Revisiting Bidder Heterogeneities in Online Auctions (The Case of Soft vs. Hard Closing Formats)

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REVISITING BIDDER HETEROGENEITIES IN ONLINE AUCTIONS
(THE CASE OF SOFT VS HARD CLOSING FORMATS)

Research-in-Progress

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Abstract

The current study offers an insight into how auction ending rules can affect distribution online bidders’ strategies. While traditional wisdom in this area suggested that auction ending rules can encourage and suppress certain bidding behaviors, limited efforts have been taken to investigate how they can affect winning likelihood and price premium distribution across different bidding strategies. To evaluate such impacts of auction ending rules, auction data were collected from two auction websites (eBay and Dellauction.com). A total of 288 auction transactions were collected and later used in the data analyses. Initial results indicate that auction ending rules do affect winning likelihood and distribution of price premium across different bidder classes. A bidding strategy that was found effective in generating higher price premium under an auction ending rule may not necessarily be effective under a different auction ending rule. Practical implications are offered at the end of the study.

Keywords: Bidder Strategies, Online Auctions, Auction Ending Rules, and Price Premium
Introduction

Online auctions have become a marketplace for businesses to explore a new group of customers. With the dynamic pricing nature of online auctions, businesses can be engaged in a demand-driven production planning and control (Bapna et al. 2001). In addition, online auction markets have become a playground for businesses to experiment new product ideas and eliminate their excess, obsolete, and perishable inventory. It also allows businesses to estimate their demand curves by using demand-driven market information. Despite these enormous benefits of online auctions, limited attention has been given to study the impact of different auction ending rules on distribution of bidding behaviors and price premium generated different bidder classes.

Understanding online bidding strategies and bidder classes is critical to developing effective auction design mechanisms (Bapna et al. 2004). Prior studies found that online bidders adopted different strategies. Each yields different winning likelihood (Bapna et al. 2004). Since online auctions allow customers to acquire products/services at different prices, different bidding strategies can also produce varying price premium to the auction sellers. This opportunity to generate price premium is becoming more critical, especially in this new economy.

The current study is built upon two baseline studies by Roth and Ockenfels (2002) and Bapna et al. (2004). The first explored the impact of auction ending rules (hard Vs soft closing) on online bidding behaviors. The latter explored bidder taxonomy in multi-itemed auctions and examined winning likelihood and distribution of normalized loss of surpluses across different bidder classes. We argue that different levels of normalized loss of surpluses reflect different levels of seller’s price premium. Their study unveiled four common bidder classes, including opportunists, evaluators, sip-and-dippers, and participators. They later suggested that these bidder classes can evolve and their likelihood of winning may change over time.

Taking the concept of bidder evolution into account, we argue that it is important that research in this domain regularly reevaluate online bidding strategies and distribution of seller’s price premium produced by different bidder profiles. Our study therefore attempts to 1) investigate how auction ending-rules influence distribution of online bidding behaviors 2) examine the heterogeneities and commonalities of bidder taxonomy across different auction formats and 3) learn how auction ending rules affect distribution of seller’s price premium and bidder’s winning likelihood.

Literature Review

Research in the area of online auctions has substantially grown for the past two decades. Its continued growth is partly driven by the limited applicability of traditional auction assumptions to online auctions. Online auction markets offer several services that were not otherwise found in traditional auction environments. One of which is the use of the auction marketplace as a knowledge repository by bidders. Online auctions also provide its customers with concurrent listings of items (Peters and Severinov 2006). With these new functionalities found in online auction markets, traditional auction theories can be violated when auctions are implemented in the online platform (Bapna et al. 2001).

The growth of online auction market has been witnessed by its popularity not only from consumer standpoint but also from business perspectives. Several large businesses such as Sam’s club have now dedicated a part of their web space for online auctions. Other businesses such as Sears, Home Depot, and Disney, etc. have been using an established auction marketplace such as eBay to release their obsolete items. Online auctioneers have several decisions to make. One of which is to decide whether to adopt a hard-closing or soft-closing ending rules. While some researchers recommended that online auction houses offer different auction formats to their participants (i.e. Bapna 2003), most online auction websites choose to employ only one ending rule to create a more consistent environment for their customers.

