Abstract

The study maps the bidding patterns of 1,051 completed English auctions from the eBay website to study their structural patterns. The overall pattern appears to be a cubic. People initially bid the price to 60–70% of the final value. The price levels off only to take off near the end of the auction, when it reaches its final price. The second part of the study measures the effects of information on bidding. The effect of secret reserve price information on auctions is compared for differences in bidder participation and resultant final values. The results indicate significant structural differences in bidding patterns and bidder behaviour for auctions with secret reserve price information. When compared to auctions without reserve price, completed auctions with reserve price attract more bidders, more competitive bidding, and consequently realize higher final values.

Keywords: online auctions, bidder behaviour, reserve price, eBay

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Auctions play a valuable role in the price discovery process when the commodity being auctioned does not have a fixed or determinable market value or when the seller is uncertain about the market price. This involves some degree of information and cost symmetries in the sense that the economic agents differ in their access to and evaluation of the information pertaining to the auctioned commodity. In a typical auction, a potential bidder faces three types of uncertainties, 1) uncertainty about the value of the object being auctioned, 2) a strategic uncertainty relative to the strategies used by other players, and 3) an uncertainty relative to the characteristics of his opponents (Laffont 1997). Geographical boundaries and interest groups limited traditional auctions, until the Internet with its dynamic interconnectivity and endless exogenous participatory potential allowed for online auctions.

Online auctions are the first form of online commerce that engages the customer, thereby creating a more efficient market by bringing together a wide variety of buyers and sellers. Consumers are attracted to online auctions primarily by the potential of finding bargains, while sellers are attracted by the network effects of popular auction websites.

The most popular online consumer auction house, eBay has over 37 million registered users who bought, sold or listed products worth over 5.8 billion dollars through its websites in 2003 (Business Wire 2003). More sites add auctions every day. While eBay might be the best known, portals such as Yahoo and Lycos, retail sites such as Amazon, and even traditional auction houses such as Sotheby’s have joined in as well. A site dedicated for auction information estimates more than a 1,000 auction sites on the Internet. This makes the study of online auctions opportune.

However, academics have only recently begun to focus on online auctions as a viable form of commerce. Most previous auction research comes from game theory applications in economics, where auctions are modelled as incomplete information games analysed by assuming that the characteristics of the players are drawn from nature from probability distributions that are common knowledge to all players (Laffont 1997). The game theoretic work has often been criticized due to its overt reliance on assumptions and controls that severely limits the validity of claims. Against this background, this study attempts to empirically examine bidder behaviour and bidding patterns.
in online auctions. The first section surveys the literature on auctions and emphasizes the limitations of game theoretic model applicability in real world settings. This is followed by a section on the Internet and online auctions, the research objectives of the study, and the methodology, results and conclusions of the study.

LITERATURE REVIEW

Auctions and game theory

Auction research draws upon Economics, Finance, Information Sciences, Marketing and Negotiation Science among others (Teich et al. 1999). Most of the theoretical models use game theory – the part of economic theory most noted for its contribution to auction design (Milgrom 1998). This section surveys the existing literature on auctions both live and online and emphasizes the limitations of the theories, particularly game theoretic model applicability in real world settings.

The most outstanding contribution to auction theory was by Vickery (1961), who examined the possibility that different auction formats might give the same expected revenue to a seller of a single object. In other words, Vickery’s theory of auctions and competitive bidding suggest that, under certain conditions, seemingly different auction mechanisms result in the same expected cost or revenue to the bid taker. This theory is sometimes referred to as the ‘Central limit theorem’ or the ‘Revenue equivalence theorem’ and forms the basis for most auction research (Engelbrecht-Wiggans 1988).

Much of the literature following Vickery analyses the robustness of his Revenue Equivalence Theorem result to the introduction of alternative bidding steps. Controlled experiments have been used to analyse Vickery’s theory (Tenorio 1993), with no conclusive support for revenue equivalence in most of these experiments. The extent to which Vickery’s theory predicts what happens in the real world, depended on how well the theory models the essence of actual situations and on how sensitive the theory was to its assumptions (Engelbrecht-Wiggans 1988). Mead (1966) did not find significant revenue differences between the high bids observed under different auctions. Johnson (1979) however, used extended data sets and found evidence to suggest that sealed bid auctions actually yield larger higher bids than open auctions.

