Analysis and Design of Business-to-Consumer Online Auctions

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1 Author names in alphabetical order
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Abstract

Business-to-consumer online auctions form an important element in the portfolio of mercantile processes that facilitate electronic commerce activity. Much of traditional auction theory has focussed on analyzing single-item auctions in isolation from the market-context in which they take place. We demonstrate the weakness of such approaches in online settings where a majority of auctions are multi-item in nature. Rather than pursuing a classical approach and assuming knowledge of the distribution of consumers' valuations, we emphasize the largely ignored discrete and sequential nature of such auctions. We derive a general expression that characterizes the multiple equilibria that can arise in such auctions and segregate these into desirable and undesirable categories. Our analytical and empirical results, obtained by tracking real-world online auctions, indicate that amongst the control factors that online auctioneers can manipulate the single most important factor is the bid increment. We show that consumer-bidding strategies in such auctions are not uniform and that the level of bid increment chosen influences them. With a motive of providing concrete strategic directions to online auctioneers we derive an absolute upper bound for the bid increment. Based on the theoretical upper bound we propose a heuristic decision rule for setting the bid increment. Empirical evidence lends support to the hypothesis that setting a bid increment higher than that suggested by the heuristic decision rule has a negative impact on the auctioneer's revenue.
1. Introduction

Business-to-consumer (B2C) online auctions are heating up as an efficient and flexible sales channel with total revenues projected to reach $12.54 billion by 2003\(^2\). Along with the other two types of online auctions, namely consumer-to-consumer (C2C) and business-to-business (B2B) auctions, they represent a new class of mercantile processes that are ushering in the networked economy, but are not fully understood yet. Van Heck and Vervest (1998) have called for an extensive examination of the pervasive impact of advance electronic communication on the theory and practice of auctions. For a wide variety of goods sold over the Internet, consumers now have an interesting choice of mercantile processes to utilize to buy these goods. Broadly, these different processes can be broken into static posted-price mechanisms and dynamic interactive pricing mechanisms such as online auctions. In this context, online auctioneers are striving to find the correct strategic and tactical direction that ensures their long-term profitability. This involves optimizing existing as well as designing interesting new mercantile processes to sell their products. This paper is an attempt to analyze this emerging market structure with respect to the welfare of the different economic agents involved, namely the B2C auctioneers (we implicitly assume the joint interest of the seller and the auctioneer, if they are different) and consumers.

There already exists a vast body of literature dealing with the theory of auctions and optimal mechanism design (see McAfee and McMillan 1987, Milgrom 1989, Myerson 1981 for a review). However, the majority of the work focuses on the analysis of single auctions and is carried out in isolation from the broader context of the markets in which these auctions take place (Rothkopf and Harstad, 1994). Without the geographic constraints of traditional auctions the behavior of the different economic agents in online

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\(^2\) *Consumers Catch Auction Fever* (March 1999), Published by Forrester Research, Cambridge, MA.
auctions is heavily influenced by the context in which they take place. For instance, the presence of *simultaneous substitutable online auctions*\(^3\), where an individual shopping for, say a computer, can simultaneously place bids at Onsale.com or Yahoo.com, impacts the efficiency of not just the isolated auction under consideration but also the external market in which it takes place. It should also be noted that despite the presence of a vast body of literature dealing with traditional auctions, one could not call these auctions 'mainstream' from a consumer's viewpoint. It is only after the synergetic combination of traditional auctions with Internet technology that this sphere of economic activity has blossomed into significance.

This paper contributes to the literature by enhancing the conceptualization of the traditional theory of auction based shopping in the emerging online context. Specifically, we contribute to the literature by addressing four questions that have not yet been resolved by researchers or practitioners.

1. Without making any distributional assumptions regarding the consumers valuations, can we derive a structural characterization of the revenue curve of B2C online auctions, and can we derive bounds on the revenue?

2. In the presence of a multitude of decision variables that can serve as control factors for online auctioneers, which are the ones that have a significant impact on revenue?

3. Are consumers' bidding strategies uniform or can we identify heterogeneous bidding strategies pursued by consumers having different risk profiles? Are there any interactions between consumer bidding strategies and key control factors of auctioneers?

4. Assuming a partial knowledge of the upper tail of the distribution of the consumers’ valuations can we prescribe a concrete and practical strategy to auctioneers that allow them to leverage the insights obtained from addressing the above two research

\(^3\) [www.auctionwatch.com](http://www.auctionwatch.com) facilitates such comparisons
questions? What are the cost implications of obtaining the distributional information mentioned above, and is it feasible?

There are a number of parameters, or control factors, that auctioneers can set prior to the commencement of the auction. These can potentially influence the eventual revenue realization from the auction. The current practice of B2C online auctions reveals to us that control factors are, the opening bid, the bid increment, and the lot size. Other candidate control factors can be the auction ending time, the time span of the auction and the hidden reserve price. The ending time is not interesting because a close examination of such auctions indicates to us that all auctioneers employ a going, going, and gone period after the passage of the announced closing time. Thus, the actual closing happens when no new bids are received for a pre-determined time interval after the closing time.

The time span of the auction is an interesting control factor and its impact is modeled in our work through the opening bid, as detailed later. Another potential control factor that auctioneers could use is a hidden reserve price, below which they will not be willing to sell the goods. While observed in consumer-to-consumer auctions on Ebay, B2C auctioneers, such as Onsale, do not use this construct. Rather, they utilize a low opening-bid as a strategic marketing tool to attract web traffic (Bajari and Horta, 2000). It should be noted that the risk characteristics of the sellers (individual consumers as opposed to corporations) and the nature of goods being auctioned on Ebay are significantly different from B2C auctions.

In this paper we do not address questions such as, “should an auctioneer sell all 50 units in a single auction, or in 10 auctions of 5 units each?” While interesting, this issue is beyond the scope of this study. Its analysis requires a different, and more restrictive, set of assumptions (Beam, Segev, Shantikumar (1999)), which include knowledge of the holding costs due to technological obsolescence and knowledge of population
characteristics that go beyond the bidding strategies we will be discussing. In this study we assume that lot-sizing decisions are simplistically made with the objective of clearing aging inventory fast.

In order to answer the first question we develop a stylized theoretical model that analytically characterizes the structure of the most popular type of $B2C$ auctions and develops a range of expected revenue for auctioneers. We do this without making any assumptions regarding the distribution of individuals’ valuations. Subsequently, using empirical evidence collected from monitoring real-world online auctions we identify the key decision variables that serve as control factors for auctioneers who are attempting to maximize their revenue. In identifying these factors we note that many of the elegant and powerful theorems and some of the typical assumptions made in the classical analysis of auctions do not hold in the emerging online context. For instance, we observe that all $B2C$ online auctions set a discrete bid increment and our analysis suggests that this is the single most important decision variable that impacts auctioneers’ revenue. This is in stark contrast to the standard auction theory assumption that the amount bid is a continuous variable. There has been very little research done on the impact of discrete bid levels in auctions. Yamey 1972 and Rothkopf and Harstad 1994b are the only researchers who have dealt with the somewhat related issue of analyzing auctions from a more decision theoretic perspective rather than a game theoretic perspective. However, their analysis deals with single item auctions. This research is an attempt to re-ignite this neglected area of auction theory research by shifting the focus from examining only the limiting behavior towards acknowledging the discrete and sequential nature of the auction process.