Prior research argued that auction formats can be influential to the formation of bidder strategies. Two theoretical pluralisms were proposed by auction researchers. The first stream of research suggested that auction formats (i.e. private vs. common value auction) can lead to different bidding patterns and different auction outcomes (i.e. Milgrom and Weber 1982; Engelbrecht-Wiggans 1987). The other stream of research however suggested that
auction winners under a certain auction rule are more likely to be winners again under a different auction rules (Myerson 1981; Bulow and Roberts 1989).

Despite these different schools of thought, auction researchers seem to agree that different bidding strategies incur different costs to the bidders such as search costs in determining a valuation of product/service of interest, monitoring cost, and opportunity cost to participate in other alternative auctions (Easley and Tenorio 2004; Bapna et al. 2004). Thus, understanding how different bidding strategies affect bidder’s winning likelihood and the distribution of price premium under different auction ending rules can be of values not only to the online auctioneers and sellers but also to the bidders. Online bidders can use this information to revise their bidding approaches in the future. Below, we discuss how auction ending rules can affect bidding behaviors in the online auction environment.

**Auction Formats and its Impacts on Bidding Behaviors**

Auction formats and their impacts on bidding behaviors have long been witnessed by prior research. For instance, it was argued that single early bid is a dominant strategy for bidders in the private-valued second-priced auction environment (Vickrey 1961). The popularity of this bidding strategy has however dwindled with the introduction of online auctions. It was claimed that late bidding strategy has become a mainstream bidding approach and it has received tremendous attention from auction researchers (i.e. Bajari and Hortacsu 2003; Roth and Ockenfels2002). In a survey report, 91% of the respondents claimed that late bidding is a part of their early planned bidding strategy (Roth and Ockenfels 2002). Its popularity is perhaps attributed to its ability to create collusive equilibrium (avoid bidding war) and to reduce unnecessary price increase (Roth and Ockenfels 2002). In addition, late bidding helps delay disclosing true valuation of the items (Roth and Ockenfels 2002). More importantly, late bidding behavior is claimed to be an effective response to naïve or incremental biddings. Despite its several benefits, late bidding behavior introduces some inherent risks and costs to its bidders. For instance, bidders have to take into consideration of the possibility that their bids will not be successfully submitted - perhaps due to erratic Internet traffic (Ockenfels and Roth 2006). It can also generate collusions against sellers (Roth and Ockenfels 2002) and produce higher monitoring costs.

With the emergence of online auctions, many more online auction formats have been proposed and adopted by various auction houses. Two of which are hard and soft-closing auctions. While hard-closing auctions are those that have fixed end time, soft-closing auctions are those that employ extendable end time. Its end time can be extended depending upon auction activities prior to the predetermined end time of the auction. Roth and Ockenfels (2002) found that hard-closing auction format accentuated late bidding behaviors. In other words, strategic benefits of late bidding behaviors are greatly attenuated by soft-closing auction (Ockenfels and Roth 2006) since bidders cannot predict with a certainty when the auction will end.

In a field study, it was found that more than two-thirds of the all eBay (hard-closing) auctions have at least one bidder active in the last hour (Roth and Ockenfels 2002). The number of active bidders in the last hour is noticeably lower (25%) in Amazon (soft-closing) auctions. The impact of auction ending rule is much more evident when considering the reported number of bidders within the last five minutes. It was reported that up to 16% of bidders were found in the last 5 minutes of eBay auctions while there is approximately only 1% of bidders found in the similar timeframe of Amazon auctions (Roth and Ockenfels 2002).

While prior studies have produced accumulated evidence of how auction ending rules affect bidding behaviors, several questions have remained unanswered. For instance, little attention has been given to examine the impact of auction ending rules on other bidding strategies such as incremental bidders. Moreover, it is still unclear if the distribution of price premium generated by different bidder profiles will vary in different auction formats. While Roth and Ockenfels (2002) argued that hard-closing format provides opportunities for bidders to suppress bids and it is likely that winners in these auctions will gain higher profits, there is little empirical evidence for this argument. In addition, the winning likelihood of different bidder classes may vary across different auction formats. Our study attempts to answer these questions by integrating the knowledge learned from Ockenfels and Roth’s studies to those that are discussed below.

