**University of Alberta**

Essays on Consumer Learning and Jump Bidding Behavior
in Online Auctions

by

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## Dedication

To my husband Yuhui and my son Alexander.

## ABSTRACT

In the first essay, I examine the extent to which experienced and inexperienced bidders differ in their bidding strategies, and the extent to which they learn to adapt their strategies in online auctions. I propose that bidders can learn how to withhold their private information in order to avoid driving up prices. We use longitudinal data obtained from eBay tracking bidding behavior of experienced and inexperienced bidders. Results of multilevel data analyses indicate that inexperienced bidders learn to adapt their bidding strategies in the following ways: (1) they enter auctions later; (2) place fewer bids in an auction; (3) condition their proxy bids on the entering time; (4) take more time to respond to competitive bids; (5) are less likely to be influenced by the number of bidders, and (6) are less likely to be influenced by the attributes of the bidding process. In addition, I find that learning exists ubiquitously among inexperienced bidders but not among experienced bidders.

In the second essay, I study the phenomenon of jump bidding in online auctions. Jump bidding, when a bidder bids more than the minimum required increment, is a frequently observed phenomenon in both traditional and online auctions. This phenomenon has long intrigued researchers. However, no consensus has yet been reached on why bidders use jump bidding, nor its effect on bidders' WTP (willingness to pay). We develop a conceptual model of the effects of jump bidding in an online auction context, and propose that jump bidding is a double-edged sword. On the one hand, jump bidding will signal a bidder's strength and

deter bidder entry and/or discourage their further bidding. This leads to less competition, which may have an indirect effect on ending prices. On the other hand, jump bidding will drive up prices and/or reveal a bidder's value, which may be informative to other bidders and increases their WTP, leading to higher ending prices. Therefore, jump bidding has both a negative and a positive effect on auction outcome. Results of two laboratory experiments support our conceptual model.

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# Chapter 1

## Introduction

Over the past decade, consumers have dramatically increased their usage of online auctions as an ordinary channel to acquire and distribute products. For example, being established in 1995, eBay has since grown into the largest online auction website. By 2006, eBay had over 222 million registered users and generated US$52.4 billion in sales, which represent a 23% and an 18% of increase respectively over the previous year (eBay Annual Report 2007).

In fact, online auctions has not only become a broad testing field for traditional auction theories, but also added new dimensions to the research of consumer behavior in a dynamic environment, making consumer judgment and decision-making in online auctions a more and more important research area. Different from traditional auctions, online auctions have some new features that shape consumers' decision-making space. For example, online auctions are conducted on the Internet, which removes the geographical and time limitations associated with traditional auctions and at the same time increases the uncertainty of decision-making. For example, consumers in online auctions cannot observe the characteristics of their competitors or examine the auctioned item beforehand. They have to rely on the feedback system or their experience to decide on the trustworthy of a seller.

Despite that considerable effort has been devoted to study consumer behavior in online auctions, the research on consumers' employment of bidding strategies and the role that learning plays in consumers' strategic behavior remain limited (Baker and Song 2007).

My dissertation makes the primary contribution by adding insightful findings to the limited literature of consumer strategy employment and consumer learning in online auctions. In particular, in the first essay, I use longitudinal data to investigate how consumers learn to use strategies in various aspects of the dynamic decision making process in online auctions. The longitudinal study allows me to gain insights into the consumers' learning process, to an extent not previously possible in the literature that has used cross-sectional data. In the second essay, I construct a unique conceptual model to elaborate the mechanism behind the effects of jump bidding, empirically test the effects of jump bidding, and examine some factors that moderate these effects. My study of jump bidding is in a comprehensive way and among the first empirical studies of jump bidding's effects. My study addresses the controversy in the literature regarding the effects of jump bidding and bridges difference streams of research in the literature.

In the first essay, I estimate four multilevel models to the longitudinal data collected from eBay to examine whether, how and to what extent bidders refine their bidding strategies as their experience accumulates. Specifically, I hypothesize that bidders will learn to strategically reveal or withhold their private information and effectively use other bidders' private information regarding the value of the object. As experiences accumulate, bidders are less likely to reveal their true willingness to pay (WTP) (e.g. use high proxy bids early in an auction), they are less likely to be influenced by other bidders/bids, and they will strategically respond to other bidders' bidding behaviour. These behavioural changes will be reflected in bidders' decisions on when to enter auctions, how much to bid at different stages in the auction, and whether and how to respond when being outbid. The results of multilevel data analyses support our hypotheses on consumer learning in online auctions.

In the second essay, I develop a conceptual model on the effects of jump bidding in the online auction context. Based on value affiliation among bidders and information integration in value construction, this model proposes that jump bidding is a double-edged sword on auction outcomes. Jump bidding may be perceived as a signal of jump bidders' strength or high valuation. This information of jump bidder' high valuation may cause other bidders to adjust their WTP accordingly. On the one hand, bidders with a perception that the auction will end with a price higher than their adjusted WTP may simply not enter or quit after seeing a jump bid. Hence, jump bidding may deter other bidders' entry and/or discourage their further bidding. This may lead to less competition and lower ending prices. On the other hand, bidders with WTP that is higher than before and the expected ending price will continue to bid. This may lead to a higher ending price. Therefore, jump bidding may have both negative and positive effects on the ending price. Many factors may influence the strength of these two opposite effects of jump bidding on the ending price, and during the auction, it is not clear which effect will dominate. I examine four variables that may moderate the effect of jump bidding: 1) bidders' degree of value uncertainty, 2) the timing of jump bidding; 3) the perceived expertise of the jump bidder, and 4) the type of auction (whether an auction is a charity auction or not).

I conducted three laboratory experiments and one controlled field experiment on a local online website. I find support to the conceptual model from the results of these experiments. I also find that value uncertainty, timing, perceived expertise of jump bidders, and the type of an auction are important moderators of the effects of jump bidding.

The underlying premise for both essays in my dissertation is that private information possessed by bidders plays a role in others' value construction process because of the uncertainty concerning the value of the auctioned object.

The uncertainty regarding the value of goods, faced by both bidders and sellers, is a fundamental feature of auctions (Klemperer 1999). Before an auction starts, bidders may have only an estimate of the object's value, based on the private information they possess (Krishna 2002). With the unfolding of the auction, bidders acquire private information from their competitors and integrate it into their valuation formation process. Therefore, bidders' valuations are often interdependent or so-called affiliated (Milgrom and Weber 1982). Results of empirical studies have also indicated that bidders construct their values during an auction (e.g. Ariely and Simonson 2003; Häubl and Popkowski Leszczyc 2003).

Auction theory has traditionally distinguished two extreme cases of value formation: 1) private values: each bidder knows the value of the object to himself/herself before an auction starts and others' private information will not change this value (Vickery 1961); 2) common values: the value is the same but unknown to bidders, and any private information from others is useful for bidders to formulate their valuation (Rothkopf 1969). Most real-world auctions are affiliated values auctions, in which both private values and common values components exist (Laffont 1997).

In an affiliated values auction, to what extent that bidders rely on others for the information of object value may depend upon how sufficient their a priori private information is. The more sufficient bidders' private information is, the more certain they are about the value and the less they make use of other bidders' private information. Therefore, it may be best for a bidder to strategically withhold or reveal his/her private information in order to influence other bidders' bidding behaviour. As experience accumulates, bidders may control the release of their private information because of strategic concerns and may be influenced less by the private information revealed by others.

Next, I will present the first essay in Chapter 2 and the second essay in Chapter 3. Then in Chapter 4, I will summarize the limitation of these two essays and discuss the direction of future research.

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# Chapter 2

# Essay 1: Learning to Bid in Online Auctions: A Multilevel Modeling Approach

## 2.1 Introduction

Learning is an important aspect of consumer behaviour in online auctions. By engaging in series of decisions on whether, when and how much to bid in the process of price construction for auctioned products, bidders in online auctions have opportunities to learn the nature of bidding interactions and the effectiveness of various bidding strategies. This kind of learning will not only change the way that bidders make decisions on bidding, but also influence auction processes and outcomes. Therefore, it has profound implications for consumer welfare and auction efficiency in online auctions.

Meanwhile, studying consumer learning in online auctions provides an important opportunity for researchers to empirically test traditional auction theories (see McAfee and McMillan 1987 for a review). Traditional auction theories assume consumers' rational (economically) behavior which is hard to find in real world auctions. Yet it is possible to track bidders, especially new bidders and study to what extent bidders, if not naive, learn to behave rationally (Rabin 1998). Theory testing with experienced consumers is more likely to be successful. Hence it is pertinent to conduct research on consumer learning in online auctions.

Research related to learning in traditional offline auctions has mostly focused on the extent to which bidders learn to avoid the winner's curse.[1] Results

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[1] Winner's curse implies that in an auction the winner is normally the bidder who overestimates the value of an item the most, and therefore paid too much for the item.

of laboratory studies indicate that inexperienced bidders are very susceptible to the winner's curse (see e.g. Bazerman and Samuelson 1983; Kagel and Levin 1986; Dyer, Kagel and Levin 1989; Kagel and Levin 1999) and experience tends to play an important role in overcoming the winner's curse (see, for example, Kagel and Levin 1999; Garvin and Kagel 1994). Garvin and Kagel (1994) conclude that bidders learn from their personal experience (e.g. a winner's curse) and from observing the consequences of overbids made by others.

However, consumer learning in online auctions remains a mostly unexplored research area (Baker and Song 2007). One exception is the work by Wilcox (2000), who compared several behavioral differences between inexperienced and experienced bidders using cross-sectional data. Also Overby and Jap (2007) found that both buyers and sellers adapt their use of online auction mechanisms in an online wholesale automotive market.

The lack of research on learning in online auctions may in part be due to the demands for data. Learning, like other behavioral changes, can only be fully examined using longitudinal data (Singer and Willett 2003). While cross-sectional data allow one to compare differences in bidder behavior for different groups of bidders (e.g., different experience levels), they cannot be used to examine actual learning – the behavioral changes within bidders over time. In order to do this, longitudinal data are needed. The conclusion of behavioral difference in cross-sectional studies may be confounded if these differences are not independent of bidders' characteristics, other than the experience level. In addition, these conclusions may not be generalized to behavioral change over time because there may be equally valid competing explanations.

In this paper, we use longitudinal data collected from eBay to examine consumer learning in online auctions in a comprehensive way. Our longitudinal data contain the bidding history of 254 coin collectors on eBay for a period of about four months. Among these coin collectors, 136 were new bidders, who registered on eBay shortly before of the data collection and have 0 feedback; 118 were experienced bidders, with over 50 feedbacks when we started to collect the data.

Collecting these longitudinal data is a tedious process. In addition, modeling these data creates several challenges. These data are time-unstructured in that different bidders have a different number of observations (auctions they participate in) and these observations are unevenly spaced in the time period of data collection. Traditional repeated measures modeling approaches cannot be applied to these data as they require time-structured data. In addition, these traditional modeling approaches can not easily deal with problems of autocorrelation, heterostasticity and endogeneity (Singer and Willett 2003). Our paper contributes to the literature by being the first study to use longitudinal data and multilevel modeling approach in real-world online auctions to examine the process of bidders learning to use different strategies over time. We examine bidders' changes on different aspects of their decision-making on bidding by fitting multilevel models regarding these aspects to these longitudinal data. Results of multilevel model estimation to these longitudinal data support our hypotheses that inexperienced bidders over time learn to adapt their strategies, while experienced bidders do not. We find that as experience accumulates, inexperienced bidders 1) enter auctions later; (2) place fewer bids in an auction; (3) condition their proxy bidding on the entering time: if they enter an auction early, they tend to place a low proxy bid; if they enter an auction late, they tend to place high proxy bid; (4) take more time to respond to competitive bids if they choose to continue; (5) are less likely to be influenced by the number of bidders, and (6) are less likely to be influenced by the attributes of the bidding process.

This research is also very timely given the large increase in online auctions. Online auctions are more and more used as an alternative channel to obtain or distribute products. For example, on eBay in 2006, the number of registered users was over 222 million and the sales were $52.4 billion, represents 23% and 18% of increase respectively over the previous year (eBay annual report 2007).

The remaining part of the paper is organized as follows: Section 2.2, provides the hypotheses on learning behavior in online auctions; in section 2.3 we present the results of the multilevel model; finally, we provide general discussion and conclusion in section 2.4.

**2.2 Theories and Hypotheses of Learning in Online Auctions**

Bidders in online auctions need to make decisions concerning the timing and the magnitude of their bids. These decisions vary from those in an off-line setting, because online auctions have design features that are fundamentally different. Therefore, we will discuss firstly some of the important design features that influence bidders decision-making, followed by different bidding strategies in online auctions, particularly on eBay.

*2.2.1 Design Features of eBay[2] Auctions*

We collected our data from completed eBay auctions. eBay uses an open ascending bid (or English auction) format with a predetermined ending time.[3] Bidding starts at either $0.01 or at a minimum starting bid set by the seller, and bidders can place incremental bids during the duration of the auction. Bidding is implemented through an automatic proxy bidding program, where bidders can enter a *proxy bid.* The proxy bidding program bids every time an amount necessary for the bidder to become the current winner, up to her maximum bid. This maximum always remains hidden. At any time, before the ending of the auction, they can increase their proxy bid.

The auction format is 'open' implying that the complete bid history is observable to all current and potential bidders (including the bidder id, the bid amount and the timing of the bid). The winner in each auction is the bidder with the highest binding bid at the end of the auction. A bid is only binding if the bid meets the minimum starting bid or a potential secret reserve price set by the seller. The winner pays a price equal to the second highest bidder's maximum bid plus the minimum required bid increment.

Compared to traditional auctions, online auctions have certain unique characteristics that strongly influence the decision-making process of bidders.

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[2] Note that our study of the decision making process is from a bidder's perspective, different from most previous research that has focused on the auction. E.g., Park and Bradlow (2005) empirically test a stochastic model of whether people bid in an auction, and if so, who bids, when they bid, and how much they bid across the duration of the auction.

[3] Some researchers have suggested that the eBay auction format is a combination of an ascending bid and a second-price sealed bid auction (Bajari and Hortacsu 2003; Wilcox 2000).

Information asymmetry between sellers and bidders and among bidders is a fundamental feature of auctions (Milgrom and McAffee 1987). This is in particular the case in online auctions where information is less transparent. Bidders cannot examine the auctioned item before purchase and need to depend on a picture and a written description of the item. In addition, multiple sellers may sell identical items and potential bidders need to infer the reliability of a particular seller (e.g. use the feedback system to judge a seller's trustworthiness). Hence bidders will need to rely on the above and other information cues generated in the auction process to judge the quality and the value of the item. Also online auctions remove the geographical limitation associated with traditional auctions as bidders from all over the world can participate by computer. Therefore, potential bidders cannot see other bidders and do not know the size or characteristics of the bidder pool. They can only infer the number of current bidders from the bidding history.

The long duration combined with a fixed ending time for online auctions not only removes the time limitation of traditional auction but also makes the decision of when to enter an auction pertinent. At any point in time during the auction, the number of bidders, the current winning price and the current winner are all different. These contextual factors may contain some information regarding the value of the auctioned item and be informative to a particular bidder. Meanwhile, a bidder's entry at a certain point in time will also signal his/her information regarding the value and/or bidding strategies. In the situation of value uncertainty, this information is informative to others, which will alter other bidders' valuation. Other bidders will then change their bidding strategies accordingly. Hence, a bidder's entry at a particular point in time may alter the bidding process and then the auction outcome. The third decision a bidder needs to make is how much to bid when they enter an auction. Online auctions often set a minimum starting bid amount. The first bidder in an auction has to bid an amount that is equal or larger than the amount of the starting bid. For bids other than the first bid, eBay requires a minimum increment over the current price, e.g., if the current price is $10, next bid should be at least $10.50. Bidders can bid as much as they want as long as the bid exceeds the minimum next bid. Bidders' bid amount will be handled by a proxy bidding program.

At any time if a bidder is outbid, she has to decide whether to continue to bid or not, and if so when and how much to bid. Bidders may face these decisions several times until the end of an auction.

*2.2.2 Bidding Strategies in Online Auctions on eBay*

A bidder in an online auction may need to make multiple decisions related to the timing and the amount to bid across the duration of the auction. Both types of decisions may reveal bidders' private information regarding valuations and/or bidding strategies. Other bidders may adapt their valuations and bidding strategies accordingly, impacting the auction outcome. Therefore, these decisions have important strategic implications.

As eBay uses a proxy bidding system, which bids on behalf of a bidder without revealing his/her proxy bid amount, eBay recommends bidders to place a single proxy bid equal to their maximum WTP at any point in time during an auction, and let the proxy bidding program take care of her bidding. However, bidders may be uncertain about their maximum WTP and use the bids of other bidders to update their WTP. Furthermore, Roth and Ockenfels (2002) have found that, under certain conditions, it is an optimum strategy for bidders to wait and bid towards the end of the auction (so-called snipe bidding). Early bidding may reveal a bidder's strategy and increase the intensity of the bidding process. Therefore, bidders should wait with bidding and not reveal their strategy early (Bajari and Hortacsu 2004). Ockenfels and Roth (2006) and Roth and Ockenfels (2002) studied snipe bidding and find that it may be an optimum strategy for both common and private values auctions. Snipe is also observed frequently in real-world auctions and even software has been developed to facilitate the implementation of this strategy. However, there is also a risk involved with using this strategy, including: not being able to successfully place a bid because of Internet traffic problems, or being outbid by other snipers, and/or a current high proxy bid. Therefore, the timing and the bidding amount are also important aspects in the snipe bidding strategy.

Other papers have studied bidding strategies in online auctions. For example, Park and Bradlow (2005) estimated a stochastic model of whether people bid in an auction, and if so, who bids, when they bid, and how much they bid across the duration of the auction. However, different from their and most previous research that has focused on the auction, our study focuses of the decision making process from a bidder's perspective. We study bidders' decisions over time and across different auctions.

As value construction plays an important role in auctions we will first discuss this next.

### *2.2.3 Value Affiliation among Bidders and Value Construction in Auctions*

Traditional auction theories have distinguished between the common-value and private-value paradigms (McAfee and McMillan 1987) based on the assumption of whether a bidder's private information is informative to others. In the *private value situation,* bidders know the value of the object with certainty before an auction starts and other bidders' private information will not be of any use; While in the *common value* situation, the true value of an item is the same but unknown to every bidder, and private information from others is useful for bidders to formulate their valuation.

A more general model including private value and common value models as special cases is called affiliated value model (Milgrom and Weber 1982). Most real-world auctions are affiliated-values auctions (Laffont 1997) where value uncertainty often presents and the information revealed by bidders during the auction is informative and valuable to other bidders. This is in particular the case in online auctions. Bidders in online auctions cannot examine the auctioned item before purchase and need to depend on pictures and a written description to judge the quality of the item. In addition, multiple sellers may sell identical items and potential bidders need to infer the reliability of a particular seller (e.g. use the feedback system to judge a seller's trustworthiness). Bidders do not know the size or characteristics of the bidder pool. They can only infer the number of active bidders and bidders' willingness to pay (WTP) from the bidding history.

Hence bidders will need to rely on the above and other information cues generated in the auction process to judge the quality and the value of the item and determine their maximum WTP.

There is considerable empirical evidence that bidders in online auctions tend to construct their values during the auction process (e.g., Ariely and Simonson 2003; Häubl and Popkowski Leszczyc 2003). To construct their values bidders will not only depend on their private information, but also different information they obtain during the auction. The number of bidders and bids in an auction can be cues for an item's value (Dholakia and Soltysinski 2001; Dholakia et al. 200x; Ariely and Simonson 2003). In addition, the magnitude of competitive bids may reveal information; in other words, bidders' valuations may be affiliated ( Milgrom and Weber 1982).

On the one hand, a particular bidder may use other bidders' bid to update their estimate of the value of the auctioned item, while on the other hand, this particular bidder's own bid can also be informative to other bidders. Hence, bidders' decisions are both input and output at the same time in the value affiliation process.

### *2.2.4 Hypotheses on Learning How to Bid*

Bidders participating in online auctions may accumulate knowledge about: 1) a particular product category; 2) price levels of a particular product in the auction market; and 3) the effectiveness of different bidding strategies. Our focus in this study is on expertise with different bidding strategies. It is important to note that while we cannot distinguish between expertise with the product and expertise with the auction format, all bidders even expert coin collectors will need to learn about the price levels and the effectiveness of bidding strategies.

In addition to static auction features (e.g., a product picture), dynamic contextual factors , such as the number of bidders, the current winning price and the current winner, may contain information regarding the value of the auctioned item and be informative to a particular bidder. Meanwhile, a particular bidder's bid, especially the first bid and its timing, will signal his/her bidding strategies and/or private information regarding the item. The bidder's entry bid in an auction will also alter the size of the observable bidder pool and draw attention from other active or potential bidders. When bidders are uncertain concerning the value of an item, the information from others are informative and may be used to update their valuation. Bidders may also adjust their bidding strategies accordingly. Hence, a bidder's timing of his/her first entry bid and subsequent bids may alter the unfolding of the bidding process and the auction outcome.

We next propose several hypotheses that pertain to learning related to different decisions made by bidders in online auctions. These hypotheses relate to the entry time decision (H1 and H2); the amount to bid (H3 and H4); to the number of bids to make (H5 and H6); and the time to respond to a competitive bid (H7). While these hypotheses are related they do measure unique aspects of bidding behavior.

*Hypotheses related to timing of bids:*

Several researchers have suggested that early bidding may be an indicator of an item's value or attractiveness (Dholakia and Soltysinski 2001 and Dholakia et al. 2002). The work by Dholakia and coauthors shows that (early) bidding activity attracts attention from other bidders resulting in higher prices; relative to comparable items with few bidders. Stern and Stafford (2006) find that pictures in the auction description influence early bidding; which in turn increases activity by other bidders resulting in higher ending prices. To avoid such competition, researchers have proposed that sniping strategy may be optimal bidding strategy (Roth and Ockenfels 2002; Dholakia and Simonson 2005).

