Licensed to Deal: Auction Design for Market Creation in a Low-Income Country

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Abstract

We study auction design where business licenses for new markets are sold to firms. The experiment varies two auction design choices: the auction mechanism and the pre-bid information provided to bidders. The results suggest that: i) open auctions, in which bidders implicitly share information with their peers, have 61 percent lower mean bid prices and 67 percent lower bid variance than closed auctions, in which bidders bid secretly; ii) bidding behavior is influenced by bidders' ex-ante beliefs, resulting in lower but potentially more accurate valuations; and iii) real-stakes auctions reduce bids by a factor of five relative to non-incentivized auctions.

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D44 Auctions

D82 Asymmetric and Private Information, Mechanism Design

Q12 Micro Analysis of Farm Firms, Farm Input Markets

1 Introduction

Missing markets are a common feature of low-income countries. As new products or services are introduced into these markets, price uncertainty has implications for profitability and scaling innovations. Eliciting prices in low income countries is challenging because market information on potential returns is limited when markets are incomplete or missing. Market participants may have high variability in their willingness to pay (WTP) for new innovations which can be itself influenced by the elicitation mechanism. When initial prices are elicited in take-it-or-leave-it pricing questions, low estimates of WTP may result when demand is actually high, or vice versa (Berry et al., 2020, Ashraf et al., 2010, Cohen and Dupas, 2010). Market surveys often elicit hypothetical prices or quantities from market participants. Survey design choices such as the price elicitation common support may introduce measurement error in market surveys when the intervals are not sufficiently granular (Delavande, 2023). Alternatively, real-stakes auctions are also common price discovery mechanisms that provide a continuous estimate of WTP, but require auction design choices related to bidding, market clearing conditions, and information provided to bidders that affect WTP estimates (Lusk and Shogren, 2007).

We design a lab-in-the-field experiment to estimate the willingness of agricultural input dealers to pay for licenses for new markets we organize, called Village Input Fairs (VIFs). VIFs are an innovation which creates rural agricultural input markets in areas where such markets are missing by aggregating village demand at a one-day fair where farmers can order inputs from input dealers. We have tested VIFs in Mali and found that aggregate input demand increases by 28 percent with respect to control villages (Dillon and Tomaselli, 2025). Though the returns are uncertain for the individual input dealer, VIFs are potentially profitable because input dealers can sell to an entire village rather than individual farmers, reducing customer acquisition and transport costs. The experiment first estimates the effect of alternative auction mechanisms on input dealers WTP for VIF licenses using the English auction, the Second price auction, and a special case of the latter, the Becker-DeGroot-Marschak, or BDM, auction.[1] Second, we vary whether

[1] Two licenses for each Village Input Fair (VIF) are sold during every auction. For every auction, 8 to 10 bidders are allowed to bid to purchase only one unit. Resale of licenses is not allowed. In our open, e.g. outcry, English clock auction, the price of the license is increased at intervals and bidders withdraw until only two remains and pays the price of the last exit. This open mechanism can be referred to as uniform-price English, or ascending, two-unit auction (Krishna, 2010c). It is a uniform-price auction since both winners pay the same price, but adapted to an open and dynamic format. In our closed, e.g. sealed-bid, Second price auction, bidders bid secretly and the top two highest bids win the license. Both winners pay the same price, which is the lower of the two, e.g., the second-highest winning bid. The characteristics of this closed auction are the ones of a uniform-price auction with two-unit allocation (Krishna, 2010c). This

information about the VIF licenses auctioned are hypothetical or drawn from the study area which provide a direct test of the relevance of dealers' ex-ante beliefs on bidding.[2] Table 1 provides a summary of the four hypotheses that we test through the interaction of these two treatments.

The context of our VIF auctions is analogous to that of a mineral-rights auction, where firms submit bids for a license to drill in an area that has not yet been explored. The amount of oil that can be extracted (in our case the demand of the VIF farmers) is an element of uncertainty for all bidders that affects their valuation. Each of them can take geological tests, and the results of these tests allow each bidder to make an imperfect estimate of the value of the mineral rights. Bidders learning about another bidder's test results are likely to revise their initial estimates based on common values, a direct result of Wilson, 1969. Our setting draws on the common values model because the value of the fair's license to all bidders is the same, as the underlying village demand for inputs is the same across input dealers. This does not imply that each input dealer will have an equivalent valuation of the return to the same license, even if provided the same information about the license for sale. Each bidder may have a different opportunity cost associated with exploiting it. In our rural Mali setting, input dealers are aware of their own operating costs, however they face different degrees of uncertainty about the market returns to VIF license.[3] Although uncertain at the time of participation in the auction, each bidder receives a distinct signal and forms a private valuation of the license being sold. These private values and signals are unlikely to be independent (a key assumption of the pure private value model) as input dealers share wholesaler relationships and are collectively organized in a national association of input dealers. Milgrom and Weber, 1982 call the correlation of information and signals *affiliation*. In summary, our environment is an intermediate between the private and common value models, where signals are affiliated. This setting can be best described as an *interdependent values* environment with affiliated signals (Krishna, 2010b).

kind of auction can be equally referred to as a multi-unit second-price auction, since all winning bidders pay the lowest winning bid. One key feature of both these formats is that bidders are not allowed to bid for more than one unit, although there are two identical licenses for sale. The third mechanism, which we call BDM auction adds to the latter a randomly drawn price that winning bidders must exceed to win the license. Section 2.2 further describes the mechanisms used in the experiment.

[2] Through this information treatment, licenses are either assigned to real villages, allowing bidders to use their ex-ante beliefs about those locations, or to hypothetical villages, preventing bidders from using their ex-ante beliefs.

[3] This setting provides insights into asymmetric auctions (Maskin and Riley, 2000, Hendricks and Porter, 1988) where we assume that the buyers' preference parameters are not drawn from a symmetric joint probability distribution. In particular, we study a situation where the auctioneer discloses license information which could affect a bidder's valuation, including expected demand and where the VIF will take place.

