because the observed items are divided into items with common values and items with independent private values, it will often be advantageous to separate statistics along this divide and observe differences. These statistics will help to qualify the results from the regression analysis, presented in Section 5.

By Auction

The 15 categories of items consist of 11 DVD movie titles – representing private value items – and four types of common value items. The 11 movie titles include “The Departed,” “Little Miss Sunshine,” “Borat: Cultural Learnings for Make Benefit Glorious Nation of Kazakhstan,” “Let’s Go to Prison,” “Fast Food Nation,” “School for Scoundrels,” “March of the Penguins,” “Hoot,” “Conversations With God,” “World Trade Center,” and “The Devil Wears Prada,” totaling 312 auctions. A total of 203 auctions are observed for four types of items with common values: (1) antique chairs, (2) pre-1900 antique rugs, (3) pre-1900 original paintings, and (4) silver items. DVD movies are assumed to have independent private values (one’s value depends only on her happiness derived from owning the item), while the chairs, rugs, paintings, and silver have resale values and varying levels of authenticity, so are assumed to have common values. Each movie title has a different number of (assumed to be perfect) substitutes, and I
assume that each common value item is unique. The table below offers several statistics for each item:

<table>
<thead>
<tr>
<th>Item</th>
<th># Auctions</th>
<th># Bidders</th>
<th># Substitutes</th>
<th>Bid Length (days)</th>
<th>Ave Price</th>
<th>Snipe per Auction</th>
</tr>
</thead>
<tbody>
<tr>
<td>Departed, The</td>
<td>56</td>
<td>283</td>
<td>202.0</td>
<td>5.4</td>
<td>$14.07</td>
<td>.393</td>
</tr>
<tr>
<td>Little Miss Sunshine</td>
<td>63</td>
<td>297</td>
<td>68.5</td>
<td>6.3</td>
<td>11.70</td>
<td>.365</td>
</tr>
<tr>
<td>Borat: Cultural Learnings</td>
<td>54</td>
<td>313</td>
<td>279.5</td>
<td>2.4</td>
<td>15.76</td>
<td>.852</td>
</tr>
<tr>
<td>Let’s Go to Prison</td>
<td>24</td>
<td>64</td>
<td>29.0</td>
<td>5.1</td>
<td>11.25</td>
<td>.167</td>
</tr>
<tr>
<td>Fast Food Nation</td>
<td>7</td>
<td>22</td>
<td>20.0</td>
<td>5.0</td>
<td>11.46</td>
<td>.000</td>
</tr>
<tr>
<td>School for Scoundrels</td>
<td>16</td>
<td>50</td>
<td>48.5</td>
<td>6.1</td>
<td>8.16</td>
<td>.250</td>
</tr>
<tr>
<td>March of the Penguins</td>
<td>20</td>
<td>52</td>
<td>61.5</td>
<td>6.6</td>
<td>8.16</td>
<td>.150</td>
</tr>
<tr>
<td>Hoot</td>
<td>8</td>
<td>24</td>
<td>12.0</td>
<td>6.8</td>
<td>8.78</td>
<td>.250</td>
</tr>
<tr>
<td>Conversations With God</td>
<td>11</td>
<td>49</td>
<td>12.5</td>
<td>4.8</td>
<td>15.97</td>
<td>.727</td>
</tr>
<tr>
<td>World Trade Center</td>
<td>8</td>
<td>25</td>
<td>70.5</td>
<td>5.8</td>
<td>9.38</td>
<td>.500</td>
</tr>
<tr>
<td>Devil Wears Prada, The</td>
<td>45</td>
<td>226</td>
<td>74.0</td>
<td>6.7</td>
<td>10.62</td>
<td>.200</td>
</tr>
<tr>
<td>Antique Chair</td>
<td>43</td>
<td>153</td>
<td>0.0</td>
<td>7.9</td>
<td>264.69</td>
<td>.581</td>
</tr>
<tr>
<td>Antique Rug</td>
<td>44</td>
<td>213</td>
<td>0.0</td>
<td>7.5</td>
<td>582.14</td>
<td>.727</td>
</tr>
<tr>
<td>Painting</td>
<td>43</td>
<td>231</td>
<td>0.0</td>
<td>8.5</td>
<td>699.48</td>
<td>.535</td>
</tr>
<tr>
<td>Silver</td>
<td>73</td>
<td>561</td>
<td>0.0</td>
<td>8.7</td>
<td>1,079.14</td>
<td>.932</td>
</tr>
</tbody>
</table>

| Total/Average                | **515**    | **2563**  | **[72.6]**    | **[6.5]**         | **[$290.62]** | **[.530]**        |

In this table, the 11 DVD movies are above the separator, and the four common value items below. The final row represents either the sum or the average over all auctions. The column labeled “# Substitutes” represents the average number of the same DVD title up for auction over several observations. This value is trivially zero for the four common value items due to the uniqueness assumption. The column labeled “Bid Length” represents the average
length of the bidding period assigned by the seller for such an item, and the column labeled “Snipe per Auction” represents the average number of bidders submitting sniping bids in an auction for such an item. The average price in the penultimate column includes the cost of shipping to my home address in Chicago. This cost may be more or less than the actual shipping cost to the buyer, but including this value controls for large changes in shipping. It must also be noted that eBay is not always able to calculate shipping, and for these cases I assume shipping cost is zero, introducing a certain level of unavoidable bias.