Roth and Ockenfels (2002) argue that rational bidders should wait till the final moments to bid in an auction because bidding late is one way to protect one's private information, and it may also help bidders to avoid competing with incremental bidders (Ockenfels and Roth 2006). In addition, Wilcox (2000) and Ockenfels and Roth (2006) find that experienced bidders are more likely to bid during the final moments of auctions, indicating that timing of bidding may be a learned behavior.

As experience accumulates, bidders may be more certain on how to infer value from static auction features and be less likely influenced by contextual factors. For example, if a bidder purchased from a particular seller before, he/she may have the knowledge of what kind of quality he/she expect from this seller given the picture and the description of the item. Therefore, we expect that as experience accumulates, bidders' decision to enter an auction will be less likely influenced by attributes of the bidding process, and more experienced bidders will try not to reveal their private information by bidding later. Therefore we propose the following hypotheses related to the entry time decision:

**H1a:** As experience accumulates, bidders' bidding behavior will be less likely influenced by the current price level in an auction, when determining their time to enter an auction and

**H1b:** As experience accumulates, bidders' bidding behavior will be less likely influenced by the current number of bids/number of bidders in an auction, when determining their time to enter an auction.

**H2:** As experience accumulates, bidders will enter an auction closer to the end of the auction.

*Hypotheses related to the proxy bid amount:*

Besides the timing of a bid, the amount of a bidders' proxy bid also reveals her private information, thereby influencing other bidders' bidding behavior in an auction. In particular, using high proxy bids during the early stages of an auction, when price levels are relative low, are more likely to encounter competitive bids that reveal the proxy bidder's strategy. In addition, early on bidders will have received less information, and may be less certain of there valuation, therefore, early proxy bidding is more likely be influential and escalate other bidders' bidding. Therefore we expect that as experience accumulates, bidders will be more cautious about revealing their private information, and we hypothesize that:

**H3**: As experiences accumulate, bidders will be less likely to use high proxy bids when entering an auction early.

A high proxy bid toward the end of an auction is less likely to escalate other bidder's bidding. Furthermore, it can be an effective device to deal with snipe bidders. First of all, high proxy bidding is less likely to encounter competitive bids because the current price is relatively high toward the end of an auction. Secondly, bidders tend to be more certain of their own valuations toward the end of an auction, when they have already incorporated considerable information from competing bidders. Hence, bidders may simply quit an auction when faced by a high proxy bid. We therefore hypothesize that,

**H4**: As experiences accumulate, bidders are more likely to submit a high proxy bid when entering an auction late.

*Hypotheses related to number of bids placed in an auction:*

Competition among bidders will drive up the ending price of an auction because of value affiliation (McAfee and McMillan 1987). When values are affiliated, the likelihood of overpaying by the winner increases when the number of bidders increases because the number of bidders is positively related to the intensity of competition. An increased number of bidders may also lead to herd behavior (Dholakia, Basuroy and Soltysinski 2002) or bidding frenzy (Popkowski Leszczyc 2004), and thus increased prices. The number of total bids in an auction can not only reflect but also enhance the degree of competition (Dholakia et. al 2002). Also multiple bids from a particular bidder may indicate bidders' strong interests in the auctioned item and/or their high willingness to pay. This may then exacerbate the intensity of bidding and competition among bidders.

Inexperienced consumers are more likely to be influenced by others (Alba and Hutchinson 1987). Therefore, inexperienced bidders will be more easily caught up in the bidding process. This is consistent with the findings that inexperienced consumers are more susceptible to context manipulations (Coupey, Irwin and Payne 1998). A rational bidder should, therefore, learn to avoid being caught up by the competition in the bidding process. Meanwhile, as experiences accumulate, bidders' familiarity with the online auction process (and with specific product categories) will increase. They may put more weight on the information accumulated in places other than the bidding process. They should also avoid exacerbating competition by reducing the number of bids and responding slower to competitive bids. Therefore,

**H5**: The likelihood of submitting multiple bids will decrease as bidders' experience with online auctions accumulates.

**H6**: The number of bids placed by a bidder will be less likely influenced by the number of bids/bidders as experience with online auctions accumulates.

A quick response to competitive bids may indicate a particular bidder's high valuation and/or determination of getting the item. Research has indicated that a fast response time to competitive bids may lead to a stage of bidding frenzy and increased WTP (Popkowski Leszczyc 2004). The faster response time creates competitive arousal and increases the competitive intensity of an auction. Therefore, it is in a bidders' best interest to not respond to quickly and we hypothesize:

**H7**: As experience accumulates, bidders' will increase the time to respond to competitive bids.

## 2.3 Methodology

### *2.3.1 Longitudinal Data*

From Dec. 1, 2004 to March 1, 2005, we collected the bidding history of a panel of coin collectors. This panel consists of 136 new bidders. Most of these bidders registered shortly before we started the data collection and have 0 feedbacks; 118 experienced bidders, with over 50 feedbacks.[4] The reason we chose coin collectors are two-fold: 1) we believe that coin collectors need to develop both expertise of coins and biding on a particular website. Private information of the product value and experience with an auction website matter in their bidding behavior; 2) coin collectors tend to focus their bidding in coin auctions, which reduces the diversity of learning due to different product categories.

We tracked the bidding history of all of the individual bidders, including the time a bidder entered each auction, the amount of his/her initial bid and each subsequent bid, the bid increments, the number of bids in each auction, and an indicator whether the bidder won the auction. We also recorded the number of bidders/bids in each auction, the duration, the seller's rating, and the response time for each bid.

During the data collection period inexperienced bidders participated in 25,024 (average 184) auctions; while experienced bidder participated in 17,582 (average 149) auctions. We include all of the auctions in which a bidder participated, regardless of whether they won or lost, since bidder will learn (and gain different experiences) from both types of auctions. Of the auctions that inexperienced bidders participated in, 91.28% are auctions for coins; while 95%

[4] Many of these experienced bidders, both bought and sold goods on eBay, but in all instances they made a significant number of purchases during the period of the data collection.

of the auctions that experienced bidders participated are auctions for coins.

We organize the longitudinal dataset into a person-period format, also known as univariate data format, in which each person has multiple records-one for each measurement occasion. This dataset contains four types of variables: (1) a subject identifier, which is bidders' ID; (2) a time indicator. We use accumulated number of auctions as a time variable in three models and accumulated number of bids in one model; (3) dependent variables. The dependent variables are the time of entering auctions, the proxy bidding amount of bidders' first bid, the number of bids, and the time it took for bidders to respond after being outbid; (4) predictor variables, including the current price when a bid was place, the current number of bids, the number of bidders, the ending price, the auction duration, and the seller rating.

We divide the data of both inexperienced and experienced bidders into two equal halves according to the time and calculate the means for some key variables respectively. The description of these variables and their means in both halves of the data are summarized in Table 2.1.

Table 2.1 List of the Variables and Descriptive Statistics

| variables | Description and Measurement | Inexperienced group | | Experienced group | |
|---|---|---|---|---|---|
| | | 1st Mean | 2nd Mean | 1st Mean | 2nd Mean |
| ***Nb*** | *Number of bids a bidder places in a particular auction* | 1.96 | 1.51 | 1.41 | 1.46 |
| ***Pb*** | *Incremental amount of a bidder's first bid* | 10.70 | 16.44 | 17.98 | 19.04 |
| ***Et*** | *Time between a bidder's entry and exit time in an auction ( in hours)* | 54.03 | 50.20 | 59.01 | 55.12 |
| ***Rt*** | *Response time after being outbid (in hours; a larger number indicates a slower response)* | 26.04 | 29.11 | 31.79 | 31.05 |

We summarize the frequency of late bidding as well as the percentages of winning and single bids for late bidding in Table 2.2. The time intervals in Table 2.2 are the same as those used in Roth and Ockenfels (2006). Table 2.2 shows that both inexperienced and experienced bidders submitted a considerable share of last bids in the last hour or minutes of auctions. Except for the last hour interval, experienced bidders submitted significantly more last bids than inexperienced bidders in all the other time intervals. This is consistent with our finding that inexperienced bidders tend to learn to enter auctions late. In addition, for both inexperienced and experienced bidders, a large percentage of last bids placed in the last hour are single bids (e.g. that is the only bid a bidder placed in an auction). Experienced bidders placed significantly more single bids in the late stage of auctions than inexperienced bidders. For example, in the last hour, 63.57% (5.28%) of the bids that experienced (inexperienced) bidders placed are single bids. Finally, a larger percentage of last bids placed in the last stage of auctions resulted in winning those auctions. For example, 43.24% of the last bids placed by inexperienced bidders in the last hour of the auction resulted in a winning bid.

Table 2.2 Late bidding of inexperienced bidder and experienced bidders

| | Inexperienced Bidders | | | Experienced Bidders | | |
|---|---|---|---|---|---|---|
| Time Remaining in an auction | Last Bid (% of all Bids) | Single Bid (% of Last Bids) | Winning Bid (% of Last Bids) | Last Bid (% of all Bids) | Single Bid (% of Last Bids) | Winning Bid (% of Last Bids) |
| 1 hour | 19.83% | 55.28% | 43.24% | 20.59% | 63.57% | 50.87% |
| 10 minutes | 10.06% | 53.14% | 55.58% | 12.22% | 63.83% | 57.65% |
| 5 minutes | 8.32% | 53.45% | 59.14% | 10.52% | 64.85% | 59.83% |
| 1 minute | 5.16% | 24.26% | 64.49% | 7.60% | 67.81% | 65.10% |
| 10 seconds | 1.82% | 68.81% | 71.70% | 2.87% | 73.33% | 64.39% |

### *2.3.2 Multilevel Models and Estimation Results*

In this section, we present four multilevel models we constructed to test our hypotheses. We assume that bidders learn or gain experience by bidding in online auctions. We use the number of auctions a bidder already participated in as a time trend variable in the first three models and the accumulated number of bids a bidder placed in auctions as a time trend variable in the last model. Therefore, the data set is time-unstructured: auctions that different bidders participated in or bids they placed are unequally spaced along the time scale. The data set is unbalanced in that bidders do not have the same number of records.

#### *2.3.2.1 Modeling the Change of Entering Time*

In order to test H1a, H1b and H2, we constructed the multilevel model (1) [5].

[5] Since number of bids and number of bidders at bidders' entry time are highly correlated (0.876), we use number of bids in this analysis.

Level-1 model: (2.1)

$$Et_{ij} = \pi_{0i} + \pi_{1i}Tr_{ij} + \varepsilon_{ij}, \text{ where } \varepsilon_{ij} \sim N(0, \sigma_{\varepsilon}^2)$$

Level-2 model:

$$\pi_{0i} = \gamma_{00} + \gamma_{10}Cp_{ij} + \gamma_{20}Cn_{ij} + \zeta_{0i}$$

$$\pi_{1i} = \gamma_{30} + \gamma_{40}Cp_{ij} + \gamma_{50}Cn_{ij} + \zeta_{1i}$$

Where,

$$\begin{bmatrix} \zeta_{0i} \\ \zeta_{1i} \end{bmatrix} \sim N\left( \begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_0^2 & \sigma_{01} \\ \sigma_{10} & \sigma_1^2 \end{bmatrix} \right)$$

Composite model:

$$Et_{ij} = [\gamma_{00} + \gamma_{10}Cp_{ij} + \gamma_{20}Cn_{ij} + \gamma_{30}Tr_{ij} + \gamma_{40}Cp_{ij} \times Tr_{ij} + \gamma_{50}Cn_{ij} \times Tr_{ij}] +$$
$$+ [\zeta_{0i} + \zeta_{1i}Tr_{ij} + \varepsilon_{ij}]$$

The level-1 model is an individual growth model of the time when a bidder enters an auction, and the level-2 model expresses variation in parameters from the growth model as random effects. We include *Cp,* the current price and *Cn*, the current number of bids at the time a bid is placed, as predictors in the level-2 models of the intercept and slope, to model a bidder's trajectory of change. The rationale for using these variables is that they reflect the competitive intensity at the time a bid is placed.

We use two subscripts, *i* and *j*, to identify individuals and occasions (auctions), respectively. For these data, *i* runs from 1 through 136 in the inexperienced bidder group and 1 through 118 in the experienced bidder group; *j* runs from 1 though 940 in the inexperienced bidder group and 1 through 622 in the experienced bidder group.

We have two level-2 residuals, we describe their underlying behavior using a bivariate distribution. The standard assumption is that the two level-2 residuals, are bivariate normal with mean 0, unknown variances, $\sigma_0^2$ and $\sigma_1^2$, and unknown covariance $\sigma_{01}$.

We use SAS PROC MIXED to estimate the model to the data of the inexperienced bidders and the data of the experienced bidders respectively. In the estimation, we allow both intercepts and slopes to vary across bidders.

The results of the estimation are summarized in Table 2.3. We denote the coefficients in the form of $\gamma^{inex}$ for inexperienced bidders and $\gamma^{\exp}$ for experienced bidders in the discussion. For inexperienced bidders, *Cp*, the *current price* ($\gamma_{10}^{inex}$ *=0.091, p<0.01)* has a positive significant effect on bidder entry time. This suggests that inexperienced bidders are more influenced by the current price level. Furthermore, over time, this influence becomes smaller as indicated by the negative interaction between bidders' entry time and *Cp* ($\gamma_{40}^{inex}$ *=- 0.019, p<0.01).* For experienced bidders, we did not find a significant effect f the current price (*Cp*), on bidders' entry time ($\gamma_{10}^{\exp}$ *=0.008, p>0.10).* This offers support for H1. For both inexperienced bidders and experienced bidders, we find that bidders entry time become closer to the end of auctions as they participated in more auctions ($\gamma_{30}^{inex}$ *=-0.764, p<0.01;* $\gamma_{30}^{\exp}$ *=-0.138, p<0.01).* This result supports H2.

For both inexperienced bidders and experienced bidders, *Cn*-the *current number of bids* has a negative effect on bidders' entry time (respectively $\gamma_{20}^{inex}$ = -*0.764, p<0.001* and $\gamma_{20}^{\exp}$ = *-0.538, p<0.001 ).* This indicates that bidders may try to avoid intense competition by entering later. For inexperienced bidders, this negative correlation become weaker overtime as indicated by the positive interaction between *Cn*-current number of bids and *Tr*-the time variable

( $\gamma_{50}^{inex}$ =0.053, p<0.01).

Table 2.3 Results of Fitting the Multilevel Model of Entering Time

| | Variable | Parameter | Inexperienced | Experienced |
|---|---|---|---|---|
| *Fixed Effects* | | | | |
| | *Intercept* | $\gamma_{00}$ | *7.428****<br>*0.250* | *7.467****<br>*0.357* |
| | *Cp* | $\gamma_{10}$ | *0.091***<br>*0.042* | *-0.093*<br>*0.066* |
| | *Cn* | $\gamma_{20}$ | *-0.764****<br>*0.083* | *-0.538****<br>*0.131* |
| | *Tr* | $\gamma_{30}$ | *-0.764****<br>*0.083* | *-0.138**<br>*0.069* |
| | *Cp by Tr* | $\gamma_{40}$ | *-0.019***<br>*0.009* | *0.008*<br>*0.014* |
| | *Cn by Tr* | $\gamma_{50}$ | *0.053***<br>*0.017* | *-0.021*<br>*0.461* |
| *Variance Components* | | | | |
| *Level-1* | *Within-person* | $\sigma_{\varepsilon}^2$ | *3.640**** | *5.413**** |
| *Level-2* | *In Intercept* | $\sigma_0^2$ | *5.716**** | *7.726**** |
| | *In Rate of Change* | $\sigma_1^2$ | *0.421**** | *0.225**** |
| *Goodness-of-fit* | | | | |
| | *Deviance* | | *56665* | *52370* |
| | *AIC* | | *56673* | *52378* |
| | *BIC* | | *56685* | *52388* |
| *~ p<.10; * p<.05; ** p<.01; *** p<.001* | | | | |

*2.3.2.2 Modeling the Change in the Magnitude of Proxy Bidding*

In order to test H3 and H4, we constructed multilevel model (2) below. The dependent variable of the level-1 model is *Pb*- proxy bidding amount of bidders' first bid. We examine only the proxy bidding amount of bidders' first bids in this model as the first bid has more strategic value for bidders.[6] We include *Et* - bidders' time of entry and *Cp*- the current price as two predictors in the level-2

[6] In addition, a large percentage of the first bids are the only bids that bidder placed in an auction. Our data show that 66.88% (76.58%) of all inexperienced (experienced) bidders only placed a single bid. For inexperienced bidders, 67.48% of the proxy bidding amount of their bids was placed in the first bids and for experienced bidders, the percentage is 78.83%.

model of intercept, but only *Et-* bidders' entering time in the level-2 model of slope. The variable for *Et-entry time* measures the time interval between the time when a bidder entered an auction and the ending time of that auction, therefore, a larger value means an earlier entry time by a bidder. For the sake of simplicity, we use the same set of notations in all the other models as that in the first model.

Level-1 model: (2.2)

$$Pb_{ij} = \pi_{0i} + \pi_{1i} Tr_{ij} + \varepsilon_{ij}, \text{ where } \varepsilon_{ij} \sim N(0, \sigma_\varepsilon^2)$$

Level-2 model:

$$\pi_{01} = \gamma_{00} + \gamma_{10} Et_{ij} + \gamma_{20} Cp_{ij} + \zeta_{0i}$$

$$\pi_{1i} = \gamma_{30} + \gamma_{40} Et_{ij} + \zeta_{1i}$$

Where,

$$\begin{bmatrix} \zeta_{0i} \\ \zeta_{1i} \end{bmatrix} \sim N\left( \begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_0^2 & \sigma_{01} \\ \sigma_{10} & \sigma_1^2 \end{bmatrix} \right)$$

Composite model:

$$Pb_{ij} = [\gamma_{00} + \gamma_{10} Et_{ij} + \gamma_{20} Cp_{ij} + \gamma_{30} Tr_{ij} + \gamma_{40} Et_{ij} \times Tr_{ij}] + [\zeta_{0i} + \zeta_{1i} Tr_{ij} + \varepsilon_{ij}]$$

We use SAS PROC MIXED to estimate the model to the data of the inexperienced bidders and the data of the experienced bidders respectively. In the estimation, we also allow both intercepts and slopes to vary across bidders.

The results of the estimation are summarized in Table 2.4. The positive coefficient ($\gamma_{10}^{inex}$ *=0.549, p<0.001)* for *Et-entry time* for inexperienced bidders implies that they tend to place larger amount proxy bid early on in the auction. In addition, we find a negative interaction ($\gamma_{40}^{inex}$ *=-0.048, p<0.001)* between *Et-entry time* and *Tr- time trend,* indicating that inexperienced bidders this practice decreases when bidders' experience accumulates. In other words, bidders learn not to use high proxy bid when then enter auctions early; they change their bidding strategy and reveal less information. This provides support for H3.

For both inexperienced bidders and experienced bidders, *Cp- Current price* is positively correlated with the amount of the proxy bid ( $\gamma_{20}^{inex}$ *=0.092, p<0.001*; $\gamma_{20}^{\exp}$ *= 0.207, p<0.001).* These results indicate that for both inexperienced and experienced bidders, when the current price is higher at the time they placed a bid, they used a higher proxy bid. For inexperienced bidders, we find that they tend to use larger proxy bids after participating in more auctions ( $\gamma_{30}^{inex}$ *=0.440, p<0.001).* Combined with the finding that bidders enter auctions later and later as their experience accumulates, we find support for H4. We did not find this learning effect for experienced bidders ( $\gamma_{30}^{\exp}$ *=-0.012, p>0.1).*

However, we still find a significant positive effect for *Et-entry time* on the proxy bid amount for experienced bidders ( $\gamma_{10}^{\exp}$ *= 0.302, p<0.001*). The result of the estimation indicates that the tendency to place larger incremental proxy bids early on in the auction does not completely disappear. The insignificance of the interaction between *entry time* and *time trend* indicates that experienced bidders do not adjust their proxy bidding strategy over time.

Table 2.4 Results of fitting a multilevel model of proxy bidding

| | Variable | Parameter | Inexperienced | Experienced |
|---|---|---|---|---|
| *Fixed Effects Composite model* | | | | |
| | *Intercept* | $\gamma_{00}$ | *-4.773*** (0.440)* | *-1.226*** (0.282)* |
| | *Et* | $\gamma_{10}$ | *0.549*** (0.046)* | *0.302*** (0.031)* |
| | *Cp* | $\gamma_{20}$ | *0.092*** (0.018)* | *0.207*** (0.011)* |
| | *Tr* | $\gamma_{30}$ | *0.440*** (0.095)* | *0.095 (0.060)* |
| | *Et by Tr* | $\gamma_{40}$ | *-0.048*** (0.010)* | *-0.012 (0.008)* |
| *Variance Components* | | | | |
| *Level-1* | *Within-person* | $\sigma_{\varepsilon}^2$ | *12.534**** | *5.502**** |
| *Level-2* | *In Intercept* | $\sigma_0^2$ | *10.481**** | *2.740**** |
| | *In Rate of Chance* | $\sigma_1^2$ | *0.292**** | *0.091**** |
| *Goodness-of-fit* | | | | |
| | *Deviance* | | *89566* | *80078* |
| | *AIC* | | *89584* | *80096* |
| | *BIC* | | *89610* | *80121* |
| *~ p<.10; * p<.05; ** p<.01; *** p<.001* | | | | |

### *2.3.2.3 Modeling the Change in the Number of Bids*

In order to test H5 and H6, we constructed multilevel model (3) below. The dependent variable of the level-1 model is *Nb*-number of bids a bidder submitted in an auction. We include *Du*-auction duration, *Ep*-ending price, *Sr*-seller rating, and *Nr*-number of bidders as predictors in the level-2 model for the intercept, but only *Nr*-number of bidders[7] in the level-2 model for the slope as we do not expect a dynamic effect of auction duration, ending price and seller rating on number of bidders.