Given this environment, the paper has three research questions and three main results. First, we investigate how different auction mechanisms affect bid levels and variance. In particular, we study if affiliated *open* English auctions, where bidders are face to face and observe their opponents' bids, influence bidding compared to affiliated *closed* Second price and BDM auctions, where bids are submitted independently. Auction theory predicts that in auctions with interdependent values, more shared information among bidders, as observed in open auctions, increases bidders' bids. This prediction, called the linkage principle (Krishna, 2010a), states that an auction mechanism will generate higher expected revenues when each bidder's signals (information and ex-ante beliefs) are more observable and better reflected in their bids.[4]

Our results show a lower bidding distribution in open auctions, and consequently lower revenues with respect to closed auctions (as in Athey et al., 2011, Koh et al., 2007). We interpret this empirical pattern as evidence against the linkage principle. The magnitude of our estimates is substantial, and varies from 34 to 75 percent lower mean bids when comparing open auctions to closed auctions. Given the uncertainty about the returns to a VIF license, lower bids in open auctions could be explained by herding behavior where bidders emulate the actions of other bidders they can observe, rather than relying on their own information or judgment (Pons-Novell, 2003, Devenow and Welch, 1996). Bidders' decisions could be negatively influenced by second-order beliefs about peers bidding strategy encouraging bidders to be more cautious about uncertainty, driving bids downwards. In open auctions, bidders who abandon the auction influence remaining bidders, leading to less bidding, lower mean bids and bid variance in comparison to a closed auction. Conversely, higher bids in closed auctions which we observe could be explained by overbidding, a behavior that is more likely to occur when bidders perceive their rivals as having similar values, in line with either the loss aversion or the 'joy of winning' hypotheses (Georganas et al., 2017, Delgado et al., 2008). The experimental results provides evidence consistent with the above mechanisms: open auctions drive down bids level, while closed auctions generate higher bidding. Although closed auctions may yield higher bids, we conclude that these bids are likely overestimates of true WTP based on our real stakes auction results.

The second result provides insights on the value of market information on bidders' willingness to pay for VIF licenses. We study how agents' bidding strategy change when

[4] A standard interpretation of the linkage principle is that bidders may view higher bids as revealing competitive advantages of competitors or a signal of better information on market returns. A quantitative analysis of the linkage principle can be found in Offerman et al., 2022.

they can use their ex-ante beliefs. In a round of auctions, the experiment provides pre-bid information about the potential returns of the license for *hypothetical* locations where the VIF would take place, such that bidders get only this reported information on market demand and ex-ante beliefs about real villages are uninformative. Then, in another sequence of auctions, the experiment introduces reported information about the potential returns of licenses in *real* locations surrounding the bidders' usual area of operation. In this case, bidders' ex-ante beliefs about the location where the fair will take place are potentially informative. The results show that the average bid level is lower when bidders know the actual locations of the fair. Moreover, the data indicates that bids converge and exhibit a variance that is 2 to 3.5 times lower than that observed with hypothetical locations. In sum, we provide evidence that input dealers ex-ante beliefs lowers bid mean and variance. In the context of scaling innovations in low income countries, auction results using hypothetical pre-bid information may not be useful in gauging market potential, even if low-cost.

These first two experimental results demonstrate that, in a setting characterized by interdependent values and uncertainty, when bidders lack knowledge about their competitors' strategies and cannot use ex-ante beliefs about the license characteristics, the auction generates relatively higher variance in bidding and higher average bids, than when more information is available. The predictions of auction theory are only partially consistent with these results which generally assumes more certainty in market signals than actually seem to exist in low-income contexts with higher risk. One mechanism at play is the limited knowledge about competitors' signals and the characteristics of the license which impedes bidders' to form their valuation. This incapacity to make an accurate valuation of the license for sale could lead to a more homogeneous bidding population and heightened competition (Ganuza and Penalva, 2010, Ganuza, 2004). When information to bidders is experimentally increased, either through observation of competitors (in an open auction) or through ex-ante beliefs (based on the real location), we observe a convergence of bids. Although this convergence may ultimately result in a relative reduction in demand, it also suggests that information helps to mitigate market uncertainty, leading bidders to make valuations that more closely reflect actual WTP.

In the third and last part of the experiment, we test how real-stakes (actual bidding for real licenses) influence bidding behavior in our Second price auction, where we compare non-incentivized bids with real-stakes bids. We find that when bids are incentivized in a real-stakes auction, mean bids range between 2.45 to 4.92 times lower than non-incentivized bids — a result that is in line with previous evidence (see for example List and Shogren, 1998). The real-stakes bids are positive, with more than 90 percent of the auctions resulting in the sale of the license. This evidence substantiates the conclusion that VIF licensing is regarded as profitable for input dealers and that the auction design is clear to the bidders.

We make three main contributions to the literature. Pricing innovations is challenging in general and specifically in our low-income country context where investors may be more risk averse and liquidity constrained. We show there are substantial trade-offs in the valuation of VIF licenses depending on the auction mechanism and the pre-bid information provided to bidders. To elicit preferences of private suppliers, open auction mechanisms and the use of real information about the object for sale may be crucial to help bidders form more accurate valuations—although this may ultimately lead to lower WTP. As more emphasis on scaling tested innovations leads to increased investment (Kremer et al., 2021), auction design trade-offs are essential for researchers and policymakers when assessing the willingness to pay for innovations.

Second, on auction mechanisms, our findings show bidding behavior inconsistent with the Vickrey's revenue equivalence theorem, which states that open auctions and closed sealed-bid auctions yield similar equilibrium outcomes (Bergemann et al., 2019, Vickrey, 1961). We largely attribute deviations from revenue equivalence in our results to signal aggregation in open auctions, where bidders bid together. When bidders' preferences are heterogeneous and differentially affected by the acquisition of auction signals, risk averse bidders (rather than risk neutral bidders assumed in Vickrey's model) may no longer have independent values (Maskin and Riley, 2000). Interdependent valuations have direct implications for pricing innovations when the returns to the product are uncertain. Our results suggests that supply side actors willingness to pay was strongly influenced when open auctions permitted the observability of peer valuations. Standard auction theory predicts that the open auction could discourage bidding as a response to the potential Winner's curse. However, the mechanism we describe operates differently. Our experimental design allows us to disentangle strategic bidding motives, as empirically we observe bids change in response to the observability of peer decisions in open auctions, rather than private information asymmetries found in closed auctions.

Third, with regard to the extent of information disclosure, our findings indicate that increasing the provision of market information to bidders is not a sufficient condition to increase bidders' bids (Eső and Szentes, 2007, Milgrom and Weber, 1982). Despite the theoretical prediction, we find that simply providing more market information to bidders does not necessarily raise their bids. This result aligns with other empirical and experimental studies including Cason et al., 2011 and Dufwenberg and Gneezy, 2002. Overall, our results suggest that preventing ag input dealers to use their ex-ante beliefs, e.g., providing hypothetical market information, could potentially increase competition among bidders ultimately raising bids. While this conclusion seems to corroborate the model of Ganuza and Penalva, 2010—that incomplete information promotes competition—and the one of Bergemann et al., 2022—that scarce information minimize informational rent[5]—our interpretation differs.

Specifically, we observe that the higher WTP resulting from the impossibility to use privately owned information (the ex-ante beliefs) is associated with greater dispersion. Thus, the higher bid levels arise from not being able to correctly form valuations. In our interdependent auctions setting, increased information reduces both bid levels and bid variance, suggesting that bidders' valuations are converging toward their actual WTP for the innovation, e.g., the price that they are actually ready to pay in the real-world. This has important implications for innovation price discovery. When initial prices are elicited with experimental auctions that withhold or distort some key information about the innovation, high estimates of WTP may result even when real-world demand is actually weak.