Our empirical analysis helps us identify three prominent bidding strategies pursued by consumers. We compare the relative performance of these strategies with
respect to the surplus they provide to their adopters and also examine their impact on the revenue generation process.

Lastly, with an objective of providing concrete directions to auctioneers regarding the design of B2C auction mechanisms, we discuss tactical issues regarding the setting of the bid increment and present an upper bound beyond which significant loss of revenue could arise. The validity of this result is tested against observed strategies pursued by auctioneers. The empirical evidence shows a negative impact on revenue when the bid increment set by auctioneers exceeds the upper bound.

The core stylized theoretical model is presented in Section 2. In Section 3, we present our empirical findings that help us identify the key decision variables for auctioneers and also the different consumer bidding strategies. Section 4 presents an approach, along with its empirical validations, towards designing auctions with near-optimal bid increments. Section 5 concludes this paper.

2. Theoretical Model

A vast majority of existing research focuses on auctions of single items, whereas most of the B2C auctions conducted on the web sell multiple identical units of an item using a mechanism analogous to, but not the same as, the first-price, ascending, English auction. We call such auctions "Multiple Item Progressive Electronic Auctions (MIPEA)". It is well known [Rothkopf and Harstad (1994a)] that single-item results do not carry over in multiple-item settings. In addition, researchers using the classical game-theoretic approach to model auctions often rely on making distributional assumptions regarding individuals' valuations to stochastically derive equilibrium conditions. We demonstrate the inappropriateness of such an approach in multi-item settings. In contrast, our approach focuses on the combinatorial dynamics of the penultimate rounds that determine which of the multiple equilibrium points is attained in a given instance.
While most of existing theory analyzes auctions under either the private or the common value setting, the online context in which these $B2C$ auctions take place, makes such a strict classification inaccurate. The empirical evidence indicates that most of the items have both idiosyncratic (private) and common value elements. This is more so given the presence of imperfect substitutes and price-comparison agents that provide information regarding the alternative comparable products and their posted prices. Thus, based on the general model of Milgrom and Weber (1982), the multi-item $B2C$ auctions lie in the continuum between the private and common value models.

The presence of price-comparison agents creates a mass of consumer valuation at or around the prevailing market price. Consequently, we would expect that in online auctions such bid levels would be realized towards the end of the auctions, rather than in the beginning or intermediate stages. This forms the motivation behind our attention to the combinatorial dynamics of the penultimate auction rounds. Next, we introduce some basic notation to describe our model.

Let there be $N$ items to be auctioned and let there be $I$ bidders, each with a value $V_i$, $i=1,...,I$, for the product. Let $B_i$ denote the current bid of consumer $i$. As mentioned earlier all MIPEA have a minimum bid increment that we denote by $k$. Ignoring monitoring costs for the present, we assume that customers maximize their net value and hence always bid at the current ask price, provided that the current ask price does not exceed their valuation of the item. Rothkopf and Harstad (1994b) characterize this as the pedestrian approach to bidding. Later in the paper we relax these assumptions and analyze the impact of alternative bidding strategies. When there are $N$ bids at the same level, the ask price is incremented by $k$.

Let $B_m$ be the highest bid that does not win the auction. In general, there can be several bidders who bid $B_m$, but fail to win the auction. We define the marginal consumer
as the first person to bid $B_m$, and who failed to win the auction. Let the value of the marginal consumer be denoted by $V$. Observe that no a priori knowledge is required about the marginal consumers’ exact valuation. We postulate that there will exist such a consumer whose position in the distribution space of valuations, along with the temporal position of her bid, will determine that no further bids can be placed. This creates a partition of the distribution space around $V$, which along with the temporal position of the marginal bid creates the multiple equilibria in such auctions. It is important to note that $B_m$ defines $V$ and not vice versa.

It is clear from the bidding process that at the end of the auction there are only two possible bid values that are in the winning list. Let us denote them by $B_m$ and $B_m + k$. By definition of the marginal customer, $B_m$ is the highest bid the marginal consumer can potentially offer, and $B_m \leq V < B_m + k$.

We partition the set of bidders who are involved in the final bidding sequences into a set $L$ of consumers who were able to bid at the level $B_m$ but failed to win the auction, and a set $W$ of auction winners. Also, let the cardinality of the set $L$ be $M$, that is $|L| = M$. By construction, $|W| = N$.

We now characterize the structure of the winning bids in terms of the temporal position of the marginal consumer's final bid $B_m$ and the bid increment $k$. Let $j$ correspond with the temporal order of the marginal consumer's bid. The case with $j=N+1$ represents the case in which the marginal consumer never gets the chance to bid at the level $B_m$, and all winners bid at this level.

**Proposition 1** If the marginal consumer is the $j^{th}$ person to bid at the level $B_m$, $j = 1...N+1$, the winning bids of MIPEA have the following structure: $B_m^1, B_m^2, ..., B_m^{j-1}, (B_m+k)^1, (B_m+k)^2, ..., (B_m+k)^{N-(j-1)}$. 
**Proof:** Let the marginal consumer be the \( j^{th} \) person to bid \( B_m \). Then, there were \((j-1)\) bidders from the set \( W \) who bid at the level \( B_m \) before the marginal consumer. By definition of the set \( L \), there are \((M-1)\) other bidders who bid their highest possible bid \( B_m \). Note that by construction \( M \leq N-(j-1) \).

This implies that, an additional \((N-j)-(M-1)\) bidders from set \( W \) bid at the level \( B_m \). However, this leaves \( N - [N - j - M + 1 + j - 1] = M \) consumers from set \( W \), who cannot bid at the level \( B_m \). These consumers will bid at the level \((B_m+k)\).

Consider the first consumer who bids at the level \((B_m+k)\). He will displace either a consumer from the set \( L \), or from \((N-j)-(M-1)\) consumers from the set \( W \) who were able to bid \( B_m \).

If the consumer displaced from the winners list at the level \( B_m \) was from the set \( W \), then note that there will still be \( M \) consumers from the set \( W \) that have to bid at the level \((B_m+k)\) to enter the winners list.

However, if the consumer displaced was from set \( L \), then the remaining consumers who have to bid \((B_m+k)\) goes down by one to \( M-1 \).

This process will be repeated at every bid at level \((B_m+k)\). Note that since all the consumers from the set \( L \) have to be displaced, there will be \( M + (N-j) - (M-1) = N - (j-1) \) bids at the level \((B_m+k)\). Thus, there will be \((j-1)\) bids at the level \( B_m \) and \( N-(j-1) \) bids at the level \((B_m+k)\) in the winning bid structure\(^4\).