Most researchers attribute the lack of generality in auction theory to the application of game theory in theoretical economics. Feldman and Mehra (1993) analysed different auction formats, and concluded that the simplifying assumptions of game theory allowed the derivation of key results, but made the application of auction theory ‘an exercise to be undertaken with caution’. The game theoretic assumptions common to most auction models are: (1) bidders are risk neutral, (2) either the independent private value assumption applies or the common value assumption applies, and (3) the bidders are symmetric, that is they use the same distribution function to estimate their valuations – implying bidders cannot discern differences among their competitors.

In a summary of the difficulties usually encountered in applying game theory to empirical economics Laffont (1997) explains how game forms or models are either not well defined (for example in bargaining theory) or are extremely complex with empirical data not being rich enough to successfully estimate those structural models. Except for three major applications: oil drilling rights in the US, timber in the US and Canada, and Treasury Bills, the applied work on game theory and auctions is quite limited. His overview concludes that the predictions of bidding behaviour are highly dependent on the unobservable restrictions made on the distribution of characteristics for which game theory offers little guidance.

Hence, most previous research on auctions either model the auction process by applying competitive game theory or test the robustness of game theoretic applications to real world auctions. Despite numerous attempts at modelling the behaviour of participants within an auction, these stylized models – due to their reliance on simplifying assumptions – create static representations of auction instances, making their application to real-world auctions limited. Smith (1993) presents a similar conclusion in his comparison of real world auctions in contrast to the neoclassical paradigm. His observation was that:

1. buyers in most auctions do not have anything like clearly defined preferences;
2. in most cases, in fact, price is quite secondary to allocation, with price being more often the result of the allocative decisions rather that vice versa;
3. in most auctions there is an explicit interest in establishing what will be considered a legitimate price, where the notion of legitimacy is tied to the consensual/social character of the auction;
4. in pursuit of this legitimacy, auctions differ significantly in the manner in which collusion, signalling, and other strategies are accepted and built in to the auction – though they are all a part of most auctions;
5. participants in most auctions have clearly defined roles that endow them with specific rights and specific responsibilities;
6. auctions tend to be a highly emotional process with instrumental rationality at best secondary – what rationality there is tends to be due to structural factors built in to the auction; and finally,
7. real-world auctions, rather than revealing how competitive individual preferences are resolved through self-interested market behaviour, underscore
the consensual and even cooperative character of most economic exchange. Real world auctions are nearly always more concerned with establishing consensual definitions of the situation than with the particular transactions.

In addition, according to Tenorio (1993) bidder participation depends on factors like reserve prices, information acquisition opportunities and bid preparation costs. Of these factors, the reserve price is a very commonly used feature in most online auctions. Of 142 auction websites reviewed by Lucking-Reiley (2000) in the autumn of 1998, 55 sites allowed the use of reserve price and typically 44 of 55 cases indicated the existence of the reserve price on the website next to the auctioned product. Vishwanath (2003, 2004) empirically examined the impact of seller-specified information levels on uncertainty reduction within and across cultures, and found significant interaction between the amounts of information and the extent of participation in the auction. In all the cases, increased information resulted in an increase in the number of bidders attracted to the auction. However, the impact of reserve prices on online auctions has received limited attention. The next section presents the extant literature on reserve price and auctions.

Reserve price and online auctions

The reserve price represents a commitment by the seller to sell if, and only if, the highest bid exceeds this reserve. It is also common for this price to be kept ‘secret’ and not announced prior to bidding but (potentially) revealed only after bidding has ended (Horstmann and LaCasse 1997). Often, in traditional auctions the very existence of a reserve or minimum price is kept secret, and the sellers refusal to sell at the end of the auction provides evidence of the existence of the secret reserve (Horstmann and LaCasse 1997). On the other hand, online auction sites such as eBay (www.eBay.com) indicate the existence of the reserve price but never reveal the value. Here again the seller’s refusal to sell at the completion of the auction is an indication of a higher reserve price than the highest bid amount for the auctioned item.

There has been considerable debate on the need for and effect of reserve price on traditional auctions. Milgrom and Weber (1982) established that if a seller of a good at a common value has private information about an object to be sold, she could increase her expected profits by following a policy of credibly revealing the information. In other words, increased information is linked to increased bidder participation. In this case the withholding of information in a ‘secret’ reserve would violate the principle of optimality of information revelation, while any revelation of its existence would constitute increased information.

Another answer to the need for secret reserve prices suggested by both Ashenfelter (1989) and Porter (1995) is that the secret reserve prices might be used to deter collusive bidding. According to Horstmann and LaCasse (1997) though this explanation has some appeal, it is not clear as to why the sellers would find a secret reserve price more preferable to an announced reserve price.