2 Study Design

2.1 Agricultural Input Dealers in Mali

Fertilizer use is low in Mali, despite its potential agronomic and economic returns. On average, only 35 percent of farmers use agricultural inputs such as chemical fertilizers in Mali (ISTAT, 2019). A large body of literature (see Suri and Udry, 2022, for a summary) analyzes the impact of various constraints on agricultural technology adoption, but one consistent constraint farmers face is market access. For example, 70 percent of the farmers

[5] Bergemann et al., 2022 provide a theoretical model demonstrating that higher bidding is possible when market information is scarce on an uncertain object for sale. If the seller restricts the information available to each bidder regarding their own value, such as by preventing the use of ex-ante beliefs about their own valuations, bidders may be less inclined to make strategic bids and may find it harder to maximize information rent, defined as the difference between their bid and their valuation.

interviewed in our study area reported that input dealers had never visited their village in the previous farming season. Input dealers are reluctant to enter new markets because of high transportation costs and demand uncertainty. With sparse markets and low population density, input dealers face barriers to aggregating demand and reaching markets large enough to break even.

We offer input dealers the opportunity to buy a license to participate in VIFs. The village input fair provides a 'bundled' solution to creating agricultural input markets. VIFs give farmers the opportunity to order inputs in the post-harvest period for delivery in the planting season and potentially gain access to credit. VIFs provide a comprehensive agricultural input market for farmers (seed, fertilizer and other phyto-sanitary products) in their village, verified by a third party, and assured delivery before planting. Input dealers can be licensed to access these new markets, increasing their potential profits.

Agricultural input dealers represent the 'last mile' in the supply chain that delivers inputs directly to West African farmers. However, bottlenecks in input supply have limited the provision of products like improved seeds and fertilizer at the rates needed to increase farmers agricultural productivity (Asante et al., 2021). Although their role is more and more recognized (Dar et al., 2024, Dillon et al., 2025, Naugler et al., 2025), there is relatively little information on the characteristics of input dealers and the constraints faced in their operations.

The bidders in our experiment are private sector input dealers sampled from the population of input dealers in the Sikasso and Bougouni regions of Mali. These agricultural firms are dominated by men. 35 percent of them are wholesalers, while the rest are downstream retailers. At baseline, these entrepreneurs serve a median of 5.5 villages, with a standard deviation of 7.8, and have been in business for an average of 10 years. There are variations in the type of inputs sold by input dealers. Among chemical fertilizers, urea is the most commonly supplied, followed by DAP and NPK. Only 15 percent of the sample supplies industrially packaged organic fertilizers. Among crop protection products, herbicides are the most popular, offered by more than 80 percent of input dealers. Only one-third provides seeds. More than half do not offer any services to farmers, although 25 percent report buying outputs, mostly cereals, from farmers. Average monthly turnover is estimated to be XOF 571,608 (USD 934), with a standard deviation twice as high. However, input dealers often have other sources of income, as 35 percent of them operate only during the agricultural season. The majority are also engaged in agriculture, followed by other private businesses. Many of these entrepreneurs own a means of transportation but do not employ permanent staff, with a mean statistic of 0.62 employees per firm. Less than 50 percent of them have ever taken out a business loan, either formally or informally. Despite operating in rural areas, more than 60 percent of these firms own at least one smartphone, computer ownership barely exceeds 15 percent. Additional descriptive statistics of input dealers that participated in the experiment are summarized in Appendix A.

2.2 Experimental Design

Figure 1 describes the study protocol which is divided in three rounds of auctions differing by: the auction mechanism, the information provided, and the pricing rule. Round 1 consisted of 18 auctions, each for two licenses to be exploited in a different VIF. Round 1 was held during four days in April 2022, and a total of 53 input dealers attended the event and bid on 18 auctions. The following round also consisted of 18 auctions. Round 2 was administered for three days in January 2023, and a total of 57 input dealers attended the event and bid on 18 auctions. While the first two rounds are conducted as lab-in-the-field experiments with non-incentivized bids, Round 3 consists of real-stake auctions. A total of 75 auctions were held in 5 different locations in four days in February 2023. Depending on the location, 5 to 18 input dealers attended the event and bid on 11 to 25 auctions. In total, 95 input dealers participated in the study. On average, two-thirds of the input dealers participated in multiple rounds of the experiment, while others participated in only one round.

During Rounds 1 and 2, a total of 16 to 20 input dealers are invited each day. Each bidder participates in 6 auctions per auction mechanism (Second price, BDM or English auction). On each experimental day, dealers are randomly divided into two groups who play auctions at the same time in Room A and Room B. In practice, the two groups bid for the same license simultaneously, but in separate rooms. These groups are re-matched every three auctions for a total of six re-matchings. Re-matching ensures that bidders do not compete with the same agents eighteen times, which could distort the experiment by introducing quasi-collusive behavior or other biases (Hu et al., 2011).[6]

[6]It should be noted that our lab in the field experiment have the characteristic of sequential auctions, in which several items are sold one after the other to the same group of potential buyers (Corrigan and Rousu, 2006). Sequential auctions are different from multiple independent auctions (Engelbrecht-Wiggans and Weber, 1983), because the sequential nature of these auctions facilitate information transfer (Corazzini et al., 2019) and information spillover from one auction to another. Information transfer in these sequential auctions could affect bidder participation and strategies (Jeitschko, 1998). The checks reported in Appendix

In advance of the auction, the auctioneer provides a *village demand report* to bidders. We conduct interviews with farmers in the study area asking farmers' input demand before the start of the agricultural season. This information is included in the village demand report that the auctioneer passes to the bidders minutes before their participation in each auction. The report provides demand information and village characteristics which may influence potential revenue or cost for the license to be auctioned. See Appendix C for examples of the village demand reports. The higher the expected demand for inputs from farmers in a village demand report, the higher the expected profitability of the business opportunity offered to the bidder. Conversely, the more difficult it is to access a location, the higher the delivery costs and the lower the expected profitability of the license. Bidders are assumed to have a valuation for the license that is increasing on the information provided by the auctioneer, but also increasing on the probability that this information actually reflects the future state of the world.

Between the first and second rounds of auctions, the information included in the village demand report changes from hypothetical to real information. This information treatment works as follow: in Round 1, bidders have access to the village demand report information about hypothetical locations, receiving only the signal included in the reported information provided by the auctioneer. Prior beliefs about the location are not relevant as bidders only have the village demand report information to form expectations about VIF profitability. In Round 2, information is associated with real locations in the study area where the input dealers usually operate, so that bidders can combine the demand information provided in the village demand report with their knowledge and ex-ante beliefs about the profitability of the location. While the locations in Round 1 are purely hypothetical, the locations indicated in the village demand report in Round 2 are drawn from the study area where input dealers usually operate.

Between Rounds 2 and 3, the village demand report information is provided in the same manner to input dealers (allowing input dealers's bids to be informed by their ex-ante beliefs), but the pricing rule of the mechanism vary, moving from non-incentivized bids to real-stakes bids. The winners of Round 3 auctions pay their bids and are invited to take advantage of the business opportunity. The auctioneer sets up the VIF that will be hosted by the licensees.

