Improving Farmers’ Income on Online Agri-platforms: Design and Field Implementation of a Two-stage Auction

Retsef Levi1, Manoj Rajan2, Somya Singhvi3, and Yanchong Zheng4

1Sloan School of Management, Massachusetts Institute of Technology, Cambridge, MA 02139, USA; 2Rashtriya e Market Services Private Limited, Bangalore 560001, Karnataka, India; 3Operations Research Center, Massachusetts Institute of Technology, Cambridge, MA 02139, USA

As a leading effort to improve smallholder farmers’ welfare, multiple countries have launched online agri-platforms to transform traditional markets. However, it remains an open question as to how these platforms can be leveraged to improve price discovery mechanisms that benefit farmers. This paper addresses this fundamental question with a multi-method approach that carefully accounts for the unique operational and behavioral characteristics of agri-markets. In particular, the paper describes work conducted in collaboration with the state government of Karnataka, India, to design, implement, and assess the impact of a new two-stage auction on the state’s Unified Market Platform (UMP). The design of the two-stage auction is informed by operational constraints and guided by theory-informed, semi-structured interviews with traders in the field. A new behavioral auction model is developed to determine when the two-stage auction can generate a higher revenue for farmers than the traditional single-stage, first-price, sealed-bid auction. The two-stage auction was implemented on the UMP for a major lentils market in February 2019. By June 2019, commodities worth more than $6 million (USD) had been traded under the new auction. A difference-in-differences analysis demonstrates that the implementation has yielded a significant 4.7% price increase, representing profit improvement of 60%-158% for over 10,000 farmers who traded in the treatment market. The detailed auction data provides empirical validation of the behavioral auction model. The results from this paper offer tangible insights on how innovative designs of price discovery mechanisms could be enabled by online agri-platforms in resource-constrained environments.

The phenomenon of severe poverty continues to persist among smallholder farmers in developing countries, in part due to unfavorable market outcomes for these farmers (1). Prior studies suggest that imperfect competition and inefficient price discovery processes in traditional markets are important factors affecting farmers’ income (2, 3). To tackle these challenges, one prevalent intervention that has been attracting substantial investment is to connect geographically isolated markets via an online platform. In such a platform, various aspects of the price discovery process are digitized and automated, including winner determination and declaration in auctions, as well as dissemination of price information. The hope is that these platforms could increase market competition, enable transparency of the price discovery process, and ultimately, improve farmers’ income.

Multiple countries have launched such online agri-platforms, for example, the commodity exchange platforms in Ethiopia, Kenya, Nairobi, and Uganda, as well as the eNational Agriculture Market (eNAM) launched by the central government of India, and the Unified Market Platform (UMP) implemented in the state of Karnataka, India. The price discovery mechanisms used in these platforms vary widely from ascending auctions, first-price sealed-bid auctions, to warehouse-based negotiation, mostly following a digital version of the traditional (pre-platform) mechanisms. It remains an open question as to how the mechanism may be “optimized” to benefit farmers (4, 5). This is further motivated by the mixed empirical evidence regarding the impacts of these platforms on farmers’ income. For example, trades on the Ethiopia Commodity Exchange are dominated by two export crops, coffee and sesame seeds, while farmers of other crops are largely left out (6, 7).

In India, only 14% of farmers have registered on eNAM, and over half of these registered farmers are reported to not have benefited from the platform (8). Recent research analyzing the UMP shows that low competition, especially in geographically isolated markets with a small number of local traders, is likely to be a major barrier to realizing price benefit for lentils farmers on the platform (9).

The literature on auction design is extensive and has analyzed “optimal” mechanisms with appealing theoretical properties. These mechanisms have also been widely adopted in practice in developed economies; for example, second-price auctions in online advertising exchanges (10), ascending auctions in wireless spectrum sales (11), descending auctions in Dutch flower markets (12), and combinatorial auctions for procurement (13). However, there exist unique operational, behavioral, and cultural characteristics in agricultural markets in developing countries. Therefore, it is observed that simply replicating what might be successful in more affluent settings does not work well in resource-constrained settings such as in

Significance Statement

Collaborating with the state government of Karnataka, India, this paper designs, implements, and evaluates the impact of a new two-stage auction on the state’s online agri-platform, the Unified Market Platform. The design of the two-stage auction incorporates operational constraints and is guided by theory-informed, semi-structured interviews with traders in the field. A new behavioral auction model is developed to determine when the two-stage auction can benefit farmers. The two-stage auction was implemented for a major lentils market in February 2019. By June 2019, commodities worth more than $6 million (USD) had been traded under the new auction. A difference-in-differences analysis demonstrates that the implementation has yielded a significant 4.7% price increase, representing profit improvement of 60%-158% for over 10,000 farmers.
agri-platforms in developing countries (8, 14).

This paper attempts to address the gap of designing effective auction mechanisms in online agri-platforms in developing countries. The paper takes an innovative approach that combines multiple methods including field-based research, behavioral game-theoretic modeling, and empirical analysis to answer this question. Specifically, the paper describes work conducted in close collaboration with the state government of Karnataka, India to design, analyze, and implement a new two-stage auction mechanism on the UMP, and empirically evaluate the impact of the new auction design on farmers' revenue. The work selects tur (pigeon pea) as the focus commodity because (i) it is a major source of protein in Indian diets, and (ii) the original implementation of UMP has not yielded a significant price increase for farmers due to low competition in the markets (9). Importantly, the research approach and auction design process developed in this work are more generally applicable beyond the case of tur.

Research Impacts. Working closely with the state government, the two-stage auction was implemented on the UMP in February 2019 for a major market of tur. By June 2019, more than 8,000 metric tons of tur worth over $6 million (USD) had been traded under the new auction in the treatment market. A difference-in-differences analysis demonstrates that the implementation has yielded a statistically significant, 4.7% average price increase in the market. The price increase translates into an average revenue gain of $452,000 (USD) for over 10,000 farmers in a matter of three months, representing an average 15% increase in their monthly income. Given low profit margins for these farmers (4%-7%), the range of profit improvement is substantial (60%-158%). These positive outcomes are particularly significant and encouraging given the lack of price gain for tur farmers from UMP's original implementation in 2014 (9). In what follows, we first elaborate on the research process to design and implement the new two-stage auction, and then empirically evaluate the impact of the implementation on market prices and farmers' revenue.

Design and Analysis of the Two-Stage Auction

To fully appreciate the operational context, it is important to understand the current trading process on the UMP (15). UMP was created in 2014 to unify all trades in agricultural wholesale markets in Karnataka to be carried out within a single platform. By November 2019, approximately 62.8 million metric tons of commodities valued at $21.7 billion (USD) had been traded across 162 markets on the UMP. The major types of commodities traded on the UMP include grains, lentils, oil seeds, and cash crops (e.g., cotton, areca nut). Trades happen every day in the physical markets. At the start of a day, farmers bring their commodities to a commission agent or a commission agent shop to identify lots they want to purchase and the prices to bid. Afterwards, they must submit their (private) bids for all the lots they want to purchase on the UMP before a preannounced cutoff time (currently 2:30 p.m.). Once the bidding window is closed, the computer compares all bids for the same lot and declares the highest bidder as the winner. The winner pays the farmer the highest bid. That is, the current auction design on the UMP is a traditional first-price sealed-bid auction.

A key objective in this work is to design an implementable auction mechanism that can generate higher revenue for the farmers than the first-price sealed-bid auction currently being used on the UMP. Figure 1 presents the multi-method process we adopt to design the new auction. We begin by carefully considering operational characteristics in the markets to determine what mechanisms are even feasible.

Operational Feasibility. This step focuses on evaluating the feasibility of alternative auction mechanisms commonly used in other settings. One particular relevant analysis is that of eNAM launched by the central government of India, due to the close similarities in market operations and cultural characteristics between the eNAM and UMP. eNAM uses ascending auctions to determine market prices. In an ascending auction, traders sequentially increase their bids on a lot until only one trader remains. This last trader wins the lot and pays the current highest bid. However, traders initially participating in eNAM complained that having to constantly monitor and potentially adjust bids for hundreds of lots involved too much effort, seriously disrupted other aspects of their operations (e.g., arranging post-auction logistics), and became operationally infeasible during peak seasons. As a result, trader participation on the eNAM was not sustained, and the platform has not realized its intended impact to date. In light of such participation constraints on the traders’ side, the Karnataka government thus rejected the idea of adopting an ascending auction.

A similar analysis concerns the farmers’ perspective. Transitioning from the traditional markets to the UMP involved substantial efforts to build trust with the farmers. Therefore, the government was very mindful of maintaining this hard-earned trust. As a result, the government rejected the design of a second-price sealed-bid auction because it would be an immense challenge to explain to farmers why they are paid the second highest bid but not the top bid. These and other in-depth discussions with the UMP officials have ruled out the operational feasibility of several theoretically-appealing and commonly-used auction designs (Table 1).

A number of critical operational requirements result from
this first phase of the design process. In particular, the new auction design must minimize disruption to the current trading and post-auction processes, be easy to explain to farmers and traders as well as satisfy their participation constraints, and require small technical changes on the platform to accommodate resource constraints. Taking these factors into account, one promising mechanism is the multistage auction with qualification requirements. This mechanism is commonly used in selling high-value assets, e.g., in mergers and acquisitions. In a multistage auction, sealed bids are solicited in multiple stages. In each stage, a fraction of the bidders are eliminated according to certain predefined qualification requirements, and some information about the current bids is disclosed. As the stages progress, bids increase and eventually, the asset is sold to the bidder with the highest bid. This design is akin to conducting multiple first-price sealed-bid auctions, and thus, has a strong implementation appeal to the government. In the end, the simplest form of a multistage auction, i.e., a two-stage auction with a qualification stage is proposed.

Figure 2 presents the timeline and rules of the proposed two-stage auction mechanism. Specifically, in the first stage, all traders bid as in the current first-price sealed-bid auction. At the end of the first stage, the current highest bid of each lot is disclosed to the top k traders (based on their first-stage bids) who have bid on the lot. These traders are then offered an opportunity to increase their bids over the highest first-stage bid in the second stage, which must be completed within a much shorter time window than the first stage. The top bidder at the end of the second stage is declared the winner.* In this design, the first stage serves as a qualification stage. Only the subset of qualified traders can bid in the second stage, and if they do, they are required to match or outbid the highest first-stage bid. Hence, the second stage is essentially another first-price sealed-bid auction with a reserve price.

**Traders’ Bidding Behavior.** Since two-stage auctions have never been used in agricultural settings, the government is very cautious and requires extra assurance that adopting this new design will not hurt farmers’ revenue. Therefore, the next phase of the design examines traders’ bidding behavior in the two-stage auction. This analysis contains three parts: (i) investigate relevant theoretical predictions of the traders’ bidding behavior from the literature, (ii) conduct semi-structured interviews to test whether these theoretical predictions apply to professional traders in the field, and (iii) develop and analyze a behaviorally-justifiable auction model based on the field insights. The model helps to provide the assurance desired by the government through rigorous mathematical analysis, and in the meantime, determines more generally when a two-stage auction may benefit farmers as compared to a single-stage first-price sealed-bid auction beyond the case of tur.

More specifically, we design and conduct a series of semi-structured interviews with a majority of tur traders in a major lentils market. The design of the interview is guided by the theories to be tested and follows well-established principles in the social sciences (20, see SI Appendix, Sample Questionnaire). In particular, we test three theories: costly information acquisition, competitive arousal, and anticipated regret. In total, we interviewed 13 traders (out of 19 major traders in the market). These traders have on average 16 years of experience in agricultural trading and have won over 68% of all the lots (over 69% of the total quantity) traded in the market between January 2018 and February 2019. Therefore, the sample represents a majority of the traders whose bids substantially influence the final market prices. Each interview took about an hour to complete.

**Costly information acquisition – quality uncertainty.** Two-stage auctions are shown to benefit the auctioneer in scenarios with high information acquisition costs (19). That is, when the valuation of the asset being auctioned is highly uncertain, potentially interested buyers can gain additional information about the asset’s value after the first-stage bid. This in turn allows the second-stage bids to better capture the true value of the asset, and hence, increase the auctioneer’s revenue (19, 21–23).

In our context, one aspect of information that substantially affects traders’ valuations of a lot is the (potentially uncertain) quality of the lot. When traders have to bid on hundreds of lots within a limited time frame, acquiring accurate quality information can be costly. Thus, adding the qualification stage

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Table 1. Commonly-used Price Discovery Mechanisms and Their Operational Feasibility on the UMP

<table>
<thead>
<tr>
<th>Mechanism</th>
<th>Adoption</th>
<th>Is it operationally feasible on the UMP?</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ascending or descending auction</td>
<td>eNAM, India (16); Dutch flower markets (12)</td>
<td>✗</td>
</tr>
<tr>
<td></td>
<td>Require substantial trader efforts to monitor bids for many lots; risk of last-minute bidding crashing the platform; require significant updates to the platform</td>
<td></td>
</tr>
<tr>
<td>Second-price auction</td>
<td>Online advertising exchange (10)</td>
<td>✗</td>
</tr>
<tr>
<td></td>
<td>Hard to get farmers’ buy-in for receiving the second highest bid (as opposed to the highest bid); require significant training to the traders</td>
<td></td>
</tr>
<tr>
<td>Double auction</td>
<td>Kudu, Uganda (17)</td>
<td>✗</td>
</tr>
<tr>
<td></td>
<td>Hard for farmers to give competitive ask prices due to information, power, and financial asymmetries between farmers and traders; farmers lack computer skills; not enough computers for all farmers; require significant updates to the platform</td>
<td></td>
</tr>
<tr>
<td>Combinatorial auction</td>
<td>Chilean school meal auction (13)</td>
<td>✗</td>
</tr>
<tr>
<td></td>
<td>Too complex to implement or explain to market participants; require significant training and updates to the platform</td>
<td></td>
</tr>
<tr>
<td>Posted price</td>
<td>ITC e-Choupal, India (18)</td>
<td>✗</td>
</tr>
<tr>
<td></td>
<td>UMP is not a buyer but a platform to enable trades</td>
<td></td>
</tr>
<tr>
<td>Warehouse-based sale</td>
<td>Ethiopia Commodity Exchange (7)</td>
<td>✗</td>
</tr>
<tr>
<td></td>
<td>Lack of infrastructure regarding warehouse storage and quality grading</td>
<td></td>
</tr>
<tr>
<td>Multi-stage auction with qualifications</td>
<td>Real estate market, mergers and acquisitions contests (19)</td>
<td>✓</td>
</tr>
<tr>
<td></td>
<td>Similar to conducting multiple first-price sealed-bid auctions, easy to explain to market participants, and requires small updates to the platform</td>
<td></td>
</tr>
</tbody>
</table>

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*Fig. 2. Timeline and rules of the two-stage auction.*
can allow the traders to obtain more accurate signals about the quality of the lots they qualify to bid on in the second stage, e.g., by reinspecting the lots or inferring quality from the highest first-stage bid.

Contrary to this hypothesis, however, the traders interviewed explain that there is little uncertainty about the lots’ quality once they physically inspect the lots before the first-stage bidding, and there is no need to inspect the lots in the second stage. This is because the primary factors determining the quality of tur are lot-level features, such as seed size, moisture level, and foreign particles in the lot, and the traders are all highly experienced in quality inspection. These results suggest that auction models considering costly information acquisition are not a good candidate for characterizing the traders’ bidding behavior in our context.

**Competitive arousal.** According to the competitive arousal theory, intensifying the competitive situation (e.g., heightening rivalry and time pressure) can motivate bidders to overbid so as to win the competition, even if doing so is costly (24). The apriori expectation is that introducing a second stage, in which there are only a few rivals, and traders need to bid in a short time frame, could intensify the traders’ feeling about the competitive situation. As a result, qualified traders will likely bid aggressively in the second stage to ensure that they win the qualified lots, thus improving the farmers’ revenue.

To test this hypothesis, the traders were asked to hypothetically bid for a lot they qualify in the second stage across different scenarios with varying numbers of qualified traders (SI Appendix, Sample Questionnaire, part C). The responses do not show higher bids when fewer traders qualify. In fact, two traders bid lower when there are fewer competitors, contrary to what the theory suggests. Therefore, we do not find evidence that the competitive arousal theory plays a role in this context. Instead, traders exhibit strong anchoring on the highest first-stage bid disclosed to them and outbid this value by no more than 0.01%.

**Anticipated regret.** The effect of anticipated regret on bidding behavior has been observed extensively in laboratory experiments of single-stage auctions (25, 26). Bidders are shown to bid higher prices if they know that the winning bid will be disclosed to them when they lose (versus no disclosure). This is because bidders anticipate feeling regret ex post that they could have won and made a profit. Based on evidence in clinical psychology (27, 28), we expect a priori that a two-stage auction would intensify such regretful emotions anticipated by the traders. In particular, traders are exposed to repetitive regret because information feedback of both not qualifying for the second stage and losing the auction is made salient. Anticipating this intensified non-qualification regret may motivate them to increase their first-stage bids, thereby benefiting the farmers.

To examine this hypothesis, the traders were presented a hypothetical scenario of a two-stage auction and asked to bid in the first stage during the interviews (SI Appendix, Sample Questionnaire, part B). Next, they were asked to imagine that they were not qualified for the second stage and to rate on a 9-point scale the intensity of different emotions (anger, envy, irritation, regret, and sadness) that they feel given this outcome. A higher score indicates a stronger feeling of the corresponding emotion, with 1 meaning no feeling at all and 9 meaning an extremely strong feeling. The design of these questions follows from (25). Figure 3 presents the distribution of intensity of different emotions stated by the traders. We observe that a considerable number of traders indeed feel substantial regret for not being qualified for the second stage. This observation supports the conjecture that (at least some of) the traders’ bidding behavior in a two-stage auction would likely be affected by anticipated non-qualification regret.

**A behavioral auction model.** Insights from the field interviews suggest two salient behavioral factors that likely affect traders’ bidding behavior in a two-stage auction: (i) anticipated non-qualification regret affects their bidding in the first stage, and (ii) anchoring on the highest first-stage bid affects their bidding in the second stage. These insights motivate the development of a simple model that jointly captures these factors to characterize the traders’ bidding strategies in the two-stage auction. Specifically, the model considers three traders bidding for a single lot and the top two traders in the first stage qualify for the second stage. To capture anticipated non-qualification regret, a trader would anticipate (when bidding in the first stage) that if he did not qualify, then he would experience a disutility of regret whose magnitude is proportional to the lost revenue from non-qualification. This modeling choice follows from the literature (25, 26). To capture anchoring, the assumption is that the top-rank trader bids the highest first-stage bid again, and the second-rank trader matches this bid if he makes a positive profit doing so. In the case that the second-rank trader matches the highest bid, either of the top two traders wins the lot with a 50% chance. Further details of the mathematical model and the theoretical results are presented in Materials and Methods.

The model analysis shows that the two-stage auction leads to higher expected revenue for the farmers than the single-stage first-price sealed-bid auction when the intensity of the traders’ anticipated non-qualification regret is sufficiently strong. This is because anticipated regret and anchoring have opposite effects on the traders’ bidding behavior. On the one hand, since a trader would win with a positive probability as long

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1 Although the traders bid for multiple lots every day, they commented in the interviews that their bidding for each lot is independent because they do not have any budget constraints and could always sell all the lots they win due to high demand from their buyers (SI Appendix, Sample Questionnaire, part D). Hence, the model focuses on the auction of a single lot.

2 The results continue to hold if the model assumes instead the top two traders outbid the highest first-stage bid by a small increment.
as he qualifies for the second stage (as opposed to having to be the highest bidder to win in a single-stage first-price auction), he would bid lower in the first stage than in the first-price auction, and anchoring would lead to a lower winning bid. On the other hand, anticipated non-qualification regret motivates a trader to bid higher in the first stage than in the first-price auction. Therefore, the two-stage auction would generate a higher revenue for the farmers than the single-stage first-price auction if the effect of anticipated regret on the traders’ bidding behavior is stronger than that of anchoring.

An immediate implication from the model analysis is that, implementing the two-stage auction would be beneficial for those commodities for which the traders tend to exhibit high anticipated non-qualification regret. This is likely to be the case for commodities whose supply is constrained relative to market demand and/or those that are of high economic values. This result strengthens our confidence that the auction intervention would benefit tur farmers, because tur, as well as other lentils, have limited supply relative to the consistently high consumption across the country due to their importance in the mostly vegetarian Indian diets. In addition, the analysis also suggests that high-value cash crops such as areca nut, cotton, and turmeric are good candidates for implementing the two-stage auction.

Evaluating the Impact of Implementing the Two-stage Auction on Market Prices

The market in which the interviews were conducted was chosen to be the treatment market for implementing the two-stage auction. This choice is driven by two key reasons. First, there exists another similar market that can serve as the control market to allow for empirical evaluation of the impact of the implementation on market prices (see SI Appendix, Comparability of Treatment and Control Markets). Second, the field interview data and the lot-level auction data from the implementation can later be combined to validate the behavioral auction model developed. To ensure a successful launch, extensive training and discussions were carried out with the market participants weeks before the implementation. Particularly to get the traders’ buy-in, the two-stage auction design was “marketed” to them as giving them an additional chance to win the lots that they would have otherwise lost. A number of implementation details resulted from interactions with the traders during the training phase. First, the traders requested that the length of the second stage should be no more than half an hour, because they had to perform a series of post-auction tasks by the end of the day (e.g., weighing, cleaning, packing, and transporting the lots, transferring payments to the farmers). Second, considering the potential average number of lots that a trader would be qualified to bid again (based on historical data) and the feasibility of doing so within half an hour, only the top 3 bidders for each lot would be qualified, i.e., \( k = 3 \) in Fig. 2. Third, the traders requested that for lots they qualify, their own rank among the top three should also be disclosed (in addition to the highest first-stage bid) to allow for more informed bidding in the second stage.

After accounting for these feedback, the final implementation was determined as follows: (i) the cutoff time for the first-stage bidding would remain at 2:30 p.m. as in the current process; (ii) at that time, the traders would receive mobile text messages that inform them for which lots they qualify for the second stage; (iii) the second-stage bidding would begin at 2:35 p.m.; (iv) the traders would observe on the UMP the highest first-stage bids for the lots they qualify and have until 3 p.m. to increase their own bids; (v) at 3 p.m., the winners for all lots in the market would be declared. A uniform winner declaration time for all lots is chosen to simplify the coordination of post-auction activities. The implementation was launched on February 22, 2019.

Empirical Analysis. To empirically evaluate the impact of implementing the two-stage auction on market prices, we utilize lot-level auction data for the control and treatment markets from one month prior to the implementation till May 31, 2019. The data contains all the bids that were placed on the UMP within this time window in both markets, including all bids placed in both stages after the two-stage auction was implemented in the treatment market. Figure 4a presents the time series of the average weekly prices in the control and treatment markets during the time window of our analysis. The vertical line indicates the date on which the two-stage auction was implemented in the treatment market. Figure 4b presents the distribution of the winning bids in the control and treatment markets pre-implementation (left) and post-implementation (right). It can be observed from both figures that the difference in market prices between the two markets widens after the implementation. These observations provide preliminary evidence that implementing the two-stage auction has resulted in better prices for farmers in the treatment market.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Average impact (Eq. [1])</th>
<th>Impact over time (Eq. [2])</th>
</tr>
</thead>
<tbody>
<tr>
<td>( I_{m,t,l} )</td>
<td>0.047***</td>
<td>-</td>
</tr>
<tr>
<td>( I_{m,t,l} \times ) (February)</td>
<td>-</td>
<td>0.016**</td>
</tr>
<tr>
<td>( I_{m,t,l} \times ) (March)</td>
<td>-</td>
<td>0.056***</td>
</tr>
<tr>
<td>( I_{m,t,l} \times ) (April)</td>
<td>-</td>
<td>0.049***</td>
</tr>
<tr>
<td>( I_{m,t,l} \times ) (May)</td>
<td>-</td>
<td>0.067***</td>
</tr>
<tr>
<td>( Q_{m,t,l} )</td>
<td>0.0006</td>
<td>0.0006</td>
</tr>
<tr>
<td>( N_{m,t} )</td>
<td>0.00002</td>
<td>0.00001</td>
</tr>
<tr>
<td>Fixed effects</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Observations</td>
<td>30,867</td>
<td>30,867</td>
</tr>
</tbody>
</table>

Notes. The variable \( I_{m,t,l} \) is the treatment dummy defined in Eq. [1]. Standard errors (in parentheses) are clustered at the market and date level. ‘\( \ast \)’ means the variable is not present in the model. ‘***’ : \( p < 0.01 \); ‘**’ : \( p < 0.05 \); ‘*’ : \( p < 0.1 \). We control for trader, market, and date fixed effects in both models.

To formally evaluate the impact, a difference-in-differences (DID) approach is employed (29). The DID approach is justified because the treatment and control markets are comparable in their overall supply and demand features, and they demonstrate parallel price trends pre implementation (see Materials and Methods). Table 2 presents the estimated average impact of implementing the two-stage auction on tur prices in the

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\^Since the second-stage bidding is done within a short time, we do not expect increased risk of collusion from the two-stage auction.
treatment market. Observe from column 2 that the implementation has yielded a statistically significant, 4.7% increase in tur prices in the treatment market. In addition, column 3 shows that the positive impact of the implementation tends to increase over time (1.6% in February to 6.7% in May).

Quality is an important factor that determines prices for agricultural commodities. While quality of a lot is not directly observable, our field interactions with the traders indicate that higher-quality lots naturally attract more bids. Hence, we use the number of bids received by a lot as a proxy for its quality and analyze heterogeneous impacts with respect to quality. The analysis demonstrates that the implementation has resulted in a stronger positive impact on the prices of higher-quality lots (see SI Appendix, Evidence of Anchoring).

The estimated 4.7% average price increase translates into a revenue gain of $452,000 (USD) for over 10,000 tur farmers who traded in the treatment market in a matter of three months, i.e., a 15% increase in their monthly income. Given low profit margins for these farmers (4%-7%), the range of profit improvement is substantial (60%-158%). These positive results are particularly significant given that the launch of the UMP itself had not significantly improved tur prices prior to the implementation of the two-stage auction.

Validating the Model with Field Data. The last step in the analysis uses the auction and interview data to provide evidence for the two key behavioral factors identified: anchoring and anticipated non-qualification regret.

Anchoring. Figure 5 illustrates the distribution of the difference between the qualified traders’ final bids and the highest first-stage bids across all lots that received second-stage bids. We observe that the bid increments in the second stage are heavily skewed toward zero and never exceed 0.75% of the highest first-stage bid, with an average of 0.2% (10 rupees/100kg compared to the average price of about 5,000 rupees/100kg). This observation provides strong evidence of anchoring behavior by the traders and suggests that the estimated impact of the implementation mainly comes from more competitive bidding by the traders in the first stage. This result is confirmed by a DID analysis (see SI Appendix, Evidence of Anchoring).

Anticipated non-qualification regret. The behavioral auction model predicts that traders with a stronger anticipated non-qualification regret would bid higher in the first stage, ceteris paribus. To test this prediction, we divide traders into two groups based on their stated intensity of regret felt in the case of not qualifying for the second stage in the interviews. Specifically, the four traders who do not exhibit any regret (stated score for regret = 1) are defined as the “low-regret” group. The remaining traders (stated score for regret ≥ 5) are defined as the “high-regret” group. We then empirically test whether there is an even larger price increase (relative to the control market) among those lots for which the top-rank trader in the first stage is in the high-regret group (Materials and Methods, Eq. [4]).

Figure 6 illustrates the difference in the estimated impact of the two-stage auction on lots for which the top-rank trader in the first stage is in the high-regret group versus in the low-regret group (see Materials and Methods, Table 3). We observe that there is a 2.2 percentage point additional increase (or 73% more increase) in the highest first-stage bid from high-regret traders versus low-regret ones. This result provides empirical support for the significant role that anticipated non-qualification regret is likely playing in affecting the traders’ bidding behavior in the two-stage auction.

Conclusions
This paper introduces a behavior-centric, field-based, data-driven methodology to design effective auction mechanisms in online agri-platforms to enhance farmers’ income. The methodology accounts for important operational and behav-
ioral considerations to ensure successful auction design in resource-constrained environments. By collaborating closely with the state government of Karnataka, we design, analyze, and implement a new two-stage auction on the state’s agri-platform for a major lentils market. A difference-in-differences analysis demonstrates significant revenue gain for over 10,000 smallholder farmers traded in the market in a matter of three months. Encouraged by the positive outcomes and guided by the research insights, the state government has selected a set of suitable commodities and markets to next implement the two-stage auction on a larger scale. We believe that the methods introduced in this paper can provide generally applicable knowledge to researchers and platform designers as they continue to enhance the design of agri-platforms to improve the livelihood of smallholder farmers.

Materials and Methods

Mathematical Details of the Behavioral Auction Model. The model considers three traders bidding for a single lot and the top two traders in the first stage qualify for the second stage. Because quality can be easily verified by the traders and is an important factor determining the bid prices, the trader’s valuation of a lot is modeled as $q + V$, where $q$ is the commonly observed quality of the lot (known to all three traders), and $V$ is each trader’s private value. This private value captures idiosyncratic factors related to the trader’s specific buyers or demand conditions that may affect his bidding. Each trader observes his own private value $v$ and knows that the other traders’ private values are independently and uniformly distributed on $[0, 1]$. Trader $i$’s bidding strategy can be characterized by a mapping $B_i(q, v) : [q, q+1] \rightarrow \mathbb{R}^+$, which specifies his bid given his valuation $q + v$. Following the auction literature, the analysis is focused on analyzing a symmetric equilibrium in which all traders’ equilibrium bidding strategies follow the same structure, denoted as $B^*(q, v)$. Given this setup, Lemma 1 presents the symmetric equilibrium in a single-stage first-price sealed-bid auction. All proofs are deferred to SI Appendix, Proofs.

Lemma 1. Under a first-price, sealed-bid auction, there exists a symmetric Bayesian Nash equilibrium in which the traders’ bidding strategy is given by $B^P_P(v, q) = q + 2v/3$.

The next step is to characterize the traders’ equilibrium bidding strategy in the two-stage auction. First recall from the interviews that traders exhibit strong anchoring on the highest first-stage bid, denoted by $q + H$. To capture this anchoring, the assumption is that the top-rank trader bids $q + H$ again, and the second-rank trader bids $q + H$ if he makes a positive profit with this bid. The expected payoff of a trader as a function of his first-stage bid, $q + H$, have three possibilities. If the trader is ranked first, then he wins and earns $(v - H)$ with probability $1/2$ if he bids again. If the trader does not qualify, then he feels non-qualification regret, with the magnitude of the regret proportional to the lost revenue from non-qualification, i.e., $(v - H)^+$. The following theorem characterizes the traders’ symmetric equilibrium bidding strategy in the first stage of the two-stage auction.

Theorem 1. In the two-stage auction, there exists a symmetric Bayesian Nash equilibrium in which the bidding strategy of a trader with a regret intensity $\lambda > 1/2$ satisfies the following conditions: $b(0) = q$ and $\partial b(v)/\partial v = 2(1 + \lambda) \int_0^v (v - b(x)) dx / [(v - b(v))^2 + 2b(v)^2]$.

Comparing Theorem 1 to Lemma 1, the following result can be shown.

Theorem 2. There exists a threshold $\lambda_H$ such that if $\lambda \geq \lambda_H$, then the expected revenue under a two-stage auction will be higher than that under a first-price sealed-bid auction.

DID Model. We estimate the following model as our main DID specification:

$$\log(P_{m,t,l}) = \gamma I_{m,t,l} + \delta_1 Q_{m,t,l} + \delta_2 N_{m,t} + (\text{trader, market, date fixed effects}) + \epsilon_{m,t,l}. \quad [1]$$

The dependent variable $\log(P_{m,t,l})$ is the logarithm of the winning bid for lot $l$ in market $m$ on day $t$. $I_{m,t,l} = 1$ for all lots in the treatment market on all dates after the implementation, and $I_{m,t,l} = 0$ otherwise. $Q_{m,t,l}$ is the size of lot $l$ in market $m$ on day $t$. $N_{m,t}$ is the total number of lots arriving in market $m$ on day $t$. We control for these two variables because they affect the price of a lot. $\epsilon_{m,t,l}$ is the idiosyncratic error term. The model controls for trader, market, and date fixed effects. The coefficient of interest is $\gamma$. A positive and significant value of $\gamma$ indicates that the implementation of the two-stage auction has led to a significant price increase in the treatment market. The errors at the market and date level are clustered to account for potential correlation across observations (30).

In addition to Eq. [1], the following model is estimated to examine whether the treatment effect changes over time as the market participants gain experience with the new auction design:

$$\log(P_{m,t,l}) = I_{m,t,l} \times \left( \sum_{j=1}^{4} \gamma_j M_{l,t,j} \right) + \delta_1 Q_{m,t,l} + \delta_2 N_{m,t} + (\text{trader, market, date fixed effects}) + \epsilon_{m,t,l}. \quad [2]$$

The variable $M_{l,t,j}$ is an indicator variable that is equal to 1 if lot $l$ is traded in the $j$th month after implementation and 0 otherwise. All the remaining variables follow from Eq. [1].

Robustness Analyses. We perform a number of robustness analyses to strengthen our results. In particular, we consider (i) commodity and time placebo tests; (ii) alternative filtering on the subset of traders who were active both pre and post implementation; (iii) alternative control variables; and (iv) alternative clustering of standard errors. We consider our main result to be robust if the direction and statistical significance of the coefficient for the implementation dummy are consistent between the main model and these robustness tests. We confirm that this is the case (see SI Appendix, Robustness Tests).

DID Assumption. The key identifying assumption for a DID approach is that the difference in market prices between the treatment and control markets would remain constant over time in the absence of the treatment; i.e., the price trends are parallel between the two markets. Following established methods in the literature (31, 32), we verify whether this parallel trend assumption is satisfied by the total number of lots arriving in the market is strongly and positively correlated with the total supply quantity and the total number of active traders in the market. Therefore, we can only include one of them as a control variable. We confirm that our results remain the same regardless of which one of these three variables we control for.

Fig. 6. Estimated average impact of the two-stage auction on lots for which the top-rank trader in the first stage is in the low-regret versus high-regret group (Eq. [4]).
estimating the following model:

$$\log(P_{m,t,l}) = I_{m,t,l} \times \left( \sum_{w=1}^{3} \gamma_w M_w + \delta_1 Q_{m,t,l} + \delta_2 N_{m,t} \right) + \text{(market, date fixed effects)} + \epsilon_{m,t,l}. $$

The variables $\log(P_{m,t,l})$, $I_{m,t,l}$, $Q_{m,t,l}$, $N_{m,t}$, and $\epsilon_{m,t,l}$ are defined the same as in Eq. [1]. $M_w$ is an indicator variable that is equal to 1 if lot $l$ is traded $w$ weeks prior to the implementation and 0 otherwise. Given this specification, the parallel trend assumption is satisfied if the estimates of $\gamma_w$ are not statistically significant. The estimation results (see SI Appendix, Parallel Trends Test) confirm that four out of the five coefficients are not statistically significant (33, 34).

Evidence of Anticipated Non-qualification Regret. We estimate the following model to test whether there is an even larger increase in prices (relative to the control market) among those lots for which the top-rank trader in the first stage is in the high-regret group.

$$\log(P^1_{m,t,l}) = \gamma_0 I_{m,t,l} + \gamma H I_{m,t,l} \times Z_{H,l} + \delta_1 Q_{m,t,l} + \delta_2 N_{m,t} + \text{(market, date fixed effects)} + \epsilon_{m,t,l}. $$

The variable $Z_{H,l}$ is an indicator variable that is equal to 1 if the top-rank trader in the first stage for lot $l$ is in the high-regret group and 0 otherwise. The dependent variable is the highest bid in the first stage. The remaining variables are defined the same as in Eq. [1]. The estimation results (Table 3) demonstrate a positive and significant value of $\gamma H$, indicating a larger price increase (relative to the control market) for lots whose top-rank trader in the first stage belongs to the high-regret group.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Estimate</th>
</tr>
</thead>
<tbody>
<tr>
<td>$I_{m,t,l}$</td>
<td>0.030*** (0.003)</td>
</tr>
<tr>
<td>$I_{m,t,l} \times Z_{H,l}$</td>
<td>0.022*** (0.007)</td>
</tr>
<tr>
<td>$Q_{m,t,l}$</td>
<td>0.002</td>
</tr>
<tr>
<td>$N_{m,t}$</td>
<td>0.00003*** (0.00000)</td>
</tr>
<tr>
<td>Fixed effects</td>
<td>√</td>
</tr>
<tr>
<td>Observations</td>
<td>25,435</td>
</tr>
</tbody>
</table>

Notes. Standard errors (in parentheses) are clustered at the market and date level. ***: $p < 0.01$; **: $p < 0.05$; *: $p < 0.1$. We control for trader, market, and date fixed effects in the model.

Table 3. Estimated Impact of the Two-stage Auction on the Highest First-stage Bids: Effect of Non-qualification Regret

ACKNOWLEDGMENTS. The authors are grateful to Ziwei Zhu for his excellent research assistance, and to Manik Joshi, Mangala Patil, Nisha Devra, and ReMS staff members for their tremendous support in the field. We gratefully acknowledge financial support from the Tata Center for Technology and Design at MIT and the National Science Foundation (Grant 1452873).

Supplementary Information for

Improving Farmers’ Income on Online Agri-platforms: Design and Field Implementation of a Two-stage Auction

Retsef Levi, Manoj Rajan, Somya Singhvi, Yanchong Zheng

Yanchong Zheng
E-mail: yanchong@mit.edu

This PDF file includes:
- Supplementary text
- Tables S1 to S5
- References for SI reference citations
Supporting Information Text

SI Comparability of Treatment and Control Markets. To confirm that a DID approach is suitable in our setting, we first verify the comparability of the two markets along a few important market features, as well as that the prices in the two markets satisfy the parallel trend assumption. Table S1 presents the summary statistics related to tur trading in the control and treatment markets. We observe that the two markets are comparable in both overall supply (e.g., total number of lots arriving in the market) and demand (e.g., number of traders, average price, average number of bids per lot) features prior to implementation. Furthermore, domain knowledge from our collaborators also assures that the two markets are both major markets of tur with similar characteristics in terms of the quality of the lots and the composition of the traders.

Table S1. Summary Statistics for Tur Trading in the Control and Treatment Markets Pre-Implementation

<table>
<thead>
<tr>
<th></th>
<th>Control market</th>
<th>Treatment market</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total no. of lots</td>
<td>11,327</td>
<td>9,642</td>
</tr>
<tr>
<td>Total no. of traders</td>
<td>45</td>
<td>43</td>
</tr>
<tr>
<td>Average no. of bids per lot</td>
<td>5.21</td>
<td>5.75</td>
</tr>
<tr>
<td>Average price (rupees/100kg)</td>
<td>4,987</td>
<td>5,126</td>
</tr>
</tbody>
</table>

SI Parallel Trends Test. Table S2 summarizes the coefficient estimates of the parallel trends test described in Materials and Methods, DID assumption.

Table S2. Estimation Results for the Parallel Trends Test

<table>
<thead>
<tr>
<th>Variable</th>
<th>Estimate (S1)</th>
<th>Estimate (S2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$I_{m,t,l} \times M_{1,l}$</td>
<td>-0.005</td>
<td>-0.0005</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.005)</td>
</tr>
<tr>
<td>$I_{m,t,l} \times M_{2,l}$</td>
<td>0.008</td>
<td>-0.0017</td>
</tr>
<tr>
<td></td>
<td>(0.009)</td>
<td>(0.005)</td>
</tr>
<tr>
<td>$I_{m,t,l} \times M_{3,l}$</td>
<td>-0.005</td>
<td>-0.009</td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
<td>(0.005)</td>
</tr>
<tr>
<td>$I_{m,t,l} \times M_{4,l}$</td>
<td>-0.017**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td></td>
</tr>
<tr>
<td>$I_{m,t,l} \times M_{5,l}$</td>
<td>-0.009</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td></td>
</tr>
<tr>
<td>$Q_{m,t,l}$</td>
<td>0.002</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td></td>
</tr>
<tr>
<td>$N_{m,t}$</td>
<td>0.00004</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.00002)</td>
<td></td>
</tr>
<tr>
<td>Fixed effects</td>
<td>Y</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>16,371</td>
<td></td>
</tr>
</tbody>
</table>

Notes. We report the coefficient estimates of $\gamma_w$ for $w = 1, \ldots, 5$ in Eq. [3] in Materials and Methods, DID assumption. Standard errors (in parentheses) are clustered at the market and date level. ***: $p < 0.01$; **: $p < 0.05$. We control for market and date fixed effects in the model.

SI Effect of Product Quality. Quality is an important factor that determines prices for agricultural commodities. Thus, it is of great interest to examine whether the impact of the implementation on tur prices depends on a lot’s quality. Since the quality of a lot is not directly observable, we consider the following proxy measure. For a given lot $l$, we calculate its normalized number of bids, $B_{m,t,l}^n$, by dividing the number of bids it received by the maximum number of bids received by any lot in the same market on the same day. Our field interactions with the traders indicate that higher-quality lots naturally attract more bids. Hence, $B_{m,t,l}^n$ would be closer to 1 (0) for lots of high (low) quality. The normalization allows us to do a fair comparison across days and markets. We then estimate the following two models.

$$\log(P_{m,t,l}) = \gamma_0 I_{m,t,l} + \gamma_1 I_{m,t,l} B_{m,t,l}^n + \gamma_2 I_{m,t,l} \left(B_{m,t,l}^n\right)^2 + \delta_1 Q_{m,t,l} + \delta_2 N_{m,t} + \text{(bidder, market, date fixed effects)} + \epsilon_{m,t,l}, [S1]$$

$$\log(P_{m,t,l}) = \gamma_0 I_{m,t,l} + I_{m,t,l} \times \left( \sum_{i \in H,L} \gamma_i B_{i,l} \right) + \delta_1 Q_{m,t,l} + \delta_2 N_{m,t} + \text{(bidder, market, date fixed effects)} + \epsilon_{m,t,l}. [S2]$$

In Eq. [S2], $B_{H,l}$ is an indicator variable that is equal to 1 if $B_{m,t,l}^n$ is greater than the third quartile of the distribution of $B_{m,t,l}^n$ in the same market on the same day, and 0 otherwise. Similarly, $B_{M,l}$ is an indicator variable that is equal to 1 if $B_{m,t,l}^n$ is between the first and the third quartiles of the same distribution, and 0 otherwise. That is, we divide all lots arriving to a given market on a given day into three groups based on a first and third quartile split. The baseline group in Eq. [S2] represents the low-quality lots, and $B_{M,l}$ ($B_{H,l}$) represents the medium-quality (high-quality) lots.* All other variables remain

* Our results remain the same under the following alternative groupings: (i) a four-group split based on the first quartile, median, and third quartile; (ii) a three-group split based on the 10th and 90th percentiles; and (iii) a median split.
the same as in the main DID model (Eq. [1] in Materials and Methods). Our method of evaluating possible differential impacts of the implementation follows from the literature (1, 2).

The regression results are presented in Table S3 and demonstrate that the implementation has resulted in a stronger positive impact on the prices of higher quality lots. First, we observe a significantly positive coefficient for $B_{m,t,l}$, our proxy measure of lot quality, in column 2 of Table S3. Furthermore, the coefficient for $(B_{m,t,l})^2$ is significantly negative. Thus, lots receiving a larger number of bids benefit more from the implementation, although this effect has a (naturally) diminishing return. Second, we observe from column 3 of Table S3 that the prices of high-quality (medium-quality) lots have increased 4% (3%) more relative to the prices of low-quality lots (which have increased by 1.7%) due to the implementation. These results highlight that in addition to generating price gains for the farmers, implementing the two-stage auction also provides them with stronger incentives to enhance the quality of the lots they bring to the market.

### Table S3. Estimated Impact of the Implementation on Tur Prices: The Effect of Quality

<table>
<thead>
<tr>
<th>Variable</th>
<th>Average impact (Eq. [1])</th>
<th>Impact over time (Eq. [2])</th>
</tr>
</thead>
<tbody>
<tr>
<td>$I_{m,t,l}$</td>
<td>0.047***</td>
<td>0.017***</td>
</tr>
<tr>
<td>$Q_{m,t,l}$</td>
<td>0.001</td>
<td>0.001</td>
</tr>
<tr>
<td>$N_{m,t}$</td>
<td>-0.000</td>
<td>-0.000</td>
</tr>
</tbody>
</table>

Notes. "-" means the variable is not present in the model. Standard errors (in parentheses) are clustered at the market and date level. ***: $p < 0.01$; **: $p < 0.05$; *: $p < 0.1$. We control for trader, market, and date fixed effects in both models.

### SI Evidence of Anchoring

As an additional analysis, we examine how first-stage versus second-stage bids may have contributed to the overall price increase observed in the treatment market. If traders indeed exhibit anchoring in the second stage, then the positive price impact from the implementation should be mainly driven by more competitive bidding in the first stage. In order to test this hypothesis, we reestimate Eq. [1] using a lot’s highest bid in the first stage as the dependent variable. Since there is only one stage of bidding in the control market, the dependent variable for the lots in the control market remains the same as before. Table S4 presents the results. We observe that the implementation dummy has a significantly positive coefficient ($\gamma = 0.046$) that is of similar magnitude as the estimated impact in our main model.

### Table S4. Estimated Impact of the Implementation on First-stage Bids

<table>
<thead>
<tr>
<th>Variable</th>
<th>Estimate</th>
</tr>
</thead>
<tbody>
<tr>
<td>$I_{m,t,l}$</td>
<td>0.046*** (0.008)</td>
</tr>
<tr>
<td>$Q_{m,t,l}$</td>
<td>0.001 (0.001)</td>
</tr>
<tr>
<td>$N_{m,t}$</td>
<td>-0.000 (0.000)</td>
</tr>
</tbody>
</table>

Notes. Standard errors (in parentheses) are clustered at the market and date level. ***: $p < 0.01$; **: $p < 0.05$; *: $p < 0.1$. We control for trader, market, and date fixed effects in the model.

### SI Robustness Tests

**Placebo tests.** We perform two placebo tests to ensure that the estimated impact discussed above is indeed a result of the field implementation. First, we reestimate Eq. [1] using data for a placebo commodity (Bengal gram, another lentil) that was traded in the same markets during the same time period of the implementation but followed the original first-price, sealed-bid auction. Second, we reestimate Eq. [1] using tur trading data from a placebo time period (the same period in 2018). If the
field implementation is the main driver of the observed impact, then we should not observe any statistically significant effect in these two tests. The regression results show no statistically significant effect in either test (Table S5, columns 2 and 3).

Alternative data filtering. We observe that not all the winning traders are active in both pre- and post-treatment periods. If traders who win only in pre- or post-treatment periods have a much higher valuation then other traders, then our impact estimate may be driven by differences in winning bidders’ private valuations. To test this hypothesis, we focus on the subset of traders who have won a lot in both pre- and post-treatment periods and reestimate Eq. [1]. The regression results show statistically significant effect in this test (Table S5, column 4).

Alternative control variables. To further ensure the robustness of our conclusions, we reestimate Eq. [1] using two additional specifications with different sets of controls. First, we reestimate Eq. [1] with a market specific time-trend. This specification allows control and treatment market to follow different time trends (3). Second, we remove all control variables and reestimate the main model. The regression results show statistically significant effect in both the tests. These results thus provide further confidence that the estimated impact is indeed due to the implementation of the two-stage auction (Table S5, columns 5 and 6).

Alternative clustering of standard errors. We consider alternative standard error clustering by doing one way market-level clustering to account for within-market correlations and reestimate the main model. The regression results show statistically significant effect in this test (Table S5, column 7).

Table S5. Regression Results of the Robustness Tests

<table>
<thead>
<tr>
<th>Variable</th>
<th>Commodity placebo</th>
<th>Time placebo</th>
<th>Active traders only</th>
<th>Market-level trend</th>
<th>No control variables</th>
<th>Alternative clustering</th>
</tr>
</thead>
<tbody>
<tr>
<td>I_{m,t,1}</td>
<td>0.008</td>
<td>0.004</td>
<td>0.048***</td>
<td>0.013**</td>
<td>0.044***</td>
<td>0.047***</td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td>(0.004)</td>
<td>(0.008)</td>
<td>(0.007)</td>
<td>(0.003)</td>
<td>(0.003)</td>
</tr>
<tr>
<td>Q_{m,t,1}</td>
<td>0.001</td>
<td>0.001</td>
<td>0.001*</td>
<td>0.001</td>
<td>-</td>
<td>0.001</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.0006)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>N_{m,t}</td>
<td>-0.0002***</td>
<td>-0.00001</td>
<td>-0.00008</td>
<td>-0.00002</td>
<td>-</td>
<td>-0.000</td>
</tr>
<tr>
<td></td>
<td>(0.0000)</td>
<td>(0.00001)</td>
<td>(0.00002)</td>
<td>(0.00001)</td>
<td>(0.0000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Observations</td>
<td>14,966</td>
<td>33,155</td>
<td>28542</td>
<td>30867</td>
<td>30867</td>
<td>30867</td>
</tr>
</tbody>
</table>

Notes. Column 2 presents results from estimating Eq. [1] based on trading data of a placebo commodity (Bengal gram) in the same period of the implementation. Column 3 presents results from estimating the same model based on tur trading data from February to May in 2018. Column 4 presents results from estimating the same model based on filtering on active traders. Column 5 presents results with additional control for market level trends. Column 6 presents results with no control variables except market and date fixed effects. Standard errors (in parentheses) are clustered at the market and date level in all specifications except for column 7 (clustered at the market level). We control for trader, market, and date fixed effects in all specifications except column 6. ***: p < 0.01; **: p < 0.05; *: p < 0.1.

SI Proofs.

Preliminary results. We follow (4) to prove Theorems 1 and 2. To do so, we need the following lemmas.

Lemma S1. Incentive compatible bidding strategy in the two-stage auction with anchoring and anticipated regret is a strictly increasing function when \( \lambda > 1/2 \).

Lemma S2. The local and global incentive constraints in a two-stage auction with anchoring and anticipated regret are equivalent.

Proof of Lemma 1. The expected profit of a trader who bids \( b \) when his valuation is \( q + v \) and the other two traders bid \( B_1 \) and \( B_2 \) is \( \pi(v, q, b) = E[(v + q - b) \mathbb{1}\{b > B_1 \cap b > B_2\}] \). This is because the trader wins only if his bid is higher than the other two bids. It is easy to check that under a first price sealed bid auction, the symmetric equilibrium bidding function, \( B^*(v, q) \), that maximizes \( \pi(v, q, b) \) is given by \( B^*(v, q) = q + \frac{2v}{3} \) (5).

Proof of Theorem 1. We will assume \( q = 0 \) w.l.o.g. to simplify exposition throughout the section. Let \( b(.) : [0, 1] \rightarrow \mathbb{R} \) be the equilibrium bidding function for a two-stage auction. Let us define \( \mathcal{E}^1 \) to be the event that bidder is ranked first and no one else bids again. Similarly, let \( \mathcal{E}^2 \) be the event that bidder is ranked first but the second ranked bidder bids again. Let \( \mathcal{E}^3 \) be the event that bidder is ranked second with but he bids again. Let \( \mathcal{E}^4 \) to be the event that bidder is ranked third and he feels regret from non qualification. Any representative bidder in the two stage auction maximizes the expected revenue maximization problem to decide the optimal incentive compatible bidding strategy:
The second inequality follows from the fact that the equilibrium bidding function is strictly increasing. Since the local and global IC constraints are equivalent (by Lemma S1), the corresponding first order condition is \( \frac{\partial b(v)}{\partial s} = 0 \) when \( s = v \). Taking the derivative and setting it to 0 gives us the condition in the theorem.

The last part is to show that for any \( \lambda \), we have that the last term is finite. Further, for all \( \lambda \), note that

\[
\partial b \left( \frac{v}{s} \right) = 2(1 + \lambda) \int_0^1 \frac{(v - b(x))^+ dx}{(v - b(x))^2 + 2b(v)^2}.
\]

The second inequality follows since the equilibrium bidding function is strictly increasing. Since the local and global IC constraints are equivalent (by Lemma S1), the corresponding first order condition is \( \frac{\partial b(v)}{\partial s} = 0 \) when \( s = v \). Taking the derivative and setting it to 0 gives us the condition in the theorem.

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The second inequality follows since the equilibrium bidding function is strictly increasing. Since the local and global IC constraints are equivalent (by Lemma S1), the corresponding first order condition is \( \frac{\partial b(v)}{\partial s} = 0 \) when \( s = v \). Taking the derivative and setting it to 0 gives us the condition in the theorem.
Adding the two equations, we get,

\[
(\lambda_2 - \lambda_1)(P(E_1^\dagger)E[v - b^w|E_1^\dagger] - P(E_2^\dagger)E[v - b^w|E_2^\dagger]) \\
(\lambda_2 - \lambda_1)(2 \int_{b_1}^{x} \int_{b_1}^{x} (v - b(x))^{+} dydx - 2 \int_{b_2}^{x} \int_{b_2}^{x} (v - b(x))^{+} dydx)
\]

[S7]

Since \(\lambda_2 > \lambda_1\), the last inequality will hold only if \(b_1 < b_2\).

**Proof of Lemma S1.** Let \(b(.) : [0, 1] \to \mathbb{R}\) be the equilibrium bidding function for a two-stage auction. Let two valuations \(v_1\) and \(v_2\) be such that \(v_2 > v_1\), and \(b^1\) and \(b^2\) be the corresponding bids. Finally, let \(b^w\) be the maximum bid. Let us define \(E_1^1\) to be the event that bidder is ranked first with bid \(b_1\) and no one else bids again. Similarly, let \(E_2^2\) be the event that bidder is ranked first with bid \(b_2\) but the second ranked bidder bids again. Let \(E_1^2\) be the event that bidder is ranked second with bid \(b_1\) and he bids again. Let \(E_2^1\) to be the event that bidder is ranked third and he feels regret from non qualification. Let \(E_{j,i}^{1}\) be the event that the trader is ranked \(j\) when he bids \(b_i\). Let \(E_i\) be the event that the trader qualifies when he bids \(b_i\).

Since we consider incentive compatible bids, following (4), we should have,

\[
P(E_1^1)(v_1 - b_1) + P(E_2^2)\frac{(v_1 - b_1) + P(E_2^2)[b^w]}{2} - \lambda P(E_1^1)[b^w](v_1 - b^w) \geq \frac{(v_2 - v_1)}{2} + P(E_2^2)[b^w] - P(E_1^1)[b^w] \geq 0
\]

[S8]

and,

\[
P(E_2^2)(v_2 - b_2) + P(E_2^2)\frac{(v_2 - b_2) + P(E_2^2)[b^w]}{2} - \lambda P(E_2^2)[b^w](v_2 - b^w) \geq \frac{(v_2 - v_1)}{2} + P(E_2^2)[b^w] - P(E_1^1)[b^w] \geq 0
\]

[S9]

Adding the two inequalities above and rearranging the terms, we get:

\[
(P(E_2^2) - P(E_1^1))(v_2 - v_1) + (P(E_2^2) - P(E_2^2))\frac{(v_2 - v_1)}{2} + (P(E_2^2)[b^w] - P(E_1^1)[b^w])\frac{(v_2 - v_1)}{2} \geq 0
\]

[S10]

Note that since \(P(E_{1,i}^1) = P(E_1^1) + P(E_2^2)\), we have the following:

\[
\frac{(v_2 - v_1)}{2}P(E_{1,2}^1) - P(E_{1,1}^1) + \frac{(v_2 - v_1)}{2}(P(E_2^2) - P(E_1^1)) + \frac{(v_2 - v_1)}{2}P(E_2^2)[b^w] - P(E_1^1)[b^w] \geq 0
\]

\[
\Rightarrow (v_2 - v_1)(P(E_{1,2}^1) - P(E_{1,1}^1)) + (v_2 - v_1)(P(E_2^2) - P(E_1^1)) + (v_2 - v_1)(P(E_2^2) - P(E_1^1)) - (P(E_{2,1}^2) - P(b^w > v_1))(v_2 - v_1) \geq 0
\]

\[
\Rightarrow (v_2 - v_1)(P(E_{1,2}^1) - P(E_{1,1}^1) + P(E_1^1) = P(E_2^1) - P(E_{2,1}^2)) + (v_2 - v_1)(P(E_{2,1}^2) - P(E_{2,1}^2) - P(E_{2,1}^2))
\]

\[
\Rightarrow (v_2 - v_1)(P(E_{2,1}^2) - P(E_{2,1}^2) + P(E_{2,1}^2) - P(E_{2,1}^2)) + (v_2 - v_1)(P(E_{2,1}^2) - P(E_{2,1}^2)) + (v_2 - v_1)(P(E_{2,1}^2) - P(E_{2,1}^2)) \geq 0
\]

[S11]

Since \(\lambda > 1/2\) and \(v_2 > v_1\), the last term is negative and a necessary condition for the inequality to hold is

\[
\frac{(v_2 - v_1)}{2}(P(E_{2,1}^2) - P(E_{2,1}^2) + P(E_{2,1}^2) - P(E_{2,1}^2)) + (v_2 - v_1)(P(E_{2,1}^2) - P(E_{2,1}^2)) \geq 0
\]

[S12]

It is easy to check that either \(P(E_{2}^2) - P(E_{1}^1)\) and \(P(E_{1}^2) - P(E_{1}^2)\) are both positive or they are both negative. Since \(v_2 > v_1\), we should have \(P(E_{2}^2) - P(E_{1}^1) \geq 0\). This gives \(b_2 \geq b_1\). Finally, \(b_2 > b_1\) since otherwise, there exists an interval \([v_1, v_2]\) such that \(b_1 = b_2 = b(v)\) for any \(v \in [v_1, v_2]\) but \(b_0 = b(v) + \epsilon\) is a profitable deviation given that all opponents are bidding \(b(v)\).
Proof of Lemma S2. Global IC constraints trivially satisfy local IC constraints. To prove the converse, consider the case when local IC constraint holds, i.e. at $z = v_1$, $\frac{\partial \pi(v_1, z)}{\partial z} = 0$ Consider any $y < v_1$

$$\pi(v_1, v_1) - \pi(v_1, y) = \int_y^{v_1} \frac{\partial \pi(v_1, z)}{\partial z} dz$$

$$= \int_y^{v_1} (\pi_z(v_1, z) - \pi_z(z, z))dz$$

[S13]

$$= \int_y^{v_1} \int_z^{v_1} (\pi_{z,k}(k, z))dkdz$$

Note that the cross derivative of $\pi(k, z)$, is $(1 + 2\lambda)(1 - z) + b(z)b'(z)$ when $b^{-1}(z) > 1$ and $(b^{-1}(k) - z) + b(z)b'(z)$ otherwise. If $v_1 > z > b(1)$, then $\pi_{k,z}(k, z)$ is positive and if $y < z < b(1)$, then since $k > z > b(z)$, we again have that $\pi_{k,z}(k, z)$ is positive. Now consider, $b^{-1}(v_1) > y > v_1$

$$\pi(v_1, v_1) - \pi(v_1, y) = -\int_y^{v_1} \frac{\partial \pi(v_1, z)}{\partial z} dz$$

$$= \int_y^{v_1} (\pi_z(v_1, z) - \pi_z(z, z))dz$$

[S14]

$$= \int_y^{v_1} \int_z^{v_1} (\pi_{z,k}(k, z))dkdz$$

Note that since $k > v_1$, $b^{-1}(v_1) > y > z$, we again have that $(b^{-1}(k) - z) > 0$ in this range as well. Therefore, we have shown for every $y$, $\pi(v_1, v_1) > \pi(v_1, y)$ and the global IC constraints hold.

References
SI Sample Questionnaire

Survey Questions for Traders

Note/ ಪ್ರಾರಂಭಿಸಿ : Trader/ ವಾರಾನ್ದು : Market license holder / ಮರಣಾಂಶ : ವಾರಾನ್ದು, ವರ್ಧ್ರ

Buyer / ವಾರಾನ್ದು : Purchaser from trader / ವಾರಾನ್ದು : ವಾರಾನ್ದು, ವರ್ಧ್ರ

General Questions/ ವಾರಾನ್ದು, ವರ್ದಾರು

Basic 1: Name/ ವಾರಾನ್ದು

Answer/ ಉತ್ತರ: _____________

Basic 2: Number of years’ experience in the business/ ವಾರಾನ್ದು ವಿವರಕ್ಕೆ ವಾರಾನ್ದು (ವರ್ಧರದ)

Answer/ ಉತ್ತರ: _____________

Basic 3: Name of other commodities that you trade in/ ವಾರಾನ್ದು ವಿವರಕ್ಕೆ ವಾರಾನ್ದು ವಾರಾನ್ದು

Answer: ಉತ್ತರ _____________

Part A/ ಹಾಗು ಇ. Advanced E-Tender / ಇತರೆ ಅ-ಸಂಕೀರ್ಣ

Qa1: What are some factors that affect your bid prices?/ ವಾರಾನ್ದು ವಾರಾನ್ದು ಪ್ರಾಂದಣ ವಾರಾನ್ದು ವಾರಾನ್ದು ವಾರಾನ್ದು ವಾರಾನ್ದು

Answer/: ಉತ್ತರ: _____________

(If no responses:/ ಪ್ರತ್ಯೇಕ ಪ್ರತ್ಯೇಕ ಪ್ರತ್ಯೇಕ ಪ್ರತ್ಯೇಕ ಪ್ರತ್ಯೇಕ ಪ್ರತ್ಯೇಕ ಪ್ರತ್ಯೇಕ)

Total Lots in the Market/ ವಾರಾನ್ದುಗರಾಮ ವಾರಾನ್ದು ವಾರಾನ್ದು ವಾರಾನ್ದು

Number of Traders/ ವಾರಾನ್ದು ವಾರಾನ್ದು

Quality of The Lots/ ವಾರಾನ್ದು ವಾರಾನ್ದು

Yesterday’s Closing Bid/ ವಾರಾನ್ದು ವಾರಾನ್ದು ವಾರಾನ್ದು
Qa2: Are there public benchmarks used by the buyers when giving a quote
(Give hint if no responses: ಹಾಗು ಅನುಮೋದಿಸಲು ಕೇಳಿ)

Stock Exchange / ವಸ್ತು ವಿಭಾಗ

Major Markets / ಮುಖ್ಯ ಮುಖ್ಯ ವಿಭಾಗಗಳು

Futures Market / ಕಾರ್ಯಾಲಯ ವಿಭಾಗಗಳು)

Answer/ಉತ್ತಮ ___________

Part B/ ಸಂಕೋಚ ವಿಭಾಗ/ Anticipated Regret/ ವೈದ್ಯಂತ ವ್ಯಾಸ

Qb1. Assume that there are 15 traders in the market today and you participate in the advanced etender auction. In particular, only top 3 bidders in the first round will qualify for the second-round bidding.

The maximum that the buyer would be willing to pay you is 5100-5300 (Average: 5200) What is your first-round bid for lots of different quality?

<table>
<thead>
<tr>
<th>Quality</th>
<th>Bid in first round of advance etender</th>
</tr>
</thead>
<tbody>
<tr>
<td>High Quality</td>
<td></td>
</tr>
<tr>
<td>Medium Quality</td>
<td></td>
</tr>
<tr>
<td>Low Quality</td>
<td></td>
</tr>
</tbody>
</table>

Suppose at the end of the first round, you find that you did not qualify for the second round. Please rate the intensity of the emotions listed below you would experience in that situation:

- ಸ್ಮಾರ್ಪಕ ಮತ್ತು ಅನುಗಮನ ವಿಭಾಗ
- ಸ್ಮಾರ್ಪಕ ಮತ್ತು ಅನುಗಮನ ವಿಭಾಗ
- ಸ್ಮಾರ್ಪಕ ಮತ್ತು ಅನುಗಮನ ವಿಭಾಗ

ಹಾಗು ಅನುಮೋದಿಸಲು ಕೇಳಿ
### Part C. Competitive Arousal in the Second Round

**Qc1.** Suppose at the end of the first round, you find that you qualify for the second round and the buyer’s maximum quote was 5300-5500. Fill the table (Rivalry)/

<table>
<thead>
<tr>
<th>Top Bid in the first round/ ಪ್ರಥಮ ಕೇಂದ್ರಪದ ಪದ</th>
<th>Number of bidders who qualify/ ಕೇಂದ್ರಪದ ಪದವಿಯ ಪಡೆದುಕಡೆಯಾದರು</th>
<th>Number of lots in the market</th>
<th>Your bid in advanced e-tender second round/ ಪ್ರಧಾನ ಪ್ರವಾಹದಲ್ಲಿಯರು ಅದ್ಯಕ್ಷ ತೇದಿ</th>
<th>Chances of winning this lot/ ಬೇಸರುವ ಪದವಿಗೆ ಸಾಧಿಸಲು ಪಡೆಯುವ ಸಾಕ್ಷಿ</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>5200</td>
<td>3</td>
<td>100 lots (Low Supply)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5200</td>
<td>3</td>
<td>600 lots (High Supply)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5200</td>
<td>7</td>
<td>100 lots (Low Supply)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5200</td>
<td>7</td>
<td>600 lots (High Supply)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Qc2.** Suppose at the end of the first round, you find that you qualify for the second round and the buyer’s maximum price your buyer is willing to pay is 5400. Fill the table (Time Pressure)/
Part D/ಪಾಂದು. Budget Constraints /ಬಿಡ್ಡಿ ಮಿಶ್ರಿತ

Qd1: Do you have a total budget everyday? / ಇಸ್ತೇಟಬಂದು ಪೂರ್ವಸ್ಥೆಯನ್ನು ಬೇಡಿಸುವ ಸಮಯವೂ ಬೆಲೆಯಲ್ಲಿ?  

☐ Yes / ಈಯೂ ☐ No/ಎಲೆ

Qd2: Do you ever exceed your everyday budget target? / ಮೂಲಕ ಪೂರ್ವಸ್ಥೆಯ ಬೇಡಿಸದ ಸಮಯವೂ ಬೆಲಿಯಬಲ್ಲದ ಸಮಯವೂ ಬೊಂದರು?  

☐ Yes / ಈಯೂ ☐ No/ಎಲೆ

Qd3: How concerned are you if you exceed your budget target? / ಸಾಮಾನ್ಯವಾಗಿ ಬೇಡಿಸದ ಸಮಯವೂ ಬೆಲಿಯಬಲ್ಲದ ಸಮಯವೂ ಬೊಂದರು ಸಂಬಂಧಿಸಿದ್ದರೆ?  

Answer/ ಉತ್ತರ:  

- Extremely concerned because I have to borrow / ಅತ್ಯಂತ ಸಂಬಂಧಿಸಿದಲ್ಲಿ ಬೇಡಿಸದ ಸಮಯವೂ ಬೆಲಿಯಬಲ್ಲದ ಸಮಯವೂ ಬೊಂದರು / ಹಲವಾರು ಸಂಬಂಧಿತವಾಗಿ

- Less concerned because I always have enough cash / ಸಂಬಂಧಿಸಿದ್ದ ಸಮಯವೂ ಬೆಲಿಯಬಲ್ಲದ ಸಮಯವೂ ಹಲವಾರು / ಸಂಬಂಧಿತವಾಗಿ

- Not concerned because I can sell it at higher price to my buyers/ ಸಂಬಂಧಿಸಿದ್ದ ಸಮಯವೂ ಬೆಲಿಯಬಲ್ಲದ ಸಂಬಂಧಿತವಾಗಿ
• Not concerned because I can sell it at higher price to other traders / ಅವುಗಳನ್ನು ಇತರ ಪರಿಚಯುಗಳಿಗಿಂತ ಉದ್ದೇಶದಲ್ಲಿಯೇ ಬಿಡಿಸುಬೇಕು

Qd4: Do you have a total inventory target everyday? / ನೀವು ಈವೇಡ್ಯು ದಿನದಿನ ಈ ತಾಧ್ಯಯನದ ನಿದ್ದೆಯಲ್ಲಿಯರು ಇರುತ್ತದೆ ಎಂಬುದನ್ನು?  ☐ Yes / ಆದು ☐ No / ಅದೆ

Qd5: Do you ever exceed your inventory target? / ನೀವು ಈ ತಾಧ್ಯಯನದ ನಿದ್ದೆಯಲ್ಲಿಯರು ಈ ತಾಧ್ಯಯನದ ನಿದ್ದೆಯಲ್ಲಿಯರು ಎಂದರೂ ಈ ತಾಧ್ಯಯನದ ನಿದ್ದೆಯಲ್ಲಿಯರು ಎಂದರೂ?  ☐ Yes / ಆದು ☐ No / ಅದೆ

Qd6: How concerned are you if you exceed your inventory target? / ನೀವು ಈ ತಾಧ್ಯಯನದ ನಿದ್ದೆಯಲ್ಲಿಯರು ಈ ತಾಧ್ಯಯನದ ನಿದ್ದೆಯಲ್ಲಿಯರು ಎಂದರೂ ಈ ತಾಧ್ಯಯನದ ನಿದ್ದೆಯಲ್ಲಿಯರು ಎಂದರೂ? 

Answer / ಉತ್ತ್ವರ್ತಿ:

• Extremely concerned because I have to store / ಅತಿ ವಿಶೇಷವಾದರೆ ಇದನ್ನು ಸ್ಥಾಪಿಸಲಾಗುತ್ತದೆ

• Less concerned because I always have enough capacity / ಲೇಖನವನ್ನು ಹೆಚ್ಚಿನ ಸಾಧ್ಯತೆ ಮತ್ತು ಸಾಧ್ಯವಾಗಿದ್ದು ಸಾಧ್ಯವಾಗಿರುವ ಸಾಧ್ಯತೆಯ ಕಳೆದುಕೊಳ್ಳಲಾಗುತ್ತದೆ

• Not concerned because I can sell more to my buyers / ಅದೆಯ ವಿದ್ಯಯಗಳಿಂದ ಮತ್ತು ಮೂಲದ ಬಿಡಿಸುತ್ತದೆ / ಅತಿ ವಿಶೇಷವಾದರೆ ಇದನ್ನು ಸ್ಥಾಪಿಸಲಾಗುತ್ತದೆ

• Not concerned because I can sell to other traders / ಅದೆಯ ವಿದ್ಯಯಗಳಿಂದ ಮತ್ತು ಮೂಲದ ಬಿಡಿಸುತ್ತದೆ / ಅತಿ ವಿಶೇಷವಾದರೆ ಇದನ್ನು ಸ್ಥಾಪಿಸಲಾಗುತ್ತದೆ