**Bidder Profiles, Price Premium, and Winning Likelihood**

While prior research have focused their attention on examining effectiveness of bidding strategies in online auction marketplace, most of the efforts were spent on the topic of late bidding behavior (i.e. Ockenfels and Roth 2006;
Shang and Ling (2004). Few have directed their attention to other bidding approaches such as naïve bidding (i.e., Deltas ad Engelbrecht-Wiggans 2005; List and Shogren 1999). In short, naïve bidder is defined as bidders who “do not infer any information about the value of the item from the bidding behavior of their opponents” (Deltas ad Engelbrecht-Wiggans 2005). It was also claimed that naïve bidders are more likely to stay active in the auction until the price reaches the expected value of the object conditional on their signal (Deltas ad Engelbrecht-Wiggans 2005). Unlike naïve bidders, rational bidders tend to remain in the auction as long as there is a possibility for s/he to gain financial savings (Deltas ad Engelbrecht-Wiggans 2005).

Traditional wisdom suggested that naïve bidders generally receive lower saving/ lower bidder’s relative surpluses and are subject to winner’s curse. Hence, this group of bidders could come to extinction and only rational bidder would survive. This traditional wisdom was however challenged in a recent study by Deltas ad Engelbrecht-Wiggans (2005). They demonstrated that naïve bidder could gain higher surpluses than rational bidders in some circumstances, especially when signal distribution is symmetric and unimodal.

Despite the constellation of works in this area, Bapna and his colleagues (Bapna et al. 2004) demonstrated that other bidder classes existed. In their study, two datasets from an online Yankee auction house with multi-itemed format were collected. They were auction transactions found in the year of 1999 and 2000. Their study is one of the first that employed three factors to examine bidder’s behaviors, including number of bids, time of entry (TOE), and time of exit (TOX). Using the three factors to perform cluster analyses, their study unveiled four common bidder profiles across the two datasets – opportunists, evaluators, sip-and-dippers, and participators. Opportunists are those that place a single bid very close to the end of the auction to improve their chances of winning. Evaluators are arguably similar to opportunist in that they make a single bid. Their bids are however placed earlier in the auction. Sip and dippers generally follow a two-bid strategy. Participators are engaged in the auction and normally put in multiple bids. The above discussion indicated that participants share several qualities with naïve bidders discussed above.

In addition to these four common bidder classes, two unique bidder classes emerged in their data. One of which is called agent bidders. The emergence of agent bidders was arguably attributed to the automatic bidding agent, a new functionality offered by the auction house in 2000. The results also revealed another unique bidder class called middle evaluators. This bidder class signified the role of TOE and TOX. It also raises a question whether other bidder classes such as sip-and-dippers and participators can be further segmented according to their TOE and TOX.

Since Bapna’s study was conducted in a multi-itemed auction environment, one may question if their findings will also be applicable in single-itemed auctions. Thus, another primary goal of this study is to explore if the bidder classes found in the multi-itemed environment can also be found in single-itemed auction platform. Rothkopf and Harstad (1994) argued that results found in single-itemed auctions may not carry over into multiple-itemed auction settings. Tenorio (1999) further supported this idea by arguing that bidders in a multi-itemed auctions are required to make lumpy bids if their goal is to acquire multiple items. Such a requirement does not however exist in a single-itemed auction.

Bapna’s study revealed additional interesting information such as distribution of winning likelihood and bidder’s normalized loss of surpluses across different bidder profiles. In short, they found that opportunists have higher winning likelihood (Bapna et al. 2004). Such higher winning likelihood may stem from the fact that these bidders have monitored the auctions for a longer period of time and therefore develop a more realistic valuation of the products. Participators are however demonstrably having lower winning likelihood when compared to opportunists. They are reportedly received higher consumer surpluses than other bidder classes. Bapna and his colleagues argued that participators are generally placed their bid at the minimum requirement, resulting in their higher surpluses (Bapna et al. 2004 p. 35). For a more complete analysis of winning likelihood and normalized loss of surplus distribution, please see Bapna et al. 2004.

**Research Method**

To investigate heterogeneities and commonalities of bidder taxonomies under different auction ending rules, two datasets were acquired from two online auction houses, including eBay and dellauction.com. With this selection of the two online auctioneers, we are able to control many external factors that can influence bidders’ strategies. Firstly, we are able to focus on a single seller who participated in auctions with different auction ending rules during the same period of time. We found that Dell Computer Inc. offered its products through its own auction sites (dellauctions.com) and also through eBay. Dell Computer Inc. has been an eBay member since 2001 while it has
operated and maintained its own online auction house since 1999. While eBay adopted hard-closing ending rule, dellauction.com employed a soft-closing auction format. If a bid is placed ten minutes prior to the end time, the auction’s end time will be further extended by another ten minutes. By having only one seller in our data set, the impacts of sellers’ reputation on bidder’s strategies are minimized. Secondly, we are able to focus only on a single product which later allows us to rule out the impact of product heterogeneities on bidding behaviors. Ockenfels and Roth (2006) suggested that product types can affect bidding strategies among online bidders.