To ensure comparability between the auction mechanisms in Rounds 1 and 2, we en-

B1 reject the hypothesis that auction sequencing may generate bias in our estimates.

sure that the pre-bid demand information transmitted to the bidders, through the village demand reports, is balanced between the three mechanisms. Village demand information varies, so that input dealers do not bid on the villages with exactly the same demand characteristics. Between rounds, we do ensure that levels of market demand are statistically equivalent across the villages that are proposed for auction. Appendix D, Panel A, shows that the three sets of six village demand reports are statistically equivalent.

An example further illustrates the design. Suppose that on the day of the experiment, 20 dealers are called to bid in 18 different auctions. They are randomly divided into two groups of 10 who enter Room A and Room B, respectively. In each of the rooms, bidders play three auctions, say auctions 1, 2, and 3. They are then re-matched and join Room A or Room B again to play auctions 4, 5, and 6. At this stage, the mechanism is changed, for example, from the English auction to the Second price. After a new re-match, bidders join the rooms to bid on auctions 7, 8, and 9, and then re-matched again to play auctions 10, 11, and 12. Finally, the mechanism switches again, this time from Second price to BDM. After a re-match, bidders enter the rooms and play auctions 13, 14, and 15, just before the last re-match, which brings them to the final auctions, 16, 17, and 18. Appendix B2 describes the order of the auctions on each experimental day, while Appendix E reports the experimental scripts. At the end of each day, we compensate bidders for their participation with a lump sum transfer uncorrelated with their bidding behavior set approximately to a daily wage.[7]

2.3 Auction Mechanisms

The lab-in-the-field experiment uses three auction mechanisms: the English auction, the Second price auction, and the Becker-DeGroot-Marschak, or BDM, auction. Bidders possess only partial information about the value of the license, that is, a noisy signal. Information held by other bidders, if shared, could modify the perceived value of the object (Krishna, 2010b, Milgrom and Weber, 1982). The environment in which our experimental auctions are conducted is characterized by interdependent bidders' values and affiliated signals.

In each auction, 8 to 10 bidders are randomly assigned to a room to bid on a license to sell inputs during a VIF in a specific village. The auctioneer sells licenses for several

[7] Note that the experimental design did not include any pay-out in Round 1 and 2, where bidding was non-incentivized. In Round 3, auctions are with real-stakes and bidders bid on real licenses. However, at no point in the three rounds cash pay-outs were given out by the auctioneer.

locations where VIFs will take place. Rather than having a single multi-location auction, the experiment is set up as a series of separate auctions — one auction for each VIF. These auctions are conducted sequentially and independently, such that the bids in one auction are not directly associated to the outcome of another. Bidders can bid for only one unit in each auction. However, since each VIF allows for two input dealers, each auction assigns two licenses so that each auction has two distinct winners. To summarize, the three auction mechanisms are rolled out sequentially as two-unit auctions, with each bidder allowed to bid for only one unit.

The English auction is played as a clock-auction. With this mechanism, the auctioneer raises the price at intervals and bidders see their competitors leave the auction signaling that the price has reached the maximum for them. This is an *open* mechanism with ascending prices. Bidders observe each other's price as they bid. The last two bidders who remain after the other bidders have dropped out are declared the winners.[8] Both winners pay a uniform price equal to the last price that they accepted, which is also the price of the last exit. Although this setting is similar to a classic uniform-price auctions given that both winners pay the same price and obtain an identical license (Krishna, 2010c), we emphasize that, in our context, bidders cannot bid for multiple units. As a result, the standard properties of uniform-price auctions do not hold.

In Second price and BDM auctions, bidders simultaneously submit sealed-bids to the auctioneer. Bidders are not aware of the amount bid by other bidders. In our Second price auction, the two highest bidders are awarded a license each, and both pay the second highest price. Here again, two identical licenses are offered, and bidders can only bid for one unit. Bidders know that they will pay a uniform price and that the second-ranked bidder will be paying the submitted bid. Although this rule reduces the incentive compatibility usually associated with Second price mechanisms, we decided to employ it because it is more closely comparable with the rule employed in our English auctions, and it is aligned with the design of real-world VIF auctions.

In the BDM auction, the procedure is similar to the one in the Second price mechanism, but bidders are informed that their sealed bid will be compared not only with the bids of their competitors, but also with a price drawn from an urn, which is also the clearing price that both winners pay. The BDM mechanism is designed to elicit truthful valuations by

[8] If the third and second highest bidders both decide to withdraw from the auction at the same time, the only remaining bidder will be declared the winner; the two withdrawing bidders will then compete for second place following the same procedure but with smaller price intervals.

introducing a random price, which helps us measure bidders' WTP in environments with incomplete information. Both Second price and BDM mechanisms are *closed* mechanisms, since bidders bid secretly. Usually, these mechanisms are incentive-compatible under private value settings (Vickrey, 1961, Becker et al., 1964). Here, they cannot be regarded as fully incentive-compatible, given the nature of our environment with interdependent values and affiliated signals (Milgrom and Weber, 1982).

2.4 Village Input Fair Profitability

The business opportunity offered to bidders at auction is a Village Input Fair (VIF) license, where input dealers are licensed to sell their products to customers at the village fair. As describe above, two licenses are sold per village so that input dealers know that they will have to share the available demand in each village with another dealer. In the VIF, input dealers accept advance orders for agricultural inputs to be delivered during the planting season, according to terms stipulated in a forward contract. At the time of the auction, the profitability of each VIF is unknown to the dealers, and they hold noisy information about it. Profitability depends largely on expectations about farmers' demand, which in our model depends on both the pre-bid information contained in the village demand report and the ex-ante beliefs of the input dealer. It also depends on the specific business structure and marketing strategy of each input dealer.

Empirical work conducted in the study area has shown that participating dealers generate market revenues that far exceed the investment made in purchasing the license. Dillon and Tomaselli, 2025 estimate that farmers in VIF treatment groups increased demand by XOF 50,780 (USD 96.84) compared to farmers in control villages. We estimate the average revenue per VIF per input dealer to be XOF 577,144 (USD 1,100.7). These calculations provide suggestive evidence that this innovation can significantly increase input suppliers' profits, although the returns are uncertain when dealers bid. We conclude that, in the absence of VIFs, input dealers are foregoing potential returns in rural markets.[9]

[9] If potential returns are available in rural areas, it is questionable why input dealers are not building these markets independently. Two reasons can explain this puzzle. Either coordination costs are excessive or private input dealers underestimate potential market returns. The paper argues that auctioned licenses serve to inform bidders that they have the potential to exploit the contractual framework of the fair and demand aggregation, thereby prompting them to revise their estimates to reflect more profitable potential returns on rural markets.

3 Theoretical Framework

We introduce a Bayesian model of bidder behavior to motivate empirical predictions from our study design. The following model yields four hypotheses that we use to test the first two research questions of the paper. The third research question, on non-incentivized vs. real-stakes bids, is not derived from this theoretical model.

