Auctioneers as Market Makers: Managing Momentum in Chittagong Tea Auctions*

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Abstract

In an auction market, the auctioneer exerts significant influence in choosing and administering a selling strategy. Using a unique data set, where the auctioneer has ownership stake on a fraction of the lots he sells (affiliated lots), we study how auctioneers manage a large auction market and show that their actions can be explained by the market structure and their incentives to maximize revenues from the entire market. Specifically, we find that a high realized price or withdrawal of a lot (presumably based on a high reserve price) exert a positive price externality on subsequent lots in a dynamic auction. As different lots are (imperfect) substitutes, high prices indicate higher potential competition in the future, which reduces continuation values and triggers more aggressive bidding. However, by reducing the probability of sale, this can be costly to an individual seller if she does not internalize the price externality on subsequent lots. Hence, to manage the momentum of market prices while maintaining his relation with sellers, the auctioneer chooses higher reserve prices for affiliated lots, which sell less frequently creating a short run cost to the auctioneer but an overall positive impact on market prices. Consistent with the role of a market maker, a desire to appear non-opportunistic, rather than opportunism, seems to better explain the auctioneer's actions.

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1 Introduction

Auctioneers are intermediaries in two-sided markets who play a major role in the markets they operate. An auctioneer is a market maker, an eBay or Amazon.com in miniature. They are emcees who "set the tone" and "draw the line"[1] to organize the auction offerings in a way to keep the auctions interesting and useful for the buyers and profitable for sellers. They must maintain a brisk price momentum to avoid "dead spots" of languid bidding (*cf.* Cassady (1967)). To accomplish this, sellers often allow the auctioneers to have significant discretion in choosing a selling strategy, communicating it to the buyers, and administering it. Thus, by analyzing their choices, we can learn about the role they play in these important market places.

While auctioneers occupy a charismatic presence in the popular imagination, they are largely absent in the auction literature, where auctions are typically assumed to be run by a passive entity whose incentives are aligned with the seller's.[2] In thinking about the role of auctioneers, one may suspect agency issues to prevail since auctioneers (auction houses) receive a share of the revenue they generate as commission. However, they are typically long run players interacting repeatedly with the same set of participants, so that their success as a market maker ultimately depends on how well they manage externalities without jeopardizing the trust of the many buyers and sellers attending their auctions.

In this paper, we empirically study how auctioneers manage a large auction market and show that their actions can be explained by the market structure and their incentives to maximize revenues from the entire market. A key feature in many large auction markets is that auctioneers sequentially auction numerous *lots* that are imperfect substitutes.[3] In such a setting, buyers have a continuation value from the option of being able to buy a future lot even if they fail to win the current lot. As a result, their bids depend on the potential competition they will face in the future lots, which they try to learn from realized outcomes of the past lots. The outcome for a lot provides information

[1] This colorful language was used by actual officials and participants in Chittagong tea auctions to describe the role of the auctioneers.

[2] While McAdams and Schwarz (2007), Skreta (2015), and Lacetera et al. (2016) theoretically and empirically analyze the role of an auctioneer, they do not explore any possible divergence in incentives between an auctioneer and sellers.

[3] We refer to the set of sequential auctions run throughout a day as an *auction* and each individual auction within it as a lot.

about overall demand, and that affects the outcome of future lots. Such informational externality creates price interdependence. How well an auctioneer manages the price interdependence proves to be an important component in our analysis. First, using a simple stylized theoretical model, we show that, because of the informational externality, the optimal reserve price for lots within an auction market will be different depending on whether the optimization problem is defined as maximizing the overall expected revenue from the entire auction or as separately maximizing the expected revenue from each lot. Specifically, if a higher reserve price increases bids in future lots by reducing the continuation value, a seller who owns a single lot will ignore this externality on the revenue of future lots while a maximizer of overall revenue will not. This suggests that there may be strategic divergence between a market maker and individual sellers. However, such strategic divergence might be difficult to identify if auctioneers closely follow sellers' directives regarding selling strategies.

To address the empirical challenges of measuring the impact of an auctioneer on market outcomes, we study a unique auction market with the special property that some auctioneers in this market happen to sell some items in which they have ownership stakes in addition to items in which they do not. Our data comes from tea auctions in Chittagong, Bangladesh, a large well-organized market for tea. This auction market, established almost a century ago, provides a rich and colorful economic environment for our analysis. On an auction day, an auctioneer sells many lots of tea individually auctioned off via sequential English auctions. We exploit a difference in ownership of tea estates, with some being *affiliated* with the auctioneer, to measure the extent of this tension between the incentives of an auctioneer vs. individual sellers.[4] Another nice feature of the data set is that the auctioneers provided us with their private quality notes about the tea they sold. These allow us to control for virtually all differences in the quality and other characteristics of tea and separate product heterogeneity from strategy. By relating the variation in auction outcomes to the level of discretion the auctioneer has over the selling strategy, while controlling for lot quality, we can cleanly discern the impact of his strategic choices.

Chittagong tea auctions are carefully structured, following processes that have been in place for decades. To create symmetric information about supply, detailed information

[4] Affiliated estates are owned by the same holding company as the auction house, providing the auctioneer with greater discretion in choosing selling strategies for tea from these estates.

about each lot of tea is provided to all buyers before the auction. This includes the practice of ensuring that the auctioneers and buyers evaluate tea quality from the same sample drawn from each lot of tea to be sold. It is mainly the uncertainty about the realized demand that is resolved on the day of the auction. Buyers attend the auction with detailed purchase plans for the entire catalog of teas on sale, and the impact of the realized demand is determined during the actual auction.

In our interviews with participants, we were repeatedly told about the importance of figuring out the *momentum in prices* for the day. If bidders believe that overall demand is high, they will bid more aggressively to avoid being stranded without enough lots as competition may be too fierce towards the end. If bidders believe that the overall demand is low, they will bid less aggressively to take advantage of the low demand.[5] We empirically verify the presence of such interdependence of prices. It may be noted that this feature would be absent if we considered each auction in isolation, as is done in much of the empirical auction literature.[6]

Auctioneers aggregate information regarding overall demand faster than individual bidders, and they incorporate this information in choosing reserve prices. *Drawing the line,* by strategically withdrawing a lot that is not receiving a high enough bid, may be needed to maintain price momentum. This helps coordinate the market, raise overall revenue, and also reduce the likelihood of buyers being left stranded without enough lots at the end. An auctioneer who is charged with *setting the tone*, therefore, would like to choose a higher reserve than sellers who benefit less from this externality. While such actions increase the price conditional on sale, they may lead to some lots going unsold. Thus, this is potentially costly for individual sellers who do not internalize the positive price externality as much as a market maker. As it is easier to take costly actions with the affiliated lots, the auctioneers use those more frequently to inform market participants about demand.

Our data largely confirms this story. We find that there is positive price interdepen-

[5] This is also consistent with the theoretical model of Rosenkranz and Schmitz (2007) where a buyer's utility from an object is affected by a reference price (a la Koszegi and Rabin (2006)) that is independent of her valuation for the object. As a result, this reference price affects her bidding behavior.

[6] While Cassady (1967) listed the behavior of prices during an auction session as a challenging open question almost five decades ago, there has been little work on interdependence of prices across lots within an auction session. Our study takes a step in that direction by analyzing how the outcome of a lot affects the outcomes of subsequent lots and how that affects strategic behavior by auctioneers.

dence across lots, and that withdrawal of a lot also positively affects the price of subsequent lots. Our theoretical model suggests that such price interdependence should lead to higher reserve prices for affiliated lots. We find that affiliated lots sell less frequently relative to tea from smaller non-affiliated sellers. While we do not observe reserve prices directly, we do find that affiliated lots generate a higher price conditional on sale. We also do not find any evidence that postponing the sale of a lot increases the price of that specific lot when it is again up for sale on a future auction day. These results suggest that higher reserve prices are chosen for affiliated lots. By taking costly actions on lots from estates with whom he enjoys greater trust and whose policies he has greater control on, the auctioneer communicates information about realized demand to improve coordination among participants, and, presumably, increases his own payoff in the process. Viewing the auctioneer as a market maker, as opposed to an insignificant agent in the market, we note that he creates opportunities for all as opposed to waiting to exploit opportunities for himself.

Our paper is closely related to and complements Lacetera et al. (2016), who have shown that auctioneers matter – using a very large data set with 60 auctioneers, they find that the probability of sale varies widely across auctioneers. Our analysis complements theirs as we can identify strategic aspects of an auctioneer's behavior relying on the variation in ownership between affiliated and unaffiliated lots, the distinctive feature of our data.[7] The theoretical insights provided in our paper is somewhat similar to that in Horstmann and LaCasse (1997). In their model, a seller, with better information about the value of the object, may use a secret reserve to withdraw the object from the auction to signal a higher common value and sell it (at a higher price) in a future auction. In contrast, in our setting, the auctioneer is better informed about the realized demand and uses strategic withdrawals to reveal high demand. While this leads to higher prices for similar lots subsequently listed on the same auction day, the strategically withdrawn lot itself may not sell at a higher price when auctioned off at a later date. Our stylized model of sequential auctions is related to the models in Zeithammer (2007), and Backus and Lewis (2016), who also explore informational externalities in dynamic auctions.

In the following section, we first describe tea auctions in Bangladesh. Then we sketch

[7] Lacetera et al. (2016) also investigate behavioral aspects for auctioneers and provide more references on the topic.

a simple model of auctioneer behavior, and derive some empirical predictions related to the auctioneer's willingness to withdraw lots of tea when a reserve price is not met. Subsequently, we test these predictions using our data.

2 Data and Market Description

2.1 Market Description

Bangladesh, where tea is the most popular and affordable drink, is a large tea producer. The bulk of the produced tea is sold in the open market via auctions as the producers are required, by government regulation, to offer at least 80% of tea for sale in the auctions.[8] The auctions are organized by the Tea Association of Bangladesh (the association of tea estate owners) and are administered by six auction houses or auctioneers in the same venue in the city of Chittagong. There are usually 45 auctions every year, with an auction held each Tuesday during the months of April to January except for the two religious holidays.[9]

We first describe the timeline or auction design. The tea to be sold on a specific auction day is entered in a catalog almost two weeks in advance. Sellers send tea from various tea estates of the country to Chittagong, where the auctioneers take control and store them in bonded warehouses dedicated for tea storage. The auction catalog by a specific auctioneer for a specific auction day lists the sequence of the lots of tea that he will put up for sale on that day and typically includes all the tea that he has in the warehouses. The catalog describes each lot by the grade of tea denoting the type or category of the tea, the name of the tea producing estate, the tea leaf processing factory, the warehouse where the tea is stored, number of bags in the lot, net weight of each bag, and the total weight of the lot. A lot typically contains 10 bags of identical weight (usually around 55-60 Kg.).

To ensure that all parties can assess the quality of tea on sale, 1.8 Kg of tea is set aside from each lot of tea to be distributed as samples among the auctioneer as well as the

[8] The purpose is to create a credible base for the excise tax government charges for tea sale. However, the restriction does not seem to be binding as sellers choose to sell almost all of their tea via the auction. These well-run auctions provide transparency in the pricing process for all the stakeholders—government, tea estates, buyers, and auctioneers. Indeed, even integrated producers, who are also retail packaged tea sellers, prefer to sell almost all their tea through the auction rather than engaging in transfer pricing between producing and marketing units.

[9] December and January are lean periods in tea production and, as a result, the auctions are not held in February and March.

buyers. Thus, participants obtain information about quality from the same sample of tea from each lot.[10] Conversations with participants suggest that differences in assessments of quality is not much of an issue in these auctions. All participants are professionals with vast experience in the business, and the auctioneers and all the significant buyers in Chittagong tea auctions are expert tea tasters. After tasting tea from each lot, the auctioneers assign a valuation for the lot which is entered into the catalog. We will say more about this valuation process later. The final catalog is sent to buyers along with tea samples from each lot, typically five days before each auction.

On the auction day, the six auctioneers sell their lots one after another. The order of auctioneers in the first auction of the year is decided by lottery. This order is changed every week where the first auctioneer in the previous auction goes to the sixth position and all other auctioneers move up one position in the order. During his turn, an auctioneer sells his lots sequentially (according to the sequence listed in the catalog) using English auctions. We will say more about the choice of lot sequencing in section 3.2. The auction determines the per Kg price of tea in the lot.[11] An auctioneer is allocated 15 seconds (on average) to auction off a lot. After he auctions off all the lots on his catalog, the auctioneer next in line sells his lots. The auction day ends after all six auctioneers auction off the lots on their catalogs. The lots that are sold in the auction are delivered to the buyers from the warehouses and the lots that are not sold are kept in the warehouses to be sold in a future auction.

Sellers, who are the owners of the tea estates, contract with an auctioneer to sell tea on their behalf. Contracts between a seller and an auctioneer are typically a year long and the seller can choose a new auctioneer once the contract expires. However, in practice, only a small number of contracts move from one auctioneer to another each year. There is variation among the sellers. As mentioned earlier, some tea estates are owned by the auctioneer's holding company, but most are owned by client companies. We refer to these two kinds of sellers as *affiliated* and *unaffiliated* sellers, respectively. Some tea estates

[10]Smallest 15% of the buyers do not receive a sample, but they can visually inspect the tea leaves at the auctioneers' office.

[11]Unlike Athey and Levin (2001), however, the total weight of a lot is clearly known to all the bidders. Any potential uncertainty about a lot from a buyer's point of view can only come from the unobserved quality as all other relevant information such as the category, the producing estate, and the processing plant for a lot are publicly known.

are stand alone operations owned by companies that own a single tea estate. On the other hand, some companies own a number of tea estates. In our data set, almost 42% of the auctioned lots are from estates owned by two large and established tea producing companies. These two companies specialize in tea production and do not engage in retail tea sale. We refer to them as *major* estates. Major estates are perceived by market participants to have greater uniformity in the quality of the tea they produce.[12]

There is also considerable variations among the buyers in this auctions, who attend the auction with their idiosyncratic purchase plans. Buyers have to be registered with the Tea Traders Association of Bangladesh. They vary by size and the types of markets they serve. Some of the buyers are wholesalers of tea who later sell the loose tea to retailers country-wide. Some buyers are large packeteers who blend and package the loose tea for retail sale to the public under recognized brand names. Some buyers buy tea for direct export as loose tea. However, with the steady income growth, the domestic demand is increasing, and the share of tea sold for export has decreased over time. With the rise in incomes, the market for blended tea packaged and sold under recognized labels is also becoming very significant.

The auctioneer receives 1% of the sale price as a commission from the seller and Tk. 0.05/Kg, irrespective of the sale price, from the buyer of each lot. These commission rates have been fixed by negotiation between the Tea Traders Association of Bangladesh, the Tea Association of Bangladesh, and the Bangladesh Tea Board of the government and have not been changed in a long time.

2.1.1 Assessment of the Realized Demand

As described above, the auction process is set up such that the quality and quantity of tea available for sale is made clear to all buyers before each auction day. Buyers attend the auctions with a purchasing plan and tea lots up for sale are usually imperfect substitutes. What is unknown is the realized demand for tea, which depends on idiosyncratic purchase plans of all the buyers. There is considerable heterogeneity among buyers and their demand for tea on a specific auction day. The key purpose of the auction is to determine a price that reflects the realized demand for the day, which is also why a posted price is not

[12] In our data set, quality ratings (described later) of tea lots from major estates are, indeed, higher on average with lower variance.

an optimal selling option. The auctioneers in Chittagong actively seek out information about demand the day prior to the auction. Moreover, they are experts in observing all the potential buyers in the room and quickly judge the level of aggregate demand.

Buyers bid according to their prior expectation of the aggregate demand and update their beliefs based on the realized prices within an auction day. While the buyers participate by bidding in the English auctions, the auctioneer participates by choosing the opening or reserve prices. Over the duration of the auction, the market participants go through a process of discovery of the realized aggregate demand. Thus, the realized prices throughout the auction day are used in this discovery process. The auctioneer is in the best position to assess the realized demand as he can aggregate information about the market demand faster than any single buyer. He can also expedite the discovery process by his choice of the opening/reserve price if he believes that the bidding behavior is too sluggish or too aggressive given the realized aggregate demand. If, for example, he observes that the realized demand for a type of tea is higher than perceived, he will have an incentive to increase the reserve price and take a chance of not selling lots to induce more aggressive bidding on subsequent lots.[13] This will be a central part of the empirical analysis below.

2.2 Data Description

We have catalog data from the two largest auction houses for 16 auction days from August 2005 to November 2005 totalling 17629 lots of tea.[14] These two houses account for more than 65% of the total tea sold. The largest auction house is a *pure auctioneer*—only sells tea lots from estates owned by client sellers. The second largest one, which we call the *integrated auctioneer*, also sells tea from estates owned by its own holding company along with lots of tea from clients. We also have the list of the lots that succeeded in selling during the auction and the final price and winner list for these auctions.

Auctioneers' private tasting and publicly announced valuation. As mentioned above, auctioneers taste the tea to be auctioned off themselves to judge the quality of each

[13] Buyers may also be modeled as having reference-dependent utility a la Kosegi-Rabin, where the reference price is determined by past prices (Rosencranz-Schmidt).

[14] The exchange rate was around USD 1 = Tk. 65.70 during the time the data was collected.

lot. They take detailed notes about their evaluation of the tea quality and have provided us with their private tea tasting notes. These notes clearly state the quality of the tea. These assessments are not strategically chosen since they are only for the auction houses' internal use and are never shared with buyers or sellers. The tasters (auctioneers) usually write detailed comments on the appearance of the tea leaves and the liquor or give some alpha-numerical rating to the lot. From these notes, in consultation with the auctioneers, we created an index of quality rating and assigned a numerical score between 1 to 10 to each lot. In our empirics, we use this index as an ordinal ranking of tea quality.

These quality ratings can be used to control for unobserved quality heterogeneity across lots, which is a particularly useful feature of our data set. Note that, as mentioned above, there is relatively little information asymmetry among all the participants - auctioneers, sellers, and buyers - about the quality of a lot in Chittagong tea auctions. However, as economists, we typically do not observe the quality of a product up for sale and quality is one of the most common sources of unobserved heterogeneity in empirical auction literature. Our quality rating aids us in disentangling the differences in auction outcomes arising from participant strategies and those arising from heterogeneity in tea quality. By directly controlling for product heterogeneity, we can more clearly analyze the strategic interaction between the auctioneer and the seller that determines reserve prices.

Auctioneers actively conduct market research about the future demand of tea due to local consumer demand and demand from exporters. They use the information on quality and future demand to estimate a valuation for each lot. This valuation is listed on the catalog and we refer to it as the publicly announced valuation. This is an indicator of the expected price for a lot.

Withdrawal of lots. On the auction day, lots are sequentially sold using English auctions, which typically start at the reserve price. If no buyer offers a bid at the reserve price, the auctioneer moves on to the following lot in the catalog without selling the current one. We refer to this as *withdrawing* a lot or keeping a lot *unsold*. The reserve price is not announced on the auction catalog. Withdrawing of a lot, hence, is a strategic variable that is exercised during the auction. If the auction outcome of a lot affects the outcome of subsequent lots, each lot acts as an instrument for the auctioneer to influence the overall auction. We will explicitly model the auctioneer's withdrawal decision during the auction of a lot in the context of the auction market in the following section.

There are costs associated with withdrawing a lot. A withdrawn lot can be re-listed in a future auction, typically two weeks after the lot is withdrawn (there must be at least a two week gap before the lot can be re-auctioned as the lots for the auction on the following week are already decided). The seller incurs costs associated with storage and bank loans, and also needs to provide an additional 1.8 Kg from the tea lot as a sample; the auctioneer incurs some re-auctioning costs which are relatively small. Moreover, while tea is not perishable, the freshness of tea reduces over time losing some of its value.

2.3 Auctioneer Behavior: A Model Incorporating Externalities

In this section, using a simplified or stylized version of the auction market, we illustrate that when the prices from lots within an auction market are correlated, optimal strategies for the seller of a single lot can diverge from those of a market maker. We present a simple model of sequential second-price auctions for identical objects and unit demands. We follow the standard approach (see, e.g., McAfee and Vincent (1993), Krishna (2002), and Mezzetti (2011)) with two main differences: we assume that there is some uncertainty regarding the realized distribution from which buyer valuations are drawn, and that there is a reserve price for each auction. There are three identical items as we require at least three lots to illustrate our main insight. There are $N \geq 4$ risk-neutral bidders denoted by $i \in \{1, 2, \ldots, N\}$. Bidders have unit demand and bidder i's independently drawn private value for a lot is denoted by v_i. It is common knowledge that all valuations are drawn from the common support $[\underline{v}, \overline{v}]$, with $\underline{v} \geq 0$, from either F_H or F_L, where, F_H first order stochastically dominates F_L. Implicitly, these distributions are meant to capture the idea of high and low aggregate demand. Bidder i knows her own valuation, but she does not know the valuations of other bidders or the realized distribution. The auctioneer does not know any bidder's private valuation. All the bidders and the auctioneer receive a public signal about whether the valuations are drawn from F_H or F_L. This signal is correct with probability $\lambda > \frac{1}{2}$. The auctioneer receives an additional independent private signal indicating whether the distribution is F_H or F_L. This signal is correct with probability $1 > q \geq \lambda$. Intuitively, the public signal represents information about aggregate demand that is publicly available. The auctioneer's private signal is derived by his active market research and ability to quickly aggregate all the information received. Thus, the auctioneer has more precise information regarding the realized demand.

The auctioneer's goal is to maximize the total revenue from the three auctions. The reserve price for lot $t \in \{1, 2, 3\}$ is denoted by r_t; that is, the lot is withdrawn if it fails to to sell even at a price of r_t. We assume that the reserve prices are not announced prior to the auction and is revealed during administering the English auction for lot t only if the lot goes unsold.[15] For modelling purposes, we assume that bidders place their bids for lot t without knowing the reserve price r_t. If all bids are below r_t, the lot remains unsold, and r_t is revealed.[16] Otherwise, only the realized price p_t, which is defined below, is revealed. The exact bids are not revealed to any of the bidders

To keep this stylized model tractable, we make a number of assumptions regarding the strategy space and information revelation. We assume that bidder i does not infer any belief about the likelihood of the distribution being F_H based on v_i. The auctioneer chooses the reserve price r_t prior to auctioning lot t and cannot update the reserve prices while the auction goes on. We also assume that there is a separating equilibrium for the optimal reserve prices and the optimal reserve price is higher if the auctioneer's private signal is F_H.

We refer to the highest amount a bidder is willing to bid in the English auction for lot t as her bid on that lot. Suppose the realized highest and second highest of all bids for lot t are denoted by p_{1t} and p_{2t}, respectively. Revenue from a lot equals the price if the lot is sold and equals the value to the seller of the unsold lot otherwise. Given the auction structure, the observed price p_t^* for lot t is generated by the following equation:

$$p_t^* = \begin{cases} 0 \text{ if } p_{1t} < r_t \\ p_t = \max\{r_t, p_{2t}\} \text{ if } p_{1t} \geq r_t. \end{cases} \tag{1}$$

Next, we introduce the dynamic price externality in a given auction. Let h_t denote the *benchmark* price for lot t; we define this benchmark as equalling the price that the previous lot (lot $t-1$) received if it was sold and the reserve price if the lot went unsold. That is, for $t \in \{2, 3\}$,

$$h_t = \begin{cases} r_{t-1} & \text{if } p_{1t-1} < r_{t-1} \\ p_{t-1} & \text{if } p_{1t-1} \geq r_{t-1}. \end{cases} \tag{2}$$

[15] For example, the auctioneer announces the lowest acceptable price if the English auction does not fetch high enough bid.

[16] These assumptions are based on the structure of Chittagong tea auctions.

The benchmark price is a measure of the "prevailing" price level around the time when lot t is on the selling block. This benchmark price can be an indicator of the overall market demand, with a high benchmark indicating that the demand is likely to be strong and a low benchmark suggesting the opposite.[17] For lot one, there is no benchmark, $h_1 = \emptyset$. For lots two and three, bidders use h_t to update their belief about the probability that v_i is drawn from F_H.

We explain next price externality across the lots. Let us start from the third and final lot and note that a bidder bids v_i if she has not won either of lots 1 or 2 and does not bid otherwise. However, for lots 1 and 2, she has a continuation value from the option of being able to bid in the following lot(s) in case she does not win lots 1 or 2. Thus, as is well known in this type of a setting, she will bid below v_i for lots 1 and 2. We assume that a bidder's continuation value for period $t+1$ is given by $c_{t+1}(v_i, h_t)$. We focus on simply characterizing how the bids are affected by the continuation value, but we do not provide an explicit solution for $c_{t+1}(v_i, h_t)$. The continuation value denotes a bidder's expected payoff from future lots and this expected payoff is increasing in v_i. To illustrate how outcomes in the previous lots affect continuation value, we focus on $c_3(v_i, h_2)$. A higher realized price p_1 indicates higher realized valuations.[18] Hence, a bidder's posterior belief that the distribution is F_H is increasing in h_2 when lot 1 sold. The reserve price is determined by the auctioneer who has more precise information about the underlying distribution. Since we assumed a separating equilibrium, if lot 1 does not sell, a higher reserve r_1 increases bidders' posterior beliefs that the distribution is F_H. Fixing bidder i's valuation v_i, a higher posterior belief will reduce her expected payoff from future lots and, hence, the continuation value. One can easily show that the optimal bid b_{it}^* is given by:

$$
\begin{aligned}
b_{it}^* &= v_i - c_{t+1}(v_i, h_t) \text{ for } t = 1, 2 \\
b_{i3}^* &= v_i.
\end{aligned}
$$

The auctioneer's objective is to maximize *overall* revenue from the auction, taking into account the dynamic price externality. He chooses the sequence of reserve prices

[17] When a lot does not sell, a high reserve indicates that the auctioneer and seller believes that the demand that day should be high. A low reserve, on the other hand, indicates that the expeceted demand is low, but the lot still did not sell.

[18] To ensure monotonicity of the bid function, we assume that $\frac{\partial c_{it+1}(v_i, h_t)}{\partial v_i} < 1$.

$\{r_1, r_2, r_3\}$ to maximize the expected revenue across *all* the lots in an auction given the information he has. Because of the dynamic price externality, the auctioneer faces a dynamic optimization problem in which the benchmark h_t is the state variable:

$$V_1(\emptyset) = \max_{r_1} \mathbb{E}\left[u_0 \mathbf{1}_{\{p_{11}<r_1\}} + p_1^* \mathbf{1}_{\{p_{11}\geq r_1\}} + V_2(r_1)\mathbf{1}_{\{p_{11}<r_1\}} + V_2(p_1^*)\mathbf{1}_{\{p_{11}\geq r_1\}}\right]$$

$$V_2(h_2) = \max_{r_t} \mathbb{E}\left[u_0 \mathbf{1}_{\{p_{12}<r_2\}} + p_2^* \mathbf{1}_{\{p_{12}\geq r_2\}} + V_3(r_2)\mathbf{1}_{\{p_{12}<r_2\}} + V_3(p_2^*)\mathbf{1}_{\{p_{12}\geq r_2\}} | h_2\right],$$

$$V_3(h_3) = \max_{r_3} \mathbb{E}\left[u_0 \mathbf{1}_{\{p_{13}<r_3\}} + p_3^* \mathbf{1}_{\{p_{13}\geq r_3\}} | h_3\right].$$

In this problem, $V_t(h_t)$ denotes the value function, the continuation revenue, starting from lot t when the current benchmark price is equal to h_t. We denote the expected net future payoff from lot t if it is not sold in the current auction by u_0. Note that, if there were no price externality, r_t would be chosen to maximize the value $\mathbb{E}\left[u_0 \mathbf{1}_{\{p_{1t}<r_t\}} + p_t^* \mathbf{1}_{\{p_{1t}\geq r_t\}} | h_t\right]$, which would maximize the revenue from each lot individually. Let us denote the optimal reserve prices for lot t that maximize overall revenue and revenue from individual lots by r_t^O and r_t^I, respectively. We refer to them as overall and individually optimal reserve prices. The following proposition shows that r_1^O is greater than r_1^I.

Proposition 1 *The optimal reserve price is higher when there is a dynamic price externality. Specifically, the optimal reserve for lot 1 that maximizes overall revenue, r_1^O, is higher than the optimal reserve r_1^I that maximizes the revenue from lot 1 individually. For lots 2 and 3, the dynamic price externality plays no role in determining the optimal reserve price.*

Proof. The optimization problem for the third (last) lot is the same from both collective and individualistic points of view, as they both maximize $\mathbb{E}\left[u_0 \mathbf{1}_{\{p_{13}<r_3\}} + p_3^* \mathbf{1}_{\{p_{13}\geq r_3\}} | h_3\right]$. Hence, the individually optimal reserve price, r_3^I is the same as the overall optimal reserve r_3^O and is independent of h_3. For lot 2, the overall optimal reserve is chosen to maximize

$$\mathbb{E}\left[u_0 \mathbf{1}_{\{p_{12}<r_2\}} + p_2^* \mathbf{1}_{\{p_{12}\geq r_2\}} + V_3(r_2)\mathbf{1}_{\{p_{12}<r_2\}} + V_3(p_2^*)\mathbf{1}_{\{p_{12}\geq r_2\}} | h_2\right].$$

As the optimal bid in the third period, $b_{i3} = v_i$, is independent of h_3, we also have $r_2^I = r_2^O$. However, a high benchmark h_2 (which equals r_1 if lot 1 goes unsold and p_1^* otherwise) indicates that the realized distribution of valuations is more likely to be F_H. Thus, an increase in r_1 will reduce bidder i's continuation value for period 3 and raise her bid b_{i2} if lot 1 remains unsold. Hence, V_2 is increasing in benchmark h_2.

Now, the overall expected revenue from the three lots prior to auctioning lot 1 is

$$\mathbb{E}\left[u_0 \mathbf{1}_{\{p_{11}<r_1\}} + p_1^* \mathbf{1}_{\{p_{11}\geq r_1\}} + V_2(r_1)\mathbf{1}_{\{p_{11}<r_1\}} + V_2(p_1^*)\mathbf{1}_{\{p_{11}\geq r_1\}}\right].$$

On the other hand, the individualistic optimization problem maximizes $\mathbb{E}\left[u_0 \mathbf{1}_{\{p_{11}<r_1\}} + p_1^* \mathbf{1}_{\{p_{11}\geq r_1\}}\right]$. As $V_2(r_1)$ is increasing in r_1, raising the reserve price r_1 provides positive externality to the overall optimization function that is not internalized in the individualistic optimization function. As a result, we will have $r_1^O > r_1^I$. ■

When the benchmark price and the underlying market demand affect a bidder's bidding behavior, a high reserve price or a high realized price decreases the continuation value, and the bid function is increasing in the benchmark price. Hence, the price function is also increasing in the benchmark price.[19] Thus, the reserve price has a positive externality on future prices. This also implies that a lot going unsold will also positively affect the price of the following lot.[20] As a result, overall optimal reserve prices are (weakly) higher than individually optimal reserve prices. This implies that the probability of sale will be lower and the price conditional on sale will be higher under the overall optimization point of view. The main intuition can be generalized to the case of more than 3 lots that are imperfect substitutes where buyers may want to buy multiple units. The intuition would suggest that the difference between overall and individually optimal reserve prices will be higher for early lots with the difference going to zero towards the end of the auction. Similarly, the difference in terms probability of sale and price conditional on sale will also be higher for earlier lots.

3 Empirical Results

In this section, we present empirical analyses that investigate how auctioneers' incentives affect their actions which, in turn, affect auction outcomes. First, Table 1 presents summary statistics on the number of lots, auction outcomes, and the publicly announced valuations for the two auctioneers. For the lots auctioned off by the integrated auctioneer, we also present the outcomes for affiliated and unaffiliated lots separately. The last

[19] We empirically verify this relationship between p_t and h_t in the following section.
[20] We also empirically verify this in the following section.

two columns suggest that there are significant differences in auction outcomes between affiliated and unaffiliated lots.

In a large auction market, substitutability across lots lead to interdependence in bidding behavior across lots. As a buyer's bid on a lot depends on his continuation value, which is affected by outcomes of previous lots, the outcome of a lot may affect the prices in a subsequent lot. To explore price interdependence, we include the benchmark price h_t for lot to analyze an empirical model where the price for lot t is given by

$$p_t = g\left(h_t, \Theta_t, \epsilon_t\right) = \alpha_0 + \alpha_1 h_t + \Theta_t^{'}\alpha + \epsilon_t. \tag{3}$$

The vector Θ_t includes variables that describe the characteristics of lot t, including the lot quality and the publicly announced valuation. Unobservables that affect price are denoted by ϵ_t. Condition (3) summarizes the auction including the impact of all strategic decisions by participants. Note that p_t is only observed if the lot is sold. As before, the observed price p_t^* equals p_t if the lot sells and 0 otherwise. Accordingly, we estimate a Heckman selection model, which accounts for the endogenous partial observability of the sale prices. Specifically, we define a latent linear index variable:

$$y_t^* = Z_t'\beta + \eta_t,$$

where $y_t^* \geq 0$ implies that lot t was successfully sold. That is,

$$y_t^* \geq 0 \quad \Leftrightarrow \quad p_t^* = p_t. \tag{4}$$

In the above, Z_t contains variables that affect whether the auctioneer withdraws lot t, including variables related to lot ownership. Moreover, η_t captures unobservables which also affect the withdrawing decision. The model consists of equations (1), (3), and (4) together with the assumption that (ϵ_t, η_t) are jointly normal distributed. The following sections present estimation results for different versions of this model.

3.1 Price Interdependence and Auction Outcomes

In Section 2.3, we argued that, as different lots are imperfect substitutes, buyers update their belief about potential competition based on lot outcomes and incorporate that in the continuation values. High prices in preceding lots suggest higher competition and lower continuation values. This will increase bids. On the other hand, low prices will reduce bids by increasing the continuation value. We also argued that, as the auctioneer has better information, *strategic withdrawals*, based on a higher reserve price, also leads to higher prices in subsequent lots. To empirically test this price interdependence and investigate its impact on auction outcomes, we present coefficient estimates for price conditional on sale using the model described above. First, we regress price on lot characteristics including whether the lot is from an affiliated or an unaffiliated estate. The basic regression equation for the price, which is observed only if the lot sells, is:

$$p_{it} = \alpha_{0i} + \alpha_1 PV_{it} + \alpha_2 BnMrk_{it} + \alpha_3 Aff_{it} + \alpha_4 Pure_{it} + \alpha_5 NT_{it} + X_{it}^{'}\gamma + \epsilon_{it}. \tag{5}$$

Here p_{it} denotes the price for lot t of auction day i. The variable PV_{it} denotes the publicly announced valuation for the lot and $BnMrk_{it}$ denotes the benchmark price for lot t. Lots from affiliated estate and lots auctioned off by the pure auctioneer are denoted by the dummy variables Aff_{it} and $Pure_{it}$, respectively. The variable NT_{it} indicates the number of times that particular lot had been brought to the auction for sale (but was unsuccessful) prior to auction day i. To control for the quality of tea, we include nine dummy variables that indicate the quality rating score generated from the auctioneers' tasting notes in the vector X_{it}. In addition to these variables, X_{it} includes independent variables pertaining to the lot such as dummy variables that indicate the tea category, variables that indicate the position of the auctioneer on the day, and whether the lot size is larger than average, etc. These variables allow us to control for most sources of lot-specific heterogeneity. The vector γ represents the coefficients associated with X_{it}. Auction day i specific constant is denoted by α_{0i}.[21]

Price interdependence. From conversations with market participants and, especially, the auctioneers, it was clear to us that the momentum of prices in the auction proceedings plays a critical role in determining auction outcomes. This is consistent with our model which surmises that participants infer the demand for future lots and their continuation values based on prior outcomes. If this bears out in data, the realized prices and withdrawals (or reserve prices) when it does not sell, will have an effect on the price a lot

[21] None of our main results change qualitatively if we allow the impact of quality ratings to be different for the two auctioneers or if we use $\ln(p_{it})$, instead of p_{it}, as the dependent variable.

receives. In particular, the auctioneer can affect the buyers' beliefs by not selling it at a low price.

Table 2 presents the determinants of the price of a lot and whether it sold based on a Heckman selection model. We use four specifications for the price regression with the same specification for the selection regression (whether a lot sells). The first specification for price presents regressions based on equation (5). It shows that the coefficient for the benchmark price is positive and significant (0.107), indicating that an increase in the previous price by Tk. 1/Kg increases the price conditional on sale by almost Tk. 0.11/Kg.[22] Clearly, we see that past prices have a strong positive externality on future prices, which would justify an auctioneer's attempts to keep price levels high as part of an overall policy of *setting the tone*.[23]

In column (2), we add two lags of the benchmark price. While the effect of the first lag is negative and the second lag is positive, the sum of the effect of the three benchmark prices is the same as the benchmark effect under specification (1). The same holds true if we add even more lags. Overall, a positive draw in the realized price for a lot raises prices of following lots. However, a negative draw brings the prices down.

In column (3), we add a dummy variable to indicate whether the previous lot went unsold to specification (1) to see if a withdrawal in lot $t-1$ affects price of lot t, if lot t sells. Consistent with our theoretical model, we find a positive and statistically very significant effect of lot withdrawal on the price of the subsequent lot. Specifically, if lot $t-1$ goes unsold, then the price of lot t increases by more than Tk. 0.57/Kg conditional on selling.

One may wonder whether the benchmark effect is different depending on whether it represents p_{t-1} or r_{t-1}. To investigate that, under specification (4), we include a dummy variable to indicate whether the previous lot went unsold and the interaction of this variable with the benchmark price. This column suggests that the benchmark effect is 0.114 and 0.089 if the previous lot sold and went unsold, respectively. Both effects are statistically significant. Thus, while the benchmark effect is smaller if the previous lot

[22] The benchmark equals r_{t-1} when lot $t-1$ goes unsold. While the exact reserve price is not recorded in our data, it typically is Tk. 2 to 4/Kg below the publicly announced valuation. So, we approximate the reserve price of a lot by its publicly announced valuation minus Tk. 3/Kg and our results do not change if we instead deduct nothing, Tk. 1, 2, or 4/Kg.

[23] This result does not change if we exclude the ownership dummy variables as regressors.

did not sell, it is still positive. Moreover, the two added variables under specification (4) together measure the effect on the current lot price if the previous lot went unsold. While the coefficient for the dummy variable is positive (2.510), the coefficient for the interaction term is negative (-0.02545). Evaluated even at a very high valuation of Tk. 100/Kg, the net impact of not selling a lot is equal to $2.51 - 97 \times 0.02545$, which is positive.[24] We will connect this result more closely to our narrative in the following subsection. Our results are robust to alternate definitions of the benchmark price when the lot does not sell.[25] Note that auction day specific fixed effects capture any systematic differences in prices across auction days. The impact of benchmark price, thus, shows how a high realization of price for a lot or a high reserve for that lot affects the bids in the next lot. Moreover, our robustness tests show that the impact of the benchmark price is statistically the same independent of whether the previous lot was from an affiliated estate.

In Table 3, we present results on how the impact of the benchmark price on future lots varies during the auction. If the benchmark price has an impact on prices of following lots by indicating the aggregate demand, the impact will be smaller for later lots as the bidders will have a much better idea regarding market conditions and aggregate demand by then. As a result, the signaling value of prices would be lower. This would suggest that the coefficient for the benchmark price will be smaller later in an auction. To investigate that, we run the same regression as in specification (1) of Table 2, but interacting the benchmark price with a dummy variable indicating the relative position of the lot within the auction. In column (1) of Table 3, we divide an auction into three segments. Lots in the first quarter are considered early lots. The lots in the second and third quarter of the auction are labelled middle lots and the remaining lots are labelled late lots. In column (2), we divide the auction into four quarters. Column (1) suggests that while Tk. 1 change in the benchmark price changed the price for a lot by Tk. 0.107 in the early part of the auctions, the impact was smaller in the middle part of the auctions. The impact for late lots are even smaller. All of these differences are statistically significant. We find

[24] Note that we assumed that the benchmark price for the following lot when a lot goes unsold equals the valuation minus Tk. 3/Kg. Thus, if a lot with publicly-announced valuation of Tk. 100/Kg goes unsold, the benchmark for the following lot equals Tk. 97/Kg. The mean of valuations of all lots is below Tk. 80/Kg and 98.7% of all lots had a valuation below Tk. 100/Kg.

[25] For example, suppose the benchmark price equals the price of the last lot that sold. The results do not change in that case.

the same pattern when we divide the auctions into the four quarters. There, the impact is largest in the first quarter, second largest in the second and third quarters, and the smallest in the last quarter. The impacts are not statistically different between second and third quarters.

Ownership impact on outcomes The above section suggests that there is positive impact of benchmark prices on subsequent lot prices leading to a negative externality from selling a lot at a low price. To manage this externality, Proposition 1 suggests that, a market maker prefers to choose a reserve price which is higher than what would be optimal if the externality were ignored. As an unaffiliated seller is less likely to internalize the externality than an affiliated seller, the auctioneer is likely to choose higher reserve prices for affiliated lots. A higher reserve for affiliated lots suggest suggests a higher rate of withdrawal and a higher price conditional on sale for those lots. To test that, we go back to Table 2.

First, from the selection regression, we find that the coefficient for affiliated estates is significantly negative (-0.257). Next, the price regressions suggest that, relative to other lots, the per Kg price for a lot owned by an affiliated estate is higher by Tk. 0.38 to Tk. 0.46. Thus, the result that affiliated lots that succeed in selling end up fetching higher prices although fewer of their lots sold, found in Table 1, survives even if we control for lot characteristics and auction specific fixed effects.

While these two results are consistent with a higher reserve for affiliated lots, one may wonder whether the auctioneer is exploiting his position to obtain higher prices for his affiliated tea lots by selling them in future auctions if the prices are not high, as the simple agency model would suggest. As a withdrawn lot is brought back for sale in an auction two weeks later, such an explanation requires that this lot would fetch a relatively high price in two weeks. Further inspection of Table 2, however, suggests that there is a *withdrawal penalty*, which would cast a doubt on this simple agency explanation. Specifically, the coefficient for the number of times the lot was previously up for sale is negative with a size of at least Tk. 0.42/Kg. This indicates that lots which have been withdrawn and subsequently resold on a future auction day suffer a substantial withdrawal penalty.[26] This result is inconsistent with the agency explanation for the results above, but is consistent

[26] Note that, we do not find any trend in overall prices across auction days in our data set.

with the idea that the auctioneer is willing to take costly actions – namely, withdrawing their affiliated lots in the face of a substantial penalty on subsequent sales – in order to maintain higher prices in the auctions, even when these higher prices do not benefit him directly. Note that, all these results are robust to analyzing high and low quality lots separately or analyzing lots at different times during the auction day separately. We also find the same results if we use only a sub-sample of auction days such as the first or last eight days from our sample of 16 auction days.

The above three findings about auction outcomes together suggest that reserve prices are higher for affiliated lots. A higher reserve on a lot leads to more aggressive bidding in subsequent lots, but individual sellers may not fully internalize the price externality from higher reserve. Hence, an integrated auctioneer uses affiliated lots to demonstrate that he does not tolerate excessive shading of bids by buyers. To clearly draw the line, he withdraws lots when the bids are too low relative to his assessed aggregate demand for the day. The auctioneer's *desire to appear non-opportunistic, rather than opportunism*, leads him to withdraw affiliated lots more frequently. One implication of this story is that the integrated auctioneer will have more flexibility in choosing optimal reserve prices. Hence, he will fetch higher prices than the pure auctioneer. Both Tables 2 and 3 show that the price is lower for lots sold by the pure auctioneer when we control for auction characteristics by almost Tk. 0.80/Kg. This further supports our story that the integrated auctioneer's strategies help his clients in getting a higher price in the auctions.

While our result that auctioneers are more willing to withdraw their affiliated lots for later sale is reminiscent of Levitt and Syverson (2008), the context and market structure are different. Thus, the underlying forces generating the outcomes are also different. In their setting, there is no withdrawal penalty in our sense. The expected price rises as a result of strategically waiting for a higher valued buyer in the future. In Chittagong tea auctions, on the other hand, auctioneers do not strategically choose the auction date to re-list an unsold lot. Moreover, they incur a loss by withdrawing their lots. Such actions are consistent with our model of auctioneers as market makers who must gain the trust of market participants and maintain a good reputation for non-opportunistic behavior. An important difference between an auctioneer and a real estate agent is that the auctioneer can influence the overall market outcomes by his actions while an individual real estate agent in a large market does not have much power to influence the overall market. As a result, the auctioneer acts more as a market maker while agency issues may be more problematic for a real estate agent.

Corroborating evidence: Impact of ownership on auctioneers' announced valuations. Next, we consider another implication of Proposition 1 above, that reserve prices will tend to be higher for the auctioneer's affiliated lots and, more generally, for lots of tea in which the incentives of the auctioneer and the seller are better aligned. While we do not observe the reserve price directly in this data set, we use the auctioneer's publicly announced valuation for each lot, which is a reasonable proxy for the reserve price. We turn next to the regression results in Table 4, where the dependent variable is the publicly announced valuation. The table suggests that the auctioneer announces a valuation for his affiliated lots that is, on average, higher by at least Tk. 2.77/Kg controlling for all auction characteristics. This further confirms that the main mechanism behind the high price conditional on sale for auctioneers' affiliated lots is the costly action of reducing the probability of sale by keeping the reserve price high.

Corroborating evidence: Lots from major estates. As described in section 2, there is heterogeneity among unaffiliated estates. Some estates are owned by two major tea growers who own about 42% of the tea up for sale in our data set. As major estates have many lots sold on an auction day, they may derive sizable benefits from the interdependence of prices within an auction. Specifically, if there is some positive externality from high benchmark prices, major estates are likely to internalize that to some extent in their objective function unlike small sellers. Moreover, they have stable contractual relationships with their auctioneers and do not usually switch auction houses. Hence, they may trust the auctioneer to take actions that are in their best interest more than do smaller unaffiliated estates. These suggest that the reserve prices for lots from major estates is likely to be higher than that of lots from non-major unaffiliated estates, but lower than reserve prices of affiliated lots. We go back to columns (2) and (3) of Table 4 to test that. Indeed, the regression of publicly announced valuation, a close indicator of the reserve price, supports this hypothesis.

Tables 2 and 3 also show that the lots owned by the major estates have a higher price by more than Tk. 0.41/Kg relative to those of a lot by a non-major unaffiliated seller. The fact that these lots have a higher price conditional on sale is not surprising in light of Proposition 1 and the above result that reserve prices for lots from major estates are higher than those for lots from smaller estates. If the lots are comparable other than the ownership, a higher reserve price will also mean a lower probability of sale. This implies that the probability of sale for lots by major estates should be lower than that for lots from non-major unaffiliated estates. However, the coefficients for major estates are positive. Thus, even after controlling for lot-specific heterogeneity such as the grade and quality of tea and the positioning of the lot, lots from major estates sold with a higher frequency while generating a higher price for sold lots.

We believe that this result arises because lots from major estates attract a higher number of potential buyers; specifically, they attract disproportionately more interest from small and infrequent buyers. Consequently, the keener competition for these lots pushes up both their prices as well as the probability of sale. Indeed, we have some indirect evidence that the smallest buyers buy significantly more frequently from major estates relative to other lots.[27] Being less informed about tea quality and market conditions, these buyers may prefer tea lots from estates with a greater reputation for tea quality and service.[28]

Corroborating evidence: Ownership outcome over an auction day. In Section 3.1, we assumed that the impact of lot ownership on auction outcomes is the same throughout the auction. Now we regress price and the probability of sale for early, middle, and late lots separately. This allows to analyze the same effects as in Table 2 but letting all the coefficients to be different at different stages of an auction. The results are presented in Table 5. First, in terms of the impact of the benchmark price on the price, we find exactly the same pattern as in Table 3. The coefficients for the benchmark price equal 0.112, 0.106, and 0.086 for regressions with only early, only middle, and only late lots, respectively. These regressions support that the impact of the benchmark price on the price of a lot is stronger earlier in the auction. More importantly, they are also supportive

[27] These results are available from the authors but are not presented here as they are not conclusive.

[28] Similarly, Bronnenberg et al. (2015) find that consumers with less knowledge of product quality choose prominent national brands over generic brands more frequently than more experienced consumers.

of the overall story presented in this paper. We find that while the price for affiliated lots (conditional on sale) is higher than that for lots from small unaffiliated estates in the early and middle parts of an auction, they are not different in the late part of the auction. Similarly, the probability of sale is lower for early and middle lots, but are not any different for late lots. This suggests that reserve prices are relatively higher for affiliated lots until the late part of an auction. On the other hand the trend in price and probability of sale for lots from major estates, described above, follows the same pattern throughout the auction. Recall that the outcome pattern for affiliated lots found in Table 2 was attributed to auctioneers using affiliated lots to avail the positive price externality present in this auction market. The impact of that is more limited towards the end of an auction and hence, auctioneers do not use such tool towards the end of an auction. On the other hand, the outcome pattern for lots from major estates comes from the fact that major lots attract more attention from bidders, and does not depend on the interdependence of lots and lot sequencing. Thus, the patterns stay prevalent throughout the auction. As these results suggest that auction outcomes vary at different stages of an auction, we briefly analyze lot sequence within an auction day.

3.2 Lot Sequencing: How do auctioneers "set the tone"?

So far, we have focused on auctioneer and bidder behavior on the day of the auction, treating the sequence of lots up for sale, published in the final catalog five days prior to the auction, as exogenous. Now we describe some characteristics of lot sequencing in our data set. By *lot sequence*, we refer to the position of a lot within a specific auctioneer's catalog for an auction day.

We define the dependent variable lot_{it} as lot i's normalized position within the auctioneer's catalog on day t, equal to the lot number divided by the total number of lots listed by the auctioneer on that day. Since the existing literature on lot sequencing in auctions has shown that product characteristics can influence sequencing at different parts of the auction day, we consider quantile regressions of lot_{it} on lot characteristics, allowing the characteristics to affect the 20%, 40%, 60%, and 80% quantiles of lot_{it} differentially. Table 6 presents the results, which show us some consistent patterns used by the auctioneer to *set the tone* for the auction. First, lots with a higher publicly announced value are more likely to be listed earlier in the auction day. Second, affiliated lots are usually listed earlier in the auction. As we have posited earlier, strategic withdrawal is easier with affiliated lots. Since such strategic behavior is likely to have a stronger impact earlier in the auction with many more lots to follow, tea from affiliated estates is listed earlier in the auction day to set the tone. Third, lots from major estates are listed earlier in the first half but later in the second half of an auction day. Fourth, lots that have previously gone unsold in an earlier auction day are listed later in the auction. Overall, the auctioneer chooses the lot sequence to manage the positive price externality on subsequent lots and also to keep the auction process interesting throughout the day.[29]

Unlike Ashenfelter (1989) and Beggs and Graddy (1997), we find no clear evidence of a decreasing price pattern within an auction day in our data, once across-lot heterogeneity is controlled for. In price regressions based on equation (5), we find a quadratic price trend if we include the variables lot and lot^2 as long as we do not control for lot ownerships. As soon as we include lot ownership dummies, as done in Tables 2, 4, and 5, both of the coefficients become statistically insignificant. Hence, we do not control for lot sequence in the price regressions presented in those tables.[30] We do, however, include lot and lot^2 in the selection regression as instruments as both of them significantly determine whether a lot gets sold.

4 Conclusions

Market makers such as eBay, Amazon.com, or stock exchanges, that administer large marketplaces, play a prominent role in the economy. There are numerous other auctioneers who run large auction markets on a regular basis throughout the world. They are private market designers who receive a small share of the transaction prices, and their actions determine the efficiency of the markets they operate. And yet, the precise role of an auctioneer has not been well-documented in the auction literature. As they typically receive only a small fraction of the revenue, the environment is ripe for clients and market participants to have agency concerns. On the other hand, since the auctioneer

[29] We find qualitatively same results using linear regressions.

[30] We checked this further, with a cleaner test, by utilizing another feature of the data. There are some large lots, which are divided into multiple *lines* and are auctioned off separately in sequence. Analyzing the price within different lines of the multi-line lots, we find no pattern either.

represents multiple clients, externalities can also play a prominent role. Hence, successful auctioneers must aim to address agency concerns and manage externalities at the same time. Therefore, strategies that build trust and establish good reputation are likely to be key to the efficient running of auction markets.

In this paper, we have highlighted the role of auctioneers as effective managers of the dynamic marketplace they oversee. In a sequential auction setting with imperfect substitutes, where bidders have the option to buy a subsequent lot if they fail to win a specific lot, we find that outcomes in prior lots affect prices for subsequent lots. To allay agency concerns, auctioneers undertake costly actions on lots over which they enjoy greater trust in order to generate a positive externality for others.

We have highlighted a role for an auctioneer based on what we observe in the data, but, presumably, auctioneers take numerous actions to communicate with participants and control the auction. For example, when we observed the actual tea auctions, the opening prices were chosen to reflect realized demand, which was also corroborated in conversations with the auctioneers. However, we do not have data on this prices. Also, by illustrating how interdependence among market offerings affect auction outcomes, our paper suggests that data from auction markets should be analyzed using the point of view of the whole market rather than individual auctions. As a result, structural estimation of bidder characteristics while treating auctions within a market as independent auctions may lead to incorrect estimates.

While our analysis shows that administrators of auction markets are better viewed as market makers, it is important to note that the market structure matters. In our setting, the auctioneer has market power and his strategies can affect all market transactions. The auctioneer interacts with the same set of participants, buyers and sellers, repeatedly over a long period of time. As a result, gaining their trusts by managing market externalities well plays a prominent role in such a setting. On the other hand, if the facilitator of trade only administers a relatively small share of all market transactions in a non-repeated setting and does not have much power to influence other trades in the market, then trust and reputation are unlikely to be important factors influencing market outcomes.

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Table 1: Summary Statistics - Auction Outcomes and Publicly Announced Valuations

	Pure Auctioneer	Integrated Auctioneer		
		All Lots	Affiliated Lots	Unaffiliated Lots
Number of Auction Days	16		16	
Total Number of Lots	11925	5704	1047	4657
Lot Size	751.31 Kg	521.17 Kg	499.38 Kg	526.07 Kg
	(314.28)	(120.49)	(129.87)	(117.73)
Publicly Announced Valuation	78.97 Tk./Kg	77.35 Tk./Kg	81.29 Tk./Kg	76.46 Tk./Kg
	(6.05)	(7.22)	(2.83)	(7.60)
Quality Rating	5.47	6.45	7.01	6.32
	(1.86)	(1.46)	(1.04)	(1.51)
Percentage of Lots Sold	91.71%	83.64%	80.04%	84.45%
	(0.28)	(0.37)	(0.40)	(0.36)
Price Conditional on Sale	78.29 Tk./Kg	77.55 Tk./Kg	80.80 Tk./Kg	76.86 Tk./Kg
	(5.73)	(6.49)	(3.13)	(6.80)
Number of Weeks Needed to Sell a Lot	1.079 Weeks	1.183 Weeks	1.226 Weeks	1.173 Weeks
	(0.341)	(0.536)	(0.560)	(0.530)

Note: Standard deviations are presented inside parentheses

Table 2: Effect of Benchmark Price and Lot Ownership on Auction Outcomes

	Price				Sold
	(1)	(2)	(3)	(4)	
Publicly Announced Valuation	0.819***	0.819***	0.811***	0.810***	0.021***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Lot from an Affiliated Estate	0.385***	0.381***	0.439***	0.458***	-0.257***
	(0.067)	(0.067)	(0.070)	(0.073)	(0.061)
Lot from a Major Estate	0.452***	0.450***	0.412***	0.406***	0.234***
	(0.037)	(0.037)	(0.039)	(0.041)	(0.046)
Lots Auctioned off by the Pure Auctioneer	-0.787***	-0.788***	-0.824***	-0.832***	0.205***
	(0.039)	(0.039)	(0.042)	(0.044)	(0.042)
Benchmark Price	0.107***	0.110***	0.111***	0.114***	-0.007**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)
Benchmark Price Lag 1		-0.011***			
		(0.004)			
Benchmark Price Lag 2		0.009**			
		(0.003)			
Previous Lot Went Unsold			0.575***	2.510**	1.093***
			(0.110)	(0.485)	(0.039)
Benchmark Price × Previous Lot Unsold				-0.025***	
				(0.006)	
Prior Number of Auctions Where the Lot Was Up for Sale	-0.473***	-0.468***	-0.424***	-0.423***	-0.103***
	(0.035)	(0.036)	(0.037)	(0.038)	(0.028)
Inverse Mills Ratio	-0.857***	-0.843***	-1.713***	-1.868***	
	(0.094)	(0.094)	(0.180)	(0.192)	
Observations	17564	17539	17564	17564	
Wald Chi^2	154891.46	155000.21	131457.57	131457.57	

Notes: We present Heckman two-step regressions of price, which is observed only when the auction results in a sale. Benchmark price equals the price of the previous lot if it sold and the reserve price of the previous lot if it did not sell. We control for tea type, tea quality, the auctioneer's position in the day's auctions, and other lot characteristics. A variable deonting the position of the lot normalized by the total number of lots listed by the auctioneer, squared of this variable, and lagged variables indicating whether a previous lot was sold are excluded variables used as instruments in the selection regressions. Standard errors are presented inside parentheses. ** and *** represent significance at 5% and 1% levels, respectively.

Table 3: Impact of the Benchmark Price on the Price Across Different Parts of the Auction

	Price (1)	Price (2)	Sold
Publicly Announced Valuation	0.819***	0.819***	0.021***
	(0.004)	(0.004)	(0.004)
Lot from an Affiliated Estate	0.358***	0.362***	-0.257***
	(0.067)	(0.067)	(0.061)
Lot from a Major Estate	0.485***	0.484***	0.234***
	(0.037)	(0.037)	(0.046)
Lots Auctioned off by the Pure Auctioneer	-0.796***	-0.795***	0.205***
	(0.039)	(0.039)	(0.042)
Benchmark Price	0.107***	0.107***	-0.007**
	(0.004)	(0.004)	(0.003)
Benchmark Price × Lot 25% to 50%	-0.0012***	-0.00142***	
	(0.0004)	(0.0005)	
Benchmark Price × Lot 50% to 75%		-0.0010**	
		(0.0005)	
Benchmark Price × Late Lots	-0.0038***	-0.0038***	
	(0.0005)	(0.0005)	
Prior Number of Auctions Where the Lot Was Up for Sale	-0.407***	-0.406***	-0.103***
	(0.037)	(0.037)	(0.028)
Inverse Mills Ratio	-0.817***	-0.819***	
	(0.094)	(0.094)	
Observations	17564	17564	
Wald Chi^2	155963.59	155943.49	

Notes: We present Heckman two-step regressions of price, which is observed only when the auction results in a sale. Benchmark price equals the price of the previous lot if it sold and the reserve price of the previous lot if it did not sell. Middle lot 1 is an indicator which equals 1 for lots placed between the 25% and 50% of the auction, Middle lot 2 equals 1 for lots placed and between the 50% and 75% of the auction, and Late lot equals 1 for lots placed later than 75% of the auction. We control for tea type, tea quality, the auctioneer's position in the day's auctions, and other lot characteristics. A variable deonting the position of the lot normalized by the total number of lots listed by the auctioneer, squared of this variable, and lagged variables indicating whether a previous lot was sold are excluded variables used as instruments in the selection regressions. Standard errors are presented inside parentheses. *** represents significance at the 1% level.

Table 4: Determinants of the Publicly Announced Valuation

	Publicly Announced Valuation		
	(1)	**(2)**	**(3)**
Lot from an Affiliated Estate	2.775***	3.507***	2.899***
	(0.164)	(0.165)	(0.177)
Lot from a Major Estate		0.691***	0.675***
		(0.098)	(0.098)
Lots Auctioned off by the Pure Auctioneer	3.087***	3.285***	3.255***
	(0.092)	(0.097)	(0.097)
Prior Number of Auctions Where the Lot Was Up for Sale	-2.616***	-2.505***	-2.730***
	(0.081)	(0.081)	(0.084)
Prior Auctions × Affiliated Lot			2.361***
			(0.251)
Observations	17629	17629	17629
R^2	0.4689	0.4833	0.4859

Notes: The table presents fixed effects panel regressions of the publicly announced valuation controlling for tea type, tea quality, the auctioneer's position in the day's auctions, and other lot characteristics. Standard errors are presented inside parentheses. *** represents significance at the 1% level.

Table 5: Separate Price Regressions for Early, Middle, and Late Lots

	Price	Sold	Price	Sold	Price	Sold
	(1)		(2)		(3)	
Publicly Announced Valuation	0.807***	0.038***	0.813***	0.032***	0.840***	0.005
	(0.008)	(0.010)	(0.006)	(0.006)	(0.007)	(0.006)
Lot from an Affiliated Estate	0.547***	-0.260*	0.427***	-0.349***	-0.103	-0.099
	(0.123)	(0.145)	(0.098)	(0.088)	(0.153)	(0.125)
Lot from a Major Estate	0.338***	0.352***	0.649***	0.232***	0.568***	0.166
	(0.072)	(0.105)	(0.050)	(0.066)	(0.096)	(0.101)
Lots Auctioned off by the Pure Auctioneer	-0.493***	0.213*	-0.612***	0.182**	-1.286***	0.400***
	(0.085)	(0.120)	(0.051)	(0.056)	(0.105)	(0.096)
Benchmark Price	0.112***	-0.015*	0.106***	-0.012**	0.086***	0.0003
	(0.007)	(0.009)	(0.005)	(0.005)	(0.007)	(0.005)
Prior Number of Auctions Where the Lot Was Up for Sale	0.381	-0.474**	-0.905***	-0.131***	-0.226***	-0.073*
	(0.312)	(0.198)	(0.065)	(0.048)	(0.054)	(0.042)
Inverse Mills Ratio	-0.852***		-0.844***		-0.772***	
	(0.094)		(0.124)		(0.193)	
	Early Lots		Middle Lots		Late Lots	
Observations	4332		8811		4421	
Wald Chi^2	37076.70		77350.52		41188.67	

Notes: We present Heckman two-step regressions of the price which is observed only when a lot sells running separate regressions for three subsamples of the data set. The subsamples are the first 25% of lots, 25% to 75% of lots, and the last 25% of the lots within an auction day. We control for tea type, tea quality, the auctioneer's position in the day's auctions, and other lot characteristics. A variable deonting the position of the lot normalized by the total number of lots listed by the auctioneer, squared of this variable, and lagged variables indicating whether a previous lot was sold are excluded variables used as instruments in the selection regressions. Standard errors are presented inside parentheses. *, **, and *** represent significance at 10%, 5%, and 1% levels, respectively.

Table 6: Determinants of Lot Sequencing

	Dependent Variable: Normalized Lot Number			
	20%	**40%**	**60%**	**80%**
Publicly Announced Valuation	-0.007***	-0.007***	-0.008***	-0.007***
	(0.001)	(0.001)	(0.0005)	(0.001)
Lot from an Affiliated Estate	-0.190***	-0.157***	-0.159***	-0.064***
	(0.008)	(0.015)	(0.013)	(0.015)
Lot from a Major Estate	-0.093***	-0.016	0.086***	0.153***
	(0.007)	(0.011)	(0.007)	(0.008)
Prior Number of Auctions Where the Lot Was Up for Sale	0.146***	0.169***	0.156***	0.139***
	(0.008)	(0.005)	(0.005)	(0.005)
Observations	17629			
Pseudo R^2	0.0993	0.1003	0.1294	0.127

Notes: The table presents simultaneous quantile regressions of the normalized lot positioning on auction and lot characteristics. We control for tea type and other lot characteristics. We also include dummy variables for the lot's quality rating. Standard errors are presented inside parentheses. *** represents significance at the 1% level.