Optimal Design of the Online Auction Channel: Analytical, Empirical and Computational Insights

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Abstract

The advent of electronic commerce over an open-source, ubiquitous Internet Protocol (IP) based network has led to the creation of new channels such as business-to-consumer online auctions, the focus of our study. They typify a new generation of mercantile processes that facilitate the flow of goods and services, connecting producers, suppliers, intermediaries and end-consumers. The vast body of economics literature on auctions notwithstanding; the lack of appropriate mechanism design considerations that factor the intricacies of the online environment can result in significant losses of revenue.

This work presents an analytical model that characterizes the revenue generation process for a popular kind of supply chain oriented online auction, namely Yankee auctions. Such auctions sell multiple identical units of a good to multiple buyers using an ascending and open auction mechanism, which has its roots in the English auction, yet is significantly different. We put forward a portfolio of tools, varying in their level of abstraction and information intensity requirements, which help the auctioneers maximize their revenues.

A critical component in supply chain management is the understanding of consumer demand. This study sheds new light on how online auctions can be used to construct empirical demand curves for the auctioned goods. The methodologies used to validate the analytical model range from empirical analysis to simulation. A key contribution is the design of a partitioning scheme of the discrete valuation space of the bidders such that equilibrium points with higher revenue structures become feasible. Our analysis indicates that the auctioneers are, most of the time, far away from the optimal choice of key control factors such as the bid increment, resulting in substantial losses in a market with already tight margins.

Keywords: emerging supply chain channels, online auctions, simulation
1. **Introduction**

Online auctions represent a model for the way the Internet is shaping the new economy. In the absence of spatial, temporal and geographic constraints these mechanisms provide an alternative supply chain channel for the distribution of goods and services. This channel differs from the common posted-price mechanism that is typically used in the retail sector. Online auctions are a testimony to the increasing participation of consumers in the price-setting process. In consumer-oriented markets, online auctions offer a dynamic pricing alternative to the age-old static posted pricing mechanism. Consumers can now experience the thrill of ‘winning’ a product, potentially at a bargain, as opposed to the typically more tedious notion of ‘buying’ it. Sellers, on the other hand, have an additional channel to distribute their goods, and the opportunity to liquidate rapidly aging goods at greater than salvage values. The primary facilitator of this phenomenon is the widespread adoption of electronic commerce over an open-source, ubiquitous Internet Protocol (IP) based network.

In this paper, we concentrate on optimizing the design of an emerging distribution channel, namely business-to-consumer (B2C) online auction, also known as Yankee auctions. Such auctions sell multiple identical units of a good to multiple buyers using an ascending and open auction mechanism, which has its roots in the English auction, yet are significantly different.

This work presents an analytical model that characterizes the revenue generation process of such auctions. *The main contribution of this work is the development of a portfolio of tools, varying in their level of abstraction and information intensity requirements, which help the auctioneers maximize their revenues.*
To validate the analytical model and to gain a better understanding of the revenue generation process of such auctions we analyze real-world empirical data collected by a software agent that tracked these auctions round the clock. An interesting by-product of the auction data collection process is our ability to construct empirical demand curves for the auctioned goods. Consumer demand information is an important input in supply chain management. It provides the feedback necessary for making key decisions downstream in the supply chain. We demonstrate, using the capabilities of the Internet, how dynamic pricing mechanisms such as online auctions can provide opportunities for integration of demand information into the mechanism design process. This enhances the mechanisms in two ways. First, by appropriately setting the online auction parameters, auctioneers can maximize their returns. Secondly, by recognizing the demand implication and visualizing the trading process \textit{apriori}, the eventual allocation is more equitable and results in higher welfare.

The second major decision aid we develop for the auctioneers is a flexible multi-agent simulation tool designed to validate the analytical model, and provide a platform for the optimization of sellers’ revenue. The flexibility comes from the varying level of information that can be provided as inputs into the tool, based on what information is actually available to the auctioneer at the decision making time frame. Such levels could range from complete and rich empirical estimates of consumers valuations and bidding strategies to partial information that is limited to just the distributional parameters of consumer valuations. The simulation is based on the theoretical revenue generating properties of the Yankee auctions and its validity is established by its ability to replicate, to a statistically significant level, the original auctions that it tracked, if fed with the
original parameters that characterized the real-world auction. The simulation tool is configured to change the values of key control factors, such as the bid increment.

In summary, the portfolio of decision-making tools provides a relatively risk-free and cost-effective approach to managing innovation in this new, web-based dynamic pricing distribution channel prevalent in the online setting, namely the Yankee auction. In section 2 we describe the revenue generation process of the Yankee auction mechanism.

The rest of this paper is organized as follows. Our understanding of the revenue generation process of Yankee auctions directs us to focus our attention to the combinatorial dynamics of the penultimate rounds of the auction, which forms the basis of our theoretical model in this paper, presented in section 3. To verify our results, we use a data set of outcomes of several online auctions and a simulation tool that replicates online Yankee auctions. The description and characteristics of the simulation tool and the collected empirical data are presented in section 4. Section 5 and 6 provide a comparative analysis of theoretical and simulation results under varying degree of information abstraction. We conclude in section 7 with an overview of our approach and summary of the findings of the paper.

2. **The Yankee Auction Mechanism**

Yankee auction is a special case of multi-item English auction. Here, multiple units of the same product are sold to multiple bidders. It is well known [Rothkopf and Harstad (1994)] that single-item results (a vast majority of auction theory studies fall under this category) do not carry over in multiple-item settings.