3.1 A Model of Bidder Behavior

Consider a seller who wants to auction an indivisible license whose value is not known in advance. We define the number of bidders as fixed and denote this number by B. The valuation of the license by bidder $b \in (1, ..., B)$ is given by a function with real values $v_b = V_b(\theta, \beta)$ which is assumed to be increasing, continuous and symmetric.

The argument $\theta = (\theta_1, ..., \theta_B)$ represents the vector of the signals of each individual bidder participating in the auction. This is their noisy estimate of the value of the license, considering both the returns that can be extracted from that license and the cost to exploit it. Consequently, θ may be influenced by factors such as the agent's perception of the market returns associated with the license and its idiosyncratic characteristics, such as the community network in which the VIF is located or prior experience in the industry.

The argument $\beta = (\beta_1, ..., \beta_C)$ is the vector of the possible state of the world that influence all bidders, such as the international price of raw materials, or forecast demand from farmer surveys. In our experiment, the pre-bid information provided in the village demand reports constitute such a forecast about the state of the world that the auctioneer provide to the input dealers. Our informational setup is such that each bidder derives a privately observed θ_b signal, as well as a signal β that correspond somewhat to the common information on the license for sale.[10] Bidders value are assumed to be interdependent and signals affiliated. If a bidder collects more favorable information about the returns of the license for a certain location, this means that this higher signal makes it more likely that the license actually has a higher value, but also that other bidders have higher signals for that same license.

Formally, Milgrom and Weber, 1982, define the random variables $Z = \{\beta, \theta_1, \dots, \theta_B\}$ where β denotes the common valuation of the state of the world and θ_n the signals of the bidders. These variables are affiliated if the joint probability density function, or PDF,

[10] Regardless of whether this information is known only to the seller or also to the bidders, an important hypothesis is that the vectors of signals θ and states of the world β enter each bidder's valuation function V_b in a non-decreasing way, such that any higher signal raises each bidder's payoff.

$f(z)$, is such that

$$\text{Definition: } \forall z, z^{'} \Rightarrow f(z \vee z^{'})f(z \wedge z^{'}) \geq f(z)f(z^{'})$$

where $(z \vee z^{'})$ is the upper least bound and $(z \wedge z^{'})$ the lower greatest bound of the joint distributions. Affiliation implies that the probability of $z, z^{'}$ of being both in the same level, e.g., high-high or low-low, is higher than being of opposite levels, e.g., high-low and low-high.

To see this, consider an example where there are only two bidders $b \in (1, 2)$ with signals θ_1 and θ_2 which may have two possible levels, $High$ and Low, denoted as H and L. We thus know that for each state of the world $\theta_1^H \geq \theta_1^L$ and $\theta_2^H \geq \theta_2^L$. Designating f as the joint PDF of these two signals, affiliation implies that

$$\text{Definition: } f(\theta_1^H, \theta_2^H)f(\theta_1^L, \theta_2^L) \geq f(\theta_1^H, \theta_2^L)f(\theta_1^L, \theta_2^H).$$

which shows that affiliation implies that the joint probability of bidders' signals being at the same level is higher than that of opposite levels.

This model establishes two predictions. First, with affiliation *open* auctions should generate higher bids than *closed* auctions because bidders signals are more observable.[11] Second, an auctioneer can expect higher bids by providing any relevant information about the value of the object for sale.[12] In our experiment, we introduce two treatments consistent with these predictions. First, we vary the auction mechanism used, comparing open and closed formats. Second, we provide village demand reports, which either allows bidders to use their ex-ante beliefs (when real village information is provided) or not (when hypothetical information is provided to bidders).

3.2 Hypotheses

By interacting the two treatments, we obtain four experimental conditions, leading to four hypothesis. Table 1 summarizes the treatments, the four hypotheses and their theoretical predictions. We also provide descriptive bidding statistics to preview the experimental results.[13]

[11] This result has been tested empirically with mixed results, for example by Athey et al., 2011, on the case of timber auctions.

[12] The effect of information release has been tested experimentally in a lab experiment (Kagel and Levin, 1986), and empirically in wholesale automobile auctions (Tadelis and Zettelmeyer, 2015).

[13] To remind, the interaction of the two treatments enables us to address the first two research questions of the paper. The third research question is empirical and is not covered by the hypotheses presented in this section.

Hypothesis 1: If bidders cannot observe each other bidding during the auction, and can only assess the license for sale using the reported information in the village demand report, then the distribution of bidders' signals in vector $\theta = (\theta_1, ..., \theta_B)$ has high variance, and the state of the world valuation β is weakly informed because it does not take into account the ex-ante beliefs of bidders. The effect of this setting is to reduce the demand of bidders.

Hypothesis 2: If bidders cannot observe each other bidding during the auction, but they can evaluate the license for sale using information coming from real locations for which they have ex-ante beliefs, then the distribution of bidders' signals in vector $\theta = (\theta_1, ..., \theta_B)$ has high variance, and the state of the world valuation β is strongly informed because it takes into account bidders' ex-ante beliefs. The effect of this setting on bidders' demand is ambiguous.

Hypothesis 3: If bidders can observe each other bidding during the auction, but can only assess the license for sale using the reported information in the village demand report, then the distribution of bidders' signals in vector $\theta = (\theta_1, ..., \theta_B)$ has low variance, and the state of the world β is weakly informed because it does not take into account the ex-ante beliefs of bidders. The effect of this setting on bidders' demand is ambiguous.

Hypothesis 4: If bidders can observe each other bidding during the auction, and they can evaluate the license for sale using information coming from real locations for which they have ex-ante beliefs, then the distribution of bidders' signals in vector $\theta = (\theta_1, ..., \theta_B)$ has low variance, and the state of the world β is strongly informed because it takes into account the ex-ante beliefs of bidders. The effect of this setting is to increase the demand of bidders.

4 Econometric strategy

Our primary specification is a reduced form bidding function. By design, auction mechanisms and information about the rural market are orthogonal to each other and to bidder observable and unobservable characteristics. Bids are a proxy for input dealers' WTP for VIF licenses, which is our dependent variable. Note that although two identical licenses are sold in each auction, bidders can only bid for one unit, thus we consider each bidder's WTP for a single license, not both. We use the last price bid by bidders in each auction, even when they do not win the auction. As explanatory variable, we first include the vector of the three auction mechanisms — English, Second Price and BDM. We then estimate models that include fixed effects for each input dealer participating in the experiment and perform the same analysis for licenses auctioned with information from hypothetical locations (Round 1) and for those with information from real locations (Round 2). We do not pool data between Rounds 1 and 2 because we have sufficient statistical power and because we are particularly interested in the relative performance of mechanisms *within* each auction round. In sum, the auction analysis examines how non-incentivized WTP is influenced by auction mechanisms and the use of ex-ante beliefs.