*Thus, the winning bids under MIPEA have the structure: \( B_m^1, B_m^2, ..., B_m^{j-1}, (B_m+k)^1, (B_m+k)^2, ..., (B_m+k)^{N-(j-1)} \).*

**Corollary 1a** The revenue for MIPEA can be represented by:

\[
\text{Revenue} = NB_m + kb, \quad (1)
\]

where \( b = N-(j-1) \) is the number of bids at the high level \( B_m+k \).

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\(^4\) Since the actual closing happens when no new bids are received for a pre-determined time interval after the closing time, it implies that marginal consumer has the opportunity to place her final bid, and consumers in general have the opportunity to bid up to their valuation \( (V_i) \), if necessary.
**Corollary 1b** The presence of \( N \) consumers having valuations \( \geq B_m \) does not guarantee that \( B_m \) will be the marginal bid.

**Proof:** This is the case where \( b = 0 \), and \( j = N + 1 \). The marginal customer never gets the chance to bid at the level \( B_m \) and the marginal bid then becomes \((B_m - k)\).

From a managerial perspective Proposition 1 indicates that unlike in single item auctions, revenue from multi-item auctions can materialize in multiple ways depending on the value of \( j \). Each of the above-defined structure of the winning bids corresponds to a different equilibrium point. These various equilibrium points will differ in the revenue they generate, as seen in Corollary 1a, where \( b \) can vary from 0 to \( N \).

Rothkopf and Harstad (1994b) show that in single item auctions \((N = 1)\) there are 3 mutually exclusive and exhaustive cases in which the final bid structure can materialize. In what follows, we demonstrate that the number of possible cases leading to the various equilibrium points of Proposition 1 grows exponentially with \( N \).

**Corollary 1c** The number of mutually exclusive and exhaustive cases in which the winning bid structure can form grows at an exponential rate with \( N \).

**Proof:** Let \( n \) be the total number of customers having \( V_i > B_m \). From Corollary 1b we need \( n \geq N + 1 \) to guarantee the equilibrium points of Proposition 1 at levels \( B_m \) and \( B_m + k \). Consider the special case where \( n = N + 1 \).

For each temporal position \( j = 1, \ldots, N+1 \) that the marginal customer places his final bid, there are \( N! \) possible sequences of the other \( N \) bidders. Hence all the equilibrium points described in Proposition 1 can be achieved through \((N+1)!\) possible bidding sequences.

Proposition 1 and its corollaries indicate that there can be multiple equilibrium points for these kinds of auctions, some of which are more desirable than others in terms of generated revenue. The exponential growth described in Corollary 1c once again highlights the inappropriateness of pursuing a more classical probabilistic approach.
towards optimizing expected revenue of auctioneers. The mathematical intractability of deriving an expected revenue function, and subsequently optimizing it, becomes evident even for the most trivial distributions as $N$ grows. Instead, we utilize the structure of the winning bids to derive the bounds of total revenue for auctioneers and focus our attention on identifying key control factors.

### 2.1 Bounds on the Revenue

It should be noted that auctioneers have the privilege of setting an opening bid, similar to a reservation price, below which they do not wish to sell the goods. Let $r$ denote the opening bid and let the '%' operator returns the remainder of the division.

Define $\delta = (V - r) \ % \ k$  \hspace{1cm} (2)

Observe that $B_m = V - \delta$ \hspace{1cm} (3)

In Equation 2, $\delta$ denotes a segment of the bid increment $k$ that measures the distance between the marginal consumer's valuation $V$ and the nearest lower feasible bid. For instance if $V = $80, $r = $8 and $k = $5 then the nearest feasible bid to $V$ is $78 which implies that $\delta = 2$.

We assume that in the presence of other fixed price alternatives consumers choose to participate in such auctions with an objective of maximizing their net worth. In the extreme we assume that a rational, net worth-maximizing consumer with valuation $V_i$ will be willing to bid his or her valuation. Bidding any higher would imply a non-positive surplus with certainty. In practice this extreme bid will be determined jointly by the bid increment $k$ and the auction opening bid $r$. We can now define the bounds on an auctioneer's total revenue in terms of the marginal consumer’s valuation $V$, the bid increment $k$ and $\delta$.

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5 With $N=17$ (the average lot size of of the 90 auctions we tracked) the number of mutually exclusive and exhaustive cases is $6,402,373,705,728,000$. 
**Proposition 2.** Let $V$ be the marginal consumers valuation, and $\delta$ be a segment of the bid increment $k$ that measures the distance between the marginal consumer's valuation $V$ and the nearest lower feasible bid. Then the lower bound and the upper bound on the revenue of a seller selling multiple units under MIPEA are respectively $N(V-\delta)$ and $N(V-\delta+k)$.

**Proof:** Lower bound follows from Corollary 1b and equation (3). The upper bound occurs when the marginal customer is the first position to bid $(V-\delta = B_m)$. Following Proposition 1, it is easy to verify that by definition of marginal customer there will be $N$ bids placed at $(V-\delta)+k$

**Corollary 2a** The upper bound is feasible provided there is a nonzero probability that $N$ or more individuals have valuations in excess of $(V-\delta+k)$.

**Corollary 2b** The range of revenues under MIPEA is $N*k$.

From a managerial perspective an understanding of the revenue bounds is important as it gives the auctioneer’s incentive to design the auction parameters in a fashion that increases the likelihood of realizing the higher revenue bid structures.

Example 1 below illustrates the sequential progression of bids that influence the derivation of these bounds. Subsequently, we deal with issues related to manipulating the bid increment, the range of auctioneer's revenues and the feasibility of the upper bound.

**Example 1** - Consider the following hypothetical scenario. Let $N=3$, $k=$ $5$ and $r=$ $9$. Let there be four bidders, say A, B, C, D with true valuations of $100$, $105$, $106$, $107$ respectively. Let A be the marginal consumer. Observe that $\delta = 1$.

- The MIPEA lower bound occurs if we observe the following sequence of progressive bids: $D(89)--C(89)--B(89)--A(94[(V-k-\delta)]--)B(94)--C(94)--D(99)--C(99)--B(99)--STOP$. At this stage 'A' the marginal consumer will have to bid $104$ to get in now which he will not since his valuation is $100$. Thus, the total revenue = $297$. 
The MIPEA upper bound occurs if we observe the following sequence of progressive bids: B(94)--C(94)--D(94)--A(99\[V-δ\])--D(99)--C(99)--B(104)--C(104)--D(104)--STOP. Observe that 'A' the marginal consumer is the first to get into the winners list at \([V-δ]\) and hence the last to get out at that level. At the terminal stage 'A' would have to bid $104 to get in now which he will not since his valuation is $100. Thus, the total revenue = $312.

Next we consider the impact on the range of total revenue of manipulating the bid increment \(k\). Consider the difference between bid increment \(k\) and \(αk\) where \(α \in \mathbb{R}^+\).