The auction is progressive in nature; however, each new bid does not have to be strictly greater than the previous bid since there are multiple units available. The set of
winning bids consists of the top $N$ bids, where $N$ is the number of units up for auction. A new bid either has to be equal to the minimum bid that is among the winning bids (if the set of winning bids has a cardinality of less than $N$) or it has to be at least equal to minimum winning bid plus a pre-specified minimum bid increment. With multiple items on offer, it is possible to observe several winning bids that are equal. Once the consumers have bid for the entire lot size, a new bid will have to be greater than the smallest winning bid. When such a bid is submitted, the winner with the smallest winning bid is replaced by the new bid. If several offers are equal and at the minimum winning bid level, a time priority is applied to determine the bid to be displaced when a new and higher offer is received. The last bid at the minimum winning bid level becomes the first to leave the auction winners’ list. This process continues until the auction closes. At this point the auction winners are determined. The auction terminates on or after a pre-announced closing time and each of the winning bidders pay the amount they last bid to win the auction. Most auctions have a going, going, gone period such that the auction terminates after the closing time has passed and no further bids are received in the last five minutes. Note that in multi-item settings this often leads to discriminatory pricing with consumers paying different amounts for the same item. Such auctions are used on a variety of auction sites on the WWW such as Egghead.com’s Surplus Auctions, and Ubid.com.

The key factors that auctioneers can control in Yankee auctions are: (i) the lot size; (ii) the bid increment; (iii) the auction duration; and (iv) the opening bid. These variables are displayed on the online auction interface presented in Appendix A.
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 (1994) characterize this as the *pedestrian* approach to bidding. Such a strategy is consistent with the rational, net worth maximizing assumption for consumers. Notably, such a strategy could involve active manual participation or could be undertaken using a programmed software agent that bids the minimum required bid at any stage during the auction. Both have been observed in practice. In adopting this strategy bidders choose to be no more aggressive than necessary to continue competing.

### 2.1 Bid Increment and Auction Revenue

In prior research Bapna, Goes, Gupta (2000) use a regression model to show that amongst all the control factors mentioned in the previous section, the bid increment is the only factor significant in explaining variations of auction revenues. Additionally, anecdotal evidence suggests that auctioneers realize the importance of bid increments. We routinely observed that similar items are auctioned, at different times, using different bid increments.

While most of existing theory [see McAfee and McMillan, (1987), Milgrom, (1989), Milgrom and Weber (1982), for a detailed overview] 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. A close observation of the types of goods sold in these liquidation kind of auctions indicates that most of the items (computer hardware, consumer electronics etc.) 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 progressive online auctions, such as the Yankee auction, 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.

Assuming that bidders are rational and follow a pedestrian bidding strategy, at the final stage of the auction, at most two bidding levels are observed. At a minimum, all bids would be at the lower level, while the other extreme would be to have all bidders at the higher level. The difference between the two bidding levels is equal to the bid increment. From an auctioneers perspective the larger the number of bidders at the higher bid level, the greater the revenue. Intuitively, the process of determining the optimal bid increment is to create a partition in the discrete valuation space of the bidders such that the higher bid level becomes feasible to the maximum possible number of bidders. It follows that such a partitioning policy would optimize the expected revenue.

In the next section we present our analytical model that characterizes the expected revenue for Yankee auctions.

3. The Theoretical Model

Prior research [Bapna, (1999) and Bapna, Goes, and Gupta (2000)] based on a multi-variate regression analysis of multi-item Yankee auctions revealed that, to a large
extent, the valuation of the marginal consumer and the bid increment set by the auctioneer, determine the range of revenues for the auctioneer. Bapna, Goes, and Gupta (2000) derive a tight lower bound on revenue that auctioneers can expect. This lower bound has two components. The first one is a guaranteed revenue component that is equal to the lot size times the valuation of the marginal bidder.

The standard practice in the literature is to define the marginal consumer as either the highest unsuccessful bidder or the lowest successful bidder [Bulow and Roberts (1989)]. Both definitions characterize the price-setting consumer and are equally useful in examining the structural characteristics of these auctions.

Let $N$ denote the lot size and let $B_0$ be the valuation of the marginal bidder. The first component of the lower bound guarantees that auctioneer’s expected revenue is at least equal to $NB_0$. The second component of the lower bound is dependent on the bid increment and the number of bidders who have valuations that are at least one bid increment higher than the marginal bidder.

In this paper we present a theoretical model for the auctioneer’s expected revenue and present theoretical and simulation tools for the determination of an optimal bid increment that maximizes the auctioneers expected revenue. Some additional notation will ease the modeling exposition.

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 Yankee auctions have a minimum bid increment that we denote by $k$. It is assumed that $I > N$, otherwise bidders who have a clear objective of maximizing their surplus would not bid any higher than the opening bid level, and the opening bid would be binding. With this situation described,
the bidders with the highest $N$ valuations will retain the items being auctioned, with variations in revenue arising from the combinatorial dynamics of the penultimate round, elaborated below.

Let $B_0$ denote the marginal bid level. Let $p$ denote the probability that a bidder’s valuation is greater than $B_0+k$. Let $p_1$ be probability that a person has a valuation value $> B_0+2k$, $p_2$ be probability that a person has a valuation value $> B_0+3k$, and so on. Figure 1 depicts an example distribution for these top $N+1$ valuations and the probabilities that a randomly chosen bidder among these top $N+1$ bidders will have a valuation greater than $B_0+k$, $B_0+2k$, and $B_0+3k$, respectively. Note that $p ≥ p_1 ≥ p_2$.

![Figure 1 – The Distribution of Critical Fractile of Top N+1 Valuations](image)

Let $E(R)$ denote the expected revenue of the auction. Given $N$, $B_0$, and the $p$’s $E(R)$ can be computed by using the following infinite series:

$$E(R) = NB_0 + (1 - p_i^{N+1}) \left[ (1 - p^{(N+1)})k \sum_{i=0}^{N} i p^i (1 - p) + p^{(N+1)} \left( Nk + k \sum_{i=0}^{N} i p^i (1 - p_i) \right) \right] + p_i^{N+1} \ldots$$

(1)
Note that in multi-item case as $N$ increases the value of $p^{N+1}$ becomes negligible and hence each subsequent term that is added in the infinite sum of equation 1 contributes little to expected revenue. Hence, in this paper we have used what we term a first order approximation where we assume that $p^{N+1}$ is negligible and, thus, we look at the following reduced equation:

$$E(R) = N B_0 + k \sum_{i=0}^{N} i p^i (1 - p) = N B_0 + k \left[ \frac{p (1 - p^{-N})}{(1 - p)} - N p^{N+1} \right]$$

(1a)

The above expression represents a geometric series that takes into account the temporal position of the marginal bidder, a key revenue determinant. As an approximation, we consider only the first term in the series, since for any $n \geq 7$ (the average lot size of the auctions we tracked) even if we were to consider high $p$ values, say $6/8$, the probability $(6/8)^8$ is a small number and would not effect estimated revenue significantly. Let us motivate the combinatorial aspects of the revenue generation using a numerical example.

**Numerical Example 1** - Lets assume $N = 3$ and $p = \frac{1}{2}$, i.e., the probability that a person will have value $> B_0 + k = \frac{1}{2}$. We need to draw 4 people randomly. There can be 5 cases possible: 1) None have value $> B_0 + k$; 2) 1 of the 4 has value $> B_0 + k$; 3) 2 of the 4 have values $> B_0 + k$; 4) 3 of the 4 have values $> B_0 + k$; 5) all 4 have values $> B_0 + k$. Total numbers of states for this case are $4! \times 2^4$. Let A, B, C, and D represent the 4 people. The underlined character means that the person has value $> B_0 + k$. Assume that the first person is currently not winning the auction while other 3 are and the second character represent the person that is replaced first. So if the
state of the world is $BCAD$ then B bids at $B_0+k$ and replaces C (since B has valuation $> B_0+k$) and the new state is $CABD$. The auction stops at this stage because C cannot bid at $B_0+k$.

Consider the case that there are 3 bidders with valuation $> B_0+k$ and (yet) the auction stops with 1 bid at $B_0+k$. This can happen in 24 different ways shown in the table below:

<table>
<thead>
<tr>
<th>3 persons $&gt; B_0+k$</th>
<th>ADBC</th>
<th>ACBD</th>
<th>ABCD</th>
<th>BACD</th>
</tr>
</thead>
<tbody>
<tr>
<td>ADBC</td>
<td>ACBD</td>
<td>ABCD</td>
<td>BACD</td>
<td></td>
</tr>
<tr>
<td>ADCE</td>
<td>ABDC</td>
<td>ABCD</td>
<td>BADC</td>
<td></td>
</tr>
<tr>
<td>BDAC</td>
<td>BCAD</td>
<td>CBAD</td>
<td>CABD</td>
<td></td>
</tr>
<tr>
<td>BDCA</td>
<td>BCDA</td>
<td>CBDA</td>
<td>CADB</td>
<td></td>
</tr>
<tr>
<td>CDBA</td>
<td>DCBA</td>
<td>DBAC</td>
<td>DABC</td>
<td></td>
</tr>
<tr>
<td>CDAB</td>
<td>DCAB</td>
<td>DBCA</td>
<td>DBCA</td>
<td></td>
</tr>
</tbody>
</table>

Table 1 – Example of Bidding Stopping With 1 Bid at $B_0+k$

Of course to compute the overall likelihood of the auction stopping at $B_0+k$ we need to enumerate all the cases when the marginal bidder in the penultimate round has a valuation $> B_0+k$ and the lowest winning bidder has valuation $< B_0+k$.

In the example these are operationalized where the first letter is underlined but the second is not, i.e., the person not winning has valuation $> B_0+k$ but person displaced has valuation $< B_0+k$.

This would mean that we have to need to also consider the states when 1 and 2 bidders have valuations $> B_0+k$ respectively, and the temporal ordering is such that marginal bidder in the penultimate round has a valuation $> B_0+k$ and the lowest winning bidder has valuation $< B_0+k$. Through a similar enumeration of these cases as in Table 1, there are 24 such cases when 1 bidder has valuation $> B_0+k$ and 48 such cases when 2 bidders have valuation $> B_0+k$. 


Therefore, in all, there are 96 such cases, implying that the likelihood of the expected revenue being $NB_0+k = 96/384= \frac{1}{4}$. This is of course identical to probability from our expected revenue (1a) function $p^k*(1-p)$ with $p = \frac{1}{2}$.

From the expected revenue expression given above, it is clear that the bid increment $k$ is a key determinant of the auction revenue. In this paper we seek to establish calibration mechanisms for the bid increment that optimize the expected auction revenue. A critical parameter necessary to optimize the bid increment is the $p$ value, which determines the probability that a bidder will in fact jump to the next higher bid level above $B_0$. To estimate $p$ the auctioneer has to have some information on the bidders valuation, a non-trivial task. Using such information, for any given bidding level, the auctioneers can infer the number of bidders who may have valuations for the product that are equal to or higher than then the next feasible bid level. A significant contribution of this paper is the development of empirical tools that help the auctioneer estimate $p$.

Before we describe the empirical estimation tools we would like to provide further intuition into the optimization of the expected revenue by setting the optimal bid increment using a numerical example:

**Numerical Example 2** – Suppose an auction has five items on sale, and the valuations for the highest six bidders is as follows:

<table>
<thead>
<tr>
<th>Bidders</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Valuation</td>
<td>110</td>
<td>111</td>
<td>112</td>
<td>115</td>
<td>121</td>
<td>132</td>
</tr>
</tbody>
</table>
Let $B_0 = $110. Without knowing the actual valuation of each bidder, it would be sufficient if the auctioneer knew the number of bidders with a valuation above a certain bidding level. With the set of bidders above, the following table summarizes the relevant information for the auctioneer.

<table>
<thead>
<tr>
<th>Bid Levels</th>
<th>110</th>
<th>115</th>
<th>120</th>
<th>125</th>
<th>130</th>
<th>135</th>
</tr>
</thead>
<tbody>
<tr>
<td>No. of Bidder</td>
<td>5</td>
<td>2</td>
<td>2</td>
<td>1</td>
<td>1</td>
<td>0</td>
</tr>
</tbody>
</table>

Therefore, if the marginal bid is 110, a bid increment can be determined that gives the optimum revenue.

<table>
<thead>
<tr>
<th>$K$</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>11</th>
<th>22</th>
<th>&gt;22</th>
</tr>
</thead>
<tbody>
<tr>
<td>No. of Bidder with valuation greater than or equal to $B_0 + k$</td>
<td>5</td>
<td>4</td>
<td>3</td>
<td>3</td>
<td>3</td>
<td>2</td>
<td>2</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>$P$</td>
<td>5/6</td>
<td>4/6</td>
<td>3/6</td>
<td>3/6</td>
<td>3/6</td>
<td>2/6</td>
<td>2/6</td>
<td>1/6</td>
<td>0</td>
</tr>
<tr>
<td>Expected revenue $E(R)$</td>
<td>551.31</td>
<td>552.59</td>
<td>552.67</td>
<td>553.56</td>
<td>554.45</td>
<td>552.94</td>
<td>555.40</td>
<td>554.39</td>
<td>550</td>
</tr>
</tbody>
</table>

From the table above, it is clear that setting the bid increment at $11$ would yield the optimal expected revenue.

The example presented above, assumes that the auctioneer knows the distribution of bidders valuations \textit{a priori}. It is common in auction theory to assume some known continuous distribution to which consumer valuations are said to belong. In this study we make use of automated software data collecting agents to track online auctions, and in
doing so build historical repositories of bid patterns that permit the empirical estimation of \( p \) values, as well as for making informed distributional assumptions regarding the bidders valuations.

We discuss these issues in the coming sections beginning with the description of a robust simulation tool that replicates real-world auctions and the empirical data collection process that can be used as an input to the simulation tool.

4. Testing Applicability of Analytical Results

In theory, there could be several approaches to test our analytical findings. One such approach would be to auction the same or similar items with different control factors, such as the bid increment. However, this is a costly endeavor and, in the era of rapid obsolescence of computer products, which by and large are the products sold in Yankee auctions, it will still not answer the question whether the auctioneers used appropriate bid increments. Instead, in order to test a variety of analytical findings, we have developed a simulation tool that can replicate a given observed auction.

Input data for this simulation tool is based on actual observed online Yankee auctions. 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 5-15 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. We tracked over 150 auctions, however, complete bidding data was available for 65 auctions. The screening process 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 levels of bid increment chosen ($10, and $20).

Our simulation tool represents a risk-free and robust experimentation platform that permits us to manipulate the value of the bid increment and study the comparative revenues generated at the theoretically determined bid increments and those that give maximum empirical results. In the next subsection we present the key constructs of our simulation model.

4.1 Simulation Model

While the intricate details of this simulation tool are beyond the scope of this paper, and are presented in Bapna, Goes, and Gupta (2001), we present an overview of the approach. The results of simulation can only be trusted if the simulation replicates an online auction's result with its original parameters. The entire simulation process can be summarized as follows:

i) The observed final bid placed by each individual during a given auction is read from a file.

ii) The values of the original bid increment ($k$), simulated bid increment ($k'$), starting bid level ($r$), and the number of units for sale ($N$) are also provided as an input to the simulator.

iii) Based on the final bid of each bidder, a valuation is generated, for that bidder, by adding a random number drawn from $U(0, k)$. We use a method of deducing a
bidder valuation from their final bids. Using real auction data, the valuation of all losers in an auction can be estimated by their final bid offer, plus some premium, which is less than one bid increment. This is a rational estimate because the final bid offer can be considered as a tight lower bound on the consumer’s valuation. On the other hand, if the upper bound on the consumer’s valuation is greater than one bid increment above the final bid, then the bidder should have been able to constitute a new bid and either be in the winners list or propel the auction to a higher bidding level. The valuations of auction winners can be inferred in a similar manner. These valuations would form a lower bound on the actual valuations of the bidders. Since we consider a pedestrian bidding strategy, these estimates of winner valuations are adequate for estimating auctioneers revenue, because and higher valuations than the estimates we use do not give bidders an incentive to offer higher bids. The Table below gives a list of bids on one of the auctions that we observed, and the consumer valuations inferred from these bids.

<table>
<thead>
<tr>
<th>Auction 10-36 (all data coded)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lot Size = 17, Opening bid = 9, Total no. of bidders = 40, Bid increment = 10</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Winners</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bidder No.</td>
</tr>
<tr>
<td>Valuations</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Losers</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bidder No.</td>
</tr>
<tr>
<td>Final Bid</td>
</tr>
<tr>
<td>Valuations</td>
</tr>
</tbody>
</table>

Table 2: Estimating bidder valuations from empirically observed final bids

iv) The valuations array is then scrambled to remove the input bias since data is read from files that store bids in sorted order and the data for each type of bidder is bunched
together in the valuations array. The original scrambled array forms the starting point for all the replications for a given auction. The details of this and other computational efficiencies we have derived are beyond the scope of this paper [see Bapna, Goes, and Gupta (2001)].

v) The simulation stops when there are no more eligible bidders in the valuation list.

Note that, by doing so we are modeling the automatic extension of the auction duration as implemented by many of the auction sites using Yankee auctions.

When simulating an environment, it is recommended that independent replications of the simulations be done to provide statistically robust results (see, for example, Banks and Carson, 1984). We can specify the number of replications in our simulation model, each starting with an independent random number stream. However, as mentioned earlier, we start with the same scrambled value array as created in the first replication. In addition, the other simulation parameters, i.e., the lot size, bid increments, and the starting bid values are kept the same. In other words, *during different replications only the order in which bids from different bidders arrive is different.*

4.2 Simulation Validity

We test the robustness of the simulator by using a goodness-of-fit procedure. Given identical starting parameters, our test procedure examines whether the observed frequencies of the various bid levels in the real world auctions matches, in a statistical sense, the expected frequencies of the same bid levels that are generated by the multiple replications of the simulation process.
Statistically, the chi-square test is ideally suited for this purpose. For some auctions that failed to meet the assumptions required to use the chi-square test we applied the binomial signs test to test equivalence. Particularly important to us is the fact that the chi-square test is non-parametric, does not assume any prior distribution, and applies to nominal data, such as frequencies.

Each auction was replicated 31 times using independent random number seeds for the bidding sequence. However, during all these runs the bidder valuations were kept constant, so the revenue variability is only the result of randomizing sequence of bid arrivals. Of the 65 auctions we tracked we fail to reject our null hypothesis (of equivalence between real-world and simulated) in all but 2 (auctions 17, 35) of the cases. Further robustness of the simulation can be deduced by examining the range of the simulated revenue. Observe that this is quite small with the maximum range being 9% of the observed revenue and the median of the revenue ranges being only 2% of the observed revenue. This is an important parameter to consider in simulations since excess variability can reduce the implications generated from simulating a process.

In the next section we describe how we estimate, using actual observed data, the optimal auction revenue based on the analytical model presented in Section 3. We also test the validity of the analytical approach by comparing its results with those generated by using the simulation tool.

5. Comparative Analysis of Optimal Auction Revenues

For computing the revenue using the analytical model (equation 1) at a given bid increment \( k \), we need to estimate the probability \( p \) that a bidder’s valuation is greater
than $B_0 + k$ where $B_0$ represents the marginal bid level. Consider the example provided in Table 2, where the top $N+1$ valuations range from $98$-$119$, with the marginal bid level $B_0 = 98$. A good estimator of the probability that a bidder’s valuation is greater than $B_0 + k$, $\hat{p}$, can be obtained by taking the ratio of $n$ the number of bidders having valuations greater than $B_0 + k$ to the number of bidders having valuations greater than $B_0$:

$$\hat{p} = \frac{n}{N+1} \quad (2)$$

In this example for a bid increment $k = 3$, $n = 15$. Since, the lot size in this example is 17, $\hat{p} = 15/18 = 0.8$. The expected revenue that corresponds to this bid increment can now be determined using equation 1. This exercise is carried out for all feasible integer values of $k$ to determine the optimal bid increment. We do not consider the fractional bid increments because a dollar is usually considered as the minimum difference in successive bid increments. The results of this exercise for this example are provided in Table 3.

<table>
<thead>
<tr>
<th>$K$ ($$$)</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
</tr>
</thead>
<tbody>
<tr>
<td>$B_0 + k$ ($$$)</td>
<td>99</td>
<td>100</td>
<td>101</td>
<td>102</td>
<td>103</td>
<td>104</td>
<td>105</td>
<td>106</td>
<td>107</td>
<td>108</td>
<td>109</td>
</tr>
<tr>
<td>$N$</td>
<td>17</td>
<td>16</td>
<td>15</td>
<td>14</td>
<td>14</td>
<td>11</td>
<td>9</td>
<td>8</td>
<td>7</td>
<td>6</td>
<td>5</td>
</tr>
<tr>
<td>$\hat{p}$</td>
<td>0.94</td>
<td>0.89</td>
<td>0.83</td>
<td>0.78</td>
<td>0.78</td>
<td>0.61</td>
<td>0.50</td>
<td>0.44</td>
<td>0.39</td>
<td>0.33</td>
<td>0.28</td>
</tr>
<tr>
<td>Revenue ($$$)</td>
<td>1,666</td>
<td>1,675</td>
<td>1,678</td>
<td>1,679</td>
<td>1,682</td>
<td>1,675</td>
<td>1,673</td>
<td>1,672</td>
<td>1,671</td>
<td>1,671</td>
<td>1,670</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>$K$ ($$$)</th>
<th>12</th>
<th>13</th>
<th>14</th>
<th>15</th>
<th>16</th>
<th>17</th>
<th>18</th>
<th>19</th>
<th>20</th>
<th>21</th>
<th>22</th>
</tr>
</thead>
<tbody>
<tr>
<td>$B_0 + k$ ($$$)</td>
<td>110</td>
<td>111</td>
<td>112</td>
<td>113</td>
<td>114</td>
<td>115</td>
<td>116</td>
<td>117</td>
<td>118</td>
<td>119</td>
<td>120</td>
</tr>
<tr>
<td>$N$</td>
<td>4</td>
<td>4</td>
<td>4</td>
<td>4</td>
<td>3</td>
<td>3</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>$\hat{p}$</td>
<td>0.22</td>
<td>0.22</td>
<td>0.22</td>
<td>0.22</td>
<td>0.17</td>
<td>0.17</td>
<td>0.11</td>
<td>0.11</td>
<td>0.11</td>
<td>0.06</td>
<td>0.00</td>
</tr>
<tr>
<td>Revenue ($$$)</td>
<td>1,669</td>
<td>1,669</td>
<td>1,670</td>
<td>1,670</td>
<td>1,669</td>
<td>1,669</td>
<td>1,668</td>
<td>1,668</td>
<td>1,668</td>
<td>1,668</td>
<td>1,666</td>
</tr>
</tbody>
</table>

**Table 3: Expected revenue computation for various bid increment levels**

Observed that the optimal bid increment for this example is $5$. 
Let us introduce the following notation:

\( k_{TO} \) - Bid increment that yields maximum theoretical revenue using bidder valuations estimated from observed data as described in Section 4.1.

\( R(k_{TO}) \) - Theoretically derived optimum revenue at \( k_{TO} \).

We numerically determine the optimal theoretical bid increment \( k_{TO} \) that maximizes equation 1 and yields \( R(k_{TO}) \). The theoretically determined bid increments are in most cases (60 out of 65) different from the bid increments that were used in the actual real-world auctions. This is not a surprising result as we expect auctioneers to be far from optimal in their current practice.

Recall, that the objective of developing the simulation model is to test the effect of changing controllable factors such as the bid increment and to examine whether the revenue generated through an auction can be improved. We ran the simulation program with different minimum bid increments ranging from $1 - $20. The simulation tool allows us to undertake this exercise efficiently, and we determine the following:

\( k_{SO} \) - Bid increment that yields maximum simulated revenue using bidder valuations estimated from observed data as described in Section 4.1.

\( R_s(k_{SO}) \) - Simulated auction revenue at a bid increment level of \( k_{SO} \).

The analytical and simulation approaches provide us with two sets of revenues for the same bid increments. Since the simulation model replicates the original auctions [Bapna et al. (2001)], we can use the data generated by the simulation to validate the analytical results.

5.1 Empirical Results
Note that while the method employed to compute optimal bid increment gives us one unique value, the revenue function itself may not be a unimodal function with respect to bid increment. For example, it may be possible to achieve same optimal points with bid increments that are multiples of each other. Therefore, since auctioneers’ primary interest is in maximizing revenue, rather than evaluating the equality of bid increment, we are more interested in the equivalence of revenue structures that are generated due to different bid increments. Therefore, our first hypothesis of interest is:

**Hypothesis 1:** Given empirically derived probability \( p \), the theoretically optimal revenue \( R(k_{TO}) \) is equivalent to the simulated maximum revenue \( R_s(k_{SO}) \).

Table 4 provides the hypothesis and the test statistic, as well as the range of p-values for the test statistic for the 65 auctions. For example, in 64 out of 65 auctions the p-value was greater than 0.1, indicating that the null hypothesis can only be rejected in 1 instance at the 90% confidence level.

<table>
<thead>
<tr>
<th>Alpha values</th>
<th>No of auctions we fail to reject ( H_o ) (total No. of auctions = 65)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.01</td>
<td>64</td>
</tr>
<tr>
<td>0.05</td>
<td>64</td>
</tr>
<tr>
<td>0.1</td>
<td>64</td>
</tr>
</tbody>
</table>

**Table 4 – Theoretical v. simulated maximum revenue, using empirically derived probabilities**

The results presented in Table 4 imply that the theoretically optimal revenue, using bidder valuations estimated from observed data, is equivalent to the maximum
simulated revenue. This justifies the use of the theoretically computed bid increment in the design of multi item online auction. In other words, by choosing the analytically determined bid increment auctioneers can expect to maximize their revenues.

The theoretically determined optimal bid increment is often different from the bid increment at which the simulated revenue is maximized. Therefore, another issue of interest is whether the simulated revenue at theoretically optimal bid increment is significantly lower than the estimated theoretical revenue. This gives rise to our second hypothesis of interest:

**Hypothesis 2:** Given empirically derived probability $p$, the theoretically optimal revenue $R(k_{TO})$ is equivalent to the simulated revenue at theoretically determined optimal bid increment, denoted by $R_s(k_{TO})$.

Note that this hypothesis serves two purposes: (i) that the simulated revenue at theoretically optimal bid increment is statistically equivalent to the optimal revenue; and (ii) the simulation model is robust with changing parameters since it provides revenue equivalence with theoretically calculated revenue.

The results from testing this hypothesis are presented in Table 5. Again the results provide overwhelming statistical support for the null hypothesis. The null hypothesis can only be rejected in only 4 out of 65 auction, even at a 90% confidence level.

The simulation tool allows us to empirically demonstrate that our theoretical model yields revenues that are robust with variations in simulation parameters. Also,
even if discrete information regarding the valuations of bidders is available, from sources such as similar past auctions, the theoretical model can be used to select a revenue maximizing bid increment.

<table>
<thead>
<tr>
<th>$H_o$ : $R_s(k_{TO}) = R(k_{TO})$</th>
<th>Alpha values</th>
<th>Test statistic: $Z = \frac{R_s(k_{TO}) - R(k_{TO})}{\sqrt{Var[R_s(k_{TO})]/30}}$</th>
<th>No of auctions we fail to reject $H_o$ (total no. of auctions = 65)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$H_a$ : $R_s(k_{TO}) \neq R(k_{TO})$</td>
<td>0.01</td>
<td>$Z = \frac{R_s(k_{TO}) - R(k_{TO})}{\sqrt{Var[R_s(k_{TO})]/30}}$</td>
<td>61</td>
</tr>
<tr>
<td></td>
<td>0.05</td>
<td>$Z = \frac{R_s(k_{TO}) - R(k_{TO})}{\sqrt{Var[R_s(k_{TO})]/30}}$</td>
<td>61</td>
</tr>
<tr>
<td></td>
<td>0.1</td>
<td>$Z = \frac{R_s(k_{TO}) - R(k_{TO})}{\sqrt{Var[R_s(k_{TO})]/30}}$</td>
<td>61</td>
</tr>
</tbody>
</table>

Table 5 – Theoretical v. simulated revenue at $k_{TO}$, using empirically derived probabilities

However, in many instances an auctioneer may even have more limited set of information regarding the consumer valuations. For example, they may only have estimates of lower and upper bounds on expected prices that consumers might be willing to pay. Note that in the online environment information regarding expected price levels can always be obtained by employing price dispersion studies for similar products as the product being auctioned. In the next section we provide further analysis, using the collected data, which allows the estimate of optimal bid increments in an information-constrained environment.

6. Estimating Bid Increments with Limited Distributional Information

We need information regarding the probability, $\hat{p}$, that a given consumer has valuation greater than $B_0 + k$ to estimate the expected revenue. To estimate this probability without the knowledge of actual distribution we rely on the key theoretical
realization that our optimization approach is based on the distribution of valuation of top $N+1$ valuations. This critical fractile, is therefore, the upper-tail of the overall consumer value distribution. Since most of the theoretical distributions are relatively flat in the tail, we conjecture that it may be possible to approximate the critical fractile distribution with a uniform distribution.

We use an innovative approach to validate our conjecture by using the data collected from the online auctions. The next subsection describes the approach that we use to derive the demand curve for the critical fractile.

### 6.1 Estimating Demand Curves for Critical Fractile Using Auction Data

For every auction that we tracked, we collected data regarding all the bids placed. This allows us to compute the number of distinct bidders that placed a bid at or above a given bid level. Therefore, we can construct a demand curve by calculating the estimated number of people that will be willing to purchase a product at any given price.

Since a uniformly distributed value distribution produces a demand curve that is a linearly descending straight line, we can test our hypothesis that the distribution in critical fractile is uniformly distributed by testing whether the demand curve is indeed linearly descending straight line. We performed this test by taking the tail data of bids (data for last 8 bidding cycles) for each tracked auction. We then constructed the demand curves by computing the number of distinct individuals that placed a bid at a given bid level or higher. Figure 2 shows a representative demand curve based on the data for auction represented in Table 2 earlier. As the figure indicates we get a fairly straight-line representation, with acceptable distortions in real data.
We tested the fit of the straight line by using a simple linear regression with demand as dependent variable and bid level as independent variable as follows:

\[ \text{Demand (Consumers willing to purchase at a given price)} = \alpha + (\beta \times \text{price}) + \epsilon \quad (3) \]

For the particular example described above we obtained a \( \beta = -1.4^{***} \) and a R-square of 98.5%. We deployed the above-mentioned procedure for all the auctions that we tracked and found extremely good support for our contention that the critical fractile valuations can be approximated by a uniform distribution. Table 6 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>
</tr>
<tr>
<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>

Table 6 – Regression results from testing for Uniformly distributes tail end valuations

The regression equation (3) representing a downward sloping demand curve can be used to estimate \( \hat{p} \). We can also compute the parameters of interest such as \( B_0 \), and \( V_{\text{max}} \) using the regression equation. For example, to determine the highest valuation of \( V_{\text{max}} \), we can solve for the bid level at which the demand is zero and, similarly, the valuation of the marginal bidder \( B_0 \) can be determined by solving for the bid level at which the demand is equal to the \( N+1 \) where \( N \) represents the lot size.

From a practical standpoint, this result can be used to compute an appropriate bid increment as long as information regarding the possible spread (range) in valuation is available. As mentioned earlier, this information can be obtained by doing simple price dispersion studies for a given product (or product class). Then, using the approach described in next subsection can use the uniform distribution assumption to estimate the best bid increment.

6.2 Optimizing Expected Revenue with Uniformly Distributed Valuations

In light of the empirical evidence suggesting that the tail-end of consumer valuations can be characterized using a Uniform\([ B_0, V_{\text{max}} ]\) distribution, for a given bid
increment $k$, the probability that a bidder will have a valuation greater than $B_0 + k$ is given by:

$$p = \frac{V_{\text{max}} - B_0 - K}{V_{\text{max}} - B_0} \quad \text{and} \quad 1 - p = \frac{K}{V - B}$$

(4)

Substituting (4) and differentiating equation (1a), $E(R)$ with respect to $k$, we obtain

$$k^* = \frac{2 \sum_{i=0}^{N} i (V_{\text{max}} - B_0 - k)^{i}}{\sum_{i=0}^{N} i^2 (V_{\text{max}} - B_0 - k)^{i-1}}$$

(5)

Equation (5) provides insights into the structure of optimal bid increment with respect to the number of items on sale. This result is formalized in the following proposition:

**Proposition 1:** Assuming the tail end of consumers’ valuations are distributed $U[B_0, V_{\text{max}}]$, as suggested by the empirical evidence, the optimal bid increment decreases as the lot size increases.

**Proof** – As $N$ increases, $\sum_{i=0}^{N} i^2$ grows at a much larger rate than $\sum_{i=0}^{N} i$. Since $\sum_{i=0}^{N} i^2$ is in the denominator of equation (5), $k$ decreases as $N$ increases. Q.E.D.

Just as we could optimize (1) with observed empirical valuations, likewise we can calculate the $p$ values assuming a Uniform demand function and compute the following optimal quantities, described along with their notation:
- Bid increment that yields maximum theoretical revenue assuming uniformly distributed bidder valuations

\[ R(k_{TU}) \] - Theoretically derived optimum revenue at \( k_{TU} \).

In the next subsection we develop and test the hypotheses that provide evidence regarding the adequacy of computing bid increment based on limited information.

### 6.3 Empirical Analysis Assuming Uniform Demand

To investigate the auction results that are based on uniformly distributed critical fractile valuations, first, we test the hypothesis that the theoretically computed optimum revenue assuming uniform distribution is equal to the maximum simulated revenue presented earlier in section 5. Recall that simulations were run using original valuations. Also, using the uniform distribution allows computation of variance in expected revenue by computing expected value of the squared revenue.

**Hypothesis 3**: Assuming that probability \( p \) is derived based on uniformly distributed valuations \( U[B_{\theta}, V_{\max}] \), the theoretically optimal revenues \( R(k_{TU}) \) is equivalent to the simulated revenue maximum revenue, \( R_s(k_{SO}) \).

<table>
<thead>
<tr>
<th>Alpha values</th>
<th>No of auctions we fail to reject ( H_0 ) (Total no. of auctions = 65)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.01</td>
<td>53</td>
</tr>
<tr>
<td>0.05</td>
<td>52</td>
</tr>
<tr>
<td>0.1</td>
<td>45</td>
</tr>
</tbody>
</table>

**Table 7** – Theoretical v. simulated revenue at \( k_{TU} \)
Table 7 indicates that at 90% confidence level, only 21 out of 65 auctions provide significant result to reject the null hypothesis. 13 and 12 auctions are significant at 95% and 99% confidence levels, respectively. These results indicate that even with limited information and assuming uniform distribution for the critical fractile distribution, good values for bid increments can be chosen.

Our final hypothesis tests whether, with Uniform valuations, we get equivalence between theoretically optimal revenues and the simulated revenues at the theoretically derived optimal $k$. Again, as with hypothesis 2, this hypothesis provides support for robustness of the simulation model. However, in this case, it also indicates the degree of loss of precision due to the limited availability of information. The hypothesis of interest is:

**Hypothesis 4:** Assuming that probability $p$ is derived based on Uniformly distributed valuations $U[B_0, V_{max}]$, the theoretically optimal revenue $R(k_{TU})$ is equivalent to the simulated revenue at theoretically determined optimal bid increment, denoted by $R_s(k_{TU})$.

<table>
<thead>
<tr>
<th>Alpha values</th>
<th>No of auctions we fail to reject $H_o$</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.01</td>
<td>54</td>
</tr>
<tr>
<td>0.05</td>
<td>46</td>
</tr>
<tr>
<td>0.1</td>
<td>44</td>
</tr>
</tbody>
</table>

Table 8 – Theoretical v. simulated revenue at $k_{TU}$
Table 8 indicates that at 90% confidence, 21 out of 65 auctions provide sufficient evidence to reject the null hypothesis. The number of auctions that support the rejection of the null hypothesis stand at 19 and 11 at 95% confidence level and 99% confidence level respectively. This means that for more than 2/3 of the auctions used for this test the null hypothesis cannot be rejected even at 90% confidence level. Another way to look at this result, in comparison to the results obtained with hypothesis 2, would be that we loose approximately 25% precision by assuming uniform distribution for critical fractile distribution.

In this paper we provide approaches at various levels of modeling and data abstractions to approach the problem of optimal auction design. The actual applicability might depend upon the specific product and/or market information availability. In the next section we conclude by providing an overall perspective of our approach in a broader context than this paper that could be used a template for designing specific components of a demand driven supply chain.

7. Concluding Remarks

We begin with a summary of our experimental design and an overview of the various levels of abstraction that we dealt with in this paper. Figure 3 provides a conceptual framework for integrating the insights provided in this paper into the design of online Yankee auctions. Beginning with tracking real online auctions to obtain estimates of consumer valuations and the demand curve, we develop a theoretical model of the revenue generation process. The optimization of this model requires estimates of the probabilities that bidders will bid at the next higher bid level, above the marginal bid.
Empirical Observations
1. Marginal Bid
2. Maximum Valuation
3. Probability bidder moving to next bid level above marginal bid

Automated Monitoring Using Web Crawling Agent

Information Intensity - High

Empirical Observations
- Theoretical estimation of optimal revenue and optimal bid increment using empirical data (Eq 1)

Information Intensity - Low

Demand Curve Estimation
- By observing actual # of bidders bidding above a bid level
- Regression significant and shows downward sloping demand curve
- Implies valuations distributed uniformly in the tail

Multi-agent Auction Simulator Module
(Validity tested by ability to replicate original auctions)

Theoretical estimation of optimal revenue and optimal bid increment using uniform distribution (Eq 1)

Simulated Max revenue and corresponding bid increment

Figure 3 - Research Metascape Depicting Varying Levels of Abstractions and Information Intensity
To summarize, we developed a theoretical basis for determining the optimal bid increment setting for online Yankee auctions, an important emerging channel in the supply chain. The theory relies on the information that the auctioneer has regarding the bidder valuations. On the one extreme, relying on the empirical distribution of bidder valuations, our theoretical model can be used to determine optimal bid increment setting. The results of the theoretical model were tested using a simulation tool and we observed that the theoretically optimal bid increment to yield maximal revenues. Similar, but not as strong results are obtained if we rely on a Uniform distributional characterization of the bidder valuation, as opposed to an empirical one. It should be noted from an information cost perspective, the former is far easier to ascertain than the latter, hence the corresponding slight weakness in the result. In other words, depending on the amount of information available to the auctioneers a low or high information intensity track could be pursued and optimal bid increments can be derived. The simulation tool can be used to explore a variety of scenarios and policies and can be used as a testbed to improve the design and/or parameterization of a given auction.

7.1 How can auctioneers use the simulation tool?

From a practical perspective we expect auctioneers to have some prior estimates of the marginal \( (B_0) \) and the maximum valuations that consumers could be expected to have for a product being auctioned. These could be obtained from historical distributional data, price comparison agents and other 3rd party sources. They could use these initial estimates to compute the optimal bid increment and initiate the auction. As the auction progresses, it may be necessary that the original estimates may need to be revised, or quite simply a more accurate estimation of \( B_0 \) may become available to the auctioneers.
The revised estimate would capture the dynamics of that particular auction and the bidding strategies being employed in it. It would then behold the auctioneer to reapply our, computationally efficient, optimization procedure with the revised parameter estimates, and dynamically adjust the auction parameters, as the auction progresses. For instance, an auction could start with a bid increment of $20 and switch to a lower bid increment of say $10 as it appears to be closing.

7.2 Future Work

The management of the modern supply chains necessitates the need to effectively handle multiple simultaneous channels, such as posted-rice and auctions. Towards this end, we demonstrate how using auction obtained from tracking multi-item online auctions producers can estimate the demand curves for their products and use that information to set posted-prices. Prior to the arrival of e-commerce technologies, the communication of this demand information had to go through many layers of intermediaries before finally reaching the manufacturer. The resultant distortion at each layer lead to degradation in the quality of the information needed to manage the supply chain. For instance, large variances in demand information would lead to poor production scheduling and inefficient allocation of resources (Lee et al., 1997). It resulted in the maintenance of buffers in the form of excess capacity and inventory throughout the chain, aptly called the bullwhip effect.

In future work we will focus our attentions to other auction parameters in the design of online auctions that require optimization. These include, but are no limited to, the auction duration and the lot size among others.
References


Appendix A – Snapshot of Yankee Auction Interface