Approximately 9,000 auction transactions were collected over the two-month period. Two spider programs were developed to automatically collect data from the two auction websites. The first program helped find new auction listings that were offered by Dell Computer Inc. It downloaded and stored the auction listing information in HTML format on an SQL server database. Information such as listing number, start date, start time, end date, and end time were later extracted and maintained in the database. The other program used the extracted information to monitor the websites and download additional information such as final price, etc after the auction ended.

It is important to note that while the baseline study focused on the distribution of normalized loss of surplus across different bidder profiles, such a measure of bidding effectiveness cannot be used in this study. The normalized loss of surpluses in the baseline study was partly calculated by finding the difference between winning price and the lowest winning price. This calculation process can be performed when there is more than one winner at an auction or in a multi-itemed auction format. Since the current study focuses on single-itemed auctions, we adopt price premium – a more commonly used measure of bidding effectiveness in online auction research. To ensure a fair comparison of price premiums across bidder profiles and auction ending rules, we narrowed our products down to one single product – Dell Optiplex GX60/SFF, rendering a final sample of 77 auctions from eBay and 211 auctions from dellauction.com. All computer products in these auctions have identical specifications such as hard drive, memory, etc. In addition, these auctions adopted 3-day auction duration which enabled us to control another external factor (auction duration) that could have an impact on bidder’s strategies. With 288 auction observations, there are 559 and 1,220 bidders participating in eBay and dellauction samples, respectively. The information regarding number of bids, TOE, and TOX of each bidder were extracted from auction bidding history pages and later used to perform cluster analyses.

**Data Analysis and Initial Results**

The data analysis technique used in the current study mirrored the approach used by our baseline study (Bapna et al. 2004). Three factors, including number of bids, TOE, and TOX, were employed in a hierarchical cluster analysis. To identify TOE, number of elapsed seconds between the auction’s end time and the time that first bids were entered were calculated. Similar process was followed to calculate TOX. The only difference is the times that bidders entered their final bids, not first bids, were used in the calculation of TOX. Thus, bidders who entered only one bid into the auctions will have identical TOE and TOX.

A guideline suggested by Hair et al. (1998) was used to identify appropriate number of clusters found in each dataset. Cluster analyses were performed separately on the two datasets. The analyses revealed 9 and 12 bidder classes in dellauction (soft-closing) and eBay (hard-closing) samples, respectively. Table 1 shows membership information across two different auction websites. Table 2 shows distribution of price premium and winning likelihood across different bidder classes.

Our initial results revealed commonalities and heterogeneities of bidder profiles under the two different auction ending rules. First, the four common bidder classes (opportunists, evaluators, sip-and-dippers, and participators) found in the baseline study were also discovered in both of our datasets. Our results demonstrated that the timing concept can be applied not only to the evaluator group but also to other bidder classes. Bapna and his colleagues (2004) found two evaluator groups (early and middle evaluators) in one of their samples. They were separated by their TOE and TOX. We however found that sip-and-dippers and participators can also be further segmented according to their TOE and TOX. For instance, the participator group in the soft-closing auction was further divided into two subgroups, including early participators and late participators (See Table 1). There are three groups of participators found in the hard-closing auctions (eBay).

We also found that the timing concept help identify more bidder classes in the hard-closing auctions. Some bidder classes that were found in the hard-closing auction did not necessarily emerged in the soft-closing auctions. Example of those bidder classes are middle participators, middle 3 (mid3) evaluators, and middle sip-and-dippers. Despite
In term of price premium distribution, we found that late participants have significantly produced higher price premium than other bidder classes in the soft-closing auction environments. ANOVA test was performed and it confirmed this finding. In the hard-closing auction, we cannot make a similar conclusion due to the limited number of winners found in each bidder class. It is however worth noting that opportunists, in the hard-closing auctions, are those that have noticeably paid lower prices when compared to other winners. A similar observation can also be drawn for the soft-closing auctions (See Table 2).
Table 2: Price Premium Distribution and Winning Likelihood across Bidder Profiles