[7] Overall number of bids and number of bidders are highly correlated (0.856). We only include number of bidders in this model.

Level-1 model: (2.3)

$$Nb_{ij} = \pi_{0i} + \pi_{1i} Tr_{ij} + \varepsilon_{ij}\text{, where } \varepsilon_{ij} \sim N(0, \sigma_\varepsilon^2)$$

Level-2 model:

$$\pi_{01} = \gamma_{00} + \gamma_{10} Du_{ij} + \gamma_{20} Ep_{ij} + \gamma_{30} Sr_{ij} + \gamma_{40} Nr_{ij} + \zeta_{0i}$$

$$\pi_{1i} = \gamma_{50} + \gamma_{60} Nr_{ij} + \zeta_{1i},$$

Where,

$$\begin{bmatrix} \zeta_{0i} \\ \zeta_{1i} \end{bmatrix} \sim N\left( \begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_0^2 & \sigma_{01} \\ \sigma_{10} & \sigma_1^2 \end{bmatrix} \right)$$

Composite model:

$$Nb_{ij} = [\gamma_{00} + \gamma_{10} Du_{ij} + \gamma_{20} Ep_{ij} + \gamma_{30} Sr_{ij} + \gamma_{40} Nr_{ij} + \gamma_{50} Tr_{ij} + \gamma_{60} Nr_{ij} \times Tr_{ij}]$$
$$+ [\zeta_{0i} + \zeta_{1i} Tr_{ij} + \varepsilon_{ij}]$$

Again, we use SAS PROC MIXED to estimate the model to the data of the inexperienced bidders and the data of the experienced bidders respectively. In the estimation, we also allow both intercepts and slopes to vary across bidders. Table 2.5 summarizes the results of the estimation. For inexperienced bidders, we find that overtime, the number of bids a bidder placed decreases as his/her experience accumulates ( $\gamma_{50}^{inex}$ *=-0.027, p<0.05).* This supports H5. For inexperienced bidders, *Nr*-the number of bidders in an auction has a positive impact ( $\gamma_{40}^{inex}$ *=0.134, p<0.001* ) on *Nb*-the number of bids a specific bidder places in that auction (after controlling for *Du*-duration, *Ep*-ending price and *Sr*-sellers rating). Overtime, as experience accumulates this impact becomes less, as indicated by the negative interaction ( $\gamma_{60}^{inex}$ *=-0.021, p<0.001)* between *Nr*-the number of bidders and *Tr-time trend.* This provides support for H6 that the number of bids placed by a bidder will be less likely influenced by the number of bidders/number of bids as experience with online auctions accumulates.

For the experienced bidders, we find that the total *Nr-* number of other bidders in the auction does not influence *Nb-* the number of bids a bidder placed in an auction ( $\gamma_{40}^{\exp}$ *=0.024, p>0.1)*. In addition, for the experienced bidders the interaction term between *Nr*-number of bidders and *Tr-time trend* is not significant ( $\gamma_{60}^{\exp}$ *=-0.003, p>0.1*) indicating no decrease in the number of bids over time, and hence no further learning.

Table 2.5 Results of Fitting a Multilevel Model of Number of Bids

| | Variable | Parameter | Inexperienced | Experienced |
|---|---|---|---|---|
| *Fixed Effects* | | | | |
| | *Intercept* | $\gamma_{00}$ | *0.163*<br>*(0.097)* | *-0.200***<br>*(0.074)* |
| | *Du* | $\gamma_{10}$ | *-0.001*<br>*(0.009)* | *-0.007*<br>*(0.007)* |
| | *Ep* | $\gamma_{20}$ | *0.061****<br>*0.004* | *0.039****<br>*0.003* |
| | *Sr* | $\gamma_{30}$ | *-0.004**<br>*0.002* | *-0.003~*<br>*0.002* |
| | *Nr* | $\gamma_{40}$ | *0.134****<br>*0.021* | *0.024*<br>*0.018* |
| | *Tr* | $\gamma_{50}$ | *-0.027***<br>*0.013* | *-0.011*<br>*0.008* |
| | *Nr by Tr* | $\gamma_{60}$ | *-0.021****<br>*(0.004* | *-0.003*<br>*0.004* |
| *Variance Components* | | | | |
| *Level-1* | *Within-person* | $\sigma_{\varepsilon}^{2}$ | *0.234**** | *0.153**** |
| *Level-2* | *In Intercept* | $\sigma_{0}^{2}$ | *0.161**** | *0.071**** |
| | *In Rate of Chance* | $\sigma_{1}^{2}$ | *0.014**** | *0.003** |
| *Goodness-of-fit* | | | | |
| | *Deviance* | | *23866* | *19519* |
| | *AIC* | | *23888* | *19541* |
| | *BIC* | | *23920* | *19571* |
| *~ p<.10; * p<.05; ** p<.01; *** p<.001* | | | | |

*2.3.2.4 Modeling the Change of Responding Time*

In order to test H7, we constructed multilevel model (4) below. The dependent variable of the level-1 model is *Rt-responding time.* We include *Cp-current price*, *Cn-current number of bids*, and *Te-time to the end of an auction* when bidders place a bid as predictors in the level-2 models of intercept and slope. In this model, we use the accumulated number of bids as the time trend variable.

Level-1 model: (2.4)

$$Rt_{ij} = \pi_{0i} + \pi_{1i} Tr_{ij} + \varepsilon_{ij}, \text{ where } \varepsilon_{ij} \sim N(0, \sigma_{\varepsilon}^2)$$

Level-2 model:

$$\pi_{01} = \gamma_{00} + \gamma_{10} Cp_{ij} + \gamma_{20} Cn_{ij} + \gamma_{30} Te_{ij} + \zeta_{0i}$$

$$\pi_{1i} = \gamma_{40} + \gamma_{50} Cp_{ij} + \gamma_{60} Cn_{ij} + \gamma_{70} Te + \zeta_{1i}$$

Where,

$$\begin{bmatrix} \zeta_{0i} \\ \zeta_{1i} \end{bmatrix} \sim N\left( \begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_0^2 & \sigma_{01} \\ \sigma_{10} & \sigma_1^2 \end{bmatrix} \right)$$

Composite model:

$$Rt_{ij} = [\gamma_{00} + \gamma_{10} Cp_{ij} + \gamma_{20} Cn_{ij} + \gamma_{30} Te_{ij} + \gamma_{40} Tr_{ij} + \gamma_{50} Cp \times Tr + \gamma_{60} Cn \times Tr + \gamma_{70} Te_{ij} \times Tr_{ij}]$$
$$+ [\zeta_{0i} + \zeta_{1i} Tr_{ij} + \varepsilon_{ij}]$$

Again, we use SAS PROC MIXED to estimate the model to the data of the inexperienced bidders and the data of the experienced bidders respectively. In the estimation, we also allow both intercepts and slopes to vary across bidders.

Table 2.6 summarizes the results of the model estimation. For the inexperienced bidders, *Cp- current price* is positively correlated ( $\gamma_{10}^{inex}=0.426$, $p<0.01$) with *Rt- responding time to competitive bids*, which means that responding times is longer when price is higher. Overtime, as experience accumulates this effect becomes less, as indicated by the negative interaction effect ( $\gamma_{50}^{inex}$ =*-0.101, p<0.01)* between *Cp-current price* and *Tr-time trend. Te-time to the end* has a positive effect ( $\gamma_{30}^{inex}$ *<0.225, p<0.01)* on the *Rt-responding time.* This effect becomes less ( $\gamma_{60}^{inex}$ =*-0.071, p<0.001)* as bidders' experience accumulates. *Cn*-current number of bids has a negative effect ( $\gamma_{20}^{inex}$ =*-1.707, p<0.01)* on *Rt-responding time* and this effect does not change as bidders' experiences accumulate. This supports H7.

For the experienced bidders, we find that *Cn- current number of bidders* has a negative effect ( $\gamma_{20}^{\exp}$ =*-3.146, p<0.01)* on *Rt-* responding time and this effect does not has a time trend ( $\gamma_{70}^{\exp}$ =*-0.064, p>0.1).*

Table 2.6 Results of Fitting the Multilevel Model of Responding Time

| | Variable | Parameter | Inexperienced | Experienced |
|---|---|---|---|---|
| *Fixed Effects* | | | | |
| | *Intercept* | $\gamma_{00}$ | *-0.091 (0.919)* | *5.230*** (<0.001)* |
| | *Cp* | $\gamma_{10}$ | *0.426** (0.007)* | *-0.039 (0.793)* |
| | *Cn* | $\gamma_{20}$ | *-1.707*** (<0.001)* | *-3.146*** (<0.001)* |
| | *Te* | $\gamma_{30}$ | *0.225** (0.004)* | *0.024 (0.747)* |
| | *Tr* | $\gamma_{40}$ | *1.067*** (<0.001)* | *0.538 (0.090)* |
| | *Cp by Tr* | $\gamma_{50}$ | *-0.101*** (0.010)* | *0.019 (0.703)* |
| | *Te by Tr* | $\gamma_{60}$ | *-0.071*** (<0.001)* | *-0.025 ( 0.333)* |
| | *Cn by Tr* | $\gamma_{70}$ | *0.014 (0.901)* | *-0.064 ( 0.815)* |
| *Variance Components* | | | | |
| *Level-1* | *Within-person* | $\sigma_{\varepsilon}^2$ | *0.474**** | *0.471**** |
| *Level-2* | *In Intercept* | $\sigma_0^2$ | *1.993*** | *1.952*** |
| | *In Rate of Chance* | $\sigma_1^2$ | *0.148*** | *0.307** |
| *Goodness-of-fit* | | | | |
| | *Deviance* | | *17737* | *20164* |
| | *AIC* | | *17761* | *20188* |
| | *BIC* | | *17829* | *20257* |
| *~ p<.10; * p<.05; ** p<.01; *** p<.001* | | | | |

2.3.2.5 Discussion of the Results

Results of the estimation for all four models indicate that learning exists in dimensions of inexperienced bidders' decision-making in online auctions. However, experienced bidders demonstrate learning only on the timing of placing the first bid. Inexperienced bidders also learn to be less influenced by contextual attributes in the bidding process, for example, the current price at the time of entering an auction.

Specifically, both inexperienced bidders and experienced bidder learn to enter auctions later and later. There are significantly more late bids being placed by experienced bidders in our data. The current price level is positively correlated with the earliness of inexperienced bidders' auction entry while the current number of bids is negatively correlated with it. As time goes by, these correlations become smaller. Although experienced bidders still have learning on the timing of auction entry, how early they enter auctions does not correlated with the current price level anymore. This is consistent with the finding that inexperienced bidders learn to be less influenced by the current price level in their timing of auction entry. However, large current number of bids still has a positive correlation with how early bidders enter auctions. This may imply that both inexperienced bidders and experienced bidders intended to avoid exacerbating the competition by bidding late.

Inexperienced bidders learned to increase their proxy bids while entering auctions later and later. At the same time, they learned to reduce the proxy bid amount if they enter auctions early. Experienced bidders, on the other hand, did not adapt their proxy bidding over time.

Inexperienced bidders learned to place smaller number of bids and be less influenced by the number of bidders in auctions. The number of bids submitted by experienced bidders did not have positive correlation with the number of bidders. Experienced bidders do not have learning effect in placing how many bids. This may indicate that inexperienced bidders needed to rely more on other bidders' information to formulate their values and they needed to update their bids more often in the beginning. At the same time, inexperienced bidders may not know the effect of number of bids but they learned it and placed smaller number of bids later on.

Inexperienced bidders learned to increase the time to place a new bid after being out bid. In addition, they learned to wait longer before they placed a new bid when the current price was high or there was long time to the auction end. Experienced bidders do not have learning in responding if being out bid. Same as inexperienced bidders, experienced bidders increase their responding time when the current number of bids is large. We find that bidders tried to avoid competition by postpone their bidding.

*2.3.2.6 Difference in learning due to winning and losing auctions*

Believing that bidders learn mainly by actually participating in auctions, we use the cumulative number of auctions or cumulative number of bids as a time trend variable in our multilevel models.

To study the effect of winning versus losing auctions, we introduced a dummy variable in the level-2 model of the first three models estimated. Results of these models indicate that both inexperienced bidder and experienced bidders used different bidding strategies in auctions they won from those in auctions they lose. Bidders bid later in auctions they won than those they lost ( $\gamma_w^{inex}$ =*-1.525, p<0.001;* $\gamma_w^{\exp}$ =*-1.947, p<0.001).* Inexperienced bidders used a lower proxy bidding amount when they entered the auctions they won ( $\gamma_w^{inex}$ =*-1.616, p<0.001)* while experienced bidders did not vary their first proxy bidding amount in auctions they won or lost ( $\gamma_w^{\exp}$ =*-0.424, p>0.1).* Both inexperienced and experienced bidders placed more bids in auctions they won ( $\gamma_w^{inex}$ =*0.085, p<0.001;* $\gamma_w^{\exp}$ =*0.068, p<0.001).*

The results imply that bidders can learn the effectiveness of different strategies in winning or losing auctions. Therefore, it is reasonable to expect that bidders' learning behavior depends on their past auction experience with winning or losing auctions.

*2.3.2.7 Potential Endogeneity Issue*

Endogeneity occurs when the independent variable is correlated with the error term in a regression model, resulting in biased model estimation (Shugan 2004). This problem is fundamental with naturally occurring data (e.g., see Theil 1971) due to (1) measurement errors in the independent variables, (2) two-way causality (the value of independent variables in period n depends on the value of dependent variable in period n-1 ) ; (3) self-selection (an exogenous choice influences both the dependent and independent variables).

Carefully examining the three sources for a potential endogeneity issue, we do not find our model estimation suffer from serious endogeneity problems. First of all, our data do not have serious measurement errors in the independent variables because the values of the independent variables were accurately recorded. For example, the bid amount of each bid recorded is exactly the amount that a bidder placed at a certain point in time. Secondly, we do not have a two-way causality issue between our dependent variable and independent variables. Our dependent variable concerns the change in bidders' bidding behaviour, which is a time-varying variable with a time trend. Our independent variables concern the attributes of on-going or completed auctions, which are not time-varying. Therefore, the value of our dependent variable in period n-1 (the previous auction) cannot cause the values of independent variables in period n.

Finally, our models may have independent variables that maybe endogenous, for example, the number of bidders in an auction. However, these potential endogenous independent variables are only level-2 variables in our multi-level model. Our modeling and estimation approach overcome the potential endogeneity bias. Our level-1 model is an individual growth model. The only independent variable is the time trend variable. It is assumed to be independent to the error term. Our level-2 model, models the random effects of the intercept and the slope of the time trend variable. After we combine the level-1 and level-2 model, the composite model consists of three parts: the fixed effects part, the random effects part and the level-1 error term (which is the error term in the composite model). For example, the composite model for the number of bids is,

$$Nb_{ij} = [\gamma_{00} + \gamma_{10}Du_{ij} + \gamma_{20}Ep_{ij} + \gamma_{30}Sr_{ij} + \gamma_{40}Nr_{ij} + \gamma_{50}Tr_{ij} + \gamma_{60}Nr_{ij} \times Tr_{ij}]$$
$$+ [\zeta_{0i} + \zeta_{1i}Tr_{ij} + \varepsilon_{ij}],$$

which is analogous to the standard linear form of the mixed effect model,

$$y = X\beta + Z\gamma + \varepsilon$$

where, $\gamma$ is an unknown vector of random-effects parameters with known design matrix **Z**, and $\epsilon$ is an unknown random error vector whose elements are no longer required to be independent and homogeneous. Here, **Z** acts as an internal instrument variable (Grilli and Rampichini 2007).

The potential correlation between the independent variables and the level-2 error term is captured in the random-coefficient matrix when we use SAS PROC MIXED to estimate our models. Therefore, our model estimates are unbiased.

## 2.4 General Discussion and Conclusion

With the phenomenal development of Internet, more and more consumers use online auctions as an ordinary channel to obtain goods. Therefore, it is important to understand consumer behavior in online auctions. One important aspect of consumer behavior in online auctions is learning. In particular, consumers learn how to make a series of decisions related to entry time, bid amount, response time after being outbid, and maximum WTP. This is so far an unexplored area.

In this paper, we examine consumer learning by fitting a series of multilevel models to the longitudinal data we collected from eBay auctions. The longitudinal study allows us to examine bidders' learning process, which is not possible in cross-sectional studies because the change observed in cross-sectional studies has confounds. Multilevel modeling approach allows us to directly deal with the issue of autocorrelation, heteroscedasticity and endogeneity problems and results in unbiased model estimations.

Using SAS PROC MIXED, we estimate the intercept (consumers' initial status of bidding) and the time trend variable as random effects. By doing so, we allow heterogeneity in consumers' prior knowledge level and in their learning behavior and directly estimate it.

Our study emphasizes the importance for bidders to learn to withhold their private information and strategically respond to other bidders' bids. There are two aspects that bidders need to consider to improve their decision-making. On the one hand, they need to learn how to strategically use other bidders' information, while on the other hand, they need to learn how to bid strategically, i.e., make wise decisions on when and how much to bid, so as not to reveal less private information to others.

It is the first study that using longitudinal data and multilevel modeling approach to examine learning in online auctions in a comprehensive way. Therefore, it contributes to the literature in that it offers insights into learning in online auctions and it is an important application of multilevel modeling approach in marketing area.

The results of model estimation indicate that learning effects do exist in inexperienced bidders' bidding behavior. We find support for our hypotheses, that as bidders gain experience, they will reveal less private information by entering an auction toward the end, and by reducing the amount of their proxy bid when they enter an auction early, and by submitting fewer bids. They will strategically raise the amount of proxy bidding when they bid toward the end of an auction. These results are consistent with predictions implied by economic theory that strategic bidders try to reduce competition and avoid potential bidding wars. Experienced bidders, on the other hand, did not adapt their strategies over time, except that they did learn to enter auctions later. .

The current study has several potential weaknesses. As always with naturally occurring data, missing unobserved exogenous variables may potentially bias our conclusions. Future research should try to identify other variables that may influence bidder learning over time. Future research should also consider the potential difference in bidders' learning for winning and losing auctions. Analyses where we controlled for bidders' winning or losing, we find that bidders employ different bidding strategies in auctions they won or lost. Therefore, learning could depend on bidders' experience of winning and losing.

Further study is also needed to study the role that learning plays in snipe bidding strategies. Snipe bidding hides a bidders private information and may be effective in dealing with incremental bidders. However, a bidder will need to trade off the timing of a snipe bid with the probability that a bid will fail to register, due to large traffic in the last moment of an auction. Therefore, learning can play a role in optimum timing of late bidding.

Another future research area is to model bidders' different decision making aspects in a comprehensive way. Our current models examine different decision making aspects separately. Therefore, we do not control the contingency among these deferent decision making aspects. Future models should also consider the simultaneous modeling of experienced and inexperienced bidders. In the current model we did not pursue this, due to multicollinearity problems.

Finally, we argue in our study that it is important for bidders not to reveal their private information and we found evidence that inexperienced bidders learn on this aspect. However, we did not investigate the effectiveness of this strategy.

In particular, do bidders who reveal less information pay less in the auctions they win? Future research will need to be conducted to investigate the effectiveness of different information release strategies; studying the effect on the likelihood of winning auctions and the effect on final prices.

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# Chapter 3

## Essay 2: Jump Bidding in Online Auctions: A Double-Edged Sword

### 3. 1 Introduction

Jump bidding, or bidding in excess of the minimum required increment, is a frequently observed phenomenon in both traditional and online ascending auctions (Isaac, Salmon and Zillante 2007; Easley and Tenorio 2004). The immediate consequence of jump bidding is to accelerate the current price and squander bidders' opportunity to win the auction at a potentially lower price.

The phenomenon of jump bidding has long intrigued researchers, in particular because it: 1) has the potential to empirically reject the theory of ascending bid auctions, where it is an optimum strategy to bid only the minimum amount required to become the current high bidder; 2) cannot be rationalized easily; and 3) concerns the welfare of consumers and has managerial implications for sellers. However, no consensus has yet been reached in the literature on motivations or effects of jump bidding.

Jump bidding has typically been ascribed to irrationality, impatient bidders trying to reduce the cost of bidding, or bidders signaling their strength or belief in high valuation (See Isaac et al. 2007 for a brief review). Explained as an irrational or cost-saving behavior, jump bidding is claimed to have a positive effect on an auction item's ending price (e.g., Cybernomics 2000), while as a signaling device, it is believed to have a negative effect on an item's ending price (e.g., Avery 1998; Daniel and Hirshleifer 1998). These conclusions of the effect of jump bidding on auction outcomes were mostly derived from analytical models with different presumptions of motivations of jump bidding in the traditional ascending auction context. They not only have conflicts but also lack empirical support.

Online auctions have provided not only a new channel for selling goods, but also a broader testing ground for studying existing auction theories. Moreover, unique features of online auctions add new dimensions to the controversy concerning the motivations and effects of jump bidding. For example, one common feature of online auctions is the significantly prolonged bidding process with a fixed duration (auctions may have a soft ending rule, where the duration is extended by five or ten minutes after a bid is made). Therefore, bidders cannot effectively use jump bidding to shorten the duration of the auction. Furthermore, proxy bidding machines that bid on behalf of bidders rule out jump bidding as a way to reduce the cost of bidding.

Important unanswered research questions include:

1) What motivates bidders to jump bid in online auctions?

2) What factors influence whether jump bidding is successfully received and interpreted by other bidders as a signal of strength or high valuation?

3) How does jump bidding influence other bidders' bidding behavior?

4) How does jump bidding affect auction outcome?

5) What factors may influence the strength and/or directions of jump bidding's effects on auction outcomes?