In specification 1, bid y for input dealer a and for license u represents the dependent variable; the mechanism M is the explanatory variable, followed by controls and the error term. We control for the demand forecast included in the pre-bid information in the village demand reports and for the socio-demographic characteristics of bidders.

$$y_{au} = \alpha + \sum_{k=1}^{3} \beta M_{ku} + controls + \epsilon_{au} \tag{1}$$

Since the Second price mechanism is the only mechanism used in Round 3, we only use the data from the Second price auctions in the following specification. We can compare Second price auction data *between* rounds by pooling these data sets and generate an indicator variable for when auctions are real-stakes (Round 3).

$$y_{au} = \alpha + \sum_{z=1}^{2} \beta R_{zu} + controls + \epsilon_{au} \tag{2}$$

In specification 2, we estimate the effect of non-incentivized and real-stakes bidding. In this case, we have only one auction mechanism and the same information setting. The explanatory variable is the binary treatment describing the pricing rule, here represented by the vector R.

Our main specifications use 811 and 831 observations for the Round 1 and Round 2, respectively, after isolating outliers and zero bids. The percentage of zero bids, depending on the round and the mechanism used, ranges from 0.3 to 22 percent. Our preferred specification uses a censored sample that excludes zero bids. In Appendix B3 and B4, we re-estimate the same specifications using OLS and Tobit with the full sample including zeros. The results are robust to these checks.

5 Results

5.1 Demand Curves

We plot the demand curves for Round 1 and Round 2, and for each of the three auction mechanisms. Figure 2, Panel A, shows in the left quadrant the distribution function for the pooled data by round. The demand curve for Round 1, where bidders lacked access to ex-ante beliefs, lies consistently to the right of the demand curve for Round 2, where bidders had information from real locations and used ex-ante beliefs. The data suggests that, when using auctions for price discovery, using information from the real-world has a marginal negative impact on demand. In contrast, the right quadrant of Panel A shows the curves of the three auction mechanisms, regardless of the round. In this case, the English auction curve exhibits a steeper slope and has more than 50 percent of the distribution lying below the curves of the Second price and the BDM, notably for higher values. The graph illustrates how open auctions aggregate bidding towards lower values, with only less than 20 percent of the distribution exceeding XOF 20,000 (32 USD).

Figure 2, panel B, disaggregates the curves by auction mechanism for each round. The shape of the demand curves remains consistent across rounds, but the right quadrant, which represents auctions where bidders were allowed to use ex-ante beliefs, demonstrates a contraction in demand for each curve. This suggests that the negative impact on demand resulting by the use of ex-ante beliefs is not mechanism-specific.

5.2 Hypotheses Tested

5.2.1 Open vs. Closed Mechanisms

We first report the results of hypothesis testing between open and closed auction mechanisms. Auction theory and the literature on experimental auctions generally finds that the more information bidders share, the more they express high demand for the item for sale (Offerman et al., 2022). Accordingly, our third and fourth hypotheses posit that open mechanisms, where bidders share information on their bids, should result in lower variance and higher bid levels. The experiment tests these hypothesis and show that open mechanisms result in a reduction in variance compared to closed mechanisms. However, our results do not support the higher bid level prediction. We find that open auctions are associated with lower bid levels compared to closed auctions. We conclude that, on average, the open auction mechanism lowers WTP relative to closed auctions.

The descriptive statistics reported in both Table 2, columns 1-3, and Table 3, show this pattern of lower bid levels with the open mechanism. To examine the distribution of bids, Table 2 reports the results of three statistical tests. T-tests and Mann-Whitney tests confirm that the mean and median bids between open and closed auction mechanisms are not statistically equivalent. Finally, we use Levene's test to reject that the bid variance of the open and closed mechanisms are statistically equivalent. The variance in open auctions is lower than in closed auctions by 61 to 67 percent.[14] To see this graphically, we report in Figure 3, panel A, the kernel density of bids. The distribution for the English open auction is steeper, multi-modal, and skewed toward lower values. The regression estimates confirm that open English auctions, where bidders share more information with their peers, have lower mean bid estimates relative to closed auctions of about 61 and 38 percent, respectively, as shown in Table 4, column 1. The magnitude of the coefficients remains consistent regardless of the control variables included, as shown in columns 2 and 3.

We interpret this pattern as if, with open auctions, bidders learn from the decisions of their peers in real time. First, these results support the idea that when competitors drop out, those remaining in the auction may perceive a decrease in competition and therefore simply reduce their bids. However, this interpretation assumes that the bidder would give up any chance of winning the auction. One could argue that seeing competitors leave might actually convince the bidder to remain in the auction with fewer competitors to increase their winning probability. Second, we consider that competitors' exit may strongly cast doubt on the expected market value of the license for sale. The exit of others from the auction signal that competitors are in possession of private information with respect to the poor profitability of the business opportunity, and thus provide a signal to the remaining bidders to lower their values. Given the uncertainty about the license returns, lower bids in open auctions could be explained by this *herding* behavior where bidders imitate or emulate the actions of other bidders they can observe, rather than relying on their own information or judgment (Pons-Novell, 2003, Devenow and Welch, 1996).

The empirical literature on experimental auctions is in part consistent with our results. Koh et al., 2007, show a similar pattern in auctions for vehicle quota licenses in Singapore. Their survey provides support for the view that an open mechanism is advantageous for car buyers, as each car buyer lowers on average about 7.5 percent of the price for

[14] Appendix F presents the OLS regression to confirm that the difference in variance is statistically significant.

a vehicle license, compared to the alternative method of closed auctions. In an open auction system, bidders exhibit lower bidding strategies compared to closed auctions, due to the increased transparency and reduced uncertainty about other bidders' signals. In a partially incentivized lab experiment with college students, Kagel et al., 1987, find higher bids with a Second price auction and an inferior, strategy proof distribution with open English auction. They attribute this deviation from revenue equivalency not to the low-end bidding in open auctions, but to the fact that closed Second price auctions induce *overbidding* among certain bidders. They associate overbidding with behavioral errors that bidders make when using the mechanism. Some bidders may be tempted to be overly optimistic in light of the fact that they would only be paying the second highest price. The result of overbidding in the Second price auction compared to the open English format has been replicated in other contexts and also with the private values format (Cooper and Fang, 2008). Gagnon-Bartsch et al., 2021 find that the tendency to overestimate the similarity of others' tastes to one's own influences bidding. Their analysis proposes that *taste projection* may cause bidders to exaggerate the competitiveness of others' bids, especially when they are unobservable, which in turn would lead them to bid above optimal levels.

Our experimental results provide evidence that open auctions lower bid levels, probably due to greater observability of peer bidding, which may favor caution or herding effects. In contrast, closed auctions seem to encourage higher bidding. Although closed auctions may appear to generate higher bids, our analysis suggests that these high bids often do not accurately reflect underlying WTP in comparison to real auction results. This misalignment has important implications in contexts where auctions serve as a pricing discovery instrument, particularly for innovative or new interventions where ex ante pricing is key. We conclude that the adoption of open auction mechanisms is preferable, particularly when the economic environment is characterized by bidders with interdependent common values. Open formats encourage more thoughtful and market-aligned bids under uncertainty.