**Proposition 3** Any change in the bid increment by a factor \(α\) induces a proportional change in the range of total revenue.

**Proof:** The range of total revenue with bid increment \(k\) is

\[
[N(V - ((V - r) \% k) + k)] - [N(V - ((V - r) \% k))] = Nk
\]

With bid increment \(αk\) the range of total revenue is

\[
[N(V - ((V - r) \% αk) + αk)] - [N(V - ((V - r) \% αk))] = αNk
\]

Thus any change in the bid increment by a factor \(α\) introduces an equal and corresponding change in the range of total revenue for the auctioneer.

The above proposition implies that auctioneers can strategically use the bid increment to control the level of uncertainty regarding the total revenue. As can be seen from the above results the bid increment also plays an important role in the revenue realization process. It should also be mentioned that the importance of setting an optimal bid increment gets magnified in multiple item settings as any misjudgment on the part of auctioneers could have \(N\)-fold consequences. Example 2 illustrates a scenario where keeping everything else constant the bid increment is manipulated to have a telling effect on the auctioneer's revenue:
**Example 2** - Consider an auction with \( N = 3 \) and \( r = $102 \). Individual valuations are ranked as follows: $110, $120, $120, $125, $125, $139, $139, $139, $143, $143. Let the individuals be labeled A, B, C… I, J, K in increasing order of their valuations. Consider the following bid sequence: A(102), B(102), C(102), F(117), G(117), C(117), I(132), J(132), K(132). In this case the marginal consumer is F with a valuation of $139.

**Case 1 (\( k = $15 \)):** The top half of Figure 1 shows the possible bid levels and the position of the marginal consumer at $139. Observe that \( \delta = 139 - 132 = 7 \) and lower bound occurs at \( N(V-\delta) = $396 \). The upper bound at \( N(V-\delta+k) \) would imply that 3 consumers would have to bid $147 which is infeasible as no consumers have valuations above $143. Hence the upper and lower bound are the same and the range = 0.

**Case 2 (\( k = $20 \)):** The bottom half of Figure 1 shows the possible bid levels for this case. Observe that \( \delta = 139 - 122 = 17 \) and lower bound occurs at \( N(V-\delta) = $366 \). In contrast to Case 1 the bid levels corresponding to \( k=20 \) facilitate the possibility of capturing the highest valuations leading to an upper bound of $426. This can be viewed as a reduction in the economic inefficiency of the auction as it reduces the gap between the price paid by the auction winners and their valuations. Additionally, in contrast to the case with \( k = $15 \), the switch to \( k = $20 \) at least makes it feasible for the auctioneer to come close to capturing the highest valuations at $143.
In the above discussion we have taken a decision-theoretic approach towards structurally characterizing multi-item B2C online auctions. Without resorting to any distributional assumptions and without focusing on the limiting behavior of individuals we explain the discrete and sequential aspects of such auction in terms of the marginal consumer's valuation, the bid increment and the auction starting point.

### 2.2 Consumer Bidding Strategies

The analysis based on Propositions 1 through 3 assumes that consumers behave rationally and participate in such auctions with a view of maximizing their net worth. This implies that all consumers employ the same strategy while bidding. Such a strategy involves active participation (manual or using a programmed agent) that bids the minimum required bid at any stage during the auction. The theoretical basis for adopting this approach can be found in Rothkopf and Harstad’s (1994b) discussion of what is called the pedestrian approach. In adopting this strategy bidders choose to be no more
aggressive than necessary to continue competing. While such behavior, termed as *participatory* by us, is exhibited in reality, it is not the only kind of strategy employed by bidders. One interesting aspect of Internet based auction markets it that makes “armchair” bidders possible, to the extent that the assumptions of rationality are more questionable. The availability of data makes electronic auction markets a perfect venue for testing the behavior of uninformed bidders, who it seems exhibit different behavior than theory predicts.

A broader and more basic question in categorizing online bidders is whether we can we capture some consistent “trait(s)” that would allow us to develop a formal typing methodology. We rely our segmentation on the basis of the theory of risk preferences (Slovic, 1972) of consumers and on Herbert Simon’s *bounded rationality*. Additionally, as recommended by Messinger (1995), we designed a segmentation scheme that is *observable* (our automatic agent tracks all incoming bids), *managerially relevant* (it impacts auctioneers’ revenue) and leads to *clear distinctions* between segments. Our empirical investigation identified three distinct bidding strategies that segmented consumers (Bapna, Goes, and Gupta, 1999). Section 3.1 specifically describes how the categories were identified from the data.

*Evaluators* think that they know the true market value of the object they are interested in and try and bid that amount early in order to get ahead in the winners’ list. However, due to bounded rationality, or lack of awareness of alternative information sources such as price-comparison agents, or by choosing not to incur the cost of monitoring the auction, they run the risk of bidding more than required to win a given auction. Their bidding higher than the minimum required amount also indicates their desire to minimize the uncertainty of being priced-out of the auction, which amounts to a risk-aversion premium that should be expected to pay. *Participators* on the other hand
never bid any higher than the current minimum required bid and can be thought of as having a low monitoring cost, or perhaps even added “gaming” utility from the process of being a part of the auction. Bucklin and Lattin (1991) first introduced the notion of *opportunistic* shopping behavior to account for the fact that households do not run out of all products simultaneously. Such consumers can be categorized to be risk seeking because they wait till the last moments to enter into an auction, and they buy when they see a bargain.

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<tr>
<th>Evaluators</th>
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<td></td>
<td>Early one time high bidders who have a clear idea of their valuation</td>
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<td></td>
<td>Bids are, usually, significantly greater than the minimum required bid at that time</td>
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<td>Rare in traditional auction settings - high fixed cost of making a single bid</td>
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<td>Risk averse</td>
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<td>Bounded rationality</td>
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<td>High monitoring costs</td>
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<td>Participators</td>
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<td>Risk neutral</td>
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<td>Derive some utility (incur a time cost) from the process of participating in the auction itself</td>
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<td>Make a low initial bid equal to the minimum required bid</td>
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<td>Progressively monitor the progress of the auction and make ascending bids never bidding higher than minimum required</td>
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<td>Low monitoring costs</td>
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<td>Bargain hunters</td>
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<td>Place minimum required bids just before the auction closes (operationalized as the 87.5-100th percentile of the duration of the auction).</td>
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Table 3. Consumer segmentation based on bidding strategy

The theoretical impact of utilizing just the participatory bidding strategy in Propositions 1 – 3 is that it leads to conservative estimates of the auctioneer's revenue. It also implies that the auctioneer's revenue is a non-decreasing function of the proportion of bidders using other strategies than the participatory strategy. This is formalized in Proposition 4 and tested empirically in the next section.
Proposition 4. An increase in the number of bidders, in the winning set, who adopt a non-participatory bidding strategy has a non-decreasing effect on the auctioneer’s revenue.