Vincent (1995) presents a secret reserve price auction within a game theoretic model to show that keeping the reserve price secret in an auction is a way of restoring the linkage between the buyers’ price paid and the value of the object by inducing greater participation and thereby increasing the seller’s profits. He demonstrates that a policy of keeping private reserve prices can be revenue enhancing for a seller in a common value auction. Though the announcement of the reserve price may have an inhibiting effect on the participation of bidders in a given auction, they would be bidders for whom the only possibility for winning the auction is to win at the reserve price and such an event may only occur when the object is not worth purchasing. In general, the bidders would submit lower bids since it is not known whether the rival price is that of another bidder or that of the seller but the seller may be willing to incur this cost if the policy encourages more bidders to participate and therefore induces a greater aggregation of information. In other words, a secret reserve price can be used to increase bidder participation at the auction (and so expected sales revenue) with low valuation bidders refusing bid whenever they expect the reserve price to be high.

Hence, though there is some agreement on the potential impact of reserve prices, it is still unclear as to why a seller would post a reserve price in a traditional auction. In addition, the impact of reserve prices on online auctions has not received much attention. If a seller does in fact procure high bidder interest, then his rejection of offers might indicate that the auction values were not high enough. Bajari and Hortacsu (2000) provide an indirect measurement of the effects of secret reserve prices in eBay auctions. However, their approach at providing a structural econometric bidding model impose a number of conditions and assumptions that reduce the generalizability of findings (Katkar and Lucking-Reiley 2000). For example, they assume that the unobserved secret reserve-price amounts are set as if they were from an independent bidder (Katkar and Lucking-Reiley 2000). To avoid the limitations imposed by prior empirical efforts, Katkar and Lucking-Reiley (2000) and Lucking-Reiley (2000) conducted a more direct assumption-free examination of the impact of reserve prices on eBay auctions. They conducted a pseudo-experiment by listing comparative pairs of ‘Magic’ (Lucking-Reiley 2000), and ‘Pokeman’ cards (Katkar and Reiley 2000), and manipulating the existence of reserve prices. Their findings suggest that
when compared to auctions without a reserve price, reserve price auctions attracted fewer bidders, increased the revenues received on the cards (conditional on their having been sold), and increased the frequency with which the cards went unsold. The biggest drawback to this approach is the limited number of unique auctions that are being measured. Also, the auctions were for low value collectible items. The item values ranged from $1.50 to $25 per card. Prior research has show marked differences in bidders for collectibles, especially when the value for the item is not easily determinable. Dholakia and Soltysinski (2001) demonstrated herd behaviour where bidders tend to be attracted to auctions where there were already a number of bids. The social influence was more pronounced for items whose values were not easily determinable i.e. collectibles, antiques etc. Rather than experimentally manipulating a few low value items, the current research focuses on actual completed eBay auctions.

RESEARCH QUESTION

The previous two sections detail the limitations of theoretical economic models of game theoretic auctions, and the lack of adequate empirical work on online auctions. Hence, this study focuses on the bidding patterns in online auction formats by taking a bidder perspective and mapping their actual bids over time to answer the following research questions:

RQ1: What is the structural (longitudinal) pattern of bidding on eBay?
RQ1A: How is this distribution best described? Is it linear, complex (curvilinear–quadratic or cubic), non-linear (exponential or logistic) or non-linear and chaotic?
RQ2: How do bid duration’s change over time on eBay?
RQ3: How do bid values and rates change over time on eBay?
RQ3A: What happens to bid values and rates near the close of an eBay auction?
RQ4: What is the effect of the existence of a reserve price on an eBay auction?
RQ5: Does the reserve price information affect bidder participation in an online auction?
RQ6: Does reserve price information affect the intensity of bidding?
RQ7: How does the structural pattern of bidding in a reserve price auction differ from that of a non reserve price auction?

METHODS

In order to capture the structure of bidding, the research uses only completed auctions. An auction is considered complete when it has reached the end of its pre-specified duration. It does not accept any further bids. Data on completed auctions provided on the eBay website, were collected on their respective completion dates. The data collection was conducted in the summer of 2000. eBay was chosen as it is the most popular auction website, and attracts thousands of bidders. The large number of bidders provides a heterogeneous sample which varies in bidding behaviour and strategy. Hence, a random sample from this group will provide a valid and reliable estimate of how most bidders behave in online auctions.