The answers to these research questions will not only deal with the controversy in the existing research on jump bidding, but also provide important insights related to managerial applications in auction design, specifically in online auctions.

In this paper, we developed a conceptual model on the effects of jump bidding and empirically test this model using data from online auctions. Our conceptual model focuses on the effects that jump bidding may have on other bidders' maximum WTP or values they attached to the auctioned item[8] and then the outcomes in online auctions. We propose that jump bidding may cause other bidders to adjust their values to a higher level and have a compound effect on an auction's ending price. We describe how the compound effect of jump bidding on an auction's ending price is formulated on the basis of value affiliation among bidders during the auction process. Our conceptual model recognizes that jump bidding may signal that a jump bidder's value is high. This information may be incorporated into another bidder's valuation construction process. After this WTP adjustment, bidders who value the item lower than the expected ending price may decide to quit the auction because bidding in an online auction has a cost (Easley and Tenorio 2004). Jump bid exhibits a deterring entry effect. Despite this, bidders who value the item higher than the expected ending price may remain in the auction with the new value that is higher than before. Thus the jump bid exhibits a positive effect on the ending price.

We also examine the moderating effect of four important factors: 1) the degree of value uncertainty. We expect that under high value uncertainty, bidders need to rely more on external information cues such as the information they get from other bidders to formulate their values. Therefore, bidders will be influenced more by jump bidding if they have a high degree of value uncertainty. 2) the

[8] We use bidders' maximum of WTP and bidder's value interchangeably in this article.

timing of jump bidding. Online auctions usually have a duration that is much longer than that in traditional auctions. At different points in time during the auction, the current price and the current number of bidders are different. A certain amount of jump bids may signal differently the strength or the value of the jump bidder; 3) the expertise of a jump bidder. Many online auctions use a feedback system to regulate transactions. The feedback score a bidder gets represents the lower bound of the number that bidder won in the past. It indicates to some extent the expertise that a bidder may have on online auctions. According to Wikipedia, an "expert" is someone widely recognized as a reliable source of technique or skill whose faculty for judging or deciding rightly, justly, or wisely is accorded authority and status by their peers or the public. We expect that the indicated expertise level of a jump bidder will moderate the effect of jump bidding; 4) the auction type (whether an auction is a charity auction or not). We are interested in this factor in particular because it has been found that charitable intent may motivate bidders to act as *voluntary shills* (Popkowski Leszczyc and Rothkopf 2007). Jump bidding is the most direct mean bidders can use to drive up the auction price. Furthermore, bidders in charity auctions also may be more likely to react positively to jump bidding because of their charity intent. Therefore, the motivation and the effects of jump bidding in charity auctions may be different from those seen in non-charity auctions.

We then use data collected through three lab experiments and one field experiment conducted on a local online auction market to test our conceptual model and the moderating effect of the above-mentioned four factors. The results support our conceptual model.

Our study makes the following contributions to the literature:

1) We directly address the controversy in the literature regarding the effects of jump bidding and provide a general theoretical model of the effects of jump bidding. Our model is based on the notion of information integration in bidders' valuation-construction process, which is common in both traditional and online ascending auctions. Therefore, the conclusions of our model can be generalized to traditional, ascending auction environments, although we test our model using online auction data.

2) We empirically test this model using both real-world online auction data and lab experimental data. Therefore, the results provide both external and internal validity for our theory.

3) We offer information concerning managerial implications for sellers on how to employ bidding rules regarding minimum increments and the jump-bidding and proxy-bidding options.

The remainder of this is organized as follows: We review the relevant literature of jump bidding and propose our conceptual model in Section 3.2. In Sections 3.3, 3.4, 3.5, and 3.6, we provide the results of three lab experiments and a field study. Section 3.7 presents our concluding remarks and a discussion of topics for future research.

## 3.2 Literature Review and Conceptual Model

### *3.2.1 Literature on the Effects of Jump Bidding*

A detailed summary of the major literature related to jump bidding is provided in Table 3.1. Avery (1998) and Daniel and Hirshleifer (1998) propose that jump bidding is a signaling device used by strategic bidders to signal strength or high valuation in their game theoretical models. Avery's (1998) model studies jump bidding in two bidder auctions with affiliated values. Due to the common value component in bidders' valuations, jump bidding acts as a correlating device in coordinating an asymmetric equilibrium to be played subsequently and causes the other bidder to quit because of the winner's curse concern, which favors the jump bidder. Daniel and Hirshleifer's (1998) model is developed under a private values context with two bidders and costly bidding. Bidding cost causes the other bidder not to continue because of a high probability of losing to the jump bidder. In both models, the auction ends if other bidders choose not to compete with the signaled value. Hence, jump bidding may have a negative effect on the ending price. However, as pointed out by Isaac et al. (2007), the jump-bidding pattern in these versions of signaling models are rarely observed in real-world auctions and have not been tested empirically.

Easley and Tenorio (2004) also propose that jump bidding is motivated by a signaling purpose. Using an extension of the model in Daniel and Hirshleifer (1998), they demonstrate that positive bidding cost and uncertainty of future entry drive jump-bidding behavior in online auctions. Using data collected from online

Yankee auctions[9], they show that earlier jump bidding can deter bidders from continuing to bid. However, the effect of jump bidding on the ending price is not investigated in their work.

A common presumption in these signaling models is that bidders with higher valuations are more likely to jump bid. Differently, Horner and Sahuguet (2007) derive a model in which they take jump bidding as an effective bluffing strategy used by moderate valuation bidders. This bluffing strategy is parallel to that used in the game of poker, where a player with a weak hand bets in order to signal strength (Prabhu and Stewart 2001). A bluff may be "called" in which case the bluffer loses, or the other player(s) may fold their hand, and the bluffer will win. Horner and Sahuguet (2007) use a two-round auction in which bidders first decide whether to enter an auction (match a jump bid) and in the second round place a sealed bid. In such an auction, jump bidding has two potential effects: a deterrence effect, as it may deter a bidder from entering the auction, and an escalation effect, since, given that a bidder enters an auction, she may bid more aggressively in the second round. Therefore, moderate valuation bidders bluff by jump bidding and drop out if their bluffing is called so as to avoid the escalation effect. High valuation bidders should randomly bid low and high because the escalation effect of jump bidding will make high valuation bidders pay more.

Motivated by the observance of small yet persistent jump bidding in some real-world auctions, Isaac et al. (2007) argue that jump bidding stems from bidder impatience or strategic concerns. Banks, Porter, and Smith (2003) and

[9] An ascending auction of multiple identical items in which the winning bidders pay the prices that they have bid.

Cybernomics (2000) propose that impatient bidders use jump bidding to accelerate the pace of the auction; and by doing so they are willing to pay a higher price. Another often-mentioned motivation in the literature is that jump bidding is an irrational behavior on the part of bidders (Rothkopf and Harstad 1994). They used a sketch of a proof to show that jump bidding is irrational for bidders and will have a positive effect on the ending price.

Isaac et al. (2005) conducted experiments with two bidders in ascending auctions to test the model in Isaac et al. (2007) and found evidence that supports the conclusions of the model that jump bidding is due to impatience and strategic concerns. However, the design of the experiments in Isaac et al. (2005) was chosen to be as close as possible to the conditions of Isaac et al. (2007). Therefore, the conclusions from these experiments may be too specific to be generalized to other field-auction environments.

However, as far as we know there has been no empirical work that has systematically tested the different effects of jump bidding in auctions. In this paper we plan to do so.

Table 3.1 Jump Bidding Literature

| **Authors** | **Presumption** | **Type of Research** | **Context** | **Conclusions and/or Findings** |
|---|---|---|---|---|
| Isaac,et al (2007) | - Strategic concerns ( "Notch" bidding)<br>- Impatience | - Game theoretical Model | - Ascending auction with two bidders | - When allowing for either impatience or strategic bidding, the auctions will be highly efficient<br>- Allowing jump bidding can increase revenue<br>- Allowing jump bidding can improve their expected utility of participating |
| Isaac et al (2005) | - None | - Lab Experiment | - Ascending auction with two bidders | - Predictions of Isaac, Salmon, and Zillante(2007) are supported |
| Rothkopf and Harstad (1994) | - Irrationality | - Sketch of a proof | - Oral auctions,<br>- Discrete bid levels,<br>- Independent-private values | - Jump bidding is not optimal on non-<br>- increasing value distributions such as the uniform distribution |
| Avery (1998) | - Signal high valuation | - Game theoretical Model | - Affiliated values<br>- Large jump bid in the first bid<br>- A second bid to end the auction | - Jump bidding may negatively impact the ending price |
| Daniel and Hirshleifer (1998) | - Signal high valuation | - Game theoretical Model | - Private values and costly bidding<br>- Jump bid in the first bid or a second bid to end the auction | - Jump bidding may negatively influence the ending price |
| Horner and Shuguet (2007) | - Jump bidding can signal strength and deter bidders from bidding further.<br>- Jump bidding may have both a deterring entry effect and an escalation effect | - Game theoretical Model | - Two stage auctions,<br>- Two bidders,<br>- Independent valuations,<br>- Costly bidding,<br>- Simultaneous bidding in the last bid. | - Non-monotonic signaling exists.<br>- Bluffing and sandbagging strategies can both be used in equilibrium. |
| Easley and Tenorio (2004) | - Cost and uncertainty about future entry | - Game theoretical model<br>- Empirical test | - Yankee auctions | - Jump bidding more likely to occur earlier in an auction and positively related to competition.<br>- Deter entry and reduce jump bidders' overall number of bids |

### *3.2.2 Value Uncertainty and Value Construction in Online Auctions*

Real-world auctions fall into the category of affiliated-value auctions (Laffont 1997) under the common- value and private-value paradigm in traditional auction theories[10]. In real-world auctions, value uncertainty often exists and therefore a bidder's private information is expected to be incorporated into other bidders' value construction process in an auction. Empirical work, e.g. Häubl and Popkowski Leszczyc 2003, provides evidence that bidders construct their values during the auction process in online auctions.

Under value uncertainty, bidders need to rely on external information cues in an auction to construct their values during the bidding process of the auction. These external information cues include static information cues, such as buy-now prices, starting bid, previous ending prices of identical items etc and dynamic information cues that are generated by bidders' bidding behavior.

Large jump bid therefore may signal a bidder values the auctioned item high.

In a real-world auction, whether bidders rely on others for further information may depend upon how sufficient their *a priori* private information is. The more sufficient bidders' private information is, the more certain they are

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[10] Auction theories have traditionally distinguished between the common value and private value paradigms (McAfee and McMillan 1987). In the situation of *private value,* each bidder knows the value of the object with certainty before an auction starts; learning others' private information will not change this value. In the situation of *common value,* the true value of an item is the same but unknown to bidders, and private information from others is useful for bidders to formulate their valuation (Rothkopf 1969). A more general model including private value and common value models as special cases is called affiliated value model (Milgrom and Weber 1982). The assumption of a common value or a private value paradigm is essential to theory development in game theoretical models. However, it is very difficult to apply the common value and private value paradigms empirically. In addition, strongly divergent opinions about the classification of common- versus private-values goods exist, even among auction experts (Boatwright, Borle and Kadane 2006). In addition, the paradigms of private value and common value do not acknowledge the functions of other information cues in bidders' value construction process.

about the value and the less they may utilize other bidders' private information. Before an auction starts, bidders may have only an estimation of the item value based on the private information they possess (Krishna 2002) and they have different degrees of value uncertainty. With the unfolding of the auction, bidders acquire others' private information and other information cues and integrate it into their valuation-formation process. Therefore, jump bidding's effect on other bidders' values may depend on the degree of value uncertainty.

The domain of value uncertainty may be different for different bidders. We consider three senarios of value uncertainty that a particular bidder may confront in an auction: uncertainty of his/her own value, uncertainty of other bidders' value but certainty of his/her own value, and uncertainty of both. We expect that in these three different situations, other bidders' information will have different impact on a bidder's WTP.

### *3.2.3 Conceptual Model*

We next present our conceptual model on the effects of jump bidding. Our model and concepts apply to auctions in general, but our discussion is specifically set in the online auction context.

*Jump bidding and bidders' valuation formation.* At a certain point in time during an auction, a particular bidder will have a temporary estimation of valuation based on: 1) the information she gets from the general auction environment, such as the retail price, ending prices of previous auctions, the buy-now price, and the seller's description of the item; 2) the information that is only available to her, for example, she may have experiences of trading with the seller in another auction; 3) the information revealed by other bidders' bids. The bidder may have a certain degree of value uncertainty. Therefore, she will continuously assimilate new information to update her valuation.

Jump bidding can be conducted by both high valuation bidders and low or moderate valuation bidders with various purposes. No matter what these purposes are, other bidders may interpret jump bidding as high valuation. This information will be incorporated into other bidders' valuation formation process. Different bidders may put different weight on this information in their information integration function.

We elaborate bidders' valuation formation process when jump bidding is present as follows:

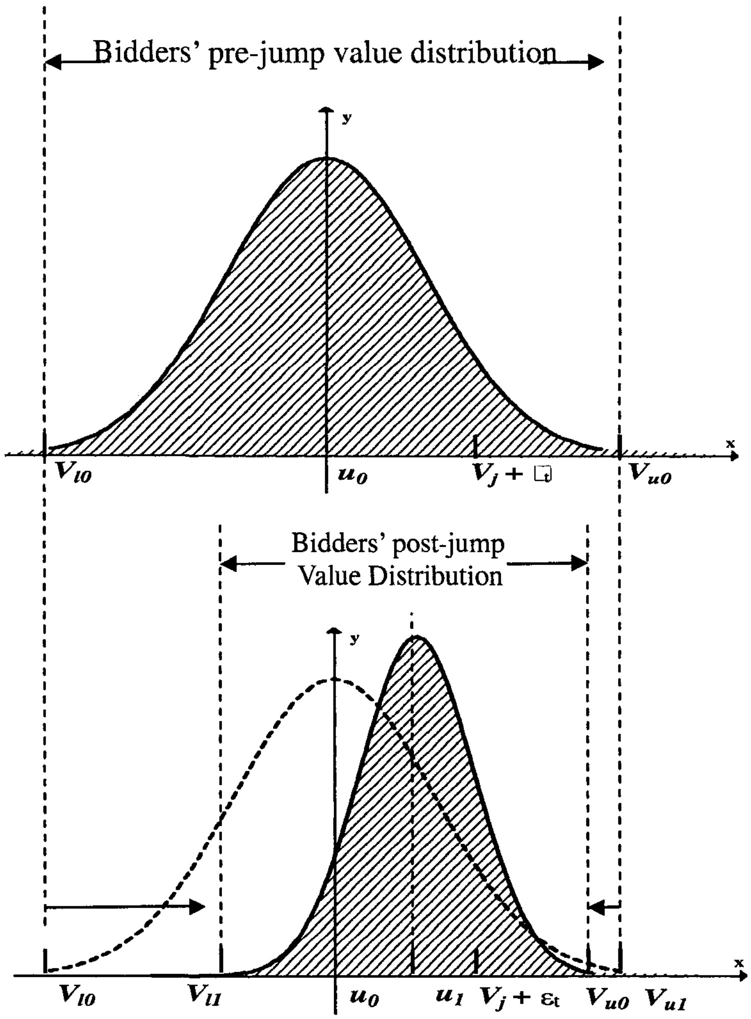
Before a jump bid is submitted, a bidder *i* has some prior information regarding the item; we denote this information as $x_{it_0}$. Based on $x_{it_0}$, bidder *i* estimates the object value as $V_i = f_i(x_{it_0}) = v_{i0}$. A jump bidder *j* may have his/her private information $x_j$ and an estimated value of $V_j = f_j(x_j) = v_j$. When jump bidder *j* submits a bid with a jump amount (bid amount minus the current price and the minimum increment) of $b_j$ at time *t*, bidder *i* infers jump bidder *j*'s valuation as $V_j^{'} = f_j^{'}(b_j \mid t) = v_j + \varepsilon_{it}$ and $x_j$ as $x_j + \varepsilon_{it}$, $\varepsilon_{it}$ is the error term of bidder *i*'s inference of $v_j$ and $x_j$. Then, bidder *i* updates his/her valuation to be $V_i^{'} = f_i^{'}[x_{it_0}, (x_j + \varepsilon_{it})] = \alpha v_{it_0} + (1-\alpha)(v_j + \varepsilon_{it})$, where $0 \le \alpha \le 1$, $\alpha$ is the weight a bidder assigns to his/her previous information when formulating a new estimation of the value, and $\alpha$ varies in the valuation formation process. To a particular bidder, when $v_{it_0} < v_j + \varepsilon_{it}$, $v_{it_0} < \alpha v_{it_0} + (1-\alpha)(v_j + \varepsilon_{it}) < v_j + \varepsilon_{ti}$;

when $v_{it_0} > v_j + \varepsilon_{it}$, $v_j + \varepsilon_{it} < \alpha v_{it_0} + (1-\alpha)(v_j + \varepsilon_{it}) < v_{it_0}$

*Effects of jump bidding on the ending price.* Assuming that bidders' valuation $V$ is normally distributed over a range $[v_{l0}, v_{u0}]$ before a jump bid is placed, we demonstrate the effect of the jump bidding on the distribution of bidders' valuation in Figure 3.1[11]:

[11] Means: The means of the distribution before and after a jump bid are $E(V_0) = u_0$ and $E(V') = E(\alpha_m u_0 + (1-\alpha_m)(v_j + \varepsilon_{tm})) = (1-\alpha_m)(v_j + \varepsilon_{tm}) + \alpha u_0$ respectively. Assuming $u_0 < v_j + \varepsilon_{tm}$, we have,
$(1-\alpha_m)u_0 + \alpha u_0 < (1-\alpha_m)(v_j + \varepsilon_{tm}) + \alpha_m u_0 < (1-\alpha_m)(v_j + \varepsilon_{tm}) + \alpha_m(v_j + \varepsilon_{tm})$,
$u_0 < (1-\alpha_m)(v_j + \varepsilon_{tm}) + \alpha_m u_0 < v_j + \varepsilon_{tm}$, therefore, $u_0 < E(V') < v_j + \varepsilon_{tm}$. We use $u'$ to denote $E(V')$ in Figure 2. Bounds of the value range: Given
$v' = \alpha_m v_{t_0} + (1-\alpha_m)(v_j + \varepsilon_{tm})$, when $v_{t_0} < v_j + \varepsilon_{tm}$,
$v_{t_0} < \alpha_m v_{t_0} + (1-\alpha_m)(v_j + \varepsilon_{tm}) < v_j + \varepsilon_{tm}$, When $v_{t_0} > v_j + \varepsilon_{tm}$,
$v_j + \varepsilon_{tm} < \alpha_m v_{t_0} + (1-\alpha_m)(v_j + \varepsilon_{tm}) < v_{t_0}$. Therefore, $v_{l1} > v_{l0}$, $v_{u1} < v_{u0}$. Bidders' values normally distribute over a new range $[v_{l1}, v_{u1}]$, which is narrower than $[v_{l0}, v_{u0}]$.

Figure 3.1 Effect of Jump Bidding on the Distribution of Bidders' Valuations




From Figure 3.1, we can derive that jump bidding has a dual effect that works in *two* opposite directions on the ending price: 1) The effect of deterring bidder entry will dampen the competition and have an indirect negative effect on the ending price. Bidders with a formulated value that is lower than $v_j + \varepsilon_{it}$ may not continue bidding. Meanwhile, bidders with a formulated value that is higher than $v_j + \varepsilon_{it}$ may also stop bidding if they expect that the ending price may escalate higher than their value. Therefore, the number of bidders in the auction may drop. Consequently, jump bidding may have a negative effect on the ending price since the number of bidders has been found to have a positive effect on the expected selling price of an auction (Holt 1979); 2) The effect of escalation that jump bidding has on bidders' valuation will have a direct positive effect on the ending price. A bidder with a new valuation that is higher than $v_j + \varepsilon_{it}$ may continue bidding with a valuation that is higher than that held previously. These two effects exist at the same time.

The overall effect of jump bidding on the ending price may exhibit three results: 1) No effect. When the positive effect and the negative effect are equally strong, the overall effect of jump bidding on the ending price is zero; 2) Positive effect. When the positive effect is stronger than the negative effect, the overall effect of jump bidding on the ending price is positive; 3) Negative effect. When the negative effect is stronger than the positive effect, the overall effect of jump bidding on the ending price is negative.

We conducted four studies to test the conceptual model and examine the role that the aforementioned four factors may play in moderating the effects of jump bidding. Using online auctions with induced bidder values, Study 1 is a laboratory experiment we used to investigate the effects of jump biding on bidder entry and bidders' WTP and the ending price. We also examined the effect of value uncertainty in Study 1. Study 2 is a survey we used to investigate the possible confounding effect of the current high price level of jump bidding. By asking questions, we directly examined whether jump bidding can be perceived as a signal of bidder aggressiveness and whether jump bidding can positively influence bidders' WTP. Study 3 is also a survey, which we used to examine the moderation of the perceived experience level of jump bidders on the effects of jump bidding. Study 4 is a field study we used to examine the effects of jump bidding in real-world ascending online auctions with multi-rounds of bidding. The moderating effect of jump bidding timing and the auction type (whether an auction is a charity auction or not) on the effects of jump bidding was also examined in Study 4.

The four studies are presented in Section 3.3, Section 3.4, Section 3.5, and Section 3.6, respectively.

**3.3 Study 1: Lab Experiment of Real Online Auctions**

The first study was conducted in a laboratory environment using online auctions with induced bidder values. The purpose of the study is threefold: 1) to investigate whether jump bidding can deter bidder entry; 2) to examine the effect of jump bidding on bidders' WTP; 3) to study the influence of value certainty on the effects of jump bidding. To manipulate value certainty, bidders were either provided with a specific valuation or with a range. We examined the influence of both a bidder's own value certainty and their knowledge of the value certainty of other bidders (the jump bidders). In the former case they were provided with either a value or a range for their own valuation, and in the latter with either a value or a range for the valuation of the jump bidder. When uncertain about their own valuation, bidders will depend more on information revealed by other bidders, including jump bidders, to formulate their valuation. Therefore, we expect that uncertain bidders are more likely to be influenced by jump bidding. In addition, the value certainty of the jump bidder relates to the signaling power of jump bidding. The certain value of a jump bidder serves as a ceiling on the value that jump bidding can signal. Note that only when bidders are uncertain of the jump bidder's valuation can jump bidding be used as a bluffing strategy.