I will first discuss the number of bidders per auction. The popular DVDs (The Departed, Little Miss Sunshine, Borat, and The Devil Wears Prada) average about five bidders per auction, while the less popular DVDs average close to three bidders. For the common value items, most averages are closer to the popular DVD titles. These correlations will impact the results of the regression since common value, number of substitute items, and number of opposing bidders are all exogenous variables in the model. Because these parameters covary (more popular DVDs tend to have more substitutes and more bidders, and common value items tend to have more bidders), the results will be slightly less robust. As far as determining a level of sniping bids, there is a positive covariance of 1.2 between the number of bidders in an auction and the number of sniping bids in that auction.

Another interesting note is that common value items tend to be put on auction for longer bidding periods. The average for common value items is 8.2 days compared to 5.3 days for DVD movies. This should theoretically have an impact on the probability of submitting a sniping bid by chance, assuming that bidders first have the opportunity to bid for an item on a uniform distribution across the bidding period. This difference is negligible, however, since the probabilities of submitting a bid in the final minute of an 8.2 day versus a 5.3 day auction period
are .000085 and .00013 respectively. In the regression, I assume these values to be negligible and use zero sniping as my null hypothesis.

The price of an item and the number of substitutes can act in similar ways on the behavior of bidders. The absence of substitutes for sale elsewhere on the internet raises the importance of winning a particular auction. If a bidder knows she wants a particular piece of art, and there are no other copies for sale, she will bid more aggressively for that art piece, leading to a greater likelihood of a sniping bid. A greater value of an item also has the effect of raising the stakes of a particular auction. In the case of a $20 DVD movie, a bidder may be likely to bid a bit higher early in the auction to secure a purchase, but for a $2,000 antique rug, the bidding increment is significant, and bidders may often feel each other out until the very end of the bidding period. I noticed many “bidding wars” for items with common values. These effects together can help to explain the positive covariance of .078 between common value and the number of sniping bids in an auction – in addition to the original concept of protecting one’s value information in such a setting. Acting against this argument is the fact that on eBay, bidders will tend to view items with many substitutes much later in the bidding period, since auctions are organized by default in order of nearest closing. The regression analysis will determine which theory proves a stronger influence, but there is a positive covariance of 17.1 between the number of substitutes and the number of sniping bids in an auction for a DVD movie.

The auctions provide some reason for caution when arguing for causation, since many of the exogenous parameters seem to depend on one another. A common value item will in general have more bidders per auction and thus more bids, and will necessarily have fewer substitutes (assumed to be zero) and a greater price. These items also encourage a larger number of sniping bids, so it is difficult at first to assert which of these parameters has a real effect on a bidder’s
behavior. Now I look to statistics measured by individual help create a clearer understanding of
the context in which the regression analysis is conceived.

**By Individual**

There are a total of 2,563 individuals present in the data set, submitting 4,326 bids in all
(roughly 1.7 bids per bidder on average). Parameters measured include the individual’s feedback
rating, the number of bids submitted, the date and time of the final bid placed, and whether or not
the individual (1) snipes and (2) wins the auction. A summary of these statistics, separated along
the common/private value divide, are below:

<table>
<thead>
<tr>
<th>Type of Item</th>
<th>Rating</th>
<th># Bids</th>
<th>Ave Time Left (hh:mm:ss)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Independent Private Value</td>
<td>328.5</td>
<td>1.4</td>
<td>30:21:44</td>
</tr>
<tr>
<td>Common Value</td>
<td>328.2</td>
<td>2.0</td>
<td>81:36:06</td>
</tr>
<tr>
<td><strong>Total Average</strong></td>
<td><strong>328.4</strong></td>
<td><strong>1.7</strong></td>
<td><strong>53:30:46</strong></td>
</tr>
</tbody>
</table>

It is clear from this table that the feedback ratings are comparable for bidders in auctions
for common and private value items. Bidders submit, on average, more than a half-bid extra for
common value items than for private value items. In a common value setting, new bids provide
value information signals and may lead to new bids from other individuals. In comparison, a
bidder should have a better idea of her private value for a DVD movie, and is therefore less
likely to submit multiple bids. These data agree with predictions.