Proof: Observe that both Opportunists and Evaluators have to pay at least the minimum winning bid to win the auction. Participators, by definition, will pay no higher than the minimum required bid. Thus the revenue contribution of one additional participator, who will replace an opportunist or an evaluator in the winner’s list, will be dominated by the contribution of the non-participatory bidder she displaces. It follows from induction that an increase in the number of bidders adopting a non-participatory bidding strategy has non-decreasing effect on the auctioneer’s revenue.

In the next section we examine whether our analytical findings can be validated empirically. In particular we wish to determine which amongst the many decision variables that auctioneers can control have a significant impact on their revenue, and what is the impact of the three different consumer bidding strategies on the welfare of the auctioneer and the consumers.

3. Empirical Investigation

Propositions 1-4 and their associated corollaries have testable implications. They suggest that the structural characteristics and corresponding auctioneer's revenue of MIPEA can largely be explained in terms of the marginal consumer's valuation, the bid increment and the auction starting point. Other researchers (Vakrat and Seidmann (1999), Beam, Segev and Shantikumar (1999)) have suggested that the key revenue impacting control factors for auctioneers are the lot size and the time-span of auctions. In order to empirically test this dichotomy of opinion we devised a data collection scheme that undertook a round-the-clock monitoring of 100 real-world online auctions conducted by a popular website6.

3.1 Data

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6 Popularity was based on www.web21.com ratings
An automatic agent was programmed to capture, directly from the website, the HTML document containing a particular auction's product description, minimum required bid, lot size and current high bidders at frequent intervals of 15 minutes. A parsing module developed in Visual Basic was utilized to condense all the information pertinent to a single auction, including all the submitted bids, into a single spreadsheet. Of the 100 auctions tracked 90 survived the screening process which was designed to ensure a) that there was no sampling loss (due to occasional server breakdowns), and b) that there was sufficient interest in the auction itself, given that some auctions did not attract any bidders. Data collection lasted over a period of 6 months so as to ensure a large enough sample-size (> 20) for each of the three levels of bid increment chosen ($5, $10, and $20).

The consumer segmentation comes straight from mining the data. As we have HTML snapshots of the winning bids at intervals of 5 minutes, we can parse the HTML and observe whether a person placed a single bid (an evaluator), or how many times a person bid, where did he start and stop, and what was the earliest time he came in (to identify opportunists).

3.1.1 Bias in the data While we have been thorough with the data collection process we do realize that there could still be potential sources for bias in the data. One such source could be the related to the bidding strategies described in Section 2.2. What if bidders were not pure participators? We tagged a bidder as a participator if we recorded a bid at a low level in the early phases of an auction and subsequently recorded a progression of higher bids. However, this assumes that the bidders never jump bid within this strategy, and always stuck to bidding the minimum required bid. Another possible source of bias could arise from the use of the automated bidding agents (whom we treat as participators) provided by the auctioneers. While most of these do in fact behave like participators, it is
beyond the scope of this study to comprehensively model their adoption and its consequent impact.

3.2 Measures and Model Specification We choose as our dependent variable the Average Offset Revenue (AOR) of an auction. The offsetting mechanism is designed to come up with a revenue metric that is independent of the magnitude of the auction (magnitude is defined as the average dollar value of the winning bids), and of other independent variables. The motivation for this metric comes from Proposition 3. Note that, for a given $k$ the difference in minimum and maximum revenue depends only on the lot size ($N$) and $k$. Thus to compare revenues from auctions with two different $k$ values it is sufficient to normalize the revenue per customer and subtract the minimum winning bid ($V-\delta$). Thus we shift each winning bid to the left by an amount equal to $B_i$, where $B_i$ is the lowest winning bid for that auction and then divide the total revenue by each auction’s lot size to get Average Offset Revenue (AOR). Mathematically,

$$AOR = \frac{1}{N} \sum_{i=1}^{N} (B_i - B_{\min})$$

where $B_i$ represents the $i^{th}$ winning bid. It is trivial to see that AOR is constructed to be independent of the magnitude of the value of an item. The AOR metric captures that for the same bid increment and the bid structure AOR would be the same for any magnitude.

3.2.1 Test Hypotheses

Our independent variables represent the three control factors that auctioneers can manipulate and the percentage of bidders adopting the participatory bidding strategy, denoted by $\%P$. Recall, that control factors are the bid increment $k$, the lot size $N$, and the auction reserve price $r$. While the impact of $\%P$ is hypothesised in Proposition 4, we wish to test the following three hypotheses through the regression model.

**H1:** The bid increment has a significant impact on the average offset revenue.
**H2:** *Lowering the opening bid has a positive impact on the average offset revenue.*

We expect to see a larger number of total number of bidders in auctions with low opening bids, and the resulting increased competition should have a positive impact on the auctioneers’ revenue.

**H3:** *An increase in the lot-size has a negative impact on the average offset revenue.*

With larger lot sizes the likelihood of having a larger number of bidders at the lower feasible winning bids increases and hence our prior is that it will result in a lower revenue per bidder.

We test for significance the model $AOR = \beta_0 + \beta_1k + \beta_2N + \beta_3r + \beta_4%P + \varepsilon \quad (4)$ and get the following results:

**Table 1.** Results from multi-variate linear regression

Table 1 indicates that on the basis of $\alpha$ risk of 0.05 the overall regression model is a good predictor; the $F$ value of 6.01 is greater than the tabulated $F(4, 86, 0.95)$. The $R^2$ value obtained is 22.30% indicating that perhaps not all of the variation is explained in terms of these independent variables.

### 3.3 Findings

Importantly, amongst the independent variables only $k$, the bid increment, is significant in explaining the variation of the average offset revenue. Neither $N$ the lot size, nor $r$ the
reserve price, nor the percentage of participators is significant. This validates our theoretical arguments, which state that the bid increment is the single most important decision variable that impacts auctioneers' revenues.

However, given the low $R^2$ value, a residual analysis of the model presented above revealed to us that the assumption of equal error variances, or homoskedasticity, was violated (the Chi-Square test statistic for the the SSR, Harvey and Gjeser tests was high and the p-values significant at the 5% level). we searched for a model with a better fit. Given that the bid-increments chosen by the online auctioneers had a logarithmic pattern to them ($5, $10, $20) our intuition led us to employ the log transformation to the dependent variable. This model is specified by

$$\ln(AOR) = \beta_0 + \beta_1k + \beta_2N + \beta_3r + \beta_4\%P + \varepsilon.$$  \hspace{1cm} (5)

This model has a better fit as indicated by the R-square value, which jumped from 22% to 40.6% and the heteroskedasticity tests, which were all insignificant. In addition the results consistently indicate the significance of the bid increment and the lack of significance of the other two controllable factors.