We included bidding cost as a conditional factor in the experiment. Without any bidding cost, a bidder should continue bidding as long as the initial competing bid is below her valuation. Therefore, to induce a stronger deterrence to entry effect of jump bidding, we include a bidding cost.

### *3.3.1 Method of Study 1*

This study was implemented using the COLDFUSION program language and was conducted in a behavioral research lab. The study has a 2 (level of subject's own value certainty: low vs. high(between)) $\times$ 2 (jump bidding amount: high vs. low(within)) $\times$ 2 (level of bidding cost: low vs. high(within)) $\times$ 2 (level of competing bidder's value certainty: low vs. high(within)) mixed within and between subjects design. We used two different sets of eight online auctions to implement these conditions. We randomized the order of the auctions (conditions) in each session.

Levels of the factors we manipulated in each condition are summarized in Table 3.2. For example, in the first condition, C11, the jump bidder (bidder A) has a certain value of \$83.99 and the subject (bidder B) is uncertain about her value, which will be randomly drawn at the end of an auction from a range between \$0 and \$169.99. Bidder A places a jump bid amount in the range of \$67.63-\$72.63; bidder B's bidding cost is \$20.53, which is 24.44 percent of the certain value.

Different from the regular induced value approach, where valuations are drawn from a uniform distribution, we assign a certain value or a value range to bidders. In the conditions where the valuations of bidder A and bidder B are certain, we set these valuations to be equal in order to control that subjects use only jump bidding; other conditional variables were manipulated as information inputs to formulate their WTPs. If we set bidder A's valuation to be different from bidder B's valuation, the difference between these two valuations could be used as an information input, which will confound our conditional variables. In the conditions where both bidder A and bidder B are uncertain of their valuations, we provide the same value range to bidder A and bidder B in each condition. In the conditions where one bidder is certain of his/her value but the other is not, we set the certain value to be equal to the mid-point of the range plus a maximum of $1.02 or minus a maximum of $1.01. We make this little variation to the mid-point of value range in order to make it more difficult for bidders to figure out that the certain value is set to be equal to the mid-point of the value range. We manipulate the jump bidding amount in each condition by controlling bidder A's bid to be placed in a certain range. The spread of the range is $5.00. We set the bidding cost associated with bidder Bs' bidding to be low or high. In the low bidding cost conditions, the bidding cost is set to be in the range of $0.00-$1.00. In the high bidding cost conditions, the bidding cost is set between 15 percent and -25 percent of the bidders' value (or expected value for value range condition). Bidding costs only apply to bidder B.

Table 3.2. Summary of the Conditional Variables

| Conditions | Unca | | Uncb | | Jump | | Cost | |
|---|---|---|---|---|---|---|---|---|
| | *dummy* | *value* | *dummy* | *Value* | *dummy* | *Value* | *dummy* | *value* |
| C11 | 0 | 83.99 | 1 | 0~169.00 | 1 | 67.63-72.63 | 1 | 20.53 |
| C12 | 0 | 115.99 | 0 | 115.99 | 0 | 9.46-14.46 | 1 | 28.60 |
| C13 | 0 | 170.00 | 1 | 0~340.99 | 1 | 133.72-138.72 | 0 | 0.10 |
| C14 | 0 | 220.99 | 0 | 220.99 | 1 | 172.05-177.05 | 0 | 0.50 |
| C15 | 0 | 282.99 | 1 | 0~565.99 | 0 | 8.93-13.93 | 1 | 44.18 |
| C16 | 0 | 325.99 | 0 | 325.99 | 1 | 251.31-256.31 | 1 | 54.71 |
| C17 | 0 | 390.99 | 1 | 0~781.99 | 0 | 7.35-12.35 | 0 | 0.40 |
| C18 | 0 | 451.99 | 0 | 451.99 | 0 | 7.92-12.92 | 0 | 1.00 |
| C21 | 1 | 0~168.99 | 1 | 0~169.00 | 1 | 66.96-71.96 | 1 | 20.53 |
| C22 | 1 | 0~232.99 | 0 | 115.99 | 0 | 7.53-12.53 | 1 | 28.60 |
| C23 | 1 | 0~342.99 | 1 | 0~342.99 | 1 | 133.26-138.26 | 0 | 0.10 |
| C24 | 1 | 0~442.99 | 0 | 220.99 | 1 | 169.98-174.98 | 0 | 0.50 |
| C25 | 1 | 0~565.99 | 1 | 0~565.99 | 0 | 5.24-10.26 | 1 | 44.18 |
| C26 | 1 | 0~652.99 | 0 | 326.99 | 1 | 249.19-254.19 | 1 | 54.71 |
| C27 | 1 | 0~781.99 | 1 | 0~781.99 | 0 | 6.04-11.04 | 0 | 0.40 |
| C28 | 1 | 0~902.99 | 0 | 451.99 | 0 | 4.78-9.78 | 0 | 1.00 |

We recruited 200 undergraduate students in a North American university to participate in the study. Subjects received course credit, as well as an amount won in the experiment. Each subject was randomly assigned a login code. After providing their contact information and research consent, they were given detailed instructions.

Subjects are told that they will be bidding in several auctions for a hypothetical product. To obtain a cleaner measure of the effect of jump bidding on bidders' WTP, we induce bidders' values by providing bidders either with a specific value or a value range for a hypothetical product; this is what the product is worth to them if they win the auction. Assigned values differ depending on the condition. We manipulate uncertainty by providing bidders either a range or a specific value. In the case of a value range, their value is randomly selected from this range at the conclusion of the auction.

At the beginning of the study, each subject was assigned a bidder type for the duration of the study; either bidder A or bidder B. Next they participated in five practice auctions, followed by eight experimental auctions.

The auction used is similar to the two-stage auction described in Horner and Sahuguet (2007). Each auction consisted of two stages and two bidders, bidder A and bidder B. Bidder A is the jump bidder. Bidder A's first round bid was manipulated to implement the high vs. low jump bid amount conditions. In the first stage, bidder A placed the first bid, which was specified within a low or high value range. Next, bidder B decided whether to match this bid or not. If bidder B did not match the bid, bidder A won the auction. If bidder B matched the bid, the auction proceeded to the second stage. The second stage is a first price sealed bid auction. In this stage, both bidder A and bidder B simultaneously placed a single bid. The bidder with the highest bid wins the auction, and wins (loses) an amount equal to the value of the hypothetical product minus his/her final bid plus any potential cost of bidding. Losing bidders receive nothing, but will have to pay any potential cost of bidding if they entered the auction. Bidders received a starting balance of $200 experimental dollars; any winnings or losses were added to or deducted from this balance. Each experimental dollar was worth $0.01.

*3.3.2 Data of Study 1*

Because bidder A's bid was part of the manipulation, we are only interested in bidder B's responses. After deleting all bidder A's responses, and responses from some bidders who bid beyond their value, we are left with 1,240 responses from 155 bidders.[12]

The data contain three dependent variables: 1) bidder B's decision to match bidder A's bid in the first round of each auction, 2) bidder B's bid amount placed in the second stage of each auction, and 3) the ending price of each auction.

We list the dependent variables as well as independent variables in Table 3.3 and summarize the descriptive statistics of the variables in Table 3.4.

Table 3.3 Variable List

| Variables | Description and Measurement |
|---|---|
| *Dependent Variables* | |
| *Match* | Dummy variable indicates whether bidder B matched bidder A's bid; |
| *Bid* | Bidder B's bid amount in the second stage of an auction. In the estimation, the logarithm of the ratio of the bid amount to the product is used; |
| *Eprice* | Ending price of an auction. |
| *Independent Variables* | |
| *Unca* | Dummy variable indicates whether the jump bidder's valuation is uncertain: 1, when it is uncertain; 0, when it is certain; |
| *Uncb* | Dummy variable indicates whether the subject's valuation is uncertain: 1, when it is uncertain; 0, when it is certain; |
| *Jump* | Jump bid amount. In the estimation, the logarithm of the ratio of jump bid amount to the value is used; |
| *Cost* | Bid cost associated with bidder B's decision to match bidder A' bid; the logarithm of the bidding cost is used in the estimation |
| *Budget* | Accumulated balance in bidders' account before each auction starts; The mean centered value of budget is used in the estimation. |

[12] Since this is a first price auction, where bidders pay the amount of their bid, any bid above one value results in a loss. These subjects clearly did not fully understand the task.

Table 3.4 Descriptive Statistics

| Conditions | Match | | Bid ($2^{nd}$ round) | | | Eprice | | | Budget | |
|---|---|---|---|---|---|---|---|---|---|---|
| | *yes* | *(%)* | *mean* | *ratio* | *Std.E* | *mean* | *ratio* | *Std.E* | *Mean* | *Std.E* |
| C11 | 0 | 0 | 0 | 0 | 0 | 67.63 | 0.81 | 3.26 | 161.29 | 60.12 |
| C12 | 83 | 0.86 | 56.36 | 0.49 | 23.58 | 61.81 | 0.53 | 22.91 | 150.53 | 50.92 |
| C13 | 87 | 0.91 | 139.90 | 0.82 | 16.57 | 112.58 | 0.66 | 44.95 | 153.33 | 61.14 |
| C14 | 88 | 0.92 | 187.80 | 0.85 | 13.58 | 158.89 | 0.72 | 66.14 | 147.01 | 65.81 |
| C15 | 77 | 0.80 | 133.86 | 0.47 | 72.13 | 66.29 | 0.23 | 46.33 | 180.99 | 41.13 |
| C16 | 52 | 0.54 | 143.90 | 0.44 | 5.92 | 152.91 | 0.47 | 90.99 | 175.36 | 52.96 |
| C17 | 95 | 0.99 | 237.80 | 0.61 | 135.08 | 147.95 | 0.38 | 131.89 | 142.55 | 56.42 |
| C18 | 93 | 0.97 | 269.20 | 0.60 | 172.73 | 182.23 | 0.40 | 172.51 | 161.65 | 46.05 |
| C21 | 41 | 0.69 | 63.20 | 0.75 | 17.04 | 80.40 | 0.95 | 17.09 | 57.45 | 143.88 |
| C22 | 51 | 0.86 | 67.98 | 0.59 | 39.64 | 71.68 | 0.62 | 33.07 | 53.20 | 141.66 |
| C23 | 53 | 0.90 | 150.90 | 0.88 | 36.99 | 139.79 | 0.82 | 64.32 | 134.25 | 144.76 |
| C24 | 56 | 0.95 | 199.80 | 0.90 | 31.44 | 145.56 | 0.66 | 83.76 | 94.42 | 135.18 |
| C25 | 48 | 0.81 | 133.11 | 0.47 | 128.50 | 101.60 | 0.36 | 117.48 | 68.33 | 125.86 |
| C26 | 40 | 0.68 | 206.10 | 0.62 | 37.79 | 191.53 | 0.58 | 115.55 | 141.33 | 101.64 |
| C27 | 58 | 0.98 | 156.94 | 0.40 | 144.87 | 105.60 | 0.27 | 112.37 | 100.45 | 116.31 |
| C28 | 58 | 0.98 | 249.60 | 0.55 | 220.07 | 233.05 | 0.52 | 209.84 | 50.13 | 141.58 |

*Note: The ratios of Bid and Eprice are equal to the mean values divided by bidder B's value or expected value.*

### *3.3.3 Results of Study 1*

A recursive model with two equations was constructed and estimated for the purpose of testing jump bidding's deterrence of entry effect and its effect on the ending price.

The first equation is a logistic regression determining whether bidder B matches bidder A's bid in the first stage of an auction. The dependent variable is a dummy variable indicating whether bidder B did or did not match bidder A's initial bid (Match=1). The dependent variable for the second equation is the logarithm of the ratio of the ending price of the auction. The dependent variable for the first equation is one of the independent variables for the second equation, providing the following recursive model:

$$\mathrm{logit}(P_{ij}) = \alpha_0 + \alpha_1 Unca_{ij} + \alpha_2 Uncb_{ij} + \alpha_3 Jump_{ij} + \alpha_4 Cost_{ij} + \alpha_5 Jump_{ij} \times Cost_{ij} + \alpha_6 Jump_{ij} \times Unca_{ij} + \alpha_7 Jump_{ij} \times Uncb_{ij} + \alpha_8 Unca_{ij} \times Uncb_{ij} + \alpha_9 Unca_{ij} \times Uncb_{ij} \times Jump_{ij} + \varepsilon_{ij1} \tag{3.1}$$

$$Eprice_{ij} = \beta_0 + \beta_1 Unca_{ij} + \beta_2 Uncb_{ij} + \beta_3 Jump_{ij} + \beta_4 Cost_{ij} + \beta_5 Budget_{ij} + \beta_6 Jump_{ij} \times Cost_{ij} + \beta_7 Jump_{ij} \times Unca_{ij} + \beta_8 Jump_{ij} \times Uncb_{ij} + \beta_9 Match_{ij} + \beta_{10} Unca_{ij} \times Uncb_{ij} + \beta_{11} Jump_{ij} \times Budget_{ij} + \beta_{12} Uncb_{ij} \times Uncb_{ij} \times Jump_{ij} + \varepsilon_{ij2} \tag{3.2}$$

We next present the results of the estimation in Table 3.5 below:

Table 3.5 Parameter Estimates for the Recursive Model of Match and Ending price

| ***Equation for decision to Match*** | | | | |
|---|---|---|---|---|
| explanatory variable | coefficient estimate | standard error | *Z*-value | p-value |
| *Intercept* | 2.506 | 0.289 | 8.661 | < 0.001 *** |
| *Unca* | -2.904 | 0.374 | -7.771 | <0.001*** |
| *Uncb* | 0.672 | 0.346 | 1.942 | 0.052* |
| *Jump* | -0.428 | 0.156 | -2.745 | 0.006*** |
| *Cost* | -0.656 | 0.061 | -10.748 | < 0.001*** |
| *Jump*Cost* | -0.035 | 0.031 | -1.113 | 0.266 |
| *Unca*Jump* | -0.683 | 0.179 | -3.808 | <0.001 *** |
| *Uncb*Jump* | 0.257 | 0.192 | 1.339 | 0.180 |
| *Unca*Uncb* | 2.247 | 0.517 | 4.347 | <0.001 *** |
| *Unca*Uncb*Jump* | 0.705 | 0.239 | 2.944 | 0.003*** |
| ***Equation for Ending Price*** | | | | |
| explanatory variable | coefficient estimate | standard error | *t*-value | p-value |
| *Intercept* | 4.373 | 0.085 | 51.644 | < 0.001*** |
| *Unca* | -0.265 | 0.085 | -3.136 | 0.002 *** |
| *Uncb* | 0.034 | 0.093 | 0.367 | 0.713 |
| *Jump* | 0.068 | 0.023 | 2.933 | 0.003 *** |
| *Cost* | 0.019 | 0.014 | 1.351 | 0.177 |
| *Budget* | 0.069 | 0.032 | 2.171 | 0.030** |
| *Unca*Jump* | -0.052 | 0.029 | -1.760 | 0.079* |
| *Uncb*jump* | -0.033 | 0.034 | -2.200 | 0.028** |
| *Budget*Jump* | 0.020 | 0.009 | 3.434 | <0.001 *** |
| *Cost*Jump* | 0.054 | 0.005 | 10.622 | <0.001*** |
| *Unca*Uncb* | 0.065 | 0.128 | 0.506 | 0.613 |
| *Unca*Uncb*Jump* | 0.082 | 0.041 | 1.984 | 0.047** |
| *Match* | 0.563 | 0.065 | 8.635 | <0.001 *** |
| Signif. codes: *** = .01; ** = .05; * = .1. | | | | |

These results support our conceptual model. Jump bidding has a direct positive effect on the ending price ( $\beta_3 = 0.068$, p<0.05) and a direct negative effect on bidder entry ( $\alpha_3 = -0.423$, p<0.01). Bidder entry has a positive effect on the ending price ( $\beta_9 = 0.563$, p<0.001). Hence, jump bidding has an indirect negative effect on the ending price.

Subjects' own value uncertainty has a positive effect on bidder entry ( $\alpha_2 = 0.672$ , p=0.052) but has no effect on the ending price ( $\beta_2 = 0.034$ , p=0.713), indicating that when subjects are uncertain of their own value they are more likely to enter an auction, but this uncertainty does not influence ending prices. Jump bidder's value uncertainty has a negative effect on bidder entry ( $\alpha_1 = -2.904$ , p<0.01) and a negative effect on the ending price ( $\beta_1 = -0.265$ , p<0.01), indicating that when subjects are uncertain of jump bidder's valuation they are less likely to continue bidding and auctions end at lower prices. The interaction of subjects' own value uncertainty and jump bidder's value uncertainty has a positive effect on bidder entry ( $\alpha_8 = 2.247$ , p<0.01) but no effect on the ending price ( $\beta_{10} = 0.065$ , p=0.063). This indicates that when subjects are uncertain of their own value and the jump bidder's value, they are more likely to enter the auctions; however, the ending prices are not significantly different from those in other situations.

The interaction of subjects' own value uncertainty and jump bidding has no effect on bidder entry ( $\alpha_7 = 0.257$ , p=0.180) but has a negative effect on the ending price ( $\beta_8 = -0.033$, p<0.05), indicating that when subjects are not certain of their own value they may bid more cautiously. The interaction term of jump bidders' uncertain valuation and jump bidding has a negative effect on bidder entry ($\alpha_9 = -0.683$, p<0.001) and a barely significant negative effect on the ending price ($\beta_9 = -0.052$, p=0.079), indicating that when bidders are uncertain of jump bidder's valuations, they bid more cautiously when there is jump bidding. The three-way interaction of subjects' own value uncertainty, jump bidder's value uncertainty, and jump bidding has a positive effect on bidder entry and a positive effect on the ending price, indicating that when subjects are uncertain of their own valuation and of the jump bidder's valuation, they bid more aggressively. Therefore, value uncertainty is an important moderator to the effect of jump bidding.

Bidding cost has a negative effect on bidder entry ($\alpha_4 = -0.656$, p<0.01) but no effect on the ending price ($\beta_4 = 0.019$, p=0.177). The interaction of bidding cost and jump bidding has no effect on bidding entry ($\alpha_5 = -0.035$, p=0.266). However, this interaction does have a positive effect on the ending price ($\beta_6 = 0.054$, p<0.01), indicating that a high jump bidding amount is associated with high ending price when bidding cost is high. This can be explained by the asymmetry of bidding cost between bidder A and bidder B. Let's look at the details of the auction outcomes. In the conditions where bidder B's bidding cost is high and the jump bidding amount is high, 87.10 percent of the 310 auctions were won by bidder A. Bidder B matched bidder A's bid in only 133 auctions, which is 42.90 percent of the 310 auctions. These auctions ended with bidder A's bid. Among the 133 auctions in which bidder B matched bidder A's bid, only forty auctions were won by bidder B, which is 12.90 percent of the 310 auctions. Hence, with high bidding costs and a high jump bid a large percentage of B bidders chose not to compete with bidder A. Among those who chose to compete with bidder A, a large percentage did not bid high enough to win the auction.

*Budget* has a positive effect on the ending price ($\beta_5 = 0.069$, p<0.01). The interaction of budget and jump bidding has a positive effect on the ending price ($\beta_{11} = 0.020$, p<0.01), indicating that when subjects have more money in their account, they may bid more when there is high jump bidding amount.

We next fit a regression model to estimate the effect of jump bidding on bidders' WTP. The dependent variable of the model is the ratio of bidders' WTP to her value (or the expected value in the condition where a subject was provided with a range of values) in an auction. The purpose of analyzing this model is to find out the effect of jump bidding on bidder's WTP. In the previous analyses we studied ending prices, which are the collective results of both bidder A and bidder B's decisions. The current analyses just focus on the effect of jump bidding on bidder B's WTP. When subjects chose to bid in an auction, their bids in the second stage of the auction reflect their WTP.

$$\begin{aligned} WTP_{ij} = \alpha + \beta_1 Unca_{ij} + \beta_2 Uncb_{ij} + \beta_3 Jump_{ij} + \beta_4 Cost_{ij} + \beta_5 Budget_{ij} + \\ \beta_6 Jump_{ij} \times Cost_{ij} + \beta_7 Jump_{ij} \times Unca_{ij} + \beta_8 Jump_{ij} \times Uncb_{ij} + \end{aligned} \quad (3.3)$$

$$\beta_9 Unca_i \times Uncb_i + \beta_{10} Jump \times Budget + \beta_{11} Uncb_i \times Uncb_i \times Jump_i + \varepsilon_{ij}$$

When subjects chose not to match the jump bidder's bid in the first stage, we cannot observe their WTP. However, we do know that their WTP does not exceed their value minus the bidding cost. Therefore, we estimated a truncated regression model, where subjects' WTP may be censored, which equals the subject's induced value minus the cost of bidding. The results of the regression analyses are summarized in Table 3.6 below.