The final column represents the average time remaining in the bidding period when the
individual submits her final bid. Part of the discrepancy can be explained by the fact that
common value items tend to have longer bidding periods by about 55 percent. Thus the bidders
who chose to submit an early bid (perhaps to signal competition to opponents) will bid earlier for
common value items than for private value items. Below is a histogram representing the distribution of final bid times:

![Histogram of Time Remaining at Last Bid](image)

It is quite visible that a significantly larger proportion of bids for common value items are submitted with longer to go in the bidding period. Though in general, a greater proportion of bids for private value items are clustered near the end of the bidding period, more sniping bids are submitted for common value items (see leftmost column). This is consistent with more strategic late bidding for common value items and more accidental late bidding for private value items, perhaps because eBay lists search results in the order of closest to the close of an auction by default.

An interesting relationship can also be seen between the feedback rating of an individual and her propensity to submit multiple bids during a bidding period. The scatterplot below highlights the negative correlation between the two parameters, suggesting that as a bidder gains experience, either she (1) has a better understanding of her own value and thus submits fewer
bids in a private value situation, or (2) learns to conceal her value information by submitting fewer bids in a common value situation.\(^1\) The peak at the feedback rating of 3,000 is due to the fact that for auctions that did not reveal exact ratings, bidders are assumed to have the midpoint of their range, one of which was 1,000 to 4,999.

![Feedback vs. Bid Frequency](image)

A puzzling relationship exists between feedback rating and the probability of winning, as suggested by the negative covariance of -10.5. It seems that the more experienced bidders should have a greater winning percentage. One explanation is that a small proportion of bidders with the highest ratings are actually resellers. These bidders submit low bids toward the beginning of the bidding period in an attempt to fend off potential opponents. They will win only a small proportion of their auctions, but will be able to post the acquired items in new auctions in order

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\(^1\) The graph omits the two greatest outliers in both the feedback rating (in the 12,000s) and in number of bids (two individuals bid 27 times)
to claim a profit. I witness at least several of these bidders, such as “patsbratbrat,” who submit low bids in the beginning of 18 different DVD movie auctions and wins none.

The covariance between feedback rating and the probability of a sniping bid tells a compelling story. The value for all individuals is slightly positive at 1.8, but the values for individuals bidding on private and common value items are -7.4 and 13.1, respectively. Thus it seems that the more experienced bidders submit fewer sniping bids for private value items and more for common value items. In a private value setting, it is possible that a more experienced bidder will have a greater understanding of her value for an item, and will submit her bid early. An experienced common value bidder, or “expert,” will learn to withhold her value information until the last possible moment.

**Summary**

Not all relationships that emerge from the data correspond to real causal relationships between parameters. It is important to beware the existence of lurking variables when considering, for example, the positive covariance of .036 between the probability of a sniping bid and the probability of winning the auction. The data support a cautionary warning on both an auction and individual level. Even so, the data seem to support several hypotheses the regression analysis will test simultaneously. Common value items have a greater likelihood than their private value counterparts of receiving a sniping bid. Of the private value items, a greater number of substitutes vary positively with late bidding. Of the common value items, the more experienced bidders choose to submit fewer bids, and to do so later in the bidding period. The number of bidders and bids in a given auction covary, and seem to have a positive affect on the frequency of sniping bids. With the statistics above, a proper understanding of the results from the regression analysis can be had.
5) Analysis

In this section, I run four separate regressions on the data set using a standard linear probability model. The first regression represents the primary economic model of this paper, and includes a log measurement of feedback rating and a new variable, the number of perfect substitutes for an item. The second regression uses the standard feedback rating measurement instead of the log form, and the third regression uses the log form but omits the interaction variable between common value and feedback rating. The final regression is an attempt to replicate the model used by Roth and Ockenfels (2006), though their use of Amazon auctions prevents an exact comparison to my data set. The exact number of observations is difficult to measure since different variables are measured by individual, auction, and item – there are 2,563 individuals, 515 auctions, and 15 types of item in the data set. This issue should not have a statistical impact on the findings of the regression.