5.2.2 Pre-bid Information and Ex-ante Beliefs

Each input dealer WTP may be predicated on pre-bid information about the characteristics of the license for sale. The second and fourth hypotheses presented in Table 1 posit that the incorporation of input dealers' ex-ante beliefs may result in a reduction in the variance of the bid distribution.[15]

To test the hypothesis that ex-ante beliefs influence bidders' valuations, we need to compare the results of the auctions from Round 1 and Round 2. Both Table 2 and Table 3 report descriptive statistics showing that when bidders lack information from their ex-ante beliefs, as in Round 1, the variance of the bids ranges between XOF 109,131 and XOF 328,642, while the same value in Round 2, with ex-ante beliefs, drops to a range between XOF 51,592 and XOF 138,623. In Round 2, the variance is between 53 and 57 percent less than in Round 1. Table 3 confirms these differences are statistically significant. We conclude that, regardless of the auction mechanism used, village demand reports with information from real villages have the effect of reducing the dispersion of bids. This result confirms the model's prediction that the introduction of ex-ante beliefs leads to the convergence of bids.

Our initial hypothesis is that the bid level should also increase when ex-ante beliefs are included in the bid equation. However, our results show, on average, a decrease in the mean bid level when bidders are allowed to use their knowledge and location-specific beliefs. The t-tests on the right quadrant of Table 3 do not reject that the difference in means is non-zero, showing that bid levels diminish instead of increase.

A plausible interpretation of this pattern is that the information reported in Round 2 from real locations is common knowledge to bidders, thus less salient to them. Bidders are relatively well informed about the expected profitability of villages in their area, for which they already have accurate beliefs about market returns. These ex-ante beliefs serve as signals, which tend to anchor valuations and reduce variability in bidding. Conversely, during Round 1 when village demand reports are the sole source of information, i.e., the only signal, bidders are more homogeneous in their uncertainty about market returns. This incomplete information, according to the predictions of Ganuza and Penalva, 2010, would tend to increase competition and generate higher average expectations which in turn result in higher monetary bids.

Empirical work similarly concludes that providing incomplete or partial information to bidders may end up increasing bid levels and dispersion. Dufwenberg and Gneezy, 2002 vary whether bidders are told others' bids and find that greater transparency does not always raise bidders' bids. Cason et al., 2011 examine sequential procurement auctions in

[15] To fix ideas, the auctions compatible with hypothesis 2 and 4 introduce village demand reports with demand forecasting from real locations where VIFs will be held, thus allowing bidders to use their ex-ante beliefs.

which they vary whether all bids or only winning bids are revealed, showing that limited information yields more aggressive bidding. All of these findings suggest that bids increase when limited information is available to bidders.

Our interpretation of the experimental results on the reduction in both bid variance and bid levels due to ex-ante beliefs, differs from the classic explanations drawn from the theoretical auction models. Our data show that when bidders use ex-ante beliefs, their bids converge and we conclude that reduced variance indicates bids that more accurately reflect the real-world WTP of input dealers. In this context, auctions serve their intended function as price discovery mechanisms: revealing the values that economic agents attach to goods under market conditions. Our data are not consistent with the idea that higher bid levels observed in Round 1 are driven by heightened competition. Instead, we conclude that, unable to use ex-ante beliefs, bidders are less informed and simply make bids toward the upper end of their distribution. In contrast, Round 2 bids are lower because bidders, now able to draw on prior information, make more informed and thus more accurate valuations that align with actual WTP.

5.3 Determinants of WTP

Table 4, columns 2 and 5, presents the results of our WTP estimates, with granular pre-bid information. We include tercile fixed effects indicating different expected license profitability levels. The results in column 2 show that, when lacking ex-ante beliefs, bidders' demand is elastic to the forecast included in the village demand reports. For decreases in expected license profitability from the top to the medium or low tier, ranging from 0.50 to 0.66 standard deviations, the experiment finds a statistically significant decrease in average bids, ranging from 0.05 to 0.98 standard deviations. We conclude that bids are correlated with pre-bid information in the absence of ex-ante beliefs, i.e, in Round 1. By allowing bidders to use their ex-ante beliefs, in Round 2 we get a similar result although less precisely estimated.[16]

We also present estimation results controlling for the granular pre-bid information provided to bidders. Table 4, columns 3 and 6, shows the coefficients of controls such as village population, forecast demand expressed by potential customers, and distance to the tarmac road, which is a proxy for the input dealers difficulty of accessing new markets.

[16]This may seem counter-intuitive if we assume that input dealers can use ex-ante beliefs when real locations are communicated in Round 2. However, if ex-ante information held by dealers about the real villages is correlated with the information included in the village demand reports, we would expect WTP to decrease as profitability decreases.

While these controls have the expected signs and are statistically significant in Round 1 with hypothetical locations, they lose their significance in Round 2 when village demand reports include information from real villages.

Finally, in Table 5, we exploit the observable characteristics of the input dealers that we collected on each day of the experiment. Here we introduce two discrete variables. *Anybid* indicates whether a bidder bid any positive value during the auction, otherwise indicating a zero bid during the auction.[17] *Winner* simply describe if the bidder wins the license. Table 5, columns 1 and 4, indicate that wholesalers and firms with a greater number of employees are more likely to submit a zero bid, but are also more likely to be the winning bidder when they do submit a bid. One interpretation consistent with this result is that some firms may have a selective bidding strategy, focusing only on those licenses that are considered highly profitable.

5.4 Non-incentivized and real-stakes bids

In Round 3, when bids are real-stakes, average bids have a lower mean value and lower variance than non-incentivized bids in Rounds 1 and 2. The percentage of null bids largely increases, reaching 51 percent of total bids. We deduce that when bidders have to pay for the licenses, they more often decide to drop out of the auction. We observe that real-stakes are associated with a reduction in bid levels between 2.45 and 4.92 times compared to non-incentivized bids, depending on whether zero bids are considered or excluded (see descriptive statistics in Appendix G). These effect size are in line with other available experimental and empirical evidence (List and Shogren, 1998).

Table 6 reports the estimation results. This time we are not comparing between auction mechanisms. Second price auctions were exclusively administered in the final real-stakes round. We pool data from Rounds 2 and 3 and use a categorical variable to indicate the pricing rule. The results corroborate the descriptive statistics and do not vary substantially if we use bidder fixed effects or location fixed effects. Appendix H reports the coefficient estimates using the same specification that we used in Table 4, with independent samples for Rounds 2 and 3. During Round 3 with real-stakes bidding, 90 percent of the auctions still have a positive WTP and a winner. Despite the reduced level of bidding, some input dealers have submitted positive bids for the licenses, indicating that VIF auctions are viewed as profitable.