Table 3.6 Parameter Estimates for the Regression of Bidders' WTP:

| Variables | Coefficients | Std.Error | Z | P-Value |
|---|---|---|---|---|
| *Intercept* | 0.173 | 0.099 | -1.756 | 0.079* |
| *Unca* | -0.598 | 0.112 | -5.315 | <0.001*** |
| *Uncb* | 0.185 | 0.116 | 1.598 | 0.110 |
| *Jump* | 0.142 | 0.033 | 4.317 | <0.001*** |
| *Cost* | -0.131 | 0.017 | -7.519 | <0.001*** |
| *Budget* | 0.015 | 0.053 | 0.289 | 0.772 |
| *Jump*Cost* | 0.038 | 0.006 | 5.896 | <0.001*** |
| *Unca*Jump* | 0.174 | 0.037 | 4.714 | <0.001*** |
| *Uncb*Jump* | 0.104 | 0.041 | 2.524 | 0.012** |
| *Jump*Budget* | 0.044 | 0.015 | 2.953 | 0.003*** |
| *Unca*Uncb* | 0.318 | 0.164 | 1.944 | 0.052* |
| *Unca*Uncb*Jump* | 0.100 | 0.051 | 1.952 | 0.051* |
| Signif. codes: *** = .01; ** = .05; * = .1. | | | | |

Results indicate that jump bidding has a positive effect on bidders' WTP ($\beta_3 = 0.142$, p<0.001). Subjects' own value uncertainty does not have an effect on their WTP ( $\beta_2 = 0.185$, p=0.110) while jump bidder's value uncertainty has a negative effect on their WTP ($\beta_1 = -0.598$, p<0.01), indicating that subjects are more cautious when jump bidder's value uncertainty is high. The interactions of bidders' own value certainty and the jump bidder's value certainty with jump bidding both have a positive effect on subjects' WTP/valuation ($\beta_7 = 0.174$, p<0.001) and ($\beta_8 = 0.104$, p<0.05), respectively. The three-way interaction of subjects' own value uncertainty, jump bidder's value uncertainty and jump bidding has a positive effect on subjects' WTP ($\beta_{11} = 0.100$, p=0.051). These results support our conjecture that jump bidding can signal high valuation and influence a bidder's WTP, in particular, when uncertainty exists concerning valuations.

*3.3.4 Discussion of Study 1*

In Study 1, we find that jump bidding does prevent bidder entry, and hence has an indirect negative effect on ending price. Meanwhile, jump bidding also has a direct positive effect on the ending price. These findings imply that jump bidding can signal jump bidder's strength or high valuation. Furthermore, bidders may use this signal to formulate their valuation or WTP.

Bidding cost has a negative effect on bidder entry, but we did not observe a significant interaction between bidding cost and jump bidding on bidder entry. These results suggest that bidding cost may deter entry even without the presence of a jump bid.

Value certainty is an important moderator of the effects of jump bidding. When bidders are uncertain both about their own valuation and the jump bidder's valuation, subjects' WTP was significantly influenced by jump bidding. This is consistent with our conjecture that when bidders are uncertain about their valuations, they tend to rely on information revealed by other bidders. When bidders are uncertain about the jump bidder's valuation, jump bidding may have more signaling power.

### 3.4 Study 2: A Lab Experiment in the form of survey

The direct consequence of jump bidding is to immediately increase the current price to a certain level. When the current price is driven up to a high level, it is not clear whether it is the high current price level or the jump bidding that prevents bidder entry or positively influences bidders' WTP. We used a survey in Study 2 to mainly investigate whether the high current price level has a confounding effect. We also directly examined whether jump bidding can be perceived as a signal of bidder aggressiveness and whether jump bidding can positively influence bidders' WTP. We included bidder's own value uncertainty in the investigation.

#### *3.4.1 Method of Study 2*

We recruited 135 undergraduate students in a university in North America to participate in this lab experiment. Subjects were told that they were going to examine some images of an online auction and answer a series of questions related to the auction. We randomly assigned the subjects to the conditions of a 2 (degree of value uncertainty: low vs. high) × 2 (jump bid amount: high vs. low) × 2 (current prices: same after-bid current prices vs. same before-bid current prices)] nested between-subjects factorial design.

Subjects first examined an image of an online auction in progress (see Appendix A). The product in the auction is a conceptual 6 GB flash key drive. Subjects' value uncertainty was manipulated by varying the retail price information in the product description. We specified either a specific retail price (CA $159.99) in the low value uncertainty condition or a range of the retail price

(CA $139.99–$179.99) in the high value uncertainty condition. The jump bid amount was manipulated by a second image of the auction having a new bid with either the minimum increment over the previous current price or a jump bid of CA $98.00. We nested two sub-conditions in the low jump bid amount condition. One of these sub-conditions is that the current price after a new minimum bid is the same as that after a jump bid in the high jump bid amount condition; the other is that the current price before a new minimum bid is the same as that before a jump bid in the high jump bid amount condition. In the same after-bid current price sub-condition, the current price was $99.00 after a new minimum bid; in the same before-bid current price sub-condition, the current price was $10 before the new minimum bid (see Table 7).

Table 3.7 Conditions in the Lab Experiment

| | Value certainty $159.99 | Value uncertainty $139.99 – $179.99 |
|---|---|---|
| Jump bid amount* $98.00:<br>*Current price is $99.00 after the jump bid and $10.00 before the jump bid;* | Condition 1 | Condition 2 |
| Jump bid amount $0: | | |
| *Current price is $99.00 after the minimum bid ($98.00 before the minimum bid)* | Condition 3.1 | Condition 4.1 |
| *Current price is $10.00 before the minimum bid ($11.00 after the minimum bid)* | Condition 3.2 | Condition 4.2 |

*Jump bid amount = bid amount:- (previous current price + minimum bid)

After subjects finished examining the two auction images, we asked them to evaluate the degree of the aggressiveness of the jump bidder in the auction. We then asked them how much they would bid if they needed to purchase the exact same key drive and that they could only place a single bid in the auction.

An option of two identical auctions followed to investigate the deterring entry effect of jump bidding. The only difference between these two auctions was whether the current high bidder's final bid was a jump bid. We counterbalanced the current prices of the two auctions by making them the same either before or after the current high bidder's bid. We then asked questions to collect demographic information from the respondents.

*3.4.2 Results of Study 2*

We first ran two two-way ANOVAs on bidders' perception of the jump bidder's aggressiveness. Results of the first two-way ANOVAs show that, not surprisingly, under the same-before-bid current price scenario, jump bidders were perceived to be more aggressive than incremental bidders ( $M_j$=5.67 vs.$M_{nj}$=2.44; $F$=96.59, $p$<0.001). Value uncertainty does not have a significant effect on subjects' perception of bidders' aggressiveness. We did not find a significant interaction effect between jump bidding and value uncertainty ($F$=2.55, $p$>0.1). Results of the second two-way ANOVA show that, under the same-after-bid current price scenario, jump bidders were perceived again to be more aggressive than incremental bidders ($M_j$=5.65 vs.$M_{nj}$=2.76; $F$=85.54, p<0.001). Bidders are perceived to be more aggressive when values are certain than when they are not ($M_c$=4.54 vs. $M_{uc}$=3.89; $F$=4.54, $p$<0.05). Again, we did not find significant interaction effect between jump bidding and value uncertainty.

We ran another two two-way ANOVA on the effect that jump bidding has on subjects' WTP. Results of the first two-way ANOVA show that, under the same-before-bid current price scenario, subjects bid significantly more when there was jump bidding than when there was not($M_j$=120.72 vs. $Mnj$=50.23; $F$=121.69,

$p<0.001$). We did not find an effect of value uncertainty nor an interaction effect between jump bidding and value uncertainty on subjects' bid. This is consistent with the results of subjects' perception of bidders' aggressiveness. Results of the second two-way ANOVA show that, under the same-after-bid scenario, subjects bid more when there was jump bidding than there was not ($M_j$=120.91 vs. $M_{nj}$=109.13; $F$=7.25, $p<0.01$). However, we did not find effect of value uncertainty nor interaction effect between jump bidding and value uncertainty on subjects' bid.

We did a t-test to compare the two conditions under value uncertainty and results show that subjects bid more when there was jump bidding than when there was not ($M_j$=120.48 vs. $M_{nj}$=110.17; $t$=5.41, $p<0.05$).

The results of subjects choosing which auction to participate in show that bidders would avoid competing with jump bidders if they had the chance to do so. Under low value uncertainty, 83.78 percent of subjects chose the auction without a jump bidder, which is significantly higher ($z=6.37$, $p<0.01$) than the 16.22 percent of those who chose the auction with a jump bidder. Under the high value uncertainty, 77.47 percent of subjects chose the auction without a jump bidder, which is also significantly higher ( $z= 4.26$, $p<0.01$) than the 22.53 percent of those who chose the auction without a jump bidder.

*3.4.3 Discussion of Study 2*

Results of Study 2 indicate that jump bidding is perceived to be a more aggressive behavior than incremental bidding when the after-bid current price levels in two situations are the same. This suggests that it is the extent to which bidders voluntarily raise the current price to a certain level, not their passive acceptance of that price level that signal's aggressiveness. Value uncertainty moderated bidders' perception of a bidder's aggressiveness but not on bidders' WTP. However, when there is value uncertainty, bidders' valuation is higher when there is jump bidding. This may be because under value certainty, bidders' valuation has a ceiling but under value uncertainty, this ceiling is removed. Therefore, jump bidding has a stronger positive effect on bidders' valuation under value uncertainty. This is consistent with the results in Study 1.

Study 2 also indicates that bidders will choose not to compete with jump bidder when they have an option. This further proved the deterring entry effect of jump bidding.

### 3.5 Study 3: Lab Experiment in the Form of Survey

We conduct this study to investigate whether the perceived experience level of jump bidder moderates the effect of jump bidding on bidders' WTP.

#### *3.5.1 Method of Study 3*

The experimental procedure is similar to that in Study 2. Eighty-two undergraduate students in a North American university were recruited to participate in the lab experiment. Subjects were told that they were going to be presented with some images of an online auction and asked to answer a series of questions related to the auction. The students were randomly assigned to the conditions of a 1 (jump bidding amount: high) $\times 2$ (degree of value uncertainty: low vs. high) $\times$ 2 (level of perceived experiment of jump bidder: low vs. high) between-subjects factorial design.

Respondents first examine an image of an online auction in progress (see Appendix B). The product in the auction is a conceptual 4 GB Apple iPod. The degree of value uncertainty was manipulated by varying the retail price information in the product description—we specified either a retail price (CA $169.99) or a range for the retail price (CA $149.99–$189.99). The jump bid amount was manipulated by showing a second image of the auction with a new bid placed. The new bid had a jump bid of CA $98.00. In the condition when the jump bidder is an expert, we told the subjects that the bidder participated in at least 525 auctions before; while in the condition when the jump bidder is not an expert, we told the subjects that the bidder had never participated in an auction before (see Table 3.8).

Table 3.8 Conditions in Study 3

| | Value certainty<br>$169.99 | Value uncertainty<br>$149.99 – $189.99 |
|---|---|---|
| Expert:<br>The jump bidder participated in at least 525 auctions | Condition 1 | Condition 2 |
| Non-Expert:<br>The jump bidder never participated in an auction before | Condition 3 | Condition 4 |

*Jump bid amount = bid amount: (previous current price + minimum increment).

After respondents had finished examining the two auction images, we asked subjects' perception of the jump bidder's knowledge of the product and bidding in auctions. We then asked them to rate the jump bidder's level of certainty of the product value and determination in her bidding.

An option of two identical-item auctions followed to investigate the influence of perceived expertise of the jump bidder on the effect of jump bidding.

The only difference between these two auctions was that in one auction, the jump bidder is an expert on auctions while in the other, the jump bidder is a non-expert. We then asked questions to collect demographic information from the respondents.

*3.5.2 Results of Study 3*

Our manipulation check by running a two-way ANOVA shows that subjects perceived the jump bidders have more product knowledge ($F$=58.95, p<0.001) in different conditions. Subjects perceived the jump bidders to have more product knowledge when they are manipulated as experts ( $M_e$=6.4) than when they are manipulated as non-experts ($M_{ne}$=4.1). Expert jump bidders Me=6.24, and Mne=3.05 F=124.09 ) were perceived to have skills of bidding than non-expert bidders (Me=12.81 vs. Mne=12.05, F=124.09). Jump bidders are believed to have different degrees of clearness of the value ( $F = 9.998$, $p < 0.001$ ). When there is value uncertainty, expert jump bidders ($M_{c2}$ =5.57)were believed to be clearer of the value of the product than non-expert bidders ( $M_{c4}$ =3.67). However, jump bidders with different level of expertise were perceived to have no difference in their determination of bidding ( $F = 0.581, p = 0.630$ ).

We ran a two-way analysis of variance (ANOVA) and found that bidders bid more ( $F = 4.237$ , $p < 0.05$ ) when the jump bidder is an expert ($M_{c1\&c2}$ = 136.7) than when the jump bidder is not ( $M_{c3\&c4}$ = 121.95). Bidders also bid more ( $F = 4.524$, $p < 0.05$ ) when the value is uncertain ( $M_{c2\&c4}$ = 137) than when the value is certain ( $M_{c1\&c3}$ = 120.65). However, we did not find significant interaction effect between expertise and value uncertainty ($F = 2.537$, $p = 0.115$).

In all four conditions, subjects try to avoid competing with the expert jump bidder as summarized in Table 3.9 below:

Table 3.9 Results of Subjects Choice of Auction to Participate in:

| Scenario | Choose Auction with Expert | Choose Auction without Expert | Z | P-value |
|---|---|---|---|---|
| 1 | 28.57% | 71.43% | 3.07 | <0.01 |
| 2 | 28.57% | 71.43% | 3.07 | <0.01 |
| 3 | 35.00% | 65.00% | 1.99 | <0.05 |
| 4 | 26.32% | 73.68% | 3.31 | <0.01 |

*3.5.3 Discussion of Study 3*

An expert is someone widely recognized as a reliable source of technique or skill whose faculty for judging or deciding rightly, justly, or wisely is accorded authority and status by their peers (Alba and Hutchinson 1987). In the context of an online auction, an expert could be a bidder who is familiar with the auctioned item and/or the bidding process. Therefore, she could be a reliable source for value information. Hence, whether a jump bidder is perceived as an expert could be an important moderator of the effect of jump bidding. The results of Study 3 are consistent with our conjecture. Other bidders' valuation was higher in auctions where the jump bidder was perceived as an expert. Interestingly, we also found that bidders would try to compete with experts.

**3.6 Study 4: Field Experiment on a Local Auction Website**

The purpose of Study 4 is to examine the effects of jump bidding in real-world ascending online auctions with multi-rounds of bidding. We also examine two moderators of the effects of jump bidding: timing of jump bidding and the auction type (whether an auction is a charity auction or not).

Study 4 was conducted on a local Internet auction site that was under complete control of the researchers. The auction website was constructed in September 2002, and had more than 4,000 registered members at the time of the data collection. One unique characteristic of this website is that both jump bidding and proxy bidding are allowed at the same time. These are therefore second price auctions with a first price twist; when the winning bidder uses a jump bid, this is a first price auction; otherwise it is a second price auction.

*3.6.1 Data Description*

We collected the data in November 2005. Among the 326 auctions in the dataset, 199 auctions were charity auctions with 100 percent of the proceeds donated to a local charity organization and 127 auctions were non-charity auctions without donations. All of these auctions were posted by the same seller and had a starting price of $0.01. There was no reserve price in these auctions. All of the charity auctions ran for fifty-four hours, while the non-charity auctions ran for about twenty-four hours. The information collected includes the auction characteristics and the bidding history of each bidder in an auction. Auction characteristics include the ending price, the number of bids, and the number of bidders. The bidding history includes each bidder's name, time of bidding, proxy-bidding amount, and jump bidding amount. We also collected the information of the retail price of each product. We divided the auction process into three stages: The beginning stage spans the first 25 percent of the auction duration; the last 25 percent, the closing stage, and the 50 percent in between, the middle stage. We then calculated the cumulative amount of jump bidding in each stage.

On average, 26.8 percent of the price increase, in the beginning stage of the charity auctions, was realized by jump bidding. This price increase is significantly different from the 16.4 percent price increase due to jump bidding in non-charity auctions ($Z=2.30$, $p<0.05$). This result is consistent with the findings of Popkowski Leszczyc and Rothkopf (2007) that bidders bid more aggressively in charity auctions because of their charitable intent. Table 3.10 summarizes the statistics of the key variables we use to estimate our model:

Table 3.10 Descriptive Summary of Variables

| **Variable** | **Mean** | | **Std** | |
|---|---|---|---|---|
| Donation | 100% | 0% | 100% | 0% |
| Number of bidders | 9 | 6 | 2.71 | 2.67 |
| Retail price | 1,730.24 | 77.99 | 3,905.28 | 110.98 |
| Ending price | 1,524.21 | 64.96 | 3,698.61 | 137.57 |
| Ratio of ending price to retail price | 0.93 | 0.86 | 0.37 | 0.33 |
| Cumulative amount of jump bidding in the closing stage of an auction (ratio to the retail price) | 4.02% | 8.49% | 6.79% | 11.00% |
| Cumulative amount of jump bidding in the middle stage of an auction (ratio to the retail price) | 8.98% | 6.28% | 14.40% | 7.39% |
| Cumulative amount of jump bidding in the starting stage of an auction (ratio to the retail price) | 26.81% | 16.44% | 16.65% | 17.56% |
| Proxy-bidding amount (ratio to the retail price) | 85.49% | 86.77% | 65.86% | 56.93 |
| Number of bids | 19 | 12 | 6.40 | 6 |
| Donation | 100% donation = 60%<br>0% donation = 40% | | | |

## *3.6.2 Model Specification*

A recursive model with two equations was constructed for the purpose of further testing our conceptual model. The dependent variable for the first equation is the logarithm of the number of bidders. The dependent variable for the second equation is the logarithm of the ratio of the ending price of auctions to the retail price of products. The dependent variable for the first equation is one of the independent variables for the second equation. Both equations are linear. We include a dummy variable for the auction type: the charity auctions are indicated by 1 and the non-charity auctions are indicated by 0.

The specifications of the two equations are as follows:

$$Lnbr_i = \alpha_0 + \alpha_1 Ltproxy_i + \alpha_2 Dona_i + \alpha_3 Ljpc_i + \alpha_4 Ljpm_i + \alpha_5 Ljps_i + \alpha_6 Dona * Ljpc_i + \alpha_7 Dona * Ljpm_i + \alpha_8 Dona * Ljps_i + e_{i1} \tag{3.4}$$

$$Lpr_i = \beta_0 + \beta_1 Lnbr_i + \beta_2 Dona_i + \beta_3 Ltproxy_i + \beta_4 Ljpc_i + \beta_5 Ljpm_i + \beta_6 Ljps_i + \beta_7 Dona_i * Ljpc_i + \beta_8 Dona * Ljpm_i + \beta_9 Dona * Ljps_i + e_{i2} \tag{3.5}$$

We show the definition of variables in Table 3.11 below:

Table 3.11 List of Variables

| Variable | Definition |
|---|---|
| *Lnbr* | Logarithm of the number of bidders in an auction. |
| *Lpr* | Logarithm of the ratio of the ending price to the market value of an item |
| *Ljpc* | Logarithm of the ratio of the cumulative dollar amount of jump bids in the closing stage of an auction to the market value of an item |
| *Ljpm* | Logarithm of the ratio of the cumulative amount of jump bids in the middle stage of an auction to the market value of an item |
| *Ljps* | Logarithm of the ratio of the cumulative dollar amount of jump bids in the starting stage of an auction to the market value of an item |
| *Ltproxy* | Logarithm of the cumulative dollar amount of proxy bids in the auction |
| *Dona*Ljps* | Interaction term between *Uncb* and *Ljps* |
| *Dona*Ljpc* | Interaction term between *Uncb* and *Ljpc* |
| *Dona*Ljpm* | Interaction term between *Uncb* and *Ljpm* |
| *Dona* | Dummy variable of auction type:<br>100 % donation =1, 0 % donation = 0 |

### 3.6.3 *Results of Study 4*

The detailed results of the model estimation are shown in Table 3.12.

Table 3.12 Parameter Estimates for the Recursive Model

| **The Number of Bidders Equation** | | | | |
|---|---|---|---|---|
| Explanatory variable | Coefficient estimate | Standard error | *t*-value | P-value |
| *Intercept* | -2.440 | 0.139 | -17.544 | < 0.001 *** |
| *Lproxy* | 0.238 | 0.025 | 9.499 | < 0.001*** |
| *Ljpc* | 0.002 | 0.013 | -0.114 | 0.909 |
| *Ljpm* | -0.014 | 0.015 | -0.973 | 0.331 |
| *Ljps* | -0.035 | 0.015 | -2.247 | 0.025** |
| *Dona* | -1.792 | 0.215 | -8.353 | <0.001 *** |
| *Dona*Ljpc* | 0.005 | 0.016 | 0.300 | 0.765 |
| *Dona*Ljpm* | 0.042 | 0.018 | 2.362 | 0.019** |
| *Dona*Ljps* | 0.275 | 0.098 | 2.817 | 0.005** |
| **The Ending Price Equation** | | | | |
| Explanatory variable | Coefficient estimate | Standard error | *t*-value | P-value |
| *Intercept* | -0.024 | 0.092 | -0.259 | 0.796 |
| *Dona* | 1.010 | 0.112 | 9.035 | < 0.001 *** |
| *Lnbr* | 0.070 | 0.026 | 2.645 | 0.009*** |
| *Lproxy* | 0.062 | 0.013 | 4.650 | <0.001 *** |
| *Ljpc* | 0.011 | 0.006 | 1.809 | 0.071* |
| *Ljpm* | 0.017 | 0.007 | 2.416 | 0.017** |
| *Ljps* | 0.045 | 0.007 | 6.123 | <0.001 *** |
| *Dona*Ljpc* | -0.003 | 0.008 | -0.423 | 0.673 |
| *Dona*Ljpm* | -0.011 | 0.008 | -1.295 | 0.196 |
| *Dona*Ljps* | 0.457 | 0.047 | 9.777 | <0.001 *** |
| Signif. codes: *** = .01; ** = .05; * = .1. | | | | |

* Closing stage, 25% of the duration; middle stage, 50% of the duration; beginning stage, 25% of the duration.