Though eBay offers both the English (ascending price), and Dutch auction formats, this study is limited to single issue (unit), ascending price auctions. Finally, the study is limited to the information that is available on the eBay website. The website provides the time and date along with bid amounts and email addresses of all bids for all completed auctions on their specific completion dates. Rather than focus on pairs of products, this study focused on actual bid listings within one product category. Of the numerous products listed and sold through online auctions, computers and computer related products are the most popular. According to Lucking-Reiley (2000) over 54 individual Internet auction sites sell computers and computer software products. Also, this category tends to have the maximum number of product listings within eBay. In addition to attracting a large number of listings, most bidders in these auctions are potentially more adept at computing, which could provide a reasonable control over differences in computing ability that could impact auction participation. Hence, the ‘desktop personal computer’ category was chosen. Only completed auctions for one brand of used personal computers with the same starting (listing) date that were accompanied by actual photographs of listed items were included in the collection. This ensured that all the products were competing and equivalent in all attributes except the variables of interest. Lastly, the data collection ignored auctions that ended early due to seller retractions. The final data collection resulted in 795 auctions without reserve prices, and 256 auctions with reserve price. Lastly, in some cases the final posted bids were arranged chronologically, whenever the data showed otherwise. Given the bid amounts and the time of each bid, we mapped the bid differentials and durational differences proportional to the final effective bid at the end of the auction.

Procedures

Data on 1,051 completed English auctions were collected. The following variables were examined, the value of the bid transformed to a percentage of final bid (Valueproportion), auction duration (Duration) and total number of bidders (No Of Bidders) per auction.
Change in duration between bids (Duradiff) was computed. Variables Initial value and Final value are the initial and final bids for each auction. The difference between the initial and final bid values was calculated to create Difference. Lastly, these differences (between initial and final bid values) were transformed into a proportion of the final bid in the variable Diff on final. Duration is calculated in seconds. To distinguish between auction formats, a dummy variable, RP was created to indicate the presence or absence of a secret reserve price for the auction.

RESULTS

Scatter plots of the variables were examined, and curve fits of percentage price (variable ‘valuepropportion’), and change in percentage price against duration and duration change were also estimated. The assumption of an English auction is that bids would monotonically increase with respect to time. But the process need not be linear. To estimate the best fit linear, quadratic, logistical and exponential curves were estimated. To test the reliability, the entire data set were split in to four sets and regressions were individually estimated for each. Lastly, the entire data set for 1,051 auctions was considered for estimation by regression.

The results of the regression analysis show that the value is positively related to duration. While the linear regression accounted for 26.8% of the variation in value proportion, the cubic was the best fit, accounting for 31.4%, (F=890.54, p<.05). This means while that the value increased over time in the following manner.

The change in the bid size (variable ‘diff on final’) was not significantly related to duration. The relation between the lag time between bids and duration was also significant. As the duration of the auction grew the time lag between bids increased. The linear regression explained 16.0% (F=987.02, p<.05). The cubic fit the data better accounting for 17.9% of the variance (F=375.83, p<.05). Also worth noting is that as the value of the bid increased the variance in the size of the difference between bids also increased. The same pattern was observed in the relationship between the length of the lag between bids and auction duration. As duration increased the variance in the lag between bids grow.

The above results suggest that the structural pattern of the bidding process is cubic, initially the price of the object increases rapidly, and then it levels off at about 70% of the final price, only to increase towards the end of the time allotted for the auction. This suggests that people are employing the following strategy: bid to an equilibrium level that the participants are willing to accept. This may be considered the ‘common value’ of the object. Near the end of the auction a small group of participants, maybe only a single person, bids above this value to secure the object. The number of bidders intensely bidding towards the end of the auction could also indicate ‘spiking’, a behaviour that is unique to online auctions. According to Lucking-Reiley (2000) in online auctions submitting an earlier bid is dominated by the strategy of submitting the same bid late in the auction, especially before the final seconds of the auction. Since, eBay auction automatically stop accepting bids after pre-specified duration, bidders who manage to bid in the final seconds, often mange to outbid high rival bidders. With free entry and exit of bidders, and a number of alternative bidding strategies, the Internet auction may be conceptualized in game theory terms as an infinite-choice, continuous-time (Feeley et al. 1997), infinite number of players’ game. During the auction the participants bid to a common equilibrium value. As the ‘game’ approaches the end, one or more players defect in an attempt to win the auction.

Next, to examine the effect of Reserve Price on auctions independent sample t-tests were performed on the variables described above. The results of the t-test are presented in Table 1. The entire data set was used (N=1,051 completed auctions). There were 256 reserve price auctions and 795 non-reserve price auctions.

The number of bidders for any auction indicates the total number of bidders who participated in the auction and is distinct from the total number of bids received in an auction. An auction could receive more than one bid from the same person. For reserve price auctions there were on an average 14.23 bidders. For auctions without a reserve price only 11.94 bidders participated. This difference is significant (t=3.22, p<.05). This result indicates that reserve price information significantly affects bidder participation.

The bid values signify the total number of bids received for that auction and captures the bidding intensity within an auction. ValueProp was significant (t=4.71, p<.05). The results indicate that the mean value of bids received in an auction with reserve price information was higher than the bids received in an auction without reserve price.

The t-test for the initial (t=3.62, p<.05) and final values (t=6.16, p<.05) of the bids were also significantly different indicating differing initial and final values for the two auction formats. The average initial values for a reserve price auction was $54.83 (SD=122.51) and for a non-reserve price auction it was $24.65 (SD=51.49). Both values were greater for the reserve price auctions. The average final values were also significantly different, $238.44 (SD=261.62) for reserve price auctions and $123.41 (SD=185.34) for auctions without a reserve price. The higher initial values signify one of the following. Either the auctioned products differed, or
the expected private valuations of the sellers of the products differed. Since the data for the study come from a random sampling of equivalent auctions, the assumption of higher valuations seems more likely.

The difference between the final and initial values indicates an increase in values for each auction. The t-test of mean values ($t = 4.70$, $p = .000$) for ‘Difference’ was significant, indicating that the average price increase for an auction with reserve price information was greater ($M = 175.31$) than that under a non-reserve price format ($M = 99.69$). Lastly, the value differences as a proportion of the final values of each auction were significant ($t = 3.009$, $p = .003$) indicating that the intensity of bidding was significantly different in value terms in proportion to the final values. Reserve price auctions gained an average of 5.2% more in price (81.8% compared to 76.6%) than auctions without one. This was done in order to control for the final prices. These results suggest that reserve price auctions tend to attract greater bidding intensity resulting in higher initial and final values. This is a very interesting finding. Though reserve price auctions had higher initial values, the average increases in bid values were also higher. If one were to assume that sellers who maintain reserve prices have higher expected values for their products, then higher bid increments could be evidence of the impact of reserve price information on bidders. Bidders who participate in reserve price auctions could assume that since the sellers’ valuations are high, a winning strategy could require higher bids. Also, since information reduces uncertainty, reserve price information provides more information on valuations than an auction without reserve prices. In order to ensure that the differences in auction were due to higher valuations, the t-tests were rerun by controlling the initial value of auctions. Even after controlling for initial values, auctions with reserve prices procured an average 5.2% higher final value, than auctions without reserve prices.

To map differences in bidding behaviour between reserve price and non-reserve price auctions, a non-linear regression was performed with value proportion as the dependent variable and duration (time) as the independent variable. The results of the regression analysis indicate that though linear regression accounted for 37.7% of the variation in value in a reserve price auction, the cubic was the best fit accounting for 44.3% ($F = 141.02$, $p < .05$) of the variation in value. It indicates that in a reserve price auction, there exist significant inflection points when the auction reaches about 60% of the final value and at approximately 80% of the final auction value. One conclusion is that the bidders in reserve price auctions are more informed about the ‘common value of the auction’ and follow a more deliberate strategy, bidding at times of change during the auction.

For non-reserve price auctions, cubic regression was also the best fit. However, it accounted for only 33.7% of the variance in the process ($F = 229.73$, $p < .05$). These results show that while the value increased over time it did so in the following manner. Initially, it increased

### Table 1. Result of independent samples t test

<table>
<thead>
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<th>Mean</th>
<th>Std dev.</th>
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<th>t</th>
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<td>Value proportion</td>
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<tr>
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<td>Initial value</td>
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<td>51.49</td>
<td>795</td>
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<tr>
<td>With RP</td>
<td>54.83</td>
<td>122.51</td>
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<td>Final value</td>
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<td>174.94</td>
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<td>175.31</td>
<td>275.59</td>
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<td>Diff Final</td>
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<td>With RP</td>
<td>.818</td>
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<td>Duration</td>
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<tr>
<td>Without RP</td>
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<td>No of bidders</td>
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<tr>
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<tr>
<td>With RP</td>
<td>14.23</td>
<td>5.30</td>
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Arun Vishwanath and George A. Barnett ■ Structure of Online Bidding
rapidly, and then it levelled off at about 70% of the final value, only to rise rapidly as the auction approached its time limit. In other words, there appeared to be a significant end game. Also, there does not appear to be intense periods of bidding around the inflection points as is the case with auctions with reserve prices. During the auction the participants bid to a common equilibrium value. As the ‘game’ approaches the end, one or more players defect in an attempt to win the auction.

**DISCUSSION**

The research empirically validates a number of theoretical propositions from prior research. Information of the existence of a secret reserve price in eBay auctions affects the average participation levels in an auction, the initial price of the auction, the final price of the auction and the intensity of bidding within the auction (research question 4). The information of the existence of a secret reserve price on an eBay auction increases the total participation of bidders within an auction (research question 5). The average number of bidders attracted to a reserve price auction is more than those without a reserve price. A secret reserve price seems to make eBay auctions more attractive to bidders, and increases the total intensity of bidding within the auction (research question 6). The average final value and initial values are higher for reserve price auctions. The controlled range of values is also higher, indicating the probability of higher average revenue to auctioneers from the reserve price auction format as against the non-reserve price format. Lastly, bidders in a reserve price auction seem to have a more defined bidding strategy that results in higher final values to the auction (research question 7). The bidding pattern in best represented by a cubic fit, with distinct inflection points characterized by intense bidding. Non-reserve price bidding patterns are less structured, with intense bidding phases only at the beginning and during the endgame.

Lucking-Reiley (2000) suggested that bidders in reserve price auctions were bidding strategically. The current paper structures and validates this notion. There are two distinct mechanisms that might explain strategic bidding. First, auctions involve high levels of uncertainty, and the reserve price seems to reduce this uncertainty by providing more information, when compared to auctions without reserve price. However, the existence of reserve price seems to communicate differences in seller valuations. Bidders presume a higher valuation of sellers who maintain reserve prices. This could result in more intense competition, higher bid increments, and a potential ‘winners curse’ for the winning bidder. Similar findings by Bajari and Hortacsu (2000) validate our results. Their estimated model predicts that the expected revenue from a reserve price auction exceeds the revenue from an ordinary non-reserve price auction. However, contrary to the findings of Lucking-Reiley (2000) who found auctions with reserve prices attracted fewer bidders, the auctions in our data with reserve prices attracted a marginally higher number of bidders.

Also, Katkar and Lucking-Reiley (2000) found that a number of auctions with a reserve price never met or realized the price. In triangulating our research, we could conclude that maintaining reserve price is an effective strategy which results in higher final values and expected revenues. One strategy would be to maintain a reserve price, and a very minimal initial value for the auction. This might attract more bidders in the initial stages of the auction. Dholakia and Soltysinski (2001) suggest that in a number of auctions bidders gravitate to auction which have other bidders, indicating social influence on bidder choice. Hence, low initial values coupled with reserve prices would attract enough bidders, resulting in competitive bidding behaviour towards the close of the auction, and realize higher final values.

This research has some noteworthy limitations. It focuses on only one category, and the findings could be typical to the category. Future research could compare intra-category variations in bidding behaviour. Also, the study assumes that the bid values increase monotonically. However, for a few completed auctions, the bid history showed lower bids appearing after high bids. Most of these instances were bids the midst of the auction, and not the winning bid. Hence the data was reorganized to reflect a monotonic increase. Next, a number of new formats and information schemes are instituted by eBay on a regular basis. For example, eBay now allows for products to be sold for an asking price without bids. Future research needs to evaluate the impact of these features on bidding behaviour. Lastly, indirect observational data such as that used in this study makes a number of assumptions about the bidder, the seller and their strategies. Hence, other methods should be employed to validate our results. For example, Koppius (2002) conducted a series of controlled experiments that demonstrated the impact of duration (length of time) of an auction, and information architecture on the outcome of an auction. Experiments using auction software and surveys of bidders and sellers are some additional methodologies which should also be explored.

However, researchers from various disciplines have begun to validate empirically prior theoretical positions. Our study contributes to this emerging understanding of online auctions. This is one of the first empirical studies to examine and structure bidding behaviour to different information formats. Future research should examine bidding behaviour as a strategic process of information exchange, and focus on structuring bidding behaviour within different formats for different information levels.
References
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