In this section, I will first analyze each regression by providing possible interpretations of the coefficients and standard errors. I will then summarize any conclusions that can be drawn from the results, and the extent to which the results agree with (1) past results in economic literature and (2) the economic model presented in Section 3. Finally, I will provide several potential issues with the model or the data set that can be improved in future research. The results of the regressions are in the table below. Each column provides the coefficient and standard error for each variable. A black number signifies statistical significance of the coefficient at the $\alpha=.05$ level (P-value less than .05), and a red number signifies statistical insignificance at this level. A blank space indicates a variable was not used in a particular regression:
The Determinants of Sniping on eBay

Regression 1

The first regression includes an indicator for a common value item, a variable for the feedback rating of the bidder, an interaction of the first two variables, the number of opposing bidders present in the auction, and the number of perfect substitutes for the item. The table shows a constant of .084, significant at the $\alpha=.05$ level with a P-value of .0021. This value represents the likelihood of a sniping bid for a new eBay member bidding for a private value item with no substitutes and no opponents (the bidder knows that nobody has yet entered the auction). The
coefficient seems to agree with the average probability of a snipe for all private value items, which is .089.

The next three parameters seem to be a bit tangled, since two are insignificant at the $\alpha=.05$ level and have opposite signs to those predicted by the model. The coefficients for the common value indicator and for the log of the individual’s feedback rating are both negative. The model predicts that both values should be positive, since common value items should have a greater probability of sniping bids (.13 versus .089 in the data set), and experience should lead to more sniping, assuming it is rational. The lack of statistical significance for each of these coefficients lessens the importance of the apparent error, and the presence of the interaction term actually justifies the coefficients.

The interaction of feedback rating with the common value indicator is very significant, with a P-value of .000023, and argues that for common value items, increased experience leads to a greater affinity for late bidding. This result agrees with the “expert” theory introduced by Wilcox (2000), whereby an experienced (and thus knowledgeable) bidder will withhold her bid to conceal her value information from others. Thus the coefficient for common value represents a bidder with a very low level of experience, who we may expect will have little information to conceal. Bidders in common value scenarios tend to submit more bids (2.0 versus 1.4 for private value items), so these novice bidders may submit early bids and then reconsider once new information is available. The feedback rating coefficient measures results in a private value setting, where we can expect late bidding to provide less benefit. Each of these explanations helps to understand why these coefficients are found to be both negative and statistically insignificant, and why the interaction term carries much of the impact on sniping.
The coefficient on the number of opponents also carries the opposite sign of what the model predicts, and it too is insignificant at the $\alpha=.05$ level, with a P-value of .39. There is not as clear a justification for this value, but there are a few possible explanations. The first is that the number of opponents is actually insignificant from a bidder’s perspective when deciding when to submit a bid. The second is that the number of opponents varies positively with the common value indicator, which may be leading to a lack of significance for each. This may not be likely because a least squares regression will internalize colinearity assuming a large enough sample size. The third explanation is that my measurement of opponents does not accurately reflect a bidder’s perception of competition at the time of placing a bid. In an auction with three bidders, each placing one bid, I mark “2” in the column for opponents, since each bidder faces two opponents. However, at the time of the first bid, the first individual does not know she is facing two opponents. It is quite possible that the results are skewed by this notation, an issue that will be discussed in more detail later in this section.

The final coefficient is the number of substitutes for the auctioned item. This new variable has two potential effects on bidding behavior. On the one hand, more substitutes may lead to more sniping because (1) a bidder will enter auctions later in the bidding period because search results are returned in order of soonest closing, and (2) a bidder will want to know sooner whether or not she wins an auction so that she may enter another soon to win a substitute. On the other hand, an abundance of substitutes may decrease overall competitiveness in an auction by lowering the stakes and the sense of urgency. The empirical results support the first hypothesis dominating the second, since the coefficient is quite small but positive (.00027), and is very significant, with a P-value of .0022.
Each coefficient and standard error can be explained using the economic model presented in Section 3 of this paper. Though not every coefficient is statistically significant at the $\alpha=.05$ level, and several seem to have the wrong sign, these apparent mistakes actually provide relevant information about the methods of measurement and the interactions between parameters. The subsequent regressions will allow for comparative analysis and insight into how the results change with the presence of different variables and methods of measurement.

**Regression 2**

The second regression differs from the first in its measurement of experience, more specifically, how experience affects sniping tendencies. Using the log of an individual’s feedback rating assumes a diminishing affect of each transaction on the likelihood of submitting a sniping bid. Instead of an additional feedback point affecting sniping in the same way regardless of one’s initial rating, it is an additional percent that has a constant effect. It seems intuitive that the “learning curve” follows a log pattern rather than a linear one, but past literature has assumed the latter. Roth and Ockenfels (2006) use actual feedback ratings rather than a log adjustment, so it is important to compare the two methods here.

The coefficients and standard errors on the variables for the number of opponents and substitutes do not change very much from the results from the first regression. The coefficient for the constant does lower from .084 to .061, but becomes more significant, with its P-value decreasing from .0021 to .00013. The coefficients on the experience measure and the interaction term lower in absolute terms by factors of .0015 and .0013, respectively, which is to be expected since the variance of feedback ratings is much greater than that of their logs. These values become slightly less significant than their correspondents in the first regression, but remain statistically significant at the $\alpha=.05$ level.
The major difference is in the coefficient on the common value indicator, which changes to the positive sign predicted in the model, and becomes statistically significant at the $\alpha=.05$ level, with a P-value of .00061. A slightly negative and insignificant value was justified through the assumption that individuals with little experience have little reason to snipe and little knowledge of strategy. The significantly positive value, however, agrees with a different assumption, argued by Wilcox (2000) along with his “expert” hypothesis. In this assumption, the novice bidder in a common value setting also has incentive to withhold her bid until late in the bidding period, in order to observe value signals from other bidders. This strategy provides no advantage given that all expert bidders are also withholding their bids, but there are still two reasons not to deviate: (1) withholding a bid can lure opposing bidders into early bids with the appearance of light competition, and (2) late bidding can only help, in case an expert does surrender value information.

This represents a significant advantage to the second regression with respect to its consistency with economic intuition. By sacrificing the assumption of a log learning curve, the data are consistent with the positive effect of a common value item on sniping prevalence, regardless of experience. A preference for one of the two models may depend on assumptions about the degree to which a novice bidder has full information and rationality. The second regression does have a slightly lower multiple $R^2$ value than the first (.10 versus .13), suggesting a tighter statistical fit, but the economic importance of the second regression cannot be overlooked.

**Regression 3**

The third regression also represents a slight deviation from the first in that it omits the interaction term between the log of the individual’s feedback rating and the indicator of a
common value item. Once again, the coefficients and standard errors for the number of opponents and the number of substitutes remain mostly unchanged. The absence of the interaction term does have a significant effect on the three remaining values: the constant, the common value indicator, and the log of an individual’s feedback rating. As in the second regression, the coefficient on the common value indicator becomes positive and very significant, with a P-value of 9.2E-6. The coefficient on the measure of bidder experience also becomes positive and significant, with a P-value of .011. This is a result that is not achieved in either of the previous regressions, and is consistent with the argument that even in a private value setting, more experienced bidders tend to submit sniping bids more often. In contrast to these seemingly optimistic results, the coefficient for the constant drops to .018 and becomes statistically insignificant at the $\alpha=.05$ level.

Though the omission of the interaction term achieves favorable results with respect to the sign and significance of the common value and experience coefficients, these results fail to capture the importance of the interaction term. The previously positive and significant coefficient on the interaction term (from regressions 1 and 2) shows that experience affects sniping positively in a common value setting. Without this term, the log of an individual’s feedback rating represents the average over both types of item values. The fact that this coefficient is positive and significant shows that the positive effect in the common value setting outweighs the negative (and insignificant) effect in the private value setting, an intuitive result. The third regression has a similar effect on the common value indicator. Whereas in the first two regressions this coefficient represents the effect of a common value item in the case of a new and inexperienced bidder, it now represents the effect on the average bidder. Thus the significantly positive effect of the combination of experience and a common value setting is distributed
between two previously insignificant parameters, achieving overly optimistic results with respect to the predictions of the original model.

This conclusion is supported by the effect of the omitted variable on the constant coefficient. The results of this regression cannot reject a scenario where sniping by a novice bidder in a private value setting is due to chance, and any deliberate sniping strategies are the result of either a common value item or greater experience. Such an argument is countered by the results of the previous two regressions. Thus while the third regression does offer valuable insight into the positive effect of common value and experience on late bidding, it fails to capture the entire picture, which is that the interaction of these two variables has the most significant influence on sniping.

**Regression 4**

The fourth regression is an attempt to replicate the results of Roth and Ockenfels (2006) in their paper entitled “Late and Multiple Bidding in Second Price Internet Auctions: Theory and Evidence Concerning Different Rules for Ending an Auction.” As mentioned in Section 2 of this paper, the authors are concerned with results both on eBay and Amazon, a site featuring a “soft-close” to its bidding periods. The data set used in this paper does not contain information from Amazon auctions, but the eBay coefficients from the Roth and Ockenfels paper can be compared approximately with those in the fourth regression here. The endogenous variable is the log of the likelihood of a sniping bid, which explains the negative constant. Computers are studied as goods with private values, and the term “1-Computer” refers to antiques, assumed to have common values. The authors provide the coefficients and P-values (in parentheses). The results of the regression are restated below:
All coefficients referring to eBay are significant at the $\alpha=.05$ level. The constant cannot be compared directly to my regression since it refers to auctions on Amazon. The results are consistent with several relevant hypotheses: (1) common value items induce more sniping than private value items, as evidenced by the fourth coefficient being larger than the second, (2) experience has a positive effect on sniping, and (3) the number of opponents has a negative effect on sniping behavior. The signs of the coefficients are consistent with my fourth regression, though my regression does not have the same level of statistical significance in the case of the number of opponents and feedback rating of the individual. My constant (corresponding roughly to the “eBay x Computer” term) and common value indicator (corresponding to the difference between the “eBay x (1-Computer)” and “eBay x Computer” terms) are both positive with P-values of 7.4E-14 and .0032, respectively. However, the P-values on the number of opponents and the feedback rating of the individual are .71 and .85, respectively, insignificant at any practical level.

These small discrepancies in significance may be due to a number of differences. Perhaps the effects are slightly different for computers versus DVD movies and for the types of antiques chosen. My fourth regression is also just an approximation to the model used by Roth and Ockenfels. I measure the number of opponents rather than the number of bidders in an auction, and my constant refers to eBay auctions rather than requiring a separate term; differences such as these in the model can cause differences in the outcomes. My results, however, are consistent.
with Roth and Ockenfels in most respects. This agreement is important for establishing the validity of my data set, yet I still believe that past literature omits several significant variables, such as the interaction term between common value and a measure of experience. The effect of this omission is visible in the drop in the multiple $R^2$ value from .13 in the first regression to .06 in the fourth. The results of this regression agree with past literature, but do not fully describe the economic effects occurring in the eBay market.

**Summary of Analysis**

The first regression, representing the primary economic model of this paper, has the best statistical fit to the data, and the three remaining runs each provide depth to the understanding of bidding strategies on eBay. The results of the fourth and final regression, though an approximate comparison, do replicate in many ways those found by Roth and Ockenfels (2006). I do not find a perfect fit to the economic model presented in Section 3 of this paper, but every result is explainable through minor modifications to the set of assumptions. The following hypotheses are supported by the data set, and each is expanded upon following the table below. Note that the first hypothesis refers to the average value of the sniping indicator for all individuals, while the latter three refer to coefficients from the first regression:

<table>
<thead>
<tr>
<th>Null Hypothesis</th>
<th>Value</th>
<th>P-Value</th>
<th>Decision at $\alpha=.05$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average of SNIPE $= 0$</td>
<td>.11</td>
<td>1.0E-70</td>
<td>Reject null hypothesis</td>
</tr>
<tr>
<td>Coefficient on CV $\times \ln$(RATING+1) $= 0$</td>
<td>.029</td>
<td>.000023</td>
<td>Reject null hypothesis</td>
</tr>
<tr>
<td>Coefficient on OPPONENTS $= 0$</td>
<td>-.0015</td>
<td>.39</td>
<td>Cannot reject null hypothesis</td>
</tr>
<tr>
<td>Coefficient on #SUBS $= 0$</td>
<td>.00026</td>
<td>.0022</td>
<td>Reject null hypothesis</td>
</tr>
</tbody>
</table>

*Sniping is a part of the bidding strategy for a subset of the bidding population.* Each of the coefficients for the constant in the four regressions run are positive, with three of four
statistically significant at the $\alpha=.05$ level. In addition, the majority of the coefficients on other variables are positive (10 of 17), and nine of these coefficients are significant at the $\alpha=.05$ level (versus none of the seven negative coefficients). As a result, the vast majority of individuals will have a positive prediction for the likelihood of a sniping bid. This argument is also supported by .11 of all bidders submitting a bid in the final minute of the bidding period, a value significantly greater than zero.

In a common value setting, experience raises the likelihood of a sniping bid. Two of the four regressions include a variable for the interaction of experience and a common value item, and each return significantly positive coefficients. In the first regression, where the interaction term is included, neither the common value indicator nor the experience variable is found to be significant individually. In the second regression, which also includes the interaction term but uses a different measure of experience, the common value indicator carries a significantly positive coefficient while the experience variable is insignificant at the $\alpha=.05$ level. Thus the data are inconclusive as to what individual effect each of these parameters has on sniping behavior. It is possible that experience does not have an impact on sniping in the private value setting because there is no benefit to late bidding. It is also possible that a novice bidder in a common value setting does not snipe more often than a bidder in a private value setting because she has no value information to hide, or that she does snipe more often to hold out for better information from opponents. The data seem to lean toward the former, since the coefficient of the first regression is more appropriate and since the multiple $R^2$ value is greater (.13 versus .10), but the results are inconclusive.

The number of opponents has little effect on the likelihood of a sniping bid. All four regressions return slightly negative coefficients on the number of opponents in an auction, none
of them significant at the α=.05 level. The model argues that with the perception of greater
competition, an individual will bid more aggressively and thus be more likely to submit multiple
and sniping bids. It is possible that the number of opponents at the close of an auction is not an
accurate reflection of the competition felt by a particular individual during the bidding period, an
argument that will be discussed in further detail below.

*The number of perfect substitutes for an item raises the likelihood of a sniping bid.* The
model argues for two opposing effects of the existence of perfect substitutes: (1) a decrease in
sniping because of a decrease in the importance of winning a particular item, and (2) an increase
in sniping because an individual will, on average, first view a particular item later in the bidding
period due to the default sorting of search results by eBay. Three of the above regressions show
small, though significant, positive coefficients on the number of substitutes, supporting the
second of these two effects as dominating the first. It is difficult to determine the significance of
the negative impact of substitutes because of the positive coefficient, so further research is
required to determine whether the data support this hypothesis.

**Potential Issues**

There are several issues either with my assumptions or with the data set itself that may
bias the results found above. These potential issues are highlighted below:

*Opponents in IPV/CV Auctions*

The covariance between the common value indicator and the number of bidders present
in the auction is .29, with the average number of bidders being 5.7 for common value items
versus 4.5 for private value items. This presents a potential issue because variables for both a
common value setting and for the number of bidders (or opponents, equal to bidders minus one),
are present in the regressions. This is one potential reason why the coefficient on the number of
opponents is both negative and insignificant at the $\alpha=.05$ level in all four regressions. It is possible that the true effect of the number of opponents a bidder faces is partially captured in the either the coefficient for the common value indicator or the interaction term between common value and experience.

**Measurement of Competition**

As mentioned several times in this section already, the measurement of competition used in the four regressions above may not accurately reflect the sense of competition an individual feels during the bidding process. In reality, the first individual who places a bid for an item will be unaware of the level of competition for the item, the second bidder will be aware only of the first individual, and so on. Thus a more accurate measure may be the number of bidders entering before an individual, rather than the total number of bidders at the close of the auction. This change may also help to dilute the issue above of covariance between common value and the number of bidders. Rather than all individuals facing the same level of competition, each auction will be guaranteed to contain an individual who faces no known opponents. An individual’s perception of competition may in some way also reflect the time at which the individual places a bid, since an individual bidding toward the beginning of an auction period may anticipate future competition, versus a late first bidder, who may believe herself to be the only potential buyer.

**IPV Assumption**

In the model, I assume that DVD movies have independent private values for potential buyers. This assumption means that each individual has an individual monetary value at which point she is indifferent between having the money or the movie. During the creation of the data set, I notice a separate type of individual bidding for movies: the reseller. The characteristics of a reseller include a very large feedback rating (from frequent transactions), a single early bid in
many auctions simultaneously, and a small likelihood of winning any particular item. A reseller will attempt to win any auction that, for one reason or another, faces low competition and sells for a low price. This way, the seller can achieve a greater surplus by resubmitting the item on eBay. Though infrequent, there are several such bidders present in my data set, and they may have the effect of artificially lowering the effect of experience on sniping behavior. To exclude these individuals would also bias the data set, since the presence of bids from resellers does affect other bidders’ perception of competition, so this is a potential hazard that one must be aware of when analyzing the data set.

**Perfect Substitute Assumption**

I also assume in the model that (1) all DVD movies of a certain title are perfect substitutes, and (2) items that are designated as having common values also have zero perfect substitutes. In reality, there are likely to be many levels of substitutability for these items depending on the individual. The private value an individual has for an item will also depend on the apparent condition of the DVD, the details of the description offered by the seller, the apparent level of integrity of the seller, and several other variables. Though this may violate a strict assumption of perfect substitutes, it should in theory affect all DVD titles roughly equally and thus have no effect on the significance of the coefficient. The assumption of zero perfect substitutes for common value items may, however, affect this coefficient. I noticed, during the creation of the data set, a number of individuals placing bids for multiple items. While two rugs may not be perfect substitutes, nor are they perfectly unique. Thus, some of the effect of search results in the order of bid closing will be felt by items with zero substitutes, and this coefficient may be underestimated as a result.
6) Conclusion

I have conducted a thorough discussion of late bidding on internet auction websites, and tested several hypotheses regarding the determinants of sniping behavior. I first introduced the concept of sniping as a bid in the final minute of a seller-defined bidding period, and posed the question of why bidders engage in sniping behavior online. I then conducted an investigation of past literature regarding late bidding, and encountered a number of important theoretical and empirical papers offering and testing determinants of sniping. In the next section I offered an economic model of my own based on previous literature, with several points of modification or extension. I also introduced the data set that I used to test hypotheses in an empirical setting, and explained how each variable in the linear probability model is constructed and used. Next, I presented relevant statistical values to gain a better understanding of the data set. These averages, distributions, and covariances helped to put the data in perspective and prepare to analyze the results of the regressions. Finally, I reported the findings of four regressions run on the data set, and found the results to be in support both of results from past literature, and of several important claims regarding the determinants of sniping. In this section, I will first summarize my findings, and then offer direction for further research to extend the economic literature on this topic.

Summary of Results

There were a number of important results taken from the data set. In Section 4, I presented several relevant averages and relationships between variables. The average number of sniping bids per auction was .53 (.40 for private value items, .72 for common value items), and the average likelihood of a sniping bid by a particular individual was .11 (.089 for private value items, .13 for common value items). These values showed a significant level of sniping behavior
in the sample – the likelihood of a sniping bid by chance is .00011 for an individual. The average feedback rating for individuals did not vary between common and private values, but the standard deviation did, with a wider spread of ratings in the market for DVD movies. Perhaps only experienced bidders trust the website with a more serious purchase like art or an antique. The distribution of bids across the bidding period showed another interesting difference between private and common value items. While each had a comparable average bidding time, common value items had significantly more sniping bids and significantly more bids very early in the bidding period. This is consistent with certain bidders attempting to discourage entry with the appearance of competition. There were also several relationships described in Section 4 that helped to pave the way for an accurate interpretation of the regressions in the following section.

In Section 5, I analyzed four regressions run on the data set, and found both statistically and economically significant results. The fourth regression was an approximate to the model presented by Roth and Ockenfels (2006). Though these authors were also looking at differences in behavior between eBay and Amazon (which features a “soft close” system), the presence of interaction terms with an indicator for eBay allowed for a rough comparison. These authors had found significant coefficients for the presence of sniping, the effect of a common value setting, the effect of experience, and the effect of the number of bidders in an auction. While my coefficients on the number of bidders and the individual’s feedback rating were not statistically significant at the $\alpha=.05$ level, all coefficients matched the past results, providing support for the accuracy of my data set.

The first regression provided support for my economic model in many ways, and also introduced some new and interesting relationships. The constant was positive and significant, consistent with the existence of sniping behavior for a new eBay member in a private value
setting. The coefficients on the common value indicator and on the log of the individual’s feedback rating were both found to be negative and insignificant. These results ran against the model, but were consistent with (1) experts in a private value setting submitting fewer sniping bids because there is no benefit in this setting, and (2) new bidders in a common value setting submitting fewer sniping bids because they have no value information to conceal. The interaction term between these two variables is significantly positive, consistent with the “expert” bidder hypotheses in a common value setting, first introduced by Wilcox (2000). The number of opponents was found to have an insignificantly negative affect on the likelihood of a sniping bid, also running against the model. The true effect of this variable was perhaps partially captured in either of the common value terms, since common value covaries positively with number of bidders. Finally, the new variable introduced in this paper was found to be significantly positive. This is consistent with the first of the two opposing arguments regarding this term, that the order of the search results forces bidders to submit later bids.

In the end, four hypotheses were supported by the data: (1) sniping is a part of the bidding strategy for a subset of the bidding population, (2) in a common value setting, experience raises the likelihood of a sniping bid, (3) the number of opponents has little effect on the likelihood of a sniping bid, and (4) the number of perfect substitutes for an item raises the likelihood of a sniping bid. Below, I offer several ways these results can be extended in further literature.

**Future Research**

Several issues to address in future research were described in Section 5 of this paper. The first issue is addressing the positive covariance between a common value setting and the number of bidders in an auction. It is possible that this relationship caused the negative and statistically
insignificant coefficient in my regression. There are two ways to counter the bias caused by this covariance: (1) choose different items such that the average number of bidders is the same for private and common value items, or (2) omit certain auctions for common value items that have many bidders. The second option should not introduce a second bias so long as the omitted sample is random along all other variables.

The second issue I believe can be improved upon in further literature is the measurement of competition in the model. In this paper, a variable is constructed based on the total number of bidders at the termination of the auction, but this is not the most accurate representation of the competition each individual feels at the time of her bid. I recommend a new measure of this variable, based on the number of individuals who have submitted bids before a given bidder, because this is how an individual feels the presence of competition. Such a change will perhaps also help to lower the bias of the first issue mentioned above, because rather than the same number of opponents being stated for each individual in an auction, each auction will have one bidder who faces no perceived opponents, one bidder who faces one, two, and so on until the final bidder perceives the full level of competition.

Beyond these two issues, I believe that my economic model captures many of the determinants of sniping behavior on eBay. There are a number of additional influences that have been proposed by various economists, but have not yet been measured empirically, so there is much room for improvement upon our current understanding. Models can contain more variables to be tested, and data sets can contain more observations for those variables to be tested against. In the moment, this paper offers significant results to the economic community, and provides a sturdy link in the chain toward understanding our own behavior.
7) Citations List