The results again indicate that jump bidding may have both a direct positive and an indirect negative effect on the ending price. Furthermore, these effects are time contingent, and diminish as the auction proceeds to the end (in the starting stage: $\beta_6 = 0.045$, p<0.001; the middle stage: $\beta_5 = 0.017$, p<0.05; and the ending stage $\beta_4 = 0.011$, p=0.071). In addition, jump bidding during the early stages of an auction has a significantly stronger direct positive effect for charity auctions ($\beta_9 = 0.457$, p<0.001).

Jump bidding also has an indirect negative effect on selling prices, during the starting stage of the auction ($\alpha_5 = -0.035$, p<0.05) by reducing bidder entry. However, in the case of a charity auction, jump bidding has a positive effect on bidder entry, during the starting stage and the middle stage of the auction ($\alpha_8 = 0.275$, p<0.01; $\alpha_7 = 0.042$, p<0.05).

Furthermore, charity auctions tend to reduce bidder entry, but lead to higher selling price. The negative effect on bidder entry may be due to increased jump bidding during the beginning stages of charity auctions. Finally proxy bids have a positive effect on both bidder entry and selling prices.

*Endogeneity of Jump bidding*. One possible limitation of the above model is that jump bidding itself may be impacted by other explanatory variables. However, using jump bidding as an explanatory variable adds considerable insights and improves the model fit, without significantly impacting the results of the other explanatory variables. Furthermore, we conducted additional analyses using jump bidding as a dependent variable and proxy bidding, auction type, and the number of bidders as independent variables. Only the coefficient of auction type is significant. Hence, we do not observe a serious endogeneity problem.

### *3.6.4 Discussion of Study 4*

Study 4 was conducted as a field study in a real-world ascending-auction context with multi-rounds of bidding. The results of Study 4 provide further evidence of the dual effect of jump bidding. On the one hand, jump bidding has a deterrence of entry effect resulting in fewer bidders, which results in an indirect negative effect on selling price. On the other hand, jump bidding may reveal a bidder's private information or signal strength, and, conditional on bidder entry, leads to higher selling prices.

The results of Study 4 indicate that the timing of jump bidding is an important moderator of the effect of jump bidding. Jump bidding at different stages of the bidding process will have different signaling power and varying impact on the information structure, which may alter the bidding process. Early jump bidding may play a more important role in the value-construction process when bidders may have more limited private information.

We find that jump bidding has a greater impact on both bidder entry and selling prices during the earlier stages of an auction. This is consistent with results from Easley and Tenorio (2004) who concluded that bidders are more likely to jump bid early in an auction when the current price is lower and jump bidding is less costly. However, different from Easley and Tenorio (2004), we report a significant positive effect of jump bidding on ending prices.

Study 4 also indicates that whether an auction is a charity auction is an important moderator of the effects of jump bidding. Early jump bidding has a positive effect on both bidder entry and selling prices in charity auctions. These findings are consistent with the finding that charitable-intent bidders try to drive up prices in charity auctions (Popkowski, Leszczyc and Rothkopf 2007).

Proxy bidding has a positive effect on selling prices. Similar to jump bidding, higher proxy bids tend to reveal a bidder's private information, leading to higher prices. Finally, proxy bidding tends to increase bidder entry, different from jump bidding, which deters entry.

### 3.7 General Discussion and Conclusion

Previous research contains two opposite views on jump bidding: the strategic view and the non-strategic view (Isaac et al. 2007). In the strategic view, the motivation of jump bidding is to signal bidding aggressiveness or high valuation. Based on this presumption, the conclusion that jump bidding is effective in deterring bidder entry is derived from game theoretical models. This conclusion implies that jump bidding has a negative effect on the ending price (e.g., Avery 1998). In the non-strategic view, jump bidding is either a mean to saving time or an irrational behavior that can lead to a higher ending price (e.g., Banks et al. 2003), because jump bidding makes a jump bidder relinquish the chance of winning an auction with a lower price, and it also reveals a bidder's high valuation to other bidders.

The controversy of the motivations and the effects of jump bidding and the lack of empirical testing on the conclusions of the existing theories make the further investigation of the phenomenon of jump bidding necessary. The development of online auctions makes this kind of investigation possible

In this paper, we developed a conceptual model that extends previous theories on the effect of jump bidding. We propose that jump bidding may signal the jump bidder's strength or high valuation. This signaling may result in two different behaviors. 1) It can deter bidder entry, and then has an indirect negative effect on the ending price; and 2) It has a positive effect on other bidders' valuation, hence it has a direct positive effect on the ending price. Therefore, jump bidding is like a double-edged sword in regards to the effect on ending price.

The effect of jump bidding is also moderated by different factors, such as the timing of jump bidding, the degree of value certainty, the level of expertise of the jump bidder, and whether an auction is a charity auction. The timing of jump bidding and whether a jump bidder is perceived to be an expert are related to the signaling power of jump bidding. The degree of value certainty and whether an auction is a charity auction are factors that influence bidders' interpretation of the signal of jump bidding. The aggregated effect of jump bidding on the ending price could be positive, negative or neutral, depending on whether the positive effect or the negative effect dominates. Our conceptual model emphasizes the importance of the information revealed by jump bidding in other bidders' valuation-formation processes.

We conducted three lab experiments and a field experiment to test our conceptual model. Results of these experiments provide support for our conceptual model that jump bidding has both a direct positive and an indirect negative effect on the ending price in an auction. The direct positive effect suggests that by placing a jump bid, a bidder may reveal her or his strategy, which leads to higher ending prices. This effect was stronger for charity auctions in the field experiment. The indirect negative effect on selling prices depends on jump bidding's ability to deter bidder entry. The influence of the four above-mentioned moderators on the effects of jump bidding has also been supported by our studies.

*Managerial Implication of this Research.* The findings of this paper have implications for both bidders and sellers in online auctions. Bidders in online auctions should be aware of the two potential effects of jump bidding and the various factors that may influence the aggregated effect of jump bidding on the ending price. They should be careful in choosing whether and when to jump bid. They should also react carefully to other bidders' jump bids. Sellers of online auctions have to abide by the rules established on different online websites. Some online auction websites allow for jump bidding, whereas others do not. When choosing a website on which to sell, sellers should pay attention to whether jump bidding is allowed and be aware of the effects of jump bidding and the moderators of these effects. Such knowledge of jump bidding may help sellers to manipulate the characteristics of auctions in strategic ways. For example, they may choose to vary the details of the product's information in the description to influence the strength of the effects of jump bidding.

*Future Research.* Research is needed to investigate the motivations of jump bidding. To our knowledge, no research thus far has investigated the motivations of jump bidding in a systematic way. In the current literature, explanations for jump bidding are mainly presumptions in analytical models. Determining rationales for this behavior, especially whether it is used in a strategic way by rational bidders, is important to fully understand jump bidding.

Another promising area for researchers is to investigate other factors that influence the size and the direction of the effect of jump bidding. In this paper, we studied four factors: 1) bidders' degree of value uncertainty, 2) the timing of jump bidding; 3) the perceived expertise of the jump bidder, and 4) the type of auction (whether an auction is a charity auction or not). Other factors may include the characteristics of the jump bidder (the information provider) and other bidders (the information receivers). One characteristic that may be important and common to a jump bidder and other bidders is experience level. On the one hand, the effects of jump bidding may depend on the credibility of the value information. An experienced bidder's jump bid may make the information of high value more credible and cause other bidders to reassess and reformulate their own valuation. Meanwhile, some bidders may not want to compete with an experienced jump bidder and simply stop bidding. Therefore, other things being equal, an experienced bidder's jump bidding might have a stronger positive effect and also a negative effect on the ending price than would that of an inexperienced bidder. On the other hand, a bidder's experience level may influence how he or she reacts to the information conveyed by a jump bid. In other words, a jump bidder's behavior might exert greater influence over inexperienced bidders as compared to more experienced bidders.

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# Chapter 4

## General Discussion

With the fast growth of online auctions, there is an increasing need for research on consumers' strategic behaviour and consumers' learning to use optimum strategies in a dynamic decision-making context. The two essays in my dissertation were written to meet this need and make the following contributions to the literature:

The first essay use longitudinal data for the first time in the marketing area to study how bidders learn to employ bidding strategies in online auctions. The longitudinal data consist of the bidding history of both experienced and inexperienced coin collectors on eBay in a four month period. Such kind of data allows me to compare the difference of learning between inexperienced bidders and experienced bidders on various aspects of their decision-making in online auctions. Multi-level modeling technique was used to analyze the data, which makes it possible for me to study the rate of behavioral change on the individual level and examine the inter-individual differences in the rate of change. I find learning exists ubiquitously among inexperienced bidders but not among experienced bidders. Inexperienced bidders learn to strategically make a series of decisions on entering time, bidding amount, responding time when being outbid, and maximum WTP. Compared to cross-sectional studies, results of my first essay eliminate the confounding explanations, if any, for the behavioral differences between experienced and inexperienced bidders. Hence, my study has high internal validity. Since real auction data were used the results also have high external validity.

In the second essay, I construct a conceptual model to directly address the controversy in the literature regarding the effects of jump bidding on bidder valuation and auction ending price and provide a general theoretical model for the effects of jump bidding. My model is based on the notion of information integration in bidders' valuation construction process, which is common in traditional and online ascending auctions. Therefore, the conclusions of the model can be generalized to traditional ascending auction environments although I test the model using online auction data. I empirically test the model using real world online auction data and laboratory experiment data. I find support for the conclusion of the conceptual model that jump bidding has a dual effect on the ending price. I also discuss managerial implications for sellers on how to employ bidding rules regarding minimum increments, jump bidding and proxy bidding options.

Despite of the aforementioned contributions, there are some limitations that need to be pointed out regarding the two essays of my dissertation:

In the first essay, a better time trend variable needs to be found for the multilevel models. Although the use of the cumulative number of auctions or bids as a time trend variable acknowledges the importance of consumer learning by participating in auctions, it does not allow me to examine the learning difference in winning and losing auctions. By controlling for bidders' winning or losing, we find bidders employ different bidding strategies in auctions they won and lose, which means that learning could depend on bidders' experience of winning and losing.

A comprehensive model that includes different decision-making aspects will also be an area of future research. Estimating the decision aspects separately does not address the issue of possible contingency among different decision making aspects although theoretically it may not be serious problem due to the fact that the bidding decisions we examined are usually made in a sequence. For example, after a bidder entered an auction, she did not know whether she would be outbid. Therefore, this bidder's decision on entering time is not contingent on her decision on responding time when being outbid.

Consumer learning to use other optimum bidding strategies in online auctions is another promising research area. For example, consumer learning to use snipe bidding strategy, which makes late bidding go to an extreme extent. Snipe bidding is effective in dealing with incremental bidders and hiding private information but has high probability of failing due to large traffic in the last moment of an auction or existing high proxy bid (Roth and Ockenfels 2006). Therefore, learning can play a role in optimum timing of late bidding. Consumer can also learn to use jump bidding or respond to jump bidding strategically.

For the second essay, further research is needed to investigate the motivations of jump bidding. In the current literature, explanations for jump bidding are mainly presumptions in analytical models. I also presume and explain jump bidding as if it is a strategy in my conceptual model. Without a systematic investigation of the reasons behind bidders' jump bidding behavior, our understanding of jump bidding is not complete. Determining the rationales for jump bidding behavior in different decision making context, especially identify whether jump bidding is used in a strategic way and if so under what conditions, is important to fully understand jump bidding.

Another promising area for researchers to further investigate is to examine the factors influencing the directions and the size of jump bidding's effects. In the second essay, we studied only four factors: 1) value uncertainty, including bidders' own value uncertainty and bidder's uncertain of jump bidder's value; 2) the timing of jump bidding; 3) the perceived expertise of the jump bidder, and 4) the type of auction (whether an auction is a charity auction or not). These factors belong to three categories: characteristics of the information receiver, characteristics of the information provider, and characteristics of the decision making environment respectively. Other factors that belong to the three categories are also important to study.

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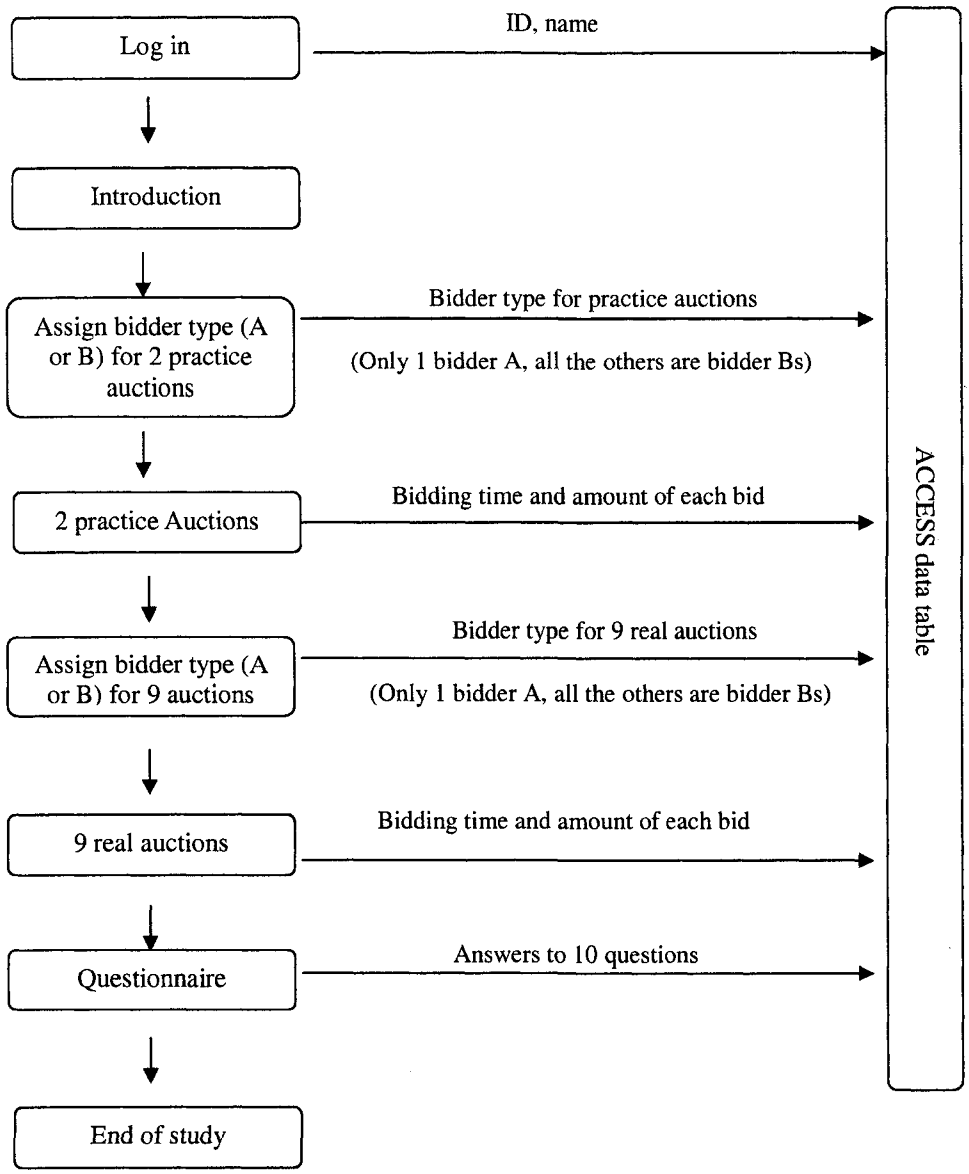
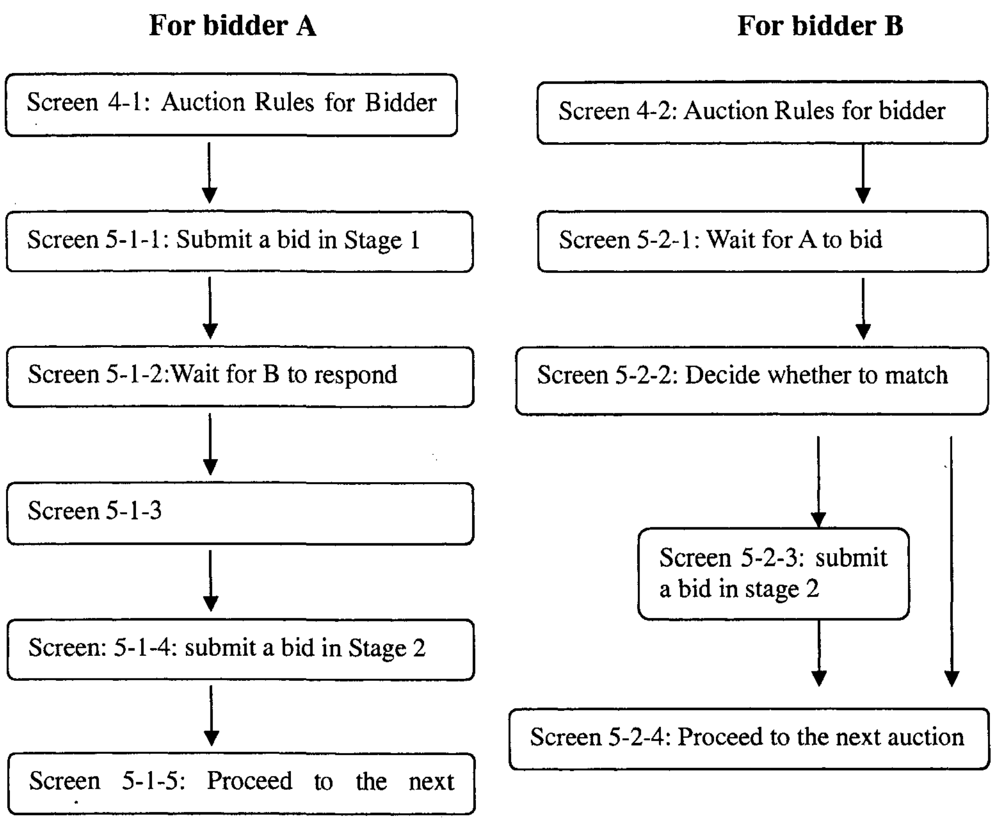
**Appendix A: Experiment script in Study 1 of Essay 2.**

1) General flowchart:



2) Flowchart of each auction ( using the 1st practice auction as an example)



3) Screens

*Screen 1: Log In*

Welcome to the Online Auction Study! To log in to this study, please provide your student ID and name below.

Your student ID: [ ]

Your name: [ ]

Log In

*Screen 2: Introduction*

Welcome to the online auction study! In this study, you will be participating in several online auctions for different hypothetical products.

During the study please remain seated and do not communicate with any of the other participants. You will need to remain seated till all participants are finished with the study.

Please pay good attention to the following instructions as you can earn cash by participating in this study!

**How does the auction work?**

At the beginning of each auction, you will be given a specific value for the hypothetical product in that auction. In some auctions, you will be told of the competing bidder's value. While in other auctions, you will only be told of the range from which the competing bidder's value is drawn. If, for example, the competing bidder's value is drawn from a range between $0-100, each value in this range is equally likely to be the value of the competing bidder.

After you receive your value, the auction will start. You will only be participating against 1 other bidder. At the start of each auction a different bidder will be randomly assigned to you. To determine who will start the bidding you will be randomly assigned as either bidder A or bidder B (this designation will remain the same across all auctions).

Each auction will consist of two stages. In the first stage, bidder A first places a bid, and next bidder B decides whether to match this bid or not. If bidder B decides not to match the bid, bidder A wins the auctions. If bidder B matches the bid, the auction proceeds to stage 2. In stage 2, each bidder simultaneous places a single bid. Hence, you only get to place one bid and before you bid you do not get to see the bid of the other bidder. The bidder with the highest bid wins the auction.

Note that at the beginning of each new auction you will be given a new value for the hypothetical product. Hence, the values you receive for the different auctions are not related to one another

**How much can I earn?**

The amount you earn will depend on your performance – it is based on your bidding decisions in the auctions in this study. If you win an auction, you will get the difference between the value of your product and the amount of your bid. If you lose the auction, you will get $0. If you bid above your value and win, that amount will be deducted from your balance. The amount you get will accumulate with each auction.

The amount in your account is in experimental dollars, which are worth $0.025 each. The result of each auction will not be provided during the study. You will be notified of the final result of your performance in the study by email within 2 weeks after the study.

By clicking the following button, you officially agree to participate in this study and proceed to the practice auctions.

Click Here to Proceed

*Screen 9-1: Assigned as bidder A*

You are assigned as ***bidder A***.

As bidder A, you will always get to place the first bid in the first stage of the auction. After you place a bid, please wait for bidder B to decide whether he/she matches your bid.

Note, if Bidder B decides not to match your bid, you win the auction. As the winner, you will receive the difference between the value provided to you and the amount of your bid. If bidder B decides to match your bid, you will continue to stage 2, where both of you get to place another bid.

For example, your value is $100, and you decide to place a bid of $60 in the first stage. If bidder B does not match your bid you will win $40 ($100 – 60). If bidder B matches the bid, the auction continues to the second round, and lets say you place a bid of $80. If you win you will receive $20 ($100 - $80). If you lose you will receive nothing.

Next we will start with the first auction, after the auction starts you will have 30 seconds to place your bid.

You are assigned: Bidder A,
Your current balance is: $0.00 (experimental dollars)

Click Here to Start the Practice Auctions

*Screen 9-2: Real auctions- for bidders who are assigned as bidder B*

You are assigned as ***bidder B.***

As bidder B, in the first stage, you have to decide whether to match the bid placed by bidder A. If you decide not to match the bid, Bidder A will win the auction. If you decide to match Bidder A's bid, you will continue to stage 2, where both of you get to place another bid.

Please note that there will be a cost to you for placing a bid in the first round, which may vary from $0-$10. There will not be a cost for placing a bid in the second round! You have a starting balance of $100 in your account, the bidding costs will be deducted from your balance.