<table>
<thead>
<tr>
<th>Bidders Groups</th>
<th>Soft-Closing Auctions</th>
<th></th>
<th></th>
<th>Hard-Closing Auctions</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Number of</td>
<td>Average Final Price</td>
<td>Average Price Premium</td>
<td>Number of</td>
<td>Average Final Price</td>
<td>Average Price Premium</td>
</tr>
<tr>
<td></td>
<td>Non-winners (% of</td>
<td></td>
<td></td>
<td>Non-winners (% of</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>winners)</td>
<td></td>
<td></td>
<td>winners)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Early Evaluators</td>
<td>24</td>
<td>0 (0.00%)</td>
<td>N/A</td>
<td>26</td>
<td>0 (0.00%)</td>
<td>N/A</td>
</tr>
<tr>
<td>Mid1 Evaluators</td>
<td>34</td>
<td>0 (0.00%)</td>
<td>N/A</td>
<td>66</td>
<td>1 (1.30%)</td>
<td>$150.00</td>
</tr>
<tr>
<td>Mid2 Evaluators</td>
<td>244</td>
<td>4 (1.90%)</td>
<td>$130.00</td>
<td>-1.12%</td>
<td>51</td>
<td>0 (0.00%)</td>
</tr>
<tr>
<td>Mid3 Evaluators</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>39</td>
<td>1 (1.30%)</td>
<td>$142.54</td>
</tr>
<tr>
<td>Late Evaluators</td>
<td>289</td>
<td>22 (10.43%)</td>
<td>$116.41</td>
<td>-11.46%</td>
<td>56</td>
<td>7 (9.09%)</td>
</tr>
<tr>
<td>Early Sip &amp; Dippers</td>
<td>22</td>
<td>0 (0.00%)</td>
<td>N/A</td>
<td>33</td>
<td>3 (3.90%)</td>
<td>$147.67</td>
</tr>
<tr>
<td>Middle Sip &amp; Dippers</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>28</td>
<td>1 (1.30%)</td>
<td>$151.00</td>
</tr>
<tr>
<td>Late Sip &amp; Dippers</td>
<td>114</td>
<td>37 (17.54%)</td>
<td>$135.08</td>
<td>2.75%</td>
<td>27</td>
<td>15 (19.48%)</td>
</tr>
<tr>
<td>Early Participators</td>
<td>2</td>
<td>2 (0.95%)</td>
<td>$122.50</td>
<td>-6.82%</td>
<td>6</td>
<td>1 (1.30%)</td>
</tr>
<tr>
<td>Middle Participators</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>14</td>
<td>5 (6.49%)</td>
<td>$180.23</td>
</tr>
<tr>
<td>Late Participators</td>
<td>48</td>
<td>31 (14.69%)</td>
<td>$149.71</td>
<td>13.87%</td>
<td>25</td>
<td>5 (6.49%)</td>
</tr>
<tr>
<td>Opportunists</td>
<td>231</td>
<td>115 (54.50%)</td>
<td>$128.50</td>
<td>-2.26%</td>
<td>111</td>
<td>38 (49.35%)</td>
</tr>
<tr>
<td>Total Winners</td>
<td>221</td>
<td></td>
<td></td>
<td>77</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Discussion, Implications, and Directions for Future Research

We believe that our study produced interesting and promising results. As mentioned earlier, the current study demonstrated that bidder classes found in a multi-itemed auction can be carried over to the single-itemed auctions (both for soft-closing and hard-closing). It also demonstrated that the timing concept can be applied to all bidder classes. This finding allowed us to investigate the impact of timing of bids more thoroughly — an extended examination from the baseline study. Firstly, we found that late bidding strategy is the most popular strategy within each bidder class but only for the soft-closing auctions. For example, late evaluator class has more bidders than any other evaluator classes. Similar finding can be observed in other bidder classes under the soft-closing ending rule. It is however worth noting that late bidding strategy did not gain as much relative popularity under the hard-closing auctions. In this auction format, bidders are almost evenly distributed such as those found in the evaluator classes (See Table 1). Despite the difference in the membership distribution of late bidders under the two auction ending rules, our result unveiled that the late bidding strategy was universally more effective within each bidder group. For instance, we found a much higher winning likelihood for late sip-and-dippers (17.54%) when compared to early sip-and-dippers (0%) under the soft-closing auctions. Similar results were observed in other bidder groups (participators and evaluators) and under both auction-ending rules (See Table 2).