\begin{table}[h]
\centering
\begin{tabular}{llllll}
\hline
\textbf{Coefficients} & \textbf{Standard Error} & \textbf{t Stat} & \textbf{P-value} \\
\hline
Intercept & 1.467892394 & 0.19189425 & 7.649486 & 3.04E-11 \\
k & 0.078589308 & 0.01244858 & 6.313114 & 1.24E-08 \\
N & -0.007499783 & 0.00410193 & -1.82835 & 0.071046 \\
r & 9.88528E-05 & 0.000469321 & 0.21063 & 0.833686 \\
\%p & -0.013056175 & 0.306270373 & -0.04263 & 0.966098 \\
\hline
\end{tabular}
\caption{Results from the log model\footnote{One observation had to be dropped for the log transformation as it had an AOR of 0, i.e. the lower bound.}}
\end{table}
3.4 Consumer Welfare

In order to compare the relative performance of these categories we introduced a metric (Bapna et al. 1999) based on 'loss of surplus.' This is the difference between an individual's winning bid and the minimum-winning bid $B_l$. Using a metric similar to the AOR we compared the relative performance of the bidder types. Specifically, for each auction, we measured how much a winning bidder was worse off than the lowest winning bidder and then averaged this quantity within bidder types. Note that the maximum amount of surplus that could be lost by an opportunist is equal to the bid increment. This is because an opportunist can always force his way through by bidding one increment more than the current lowest winning bid at the expense of the last person to bid that amount.

<table>
<thead>
<tr>
<th>Relative Loss of Surplus</th>
<th>Participators</th>
<th>Evaluators</th>
<th>Participators</th>
<th>Opportunists</th>
<th>Evaluators</th>
<th>Opportunists</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>7.687531</td>
<td>13.13847</td>
<td>7.687531</td>
<td>10.98329</td>
<td>13.13847</td>
<td>10.98329</td>
</tr>
<tr>
<td>Variance</td>
<td>61.17528</td>
<td>626.2408</td>
<td>61.17528</td>
<td>74.16433</td>
<td>626.2408</td>
<td>74.16433</td>
</tr>
<tr>
<td>Hypothesized Mean Difference</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>df</td>
<td>91</td>
<td>146</td>
<td>94</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>t Stat</td>
<td>-1.82328</td>
<td>-2.45165</td>
<td>0.713055</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>P(T&lt;=t) one-tail</td>
<td>0.035772</td>
<td>0.0077</td>
<td>0.238789</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 3- Pair wise t-tests for bidder type loss-of-surplus comparisons. Higher values indicate more money left on the table.

The results of Table 3 can be best interpreted if one thinks of the ‘Mean’ row to reflect the average money left on the table by a given bidder type. We can see that participators are significantly better off than evaluators and opportunist, while the difference between the evaluators and opportunists is not significant. The evaluators chose not to utilize the current information regarding the winning bids that was available to them and essentially missed out on capitalizing on the sequential and discrete nature of these auctions. The participators on the other hand, made full use of such information and were rewarded for it.
Observation 1: The difference between the relative loss of surplus of the evaluators and the participators is a joint estimate of the monitoring cost and the risk-averseness of bidders participating in Internet auctions.

Future research is needed to isolate these two factors and refine their understanding. Figure 2 below depicts how the percentage of bidders pursuing these strategies varies with bid increment $k$. It is interesting to note that as bid increment increases from $5 to $20 there are systematic changes in the population mix of bidders.

The percentage of participators increases significantly, that of evaluators (the group most desirable to auctioneers) reduces by more than half, from 59% to 23%, and that of opportunists increases marginally from 20 to 27%. Thus we see clear empirical evidence of interaction between the bid increment, an important decision variable that auctioneers can control, and consumers' bidding behavior.

![Figure 2. Bidder Classification Aggregated by Bid Increment](image)

In the next section we discuss certain strategic policies that auctioneers can use in order to set near-optimal bid increments. We test the proposed policies against the
observed strategies utilized by online auctioneers and present empirical evidence in favor of the former.

4. Setting Near-Optimal Bid Increments

In Section 2 we demonstrated that the number of different equilibrium points of multi-item auctions grows exponentially with the lot size $N$. In addition, we also brought to attention that not all of these equilibria are economically efficient. Our objective in this section is to provide strategic directions to online auctioneers so as to ensure that they are guaranteed at least the lower bound on the revenue. Drawing upon our analytical and empirical findings of Sections 2 and 3 respectively, we base such a strategy upon deciding an appropriate bid increment that partitions the distribution space of the individuals' valuations in an efficient fashion. Such a strategy maximizes the likelihood of realizing higher revenue yielding bid structures as outlined in Section 2.

For such a strategy to be operationalized in practice it requires a priori a partial knowledge of the distribution of consumer valuations, an estimate of the population size interested in a given auction and the lot size (which is under the auctioneer's control). While in traditional markets it may be difficult to obtain even partial insights into consumers’ valuations, the emerging electronic marketplace is different. Estimates of current valuations can be obtained from alternative channels, such as posted-price catalogs, that sell exactly the same goods, as well as from other exogenous sources of information, such as price-comparison agents. Using data collection tools such as ours, online auctioneers can systematically track each individual's actions and create a historical repository of information. Onsale.com already is using such a technique to signal a maximum suggested bid, which gives us further reason to believe that the above-mentioned parameters can be estimated at a cost that is lower than the potential benefit form optimizing the bid-increment.
The strategy itself is conservative, ensuring that auctioneer's revenues are at least as great as the lower bound $N(V-\delta)$. By construction, at least the lower bound would be achieved provided there are $(N+1)$ or more individuals with valuations greater than or equal to the feasible bid level corresponding to the marginal valuation. Thus, we base our strategy on partitioning the distribution space so as to maximize the likelihood of having $(N+1)$ or more individuals with valuations $\in [V-\delta, V-\delta+k)$ and none with valuations $\geq (V-\delta+k)$. Our strategy is to compute an upper bound for the bid increment beyond which the likelihood of not even realizing the lower bound on revenue increases.

Let $P$ denote the total population interested in a given auction. Assume that individuals' valuations are independent and can be drawn from a distribution with a distribution function $F(.)$. Let $V_{max}$ be the maximum possible valuation for the object being auctioned amongst the population of consumers. Recall that $N$ represents the lot size of the auction.

**Theorem 1.** The upper bound on the bid increment, $k_{max}$, can be defined as 

$k_{max} = V_{max} - x^*$, where $x^* = F^{-1}[1 - (N+1)/P]$: Exceeding $k_{max}$ has a strictly negative impact on the auctioneer's revenue.

**Proof.** By construction, in order to guarantee at least the lower bound $N(V-\delta)$ on revenue being obtained we need at least $N+1$ valuations $\in [V-\delta, V_{max}]$. Given a finite population $P$, we choose to partition the distribution such that the expected number of bidders with valuations $\in [V-\delta, V_{max}]$ is $(N+1)$. Clearly $N$ out of these $(N+1)$ bidders make up the set $W$ of winners. As per Proposition 1, since there are no feasible bid levels in $[V-\delta, V_{max}]$, the auctioneer's expected revenue is $N(V-\delta)$.

Figure 3 shows what happens if $k$ is increased to $\theta k_{max}$ where $\theta > 1$. This implies that the feasible bids are wider apart. In such a case the bid immediately lower than the lowest valuation of consumers in set $W$ shifts from $B_m$ to $B'_m$ as shown in Figure 3. This implies
that the expected number of bidders with valuations \( \in [B_m', V_{max}] \) is \( \geq (N+1) \). Following Proposition 1 again, since there is no feasible bid \( \in [B_m', V_{max}] \), N winners will win at lower level \( B_m' \), which results in the auctioneer’s revenue being \( N \cdot B_m' \leq N \cdot B_m \) since \( B_m' < B_m \) by construction.

![Diagram](image)

**Figure 3.** Increasing \( k \) to \( \theta k_{max} (\theta > 1) \) permits more than \((N+1)\) valuations \( \in [V-\delta, V_{max}] \)

**Corollary to Theorem 1.** Since Proposition 1 indicates that there are only two possible bid levels in equilibrium, the expected value of \( B_m = V_{max} - k_{max} \).

**Proposition 5.** The optimal bid increment is strictly less than \( k_{max} \), the upper bound on the bid increment.

**Proof.** We can prove this by contradiction. Let \( k^* = k_{max}/\theta, \theta > 1 \), be an additional partition of the distribution space \([V-\delta, V_{max}]\). We denote the upper half of this distribution space as \( F_u(.) \) and the lower half as \( F_l(.) \). By definition, setting \( k > k_{max} \) implies that \( B_m \) is the last feasible bid level. If on the other hand \( k < k_{max} \) and as long as there are at least \( N+1 \) consumers in the interval \([V-\delta, V_{max}]\) there exists a likelihood that the \((N+1)\)th consumer falls in the upper half of the distribution space \( F_u(.) \). Thus, this consumer will get another chance in the form of an additional feasible bid level, to enter the winning list of bidders. The process will converge to equilibrium when there are only \( N \) consumers left in the above interval.
The above theorem and proposition suggest that continued reduction in bid increment can have a positive impact on the auctioneer's revenue. We refute that argument by noting that after a certain level of reduction in the bid increment, the time cost of conducting such an auction increases inordinately. Instead, we direct our attention towards deriving a practically useful recommendation to auctioneers that can help them set their bid increment on a day-to-day basis.

4.1 Recipe for Designing MIPEA

The necessary ingredients are i) knowledge of the lot size, ii) knowledge of the distribution of the consumers valuation, and iii) an estimate of the populations size.

**Step 1** is to calculate $k_{\text{max}}$, the upper bound on the bid increment. We can compute $k_{\text{max}}$ based on Theorem 1. Note that this implies that the expected number of consumers with valuations $\in [B_m=(V_{\text{max}} - k_{\text{max}}), V_{\text{max}}]$ is $N+1$.

In **Step 2**, since Proposition 5 states that the optimal bid increment is strictly less than $k_{\text{max}}$, we need to determine the desired bid increment $k^* < k_{\text{max}}$. Example 3 below demonstrates the process of determining $k^*$ for a single item assuming that the distribution of the valuations is Uniform (Appendix A details a procedure that can be deployed to estimate the valuations of the bidders, and finds strong support for the uniform distribution in the current data). Note that a similar approach can be employed for the multi-item case upon derivation of the expected revenue function, which takes into account all possible combinations of bid structures. Recall from the empirical results of Sections 3.2 and 3.3 that the coefficient for $k$, the bid increment, has a positive value in the least squares regression model. This implies that increasing $k$ has a positive impact on the revenue. Consider the case where we set the bid increment $k$ such that it is greater than or equal to half the density between the maximum valuation $V_{\text{max}}$ and the marginal
bid $B_m$, i.e., $k^* \geq [V_{\text{max}} - B_m] / 2$. Note that $B_m = V - \delta$. This implies that there is one feasible bid level between $V_{\text{max}}$ and $B_m$, and that is $B_m + k$.

**Example 3** – Let $\mu \geq 1$ be a multiplier such that $\mu B_m$ is the next feasible bid after $B_m$. In other words, $k = \mu B_m - B_m$. With a uniform distribution of valuations in $[B_m, V_{\text{max}}]$ for single item the auctioneer’s expected revenue is:

$$\frac{1}{1-F(B_m)} \left[ B_m(F(\mu B_m) - F(B_m)) + \mu B_m(1-F(\mu B_m)) \right]$$

(5)

Differentiating (4) with respect to $\mu$ and setting to zero we obtain

$$\mu^* = 1 + \frac{1 - F(\mu B_m)}{B_m f(\mu B_m)}$$

(5A)

For a uniform distribution we obtain,

$$\mu^* B_m = B_m + \frac{[V_{\text{max}} - \mu B_m/V_{\text{max}}]}{1/V_{\text{max}}}$$

(5B)

Which simplifies to

$$\mu^* B_m = (B_m + V_{\text{max}}) / 2$$

(5C)

Since, $k^* = \mu^* B_m - B_m$,

$$k^* = k_{\text{max}} / 2$$

is the optimal bid increment in case of uniform distribution and a single item.

The numerical example above illustrates an interesting property that $k^*$ equally divides the probability mass between $V_{\text{max}}$ and $B_m$. As a rule of thumb, this seems to be an easy to use approximation, one that we recommend. In the next subsection we provide empirical evidence in support of this strategy.

**Step 3** for the auctioneers is to decide on the rate of convergence to equilibrium, which can otherwise be thought of as duration of the auction. This in turn will determine $r$ the auction starting point. We explain these three steps by means of an example.

**Example 4** - Consider the case of an auction where individuals' valuations for $N = 12$ items were drawn from a uniform distribution $[V = $52, $V_{\text{max}} = $112]. Assume that the
auctioneer set \( r \), the auction opening bid = $7 and that the bid increment \( k \) was set at $5. Assume that the estimate of the population for this auction, \( P \), was 55.

Recall that \( k^* = k_{max}/2 \) where \( k_{max} = V_{max} - x^* \), and \( x^* = F^{-1}[1 - (N+1)/P] \). Thus we obtain \( k^* = 0.5[(112-52)*12/55] = 6.55 \). Thus, the auctioneer did not violate the rule of thumb, which requires it to set the bid increment \( k \) below \( k^* \). If on the other hand the population estimate was larger, say 75 than \( k^* \) would be 4.8. In which case the auctioneer's \( k = 5 \) would be in violation of the rule of thumb.

Also, there would have to be at least 9 rounds of bidding (or 108 bids) for the auction to reach equilibrium (assuming everyone behaved like participators). For a 24-hour auction this implies an arrival rate of 4.5 bids per hour. If the auctioneer wanted to conduct this auction in 6 hours than she could expect to have approximately 3 rounds (ceiling(4.5*6/12)) of bidding before equilibrium and hence would need to set the opening bid at $37. This of course assumes that the arrival rate would be the same.

In this sub-section, we presented a practical approach to designing MIPEA based on our analytical and empirical findings. The strategy revolves around determining the correct bid increment that maximizes the likelihood of the desirable (high revenue) bid structures presented in Section 2. The other two control factors, namely the lot size and the auction starting point are relevant too, but only in helping determine the correct bid increment. In the next sub-section we validate our approach empirically.

4.2 Empirical Validation of Upper Bound on Bid Increment

In order to determine which distribution best fits the consumers' valuations we first revisited our data to exclude the evaluators from the population count and their effect on \( AOR \) (average offset revenue) calculation. This was done because, by definition, evaluators are not affected by the bid increment \( k \). We found that the distribution function of the individuals' valuations was flat around and after the marginal valuation
leading us to assume that it was uniformly distributed. Using the results from Theorem 1 and Proposition 4 we calculated the bid increment using the heuristic decision rule $k^* = k_{\text{max}}/2$ and compared it to the actual bid increment $k$ by measuring the gap $\varepsilon = k^* - k$. Our hypothesis of interest was:

**Hypothesis**: Setting the bid increment at $k_u \geq k_{\text{max}}/2$ is a dominant strategy for revenue maximizing auctioneers over setting the bid increment at $k_i < k_{\text{max}}/2$. Alternatively, $AOR(k_u) \geq AOR(k_i)$.

We split the data set into 2 parts based upon the sign of $\varepsilon$. Negative values of $\varepsilon$ indicated that the auctioneer had used a bid increment higher than $k^*$ and vice versa. We empirically tested the validity of our upper bound by conducting a means test to compare the revenues from the positive and negative data. Table 4 presents the results of the t-test which indicate that auctioneers revenues were significantly lower when the upper bound was violated (the negative data set).

The empirical evidence presented in Table 4 below clearly suggests that online auctioneers paid a heavy price for misjudging the values of the bid increment. It should be re-emphasized that the multi-item nature of these auctions only amplifies any misjudgment on their part, as the consequences are $N$-fold. Auctioneers can do better by setting up technologies that help them learn about the nature of the distribution of consumers' valuations. Using such knowledge they can ensure that they do not set bid increments in excess $k^* = k_{\text{max}}/2$ where $k_{\text{max}} = V_{\text{max}} - x^*$, and $x^* = F^{-1}[1 - (N+1)/P]$.

<table>
<thead>
<tr>
<th>t-Test: Two-Sample Assuming Unequal Variances</th>
</tr>
</thead>
<tbody>
<tr>
<td>$K &gt; k_{\text{max}}/2$</td>
</tr>
<tr>
<td>Mean</td>
</tr>
<tr>
<td>Variance</td>
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<tr>
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<tr>
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<tr>
<td>t Stat</td>
</tr>
<tr>
<td>P(T&lt;=t) one-tail</td>
</tr>
</tbody>
</table>

**Table 4.** Auctioneers revenues significantly lower when upper bound violated
5. Conclusion and Directions for Future Research

We deal with the important issues concerning the design of business-to-consumer multi-item online auctions. Rather than pursuing the traditional approach of maximizing expected revenues of auctioneers assuming distributional characteristics of consumers' valuations, we derive a structural characterization of the multiple equilibria using the observable characteristics of such auctions. We observe that while much of the literature has largely ignored the sequential and discrete nature of such auctions, it does indeed play a significant role in the revenue realization process.

Our primary finding is that amongst the many control factors that are available to online auctioneers, the bid increment is the single most important factor. We provide both analytical and empirical evidence regarding the importance of bid increment in revenue generation. We also identify three different bidding strategies employed by consumers engaging in online auctions and show that these strategies are influenced by the bid increment. In particular, the strategy adopted by the evaluators reflects the fact that the Internet makes auctions accessible to novice bidders and the availability of data makes electronic auction markets a perfect venue for testing the behavior of uninformed bidders. With a motive of providing concrete and easily usable strategic guidance to B2C auctioneers we derive an upper bound to the bid increment that should never be violated by auctioneers. Further, using this upper bound we suggest a rule of thumb for setting bid increment. Our empirical analysis provides support for using this heuristic decision rule.

As the networked economy makes auction based dynamic pricing increasingly prevalent and expands its reach to a wide variety of goods and services, the challenges to the academic community are many. Firstly, no longer can these online mercantile processes be analyzed in a vacuum, out of context of the markets in which they take
place. In online settings the consumers can not only simultaneously participate in various auctions, they could simultaneously participate in various auction types as well as other dynamic and static pricing mechanisms such as quantity-discounting and posted-pricing respectively. Readers will be interested in knowing how would consumer gains change in competing between these various mercantile processes? Our ‘loss of surplus’ metric utilized to compare the relative comparison the bidder types represents an initial quantification of this interesting research question. Our work reinforces the notion that the rapidly changing economic landscape calls for fresh and unconventional approaches towards tackling new problems and revisiting age-old ones.

References


Appendix A – Estimation of Consumer Valuations, A Case for the Uniform Distribution

We use the maximum bid placed by a bidder, winning or losing, to be a proxy for the consumer’s valuation. Observe that this is a conservative estimate. In our auctions, a bidder is not allowed to bid between 2 successive feasible bid levels. Therefore, a person that has bid say $103, may actually have a true valuation of $108 (at $108, person may or may not bid because she is indifferent) given that the minimum bid increment is $5. Therefore, if the $j$th bidder’s highest bid was $B_j$, then his true valuation may be anywhere between $B_j$ and ($B_j + k$).

The following is a representative demand curve of an actual auction drawn by taking the number of people who bid at a given level or higher than that. This curve represents only the last 8 bidding cycles since our assertion is that valuations are distributed flatly in the tail. Note that a uniform value distribution results in a downward sloping straight line. The curve in this figure is a straight line, with acceptable distortions in real data. Therefore, our assertion regarding the flat tale is empirically verified.

For the same auction, we used a simple linear regression model of the form:

\[(\text{No of bidders who bid } \geq \text{ bid level}) = \alpha + (\beta \times \text{ bid level}) + \varepsilon,\]

and obtained a $\beta = -0.41607^{***}$ and a R-square of 99.53%.

Subsequently, we deployed the above-mentioned procedure for all the auctions that we tracked and found very good support for the valuations to belong to a uniform distribution. The table below presents the R-Square values of tests performed on a percentile basis. As is evident, more than 94 percent of the auctions had an R-square of 90 and above and close to 60% of the auction had a fit with an R-square of 96 and above.

<table>
<thead>
<tr>
<th>R-SQUARE</th>
<th>PERCENT ABOVE</th>
<th>R-SQUARE</th>
<th>PERCENT ABOVE</th>
</tr>
</thead>
<tbody>
<tr>
<td>88</td>
<td>100.0%</td>
<td>96</td>
<td>59.3%</td>
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<td>90</td>
<td>94.2%</td>
<td>98</td>
<td>36.0%</td>
</tr>
<tr>
<td>92</td>
<td>83.7%</td>
<td>99</td>
<td>15.1%</td>
</tr>
<tr>
<td>94</td>
<td>72.1%</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>