For example, your value is $100 and the bidding cost is $10. Bidder A places a bid of $60 in the first stage, and you decide to match the bid. Next you place a bid of $70 in the second stage. If you win you will receive $20 ($100 - $70 - $10 –bidding cost). If you lose you will receive nothing but still have to pay the $10 bidding cost. Either the +$20 or the -$10 is added to your account.

Next we will start with the first auction. First bidder A will place a bid, after this you will have 15 seconds to place a bid.

You are assigned: Bidder B,
Your current balance is: $200.00 (experimental dollars)

Click Here to Start the Practicing Auctions

*The 1st real auction: (condition 1: high aggressiveness, high bidding cost, high value uncertainty, product 1: $101.99, jump bid $76.50. range: $0-$204)*

*Screen R1-1-1: for bidder A*

***Auction 1- Stage 1: The ascending auction.***

Your value for the hypothetical product in this auction is $101.99. Please place your bid amount within the range specified below. Next wait for the other bidder to decide whether to match your bid. Please note that the value you receive for this auction is not related to values you receive for other auctions.

| **Hypothetical Product 1** | |
|---|---|
| **Starting bid** | **$76.50** |
| **Next bid** | **$76.50** |
| **Note: Next bid is the minimum amount of any additional bid** | |
| ***The auction will start in X seconds.*** | ***Time left: XX seconds*** |
| **Your bid:** [ ] | **(Between $76.5 and $81.5)** Submit |

*Screen R1-1-2 : What bidder A will see after submitting his/her bid*

***Please wait for Bidder B to decide whether to match your bid.***

*Screen R1-1-3: What bidder A will see*

***Bidder B has decided to MATCH your bid.***

Click Here to Proceed

*(Proceed to the first price sealed bid auction. Screen R1-1-4.)*

*Screen R1-1-4: What bidder A will see*

***Auction 1-Stage 2: The first price sealed-bid auction***

In the second stage, each bidder gets to place a single bid. The bid is "sealed" such that the other bidder does not know the amount of your bid. After both bids have been submitted the winner is determined – the winner is the bidder with the highest bid.

Your bid amount: [ ] Submit

*Screen R1-1-5: Proceed to the next auction*

***The current auction has ended. Please proceed to the next auction.***

Click Here to Proceed

*( Proceed to the next real auction.)*

*Screen R1-2-1: for Bidder B*

***Auction 1- Stage 1: The ascending auction.***

Your value for the hypothetical product in this auction is $101.99. The competing bidder, bidder A's value is randomly drawn from the range of $0-$204. Any number in the range of $0-$204 is equally likely to be bidder A's value. Therefore, bidder A's value is uncertain. Please wait for Bidder A to place his/her bid and then decide whether you want to match his/her bid. Please note that the value you receive for this auction is not related to values you receive for other auctions.

***The initial balance in your account is: $ 100.00 (experimental dollars)***

## Hypothetical Product 1

**Bidder A is placing a bid.**

*Screen R1-2-2: After bidder A placed a bid*

## Hypothetical Product 1

***Bidder A has placed a bid of $$.*** ***Time left for your decision: XX seconds***

**Do you want to match bidder A's bid?** YES NO

**( The bidding cost is $9.00)**

*(If Bidder B click Yes button, proceed to the first price sealed bid auction Screen R1-2-3. If Bidder B click NO button, proceed to Screen R1-2-4)*

*Screen R1-2-3:*

***Auction 1-Stage 2: The first price sealed-bid auction***

In the second stage, each bidder gets to place a single bid. The bid is "sealed" such that the other bidder does not know the amount of your bid. After both bids have been submitted the winner is determined – the winner is the bidder with the highest bid.

Your Bid amount: [      ] [Submit]

*Screen R1-2-4:*

***The current auction has ended. Please proceed to the next auction.***

[Click Here to Proceed]

*(Proceed to the next real auction.)*

4) Qestionnaire

(Note: A summary of each round of auction will be provided at the end of the 8 rounds of auctions.)

Please answer the following questions:

1. How aggressive was the bidder you competed with in each auctions?

| | Not aggressive 1 | 2 | 3 | Neutral 4 | 5 | 6 | Aggressive 7 |
|---|---|---|---|---|---|---|---|
| The bidder in Auction 1: | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |
| The bidder in Round 2: | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |
| The bidder in Round 3: | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |

The bidder in
Round 4:

☐ ☐ ☐ ☐ ☐ ☐ ☐

The bidder in
Round 5:

☐ ☐ ☐ ☐ ☐ ☐ ☐

The bidder in
Round 6:

☐ ☐ ☐ ☐ ☐ ☐ ☐

The bidder in
Round 7:

☐ ☐ ☐ ☐ ☐ ☐ ☐

The bidder in
Round 8

☐ ☐ ☐ ☐ ☐ ☐ ☐

2. To what extent did the bidder you compete with in each round of the auctions lead you to bid more than you planned to?

| | Not at all | | | Neutral | | | Very much |
|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| The bidder in Round 1: | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |
| The bidder in Round 2: | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| The bidder in Round 3: | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |
| The bidder in Round 4: | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |
| The bidder in Round 5: | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |
| The bidder in Round 6: | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |
| The bidder in Round 7: | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |
| The bidder in Round 8 | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |

**3. To what extent did the bidding cost prevents you from competing with the other bidder?**

| | Not aggressive 1 | 2 | 3 | Neutral 4 | 5 | 6 | Aggressive 7 |
|---|---|---|---|---|---|---|---|
| The bidder in Round 1: | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |
| The bidder in Round 2: | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |
| The bidder in Round 3: | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |
| The bidder in Round 4: | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |

The bidder in Round 5: ☐ ☐ ☐ ☐ ☐ ☐ ☐

The bidder in Round 6: ☐ ☐ ☐ ☐ ☐ ☐ ☐

The bidder in Round 7: ☐ ☐ ☐ ☐ ☐ ☐ ☐

The bidder in Round 8 ☐ ☐ ☐ ☐ ☐ ☐ ☐

**4. Do you have any other thoughts or comments concerning this auction?**

------------------------------------------------------------------------------------------------

------------------------------------------------------------------------------------------------

------------------------------------------------------------------------------------------------

**5. Please indicate your level of knowledge about bidding in an auction:**

| Not knowledgeable | | | Neutral | | | Knowledgeable |
|---|---|---|---|---|---|---|
| 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |

| Not competent | | | Neutral | | | Competent |
|---|---|---|---|---|---|---|
| 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |

| Not expert | | | Neutral | | | Expert |
|---|---|---|---|---|---|---|
| 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |

| Not experienced | | | Neutral | | | Experienced |
|---|---|---|---|---|---|---|
| 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |

## Appendix B: Questionnaire in Study 2 of Essay 2

1) Conditions:

| | Value certainty $159.99 | Value uncertainty $139.99 – $179.99 |
|---|---|---|
| Jump bid amount $99.00 | C1 | C2 |
| Jump bid amount $0 | C3.1 & C3.2 | C4.1 & C4.2 |

C3.1 vs. C1, same after-jump current prices $99.00;
C3.2 vs. C1, same before-jump current prices $10.00;
C4.1 vs. C2, same after-jump current prices $99.00;
C4.2 vs. C2, same before-jump current prices $10.00.

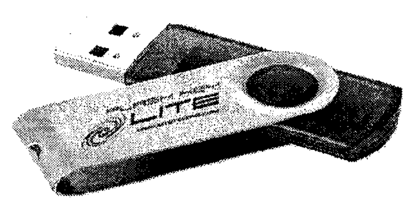
2) Questionnaire in condition C1:

**Introduction**

Below you will see some images of an online auction in progress. Please study the images carefully, as you will be asked some questions related to the auction. The auction you are going to examine is an online "English" or ascending bid auction for a **new Cyclone 6 GB flash key drive.** In this "English" or ascending bid auction, the bidder who places the highest bid wins the auction and pays the amount of her/his bid.

*The Auction*

**NEW Cyclone 6 GB Flash Key Drive Free Shipping**



| | |
|---|---|
| **Current Price:** | **CA $10.00** |
| **Bid History:** | **5 bids** |
| **Highest Bidder:** | **Summer2** |
| **Next bid:** | **CA $11.00** |

*Note:*

Next bid is the minimum amount of any additional bid.

**Description**

**Factory sealed package with 1 year warranty**
**Money back guarantee if not satisfied**

**Retail price: CA $159.99**

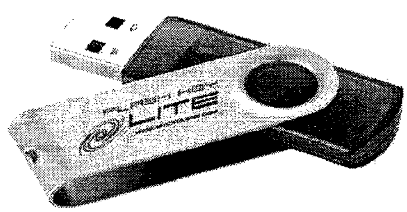
- High speed USB 2.0 certified;
- Silver swing cap;
- Case color: dark blue.

*5 minutes and 25 seconds later*

***Sunnyday* placed a jump bid of CA $99.00. He/she becomes the highest bidder and the current price increases to CA $99.00.**

A jump bid implies that the bidder places a bid that is larger than the minimum required bid increment; this is called *jump bidding*. For example, the current price is $4, and the minimum required bid is $5.00 (the high bid plus the minimum bid increment). If the bidder places a jump bid of $10, the current price will immediately jump to $10, instead of $5, the minimum required bid.

**NEW Cyclone 6 GB flash key drive Free Shipping**



| | |
|---|---|
| **Current Price:** | **CA $99.00** |
| **Bid History:** | **6 bids** |
| **Highest Bidder:** | **Sunnyday** |
| **Next bid:** | **CA $101.00** |

*Note:*

Next bid is the minimum amount of any additional bid.

**Description**

**Factory sealed package with 1 year warranty**
**Money back guarantee if not satisfied**

***Retail price:* CA $159.99**

- High speed USB 2.0 certified;
- Silver swing cap;
- Case color: dark blue.

**1. Please answer the following questions about the above auctions:**

**Indicate your level of agreement with the following statements:**

1a. The bidder ***Sunnyday*** is very aggressive in the auction shown above.

| Strongly disagree 1 | 2 | 3 | Neutral 4 | 5 | 6 | Strongly agree 7 |
|---|---|---|---|---|---|---|
| ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |

1b. The bidder ***Sunnyday*** will bid whatever is needed to win the auction.

| Strongly disagree 1 | 2 | 3 | Neutral 4 | 5 | 6 | Strongly agree 7 |
|---|---|---|---|---|---|---|
| ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |

1c. The bidder ***Sunnyday's*** bid will lead to an ending price that is close to the retail price.

| Strongly disagree 1 | 2 | 3 | Neutral 4 | 5 | 6 | Strongly agree 7 |
|---|---|---|---|---|---|---|
| ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |

**2. Imagine you need to purchase a Cyclone 6 GB flash key drive (either because you really need one or as a present for a friend). The item you need is identical to the model in the auction above.**

**You have seen this model at a local retail store for CA $159.99. However, while shopping you see the ABOVE ongoing auction, from a reputable retailer.**

**Rather than just going to the store and paying the retail price, you decide to participate in the <u>ABOVE</u> auction. If you were allowed to place a single bid, how much would you bid? Please note that if you are the winner, you will have to pay the amount of your bid.**

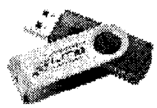
2a. My bid would be CA $ _______.

2b. To what extent do you think ***Sunnyday***'s bid influenced your bid amount?

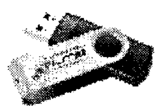
| Not at all 1 | 2 | 3 | Neutral 4 | 5 | 6 | Very much 7 |
|---|---|---|---|---|---|---|
| ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |

2c. Below you see the bidding history of two auctions in progress.

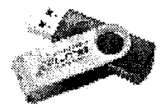
**Auction 1**

| NEW Cyclone 6 GB flash key drive | | |
|---|---|---|
|  | **Current Price:** | **CA $10.00** |
| | **Highest Bidder:** | ***Summer2*** |
| | **Next bid:** | **CA $11.00** |

***After Sunnyday placed a*** ***<u>jump bid</u> of CA 99.00***

| NEW Cyclone 6 GB flash key drive | | |
|---|---|---|
|  | **Current Price:** | **CA $99.00** |
| | **Highest Bidder:** | ***Sunnyday*** |
| | **Next bid:** | **CA $101.00** |

**Auction 2**

| NEW Cyclone 6 GB flash key drive | | |
|---|---|---|
|  | **Current Price:** | **CA $97.00** |
| | **Highest Bidder:** | ***Mynote*** |
| | **Next bid:** | **CA $99.00** |

***After Teatree placed a*** ***<u>minimum bid</u> of CA $99.00***

| NEW Cyclone 6 GB flash key drive | | |
|---|---|---|
|  | **Current Price:** | **CA $99.00** |
| | **Highest Bidder:** | ***Teatree*** |
| | **Next bid:** | **CA $101.00** |

If you have to choose *one* of the above two auctions to participate in, which one would you choose?

**Auction 1 with a jump bidder** ☐

**Auction 2 without a jump bidder** ☐

**3. Please check one of the numbers below, indicating your level of knowledge about the auctioned product:**

| Not knowledgeable | | | Neutral | | | Knowledgeable |
|---|---|---|---|---|---|---|
| 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |

| Not experienced | | | Neutral | | | Experienced |
|---|---|---|---|---|---|---|
| 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |

**4. Please indicate your level of knowledge about bidding in an auction:**

| Not knowledgeable | | | Neutral | | | Knowledgeable |
|---|---|---|---|---|---|---|
| 1 | 2 | 3 | 4 | 5 | 6 | 7 |

| Not competent | | | Neutral | | | Competent |
|---|---|---|---|---|---|---|
| 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |

| Not expert | | | Neutral | | | Expert |
|---|---|---|---|---|---|---|
| 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |

| Not experienced | | | Neutral | | | Experienced |
|---|---|---|---|---|---|---|
| 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |

**Appendix C: Questionnaire in Study 3 of Essay 2:**

1) Conditions:

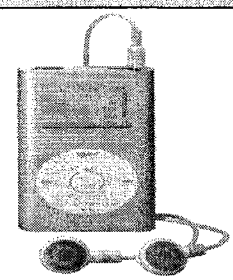
| | Value certainty<br>$169.99 | Value uncertainty<br>(No price information) |
|---|---|---|
| High level of experience | C1 | C2 |
| Low level of experience | C3 | C4 |

2) Questionnaire in condition C1:

**Introduction**

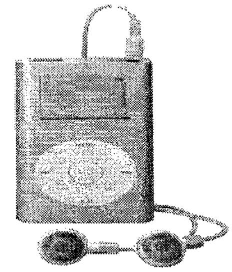
Below you will see some images of an online auction in progress. Please study the images carefully as you will be asked some questions related to the auction. The auction you are going to examine is an online "English" or ascending bid auction for an ***Ipod***. In this "English" or ascending bid auction, the bidder who places the highest bid wins the auction and pays the amount of her/his bid.

***The Auction***

<table>
<tr><td colspan="3">APPLE IPOD MINI 4GB - SILVER - MP3 PLAYER 4 GB MAC + PC Free Shipping</td></tr>
<tr><td rowspan="5"></td><td>Current Price:</td><td>CA $10.00</td></tr>
<tr><td>Bid History:</td><td>5 bids</td></tr>
<tr><td>Highest Bidder:</td><td>Summer (2)</td></tr>
<tr><td>Next bid:</td><td>CA $11.00</td></tr>
<tr><td colspan="2">Note:<br><br>Next bid is the minimum amount of any additional bid.</td></tr>
<tr><td colspan="3">Description</td></tr>
<tr><td colspan="3">New APPLE Ipod - 4GB<br>Factory sealed package with 1 year warranty<br>Money back guarantee if not satisfied<br><br>Retail price: CA $169.99<br><br>Now up to 1,000 songs<br>1.67-inch color display, 3.6 ounces, 2 x 0.5 x 3.6 inches<br>Up to 18 hours of battery life, 60% brighter display, and new search feature.</td></tr>
</table>

***<u>Now</u>***

*Apple-lover* **(525) placed a bid of CA $99.00. He/She becomes the highest bidder and the current price increased to CA$99.00.**

<table>
<tr><th colspan="3">APPLE IPOD MINI 4GB - SILVER - MP3 PLAYER 4 GB MAC + PC Free Shipping</th></tr>
<tr><td rowspan="5"></td><td>Current Price:</td><td>CA $99.00</td></tr>
<tr><td>Bid History:</td><td>6 bids</td></tr>
<tr><td>Highest Bidder:</td><td>Apple-lover(525)</td></tr>
<tr><td>Next bid:</td><td>CA $101.00</td></tr>
<tr><td colspan="2">Note:<br><br>Next bid is the minimum amount of any additional bid.</td></tr>
<tr><th colspan="3">Description</th></tr>
<tr><td colspan="3">New APPLE Ipod - 4GB<br>Factory sealed package with 1 year warranty<br>Money back guarantee if not satisfied<br><br>Retail price: CA $169.99<br><br>Now up to 1,000 songs<br><br>1.67-inch color display, 3.6 ounces, 2 x 0.5 x 3.6 inches<br>Up to 18 hours of battery life, 60% brighter display, and new search feature.</td></tr>
</table>

**Profile of the current high bidder Apple-lover(525):**

The current high bidder "apple-lover" is an experienced bidder who has successfully participated in over 525 auctions (as a bidder and/or a seller), mostly for computer and electronic products.

In addition, "apple-lover" has an online store, which sells Ipod related products.

**Please answer the following questions about the above auctions:**

**1. Please check one of the numbers below, indicating your perception of *<u>Apple-lover(525)</u>*'s knowledge about the auctioned product:**

| Not knowledgeable | | | Neutral | | | Knowledgeable |
|---|---|---|---|---|---|---|
| 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |

| Not experienced | | | Neutral | | | Experienced |
|---|---|---|---|---|---|---|
| 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |

**2. Please indicate your perception of *Apple-lover(525)*'s knowledge about bidding in auctions:**

| Not knowledgeable | | | Neutral | | | Knowledgeable |
|---|---|---|---|---|---|---|
| 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |

| Not competent | | | Neutral | | | Competent |
|---|---|---|---|---|---|---|
| 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |

| No expert | | | Neutral | | | Expert |
|---|---|---|---|---|---|---|
| 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |

| Not experienced | | | Neutral | | | Experienced |
|---|---|---|---|---|---|---|
| 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |

**3. Please indicate your level of agreement with the following statements**

3a. The bidder ***Apple-lover(525)*** knows clearly the value of the flash key drive in the above auction.

| Strongly disagree | | | Neutral | | | Strongly agree |
|---|---|---|---|---|---|---|
| 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |

3b. The bidder ***Apple-lover(525)*** is very determined in his bidding in the above auction.

| Strongly disagree | | | Neutral | | | Strongly agree |
|---|---|---|---|---|---|---|
| 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |

**4. Imagine you need to purchase an IPOD (either because you really need one or as a present for a friend). The item you need is identical to the model in the auction above.**

**You have seen this model at a local retail store for $169.99. However, while shopping you see the ABOVE ongoing auction, from a reputable retailer.**

**Rather than just going to the store and paying the retail price, you decide to participate in the ABOVE auction. If you were allowed to place only a single bid, how much would you bid? Please note that if you are the winner you will have to pay the amount of your bid.**

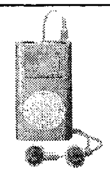
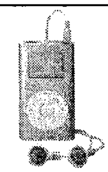
4a. My bid would be CA $ _______

4b. To what extent do you think ***Apple-lover(525)***'s bid influenced your bid amount?

| Not at all | | | Neutral | | | Very much |
|---|---|---|---|---|---|---|
| 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |

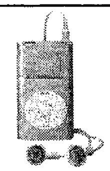
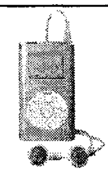
4c. Below you see the bidding history of two auctions in progress.

**Auction 1** **Auction 2**

| APPLE IPOD MINI 4GB - SILVER | | | | APPLE IPOD MINI 4GB - SILVER | | |
|---|---|---|---|---|---|---|
|  | **Current Price:** | **CA $10.00** | |  | **Current Price:** | **CA $10.00** |
| | **Highest Bidder:** | ***Summer(2)*** | | | **Highest Bidder:** | ***Mynote(1)*** |
| | **Next bid:** | **CA $11.00** | | | **Next bid:** | **CA $99.00** |

***Next, Apple-lover(525) placed a bid of CA 99.00***

***Next, Teatree(0) placed a bid of CA $99.00***

| APPLE IPOD MINI 4GB - SILVER | | | | APPLE IPOD MINI 4GB - SILVER | | |
|---|---|---|---|---|---|---|
|  | **Current Price:** | **CA $99.00** | |  | **Current Price:** | **CA $99.00** |
| | **Highest Bidder:** | ***Apple-lover(525)*** | | | **Highest Bidder:** | ***Teatree(0)*** |
| | **Next bid:** | **CA $101.00** | | | **Next bid:** | **CA $101.00** |

If you have to choose ***one*** of the above two auctions to participate in, which one would you choose?

**Auction 1 with *Apple-lover(525)*** ☐

**Auction 2 with *Teatree(0)*** ☐

Why?

________________________________________________________________________
________________________________________________________________________
________________________________________________________________________
________________________________________________________________________
_______

**5. Please check one of the numbers below, indicating your level of knowledge about the auctioned product:**

| Not knowledgeable | | | Neutral | | | Knowledgeable |
|---|---|---|---|---|---|---|
| 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |

| Not experienced | | | Neutral | | | Experienced |
|---|---|---|---|---|---|---|
| 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |

**6. Please indicate your level of knowledge about bidding in an auction:**

| Not knowledgeable | | | Neutral | | | Knowledgeable |
|---|---|---|---|---|---|---|
| 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |

| Not competent | | | Neutral | | | Competent |
|---|---|---|---|---|---|---|
| 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |

| No expert | | | Neutral | | | Expert |
|---|---|---|---|---|---|---|
| 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |

| Not experienced | | | Neutral | | | Experienced |
|---|---|---|---|---|---|---|
| 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |