Impact of Auction Closing Mechanism on Price Discovery: Evidence from Tea Auctions in India

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The ending rule is an important aspect of auction design, wherein two common rules are a fixed deadline and an extendable deadline. In a fixed-deadline auction, sniping by experienced bidders is found to limit participant learning, thereby impeding price discovery. Extendable-deadline auctions are found to attract a larger number of bidders, create a better learning opportunity, and thus lead to higher prices. However, they can also increase transaction costs for the participants. We attempt to uncover factors that influence the effect of auction-ending rules on price discovery. We analyze the outcomes of a field experiment conducted by the Tea Board of India, wherein the ending rule was changed from a fixed deadline to an extendable deadline for a short while. Through cluster analysis, we observe that bidding styles are significantly altered during the intervention. Our model will structurally estimate the impact of determinants of compounding costs on reducing prices.

Keywords: soft-close auctions, learning opportunities, transaction cost

Track: Methods, Modelling & Marketing Analytics

1. Introduction

Auctions are an important market mechanism that produces efficiency by matching sellers with bidders who have a higher willingness to pay (Milgrom & Weber, 1982), and allow for third-degree price discrimination (Bulow & Roberts, 1989). Internet-based auctions gained prevalence owing to reduced transaction costs. Internet-based ascending auctions allowed for asynchronous bidding, lowered administration costs, heightened competition, and better price discovery.

These auctions can consider various compositions – C2C e.g., Craigslist, B2C e.g., priceline.com, or B2B e.g., FreeMarkets. Researchers have largely ignored B2B auctions, though they ease procurement processes, and have a significant economic impact (Lu, Gupta, Ketter, and Van Heck, 2016). These auctions involve repeatedly participating players with experience, and learning is key. Literature suggests that experienced bidders act strategically, engage in late bidding (Srinivasan & Wang, 2010), and inhibit price discovery.

India is the largest producer of black tea, producing about 132 crore kilograms in FY 2016-17. Approximately half of the produce is sold through e-auctions by the Tea Board of India. However, the average price has been stable at ~2 USD since 2013. Since the small farmers provide for about 30% of the total production, bettering the average price by INR 1 would improve their revenues by INR 16 crores. Improvement in realized prices can bring more growers to the auction system and sell their harvest at higher prices.

These e-auctions follow a fixed deadline (hard-close) ending rule, wherein the bidding activity comes to a hard stop in 1-2 minutes depending on the auction center. In such a fixed-deadline auction, bidders are found to engage in sniping, i.e., heightened last-minute bidding (Onur & Tomak, 2006). In an alternative closing mechanism i.e., an extendable deadline (soft-close), the duration for bidding is extended if a last-minute bid is received. We consider the context of a field experiment with the soft-close ending rule by the Tea Board of India.

This paper studies the experiment and attempts to explore the influence of the closing mechanism on bidding behavior and price discovery. Section #2 lists the observations from the extant literature to suggest the gaps in understanding the impact of ending rules. Section #3 offers details on the data captured regarding the bidding patterns and indicates the broad impact of the intervention on bidding activity and realized prices. Section #4 presents the results of the analysis of bidding styles. Section #5 suggests the model considerations and the way forward.

2. Literature Review

Researchers considered B2B auctions to achieve significant savings in cost and improved efficiencies in time (Haruvy & Jap, 2022). Of late, literature has considered auctions of digital advertising slots to realize efficient auction design and optimal prices (Despotakis, Ravi, and Sayedi, 2021). However, a less observed strand is the study of procurement via B2B auctions, especially the impact of bidder heterogeneity. This paper continues the work of Lu, Gupta, Ketter, and Van Heck (2019a, b), but on English auctions.

Bidders with more access to resources outbid those with moderate understanding can impact price discovery. Valuation of an experienced player, when learned by a smaller bidder can aid in increased price competition. Engelbrecht-Wiggans and Katok (2009) refer to the learning direction theory and suggest that learning leads to the adjustment of bids and that the regret increases with the bidder experience.

Greiner, Ockenfels, and Sadrieh (2012) suggest that experienced players participate in late bidding (sniping) and impede learning by naïve players. Extant literature posits that sniping is closely related to the auction ending rules. In a hard close auction, late bidding by experienced bidders is observed (Roth & Ockenfels, 2002). Thus, learning opportunities are reduced and impact the sellers' revenues negatively (Onur & Tomak, 2006).

Whereas a soft close auction attracts more bidders (Onur & Tomak, 2006), offers better learning opportunities (Ariely, Ockenfels, and Roth, 2005), and higher selling prices (Glover and Raviv, 2012). Literature (Ockenfels & Roth, 2006) suggests that sniping is sub-optimal in soft-close auctions. However, Cao, Sha, Yao, Gu, and Shao (2019) find that sniping is evident in soft close auctions and that it is more detrimental than that in hard close auctions. They also find that experience of the bidder is significant in such online auctions.

Chakravarti et al. (2002) call for more research explaining the bidder behavior, learning of quality, and consideration of ending rules. We consider the context of a field experiment by the Tea Board and attempt to cover all these aspects. The intervention includes the introduction of a soft close auction across various centers, for a brief period. This paper attempts to understand the impact of closing rules on realized price and learning behavior by naïve players. Thus, this paper contributes to the literature on B2B commodity auctions and to that on ending rules.

3. Data

Traditionally, two states i.e., Assam and West Bengal contributed to 80% of total tea production in India. Tea leaves are sold via an open bid, ascending auction. Across three important centers, the Tea Board of India introduced a soft close mechanism. Under the new ending rule, the auction of a lot ends only when there is no activity for 10 seconds after the minimum duration. The intervention in the most important center i.e., Guwahati lasted only for a week, and then the ending rule reverted to the older fixed deadline rule.

Thus, Guwahati offers an apt field experiment setup, untainted by other factors such as seasonality or collusion, etc. We consider data from Guwahati for this project and study the other centers in pursuit of robustness checks. With the introduction of a soft close, we expect a change in bidding activity, leading to a reduction in sniping, and an improvement in learning. And the duration of the auction lots, price, and quantity sold should increase.

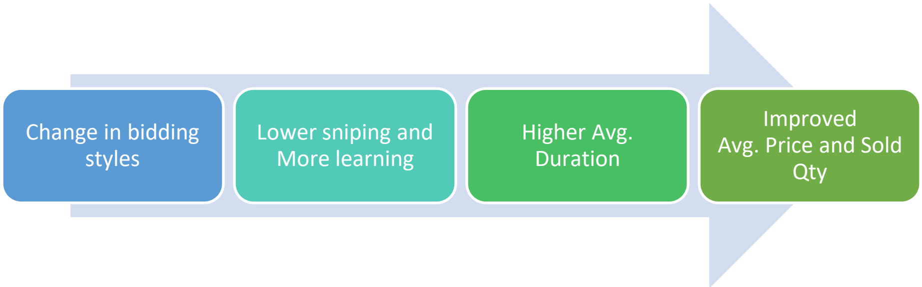


Figure 1. Supposed flow of activities in the experiment

Studies on Dutch auctions by Lu, Gupta, Ketter, and Van Heck (2016, 2019a, b) refer to the handicap of not having a bidding history, and that such an assessment helps better understand the intricacies. The e-auction by Tea Board allows for a detailed examination of the rich data of bidding history.

A collection of lots under the same Markname-Grade pair, a representation of the quality, is our unit of analysis. We consider 266 common Markname-Grade pairs (i.e., approx. 30-40% of the total quantity), for further analysis. Contrary to our initial understanding, we find that the average duration decreased during the intervention, only to rise after. The bidding activity also dips but rises after the intervention. And the quantity sold, or the price realized during the intervention is lower compared to the other two phases.

Guwahati (Common Markname-Grades)	**Before**	**During**	**After**
# of Markname-Grade Pairs	266	266	266
Total - No. of bids	9698	9676	13167
Total - No. of bidders	1612	1527	1986
Total - No. of bids in the last 10 secs	1759	1762	2142

Avg. Duration	1495	1462	1563
Sold Kgs	739442	631169	844803
Avg. Price	90	85	85

Table 1: Bidding activity and outcomes at Guwahati

We observe that the overall characteristics did not change in the three phases (contribution of the top 10 Markname-Grade pairs, top 10 buyers). And the extendable deadline should have induced more uninformed bidders to participate, learn more and win the bids. However, we find that bidding activity i.e., the number of bids, and bidders, during the intervention were lower than that in the other two phases. The late bidding activity (sniping) improved, unfavorably. The average duration during the intervention was lower by 2% and 6% than the before and after phases, respectively.

In summary, it can be surmised that the participation of uninformed bidders did not improve, contrary to expectations. Also, the average price is significantly lower (by 6%) than that in the before phase. Thus, the increase in the available time failed in improving the realized price.

4. Analysis

The reduction in the realized price during the intervention eludes existing theoretical explanations. In line with Lu, Gupta, Ketter, and Van Heck (2019a), who studied Dutch auctions, we consider heterogeneity in bidder strategies for a better explanation. We suppose that conflicting mechanisms could be at play per varying bidding styles. As with research on heterogeneity in bidding activity (Lu, Gupta, Ketter, and Van Heck, 2016), we consider the clusters of bidding styles and attempt to explain the price reduction.

We consider bidder characteristics i.e., experience, risk aversion, etc. (Greiner, Ockenfels, and Sadrieh, 2012), and bidding activity characteristics i.e., auction fever (Yao & Mela, 2008), sniping (Cao, Sha, Yao, Gu, and Shao, 2019), etc. for clustering. We also consider opportunities for learning and cognitive costs due to higher time pressure.

4.1 Clustering approach

The top 10 bidders contributed at least half of the quantity sold. These firms are known to be large and bid strategically as per their extensive experience. And so, the first two parameters represent the bidder's characteristics i.e., the experience of the bidder. The next six parameters account for the various bidding activity characteristics. The third and the fourth parameter represent the auction fever and the next two account for sniping. The seventh parameter represents opportunities for learning by smaller players. And the last parameter refers to cognitive overload. The operationalization of the 8 parameters is:

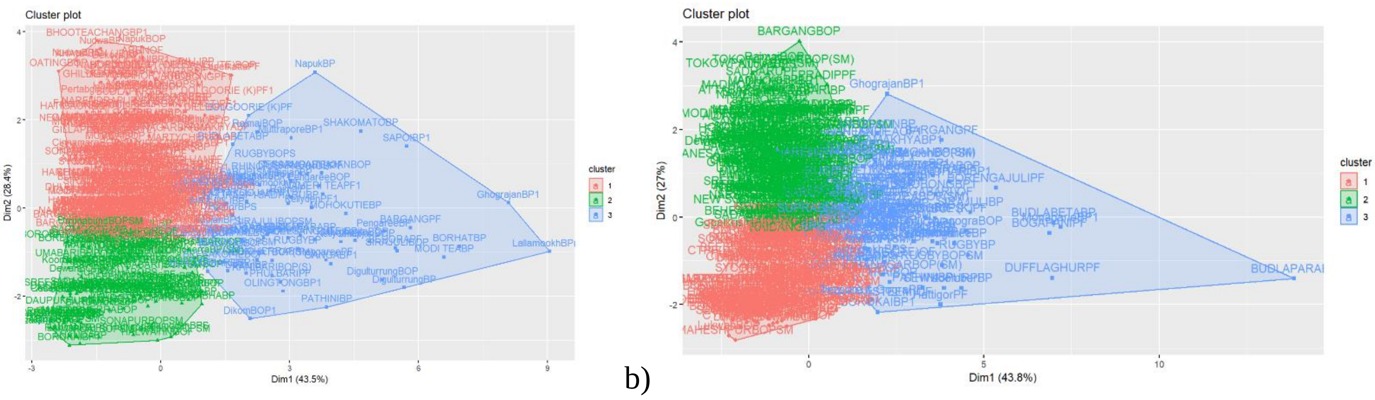
Sl. No	**Variable**	**Description**
1 (Bidder)	The proportion of large bidders (%)	No. of firms within the top 10 as a proportion of the firms that bid
2 (Bidder)	The proportion of large winners (%)	No. of firms within the top 10 that won (factoring for winning, not just participation)
3 (Activity)	Total number of bids	The total number of bids by all bidders averaged across all the lots
4 (Activity)	Total number of bidders	The number of unique bidders
5 (Activity)	No. of bids in the last 10 secs	Represents sniping activity, across all bidders
6 (Activity)	No. of bidders in the last 10 secs	The number of unique bidders participating in late-bidding
7 (Activity)	Participation duration by small players	Average duration per lot per bidder not in the top 10 (to allow for learning)
8 (Activity)	No. of parallel lots participated	Cognitive overload operationalized as costs for participating in multiple, parallel lots

Table 2: Operationalization of variables used for clustering

We consider clustering by k-medoids, as the approach is less sensitive to noise and outliers. The clustering coefficient using the ward method for Agglomerative Hierarchical Clustering is the highest, i.e., a better strength of the clustering structure. We perform a comparison of 30 indices and consider the number of clusters using a simple majority rule. We cross-check for an optimal number of clusters using the Elbow method for the classification by the k-medoids algorithm.

4.2 Clustering results

We realize that 3 clusters for the bidding activity in both phases are optimal. We plot these clusters in two dimensions, by a Principal Component Analysis.



a) b)

Figure 2: Graphical representation of clusters

The graphical representation, as above, also supports the presence of 3 clusters (a: Before, b: During phase). Across both phases, we note that the first cluster is characterized by less aggressive participation by large players, and the third cluster by more aggressive participation by these experienced players. And the second cluster characterized by non-participation represents the lots with the least duration, quantity sold, and a price realized.

However, the first cluster in the During phase boasts the highest duration and price among the three clusters. The second cluster of Markname-Grades reflects high duration but the least price, in the During phase. The learning and cognitive load in cluster 1 are the highest and least in cluster 2 except for high learning the during phase. And so, without a change in the quality of the teas, we find a significant difference in the bidding strategies with only a change in the ending rule. A snapshot of the cluster characteristics is below.

Cluster Classification		Before						During					
		Cluster #1		Cluster #2		Cluster #3		Cluster #1		Cluster #2		Cluster #3	
# of MarkName-Grades		216		90		73		157		131		91	
Qty Sold (Kgs per MarkName-Grade)		2011		1839		5244		1558		1290		4820	
Sold Price (INR per MarkName-Grade)		93		87		94		90		84		86	
Avg Duration (secs)		1627		1427		1969		1499		1451		1392	
Proportion of large bidders (%)	Large players	0.5	Most	0.2	Non	0.4	Medium	0.5	Most	0.1	Non	0.3	Medium
Proportion of large winners (%)	Large players	0.6	Most	0.1	Non	0.5	Medium	0.6	Most	0.1	Non	0.5	Medium
Total number of bids	Auction fever	26.5	Low	25.8	Low	97.6	High	23.6	Low	24.5	Low	90.5	High
Total number of bidders	Auction fever	5.5	Low	5.2	Low	11.8	High	4.4	Low	4.9	Low	11.0	High
No of bids in last 10 secs	Sniping	4.7	Low	4.3	Low	16.4	High	4.5	Low	4.3	Low	15.3	High
No of bidders in last 10 secs	Sniping	3.2	Low	3.0	Low	10.5	High	2.4	Low	2.3	Low	6.3	High
Participation duration by small players	Learning	224.7	Most	169.0	Least	197.2	Medium	168.2	Most	169.5	Most	108.3	Least
No of parallel lots participated	Cognitive overload	324.0	Highest	179.1	Least	299.6	Medium	241.9	Highest	140.2	Least	199.9	Medium
Style		Less aggressive participation		Avoided by large players		More aggressive participation		Less aggressive participation		Avoided by large players		More aggressive participation	

Table 2: Description of the three clusters

We notice that the cluster membership of the Markname-Grade pairs shifted for more than half of the occasions, and these pairs contribute to 65% of the decline in the sold quantities. It is interesting to note that the top 10 firms participated more in bidding for the quality of teas in the first cluster than in the second cluster (57% to 10% of all participated pairs). However, their participation in the less aggressive style was reduced (37%), and that in the avoidance cluster improved (31%).

Thus, it can be surmised that with the change in the auction ending rule, the avoidance by large firms increased. Also, learning by smaller firms increased with duration, however, they could have learned only from similar smaller players.

5. Way Forward

The choice of a bidding strategy, for any lot, is a function of the benefits availed and costs incurred in participating in the auction of previous lots. These trade-offs in turn are a result of the intensity of participation by the players.

We will consider the autoregressive models of estimating the utility of larger players (Montgomery, Li, Srinivasan, and Liechty, 2004; Li & Kannan, 2014), as the costs of the bidder in previous lots impact the costs and bids in the subsequent lots. We observe that the cluster membership of the same Markname-Grade differs across the phases, thus further impacting the realized price. We posit that the utility from participation for each bidder (i), per each lot (l), for the Markname-Grade (m) varies across the clusters and the phases.

The perceived utility (U_{iml}) depends on the expected benefits of winning the bid (B_{iml}), diminished by the costs (C_{iml}) of participating in the auction of multiple lots, an idiosyncratic error term (ε_{iml}). The error term is assumed to be an i.i.d extreme error.

$$U_{iml} = B_{iml} - C_{iml} + \varepsilon_{iml} \quad (1)$$

The expected benefit of winning the bid (B_{iml}) is the monetary value derived from reselling the tea (M_{iml}) reduced by the price paid for winning the bid (P_{iml}), considering the probability of winning the lot (Pr_{iml}). And thus,

$$B_{iml} = Pr_{iml} * (M_{iml} - P_{iml}) \quad (2)$$

The probability of winning the bid (Pr_{iml}) is realized by considering a Normal distribution of the maximum of bids per bidder. The mean bid (μ_{ml}) is a function of the proportion of large bidders (lb_{ml}), winners (lw_{ml}), and learning by the small players (l_{ml}).

$$\mu_{ml} = \left(\alpha_{lb,ml} * lb_{ml}\right) + \left(\alpha_{lw,ml} * lw_{ml}\right) + (\alpha_{l,ml} * l_{ml}) \quad (3)$$

where (α) are the weights of these variables that need to be estimated.

The monetary value of the reselling (M_{iml}) is specific to a bidder and a Markname-Grade, and so we estimate this value by considering it as another individual-specific parameter. The price (P_{iml}) is recorded for each winning bid per each lot, in the available bid history data. However, the bid price (P_{iml}) is also a function of the monetary value (M_{iml}) and costs of participating in previous lots ($C_{im(l-1)}$).

$$P_{iml} = \beta_M(M_{iml}) - \beta_C C_{im(l-1)}) \quad (4)$$

We consider that the costs of participating in bidding for every lot compound with an increase in the duration of the current lot and the time pressure of participating in parallel lots. Also, the costs are a function of the cost of participating in all previous lots.

And so,

$$C_{iml} = \delta_D(D_{ml}) + \delta_T(T_{iml}) + \delta_C C_{im(l-1)}) \quad (5)$$

where (D_{ml}) is the duration for which the bidders participating in the auction of the current lot, (T_{iml}) is the time pressure faced by each bidder, and ($C_{im(l-1)}$) is the cost of participating in the auction of the previous lots.

We will attempt to estimate the parameters of this model, via the Markov chain Monte Carlo approach, along the lines of Li and Kannan (2014). We expect a variation in the parameter estimates for costs and prices for the same Markname-Grades across clusters in both phases. This difference can help realize the impact of increased cognitive load on the transaction costs, and the compounded effect on the realized prices, owing to longer duration.

Thus, we can establish the influence of the revised ending rule and suggest cases when a soft close might be more favorable than a hard close.

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