Secondly, we observed an implicit relationship between bid timing and number of bids placed by online bidders. In the soft-closing auctions, for instance, average number of participant’s bids decreased from 6.5 bids (early participators) to 3.28 bids (late participators). Similar observation was also made for the hard-closing auctions. Such a relationship suggested that participants placed fewer bids as the auctions came closer to the end. This relationship can perhaps be attributed to the fact that auction prices are generally becoming higher as the auctions approach the end time. These higher prices therefore become prohibitive for participants to be aggressive in placing more bids.

We additionally compared our results to those reported in the baseline study. To ensure a fair comparison, we combined common bidder classes in our dataset to match the four bidder classes in the baseline study. In the
baseline study, there appears a significant disparity in the bidder strategy popularity, especially in their year 2000 dataset. Evaluators and opportunists strategies were reported to be used almost as often by online bidders (39% and 35%, respectively) while others have gained much lower acceptance (i.e. participators – 12% and sip-and-dippers – 10%). We however found that evaluator strategy, in our samples, was much more popular than other bidding strategies (44.19% in hard-closing and 50.57% in soft-closing auctions). Opportunists are also considered a frequently used strategy but not as popular as those found in the baseline study (26.65% in hard-closing and 28.44% in soft-closing auctions).

The current study additionally found that opportunist and sip-and-dipper strategies yielded higher winning likelihood in both auction formats. This finding is similar to those reported in the baseline study but there appears to be a larger disparity in their winning likelihood. For instance, opportunist strategy was reportedly won approximately 50% of the auctions in our dataset (both soft and hard-closing) while sip-and-dipper strategy won approximately 17% (soft-closing) to 25% (hard-closing) of all auctions. Such a disparity is perhaps attributed to the different auction formats used in the two studies (multi-itemed Vs single-itemed auctions). In the current study, we focused only on single-itemed auctions where there can be only one winner per auction. The baseline study employed data from multi-itemed auctions. This auction format allows multiple winners per auction and perhaps increases winning likelihood of sip-and-dippers.

When comparing distribution of price premium to the baseline study, our results revealed a very different story. Bapna and his colleagues (2004) reported that participators had significantly lower loss of surpluses or gained larger saving than the three other bidder classes. Our results indicated otherwise. Participators, in our study, were found to produce highest price premium to the auction sellers and thus receiving lowest relative financial saving. They paid on average up to 25% higher than other bidder classes. The baseline study claimed that the larger saving of participators stems from their marginal/incremental bidding strategy. We however argue that the higher number of bids found in the participator group is indicative of their high commitment and perhaps their high emotional involvement to win the auctions. This bidder characteristic is probably an attributable cause of higher price premium generated by this bidder class. Further, there is only one winner in the single-itemed auction while there can be more than one winner in multi-itemed auctions. Bidders in the single-itemed auctions therefore have to be more aggressive and avoid using incremental bidding strategy since the risk of not winning the auction is higher.

Taking the higher price premiums produced by participators into account, we recommend that online auctioneers should develop an auction mechanism that promotes this bidding behavior. One alternative is to consider revising bid increment rule to draw more participatory behaviors to the auctions. eBay, for example, is currently adopting a progressive bid increment policy where bidders are obligated to place higher bid increments as the auction prices reach higher levels (see http://pages.ebay.com/help/buy/bid-increments.html). Such a policy may prohibit bidders from being aggressive in placing multiple bids. Thus, reducing bid increment as the auction approaches the end time may create more excitement and enhance bidder’s commitment to win the auction. Such a strategy is currently adopted by some other auctioneers such as uBids.com.

Our study faces some limitations and constraints. First, the nature of field study provided us with a limited control over sample sizes. The imbalanced of sample sizes across the two auction formats (soft and hard-closing auctions) prevented us from examining some issues at a more granular level. Second, by using auction data that were offered from the same seller, the current study did not offer an insight of how other auction design factors can affect bidding behaviors. We argue that auction duration and opening bids, among many auction design factors, can also have influential role in shaping bidders’ strategies and their effectiveness. For instance, auctions that were offered for a longer period of time may experience more bidder classes since their TOE and TOX can vary more. Also, auction with higher opening bids may be more or less attractive to some bidder classes –potentially producing different results in the winning likelihood and price premium distribution. We encourage future research to explore such factors and their impacts on bidder strategies in their own right.
References