[17] The experiment does not allow disentangling which of these zero bids are true WTP, from which are censored values that could have been negative bids.

When bidders are faced with either a real-stake or a non-incentivized bid, the latter could potentially produce two opposite results. On the one hand, higher bidding may occur due to the perception that the money offered is not real. On the other hand, lower bid levels may result from a lack of motivation to engage in the dynamics of the game, given that there are no tangible stakes involved (Irwin et al., 1992). The results obtained in our lab in the field demonstrate that both the bid levels and the bid variance are higher in non-incentivized bids in comparison to real-stakes bids.

6 Conclusion

We estimate the WTP for Village Input Fair (VIF) licenses in a series of experiments where the auction mechanism and the market information may influence bidding behavior. Building on Milgrom and Weber, 1982, we show that in open auctions, higher levels of information sharing among bidders reduces bid dispersion but do not necessarily lead to higher bid levels. On average, open auctions show lower mean bid levels between 34 and 75 percent with respect to closed auctions. The results indicate that observing peer bids in an open auction mechanism decreases bids. This is because dropping bidders signal low expectations for the market returns of the auctioned license, particularly when bidders form interdependent valuations. In our case, potential bidders are uncertain about both the expected revenue of the business opportunity and their own costs to provide inputs in the rural village setting. In a low-income country context, bidders face higher information costs and are more likely to be risk averse, a deviation from Milgrom and Wilson's common values auction theory which assumes bidders are risk neutral.

The experiment also shows the behavioral responses of bidders when they rely on their ex-ante beliefs or not, i.e., when the pre-bid information is either hypothetical or real. For licenses auctioned for real villages, providing market information on expected demand does not substantially change bidder valuations for the license, suggesting that bidders hold strong ex-ante beliefs about market returns in their usual area of work. However, the use of ex-ante beliefs concentrates bids around lower values that are perceived as more reflective of actual WTP (lower variance). We conclude that integrating as much real world information on the auctioned object allows bidders to use their ex-ante beliefs. Increased information and bidders use of their ex-ante beliefs tends to reduce demand on average, but bids may be closer to the real value of the license for sale. When using auctions as a price discovery mechanism for innovations in low-income countries, hypothetical descriptions of the good or service being auctioned can lead to uninformed bidding, and ultimately to inflated WTP estimates, overstating an innovation's potential for scale.

Last, we find that real-stakes bids are on average between 2.45 to 4.92 times lower than non-incentivized bids. This effect size is in line with other experimental evidence on real-stakes and non-incentivized bids (List and Shogren, 1998). A standard interpretation of this result, is that individuals tend to make more risk-loving decisions under hypothetical conditions compared to incentivized ones (Holt and Laury, 2002).

This paper shows how auctions can support scaling market innovations in low income countries with evidence about supply side actors that can be complementary to demand-side impact evaluations. Significant evidence of impact is a necessary but not sufficient condition for scaling innovation across multiple contexts (List, 2022, Kremer et al., 2021). As many innovations are tested from a demand-side perspective, auctions provide an opportunity for innovations, particularly those scaling through the private sector, to be tested when impact evaluations may not be possible due to small sample sizes of supply side actors. The bid amounts elicited in the auctions provide a definitive reflection of the private sector supply-side WTP for exploiting the new business opportunities and the potential for private sector scaling strategies.[18] These results largely corroborate findings from the demand-side impacts estimated in Dillon and Tomaselli, 2025.

Auctions can also be integral to scaling strategy independent of their advantages for price discovery. Auctions support allocative efficiency when scaling with large groups of potential participants, a key implementation challenge as innovations are taken to scale. In subsequent work, we have used auctions to identify input dealers with the highest motivation to participate in fairs. By transparently awarding VIFs to input dealers with the highest motivation, we avoid political economy issues and increase business competition for subsequent VIF markets. Future research will focus on whether auction winners increase their profits and grow their businesses in response to expanded market access.

[18] In our first seasons of scaling VIFs, auctions generated between 50 and 60 percent of the marginal costs of implementing VIFs.

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Figures

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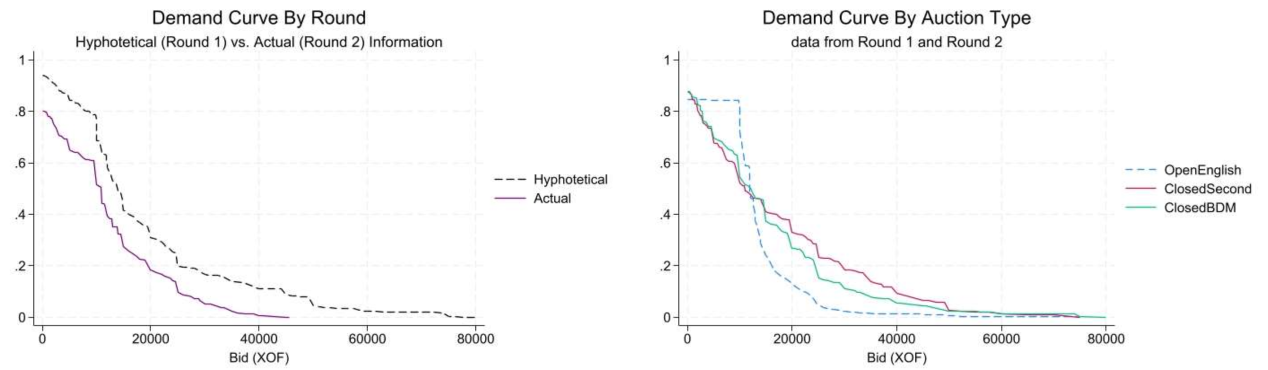
Figure 1: Lab in the Field Protocol

	Round 1	**Round 2**	**Round 3**
Pre-bid Information	Hypothetical information	Actual information (Ex-ante Beliefs)	Actual information (Ex-ante Beliefs)
Auction Mechanism	English Second price BDM	English Second price BDM	Second price
Pricing rule	Non-incentivized bids	Non-incentivized bids	Real-stakes bids

Note: Round 1 consisted of 18 auctions, each for a different village in which a Village Input Fair would be organized. Round 1 was administered in April 2022, and a total of 53 input dealers showed up for the event. Input dealers bid for the 18 auctions. Round 2 consisted of 18 auctions, each for a different village in which a Village Input Fair would be organized. Round 2 was administered in January 2023, and a total of 57 input dealers showed up for the event. Input dealers bid for the 18 auctions. Round 3 consisted of 75 auctions organized in 5 different locations. Each auction was for a different village in which a Village Input Fair would be organized. Round 3 was administered in February 2023. In the first location, 18 input dealers showed up for the event and bid for 11 auctions; in the second location 12 input dealers showed up for the event and bid for 11 auctions; in the third location, 12 input dealers showed up for the event and bid for 15 auctions; in the fourth location 7 input dealers showed up for the event and bid for 13 auctions; in the fifth location, 5 input dealers showed up for the event and bid for 25 auctions.

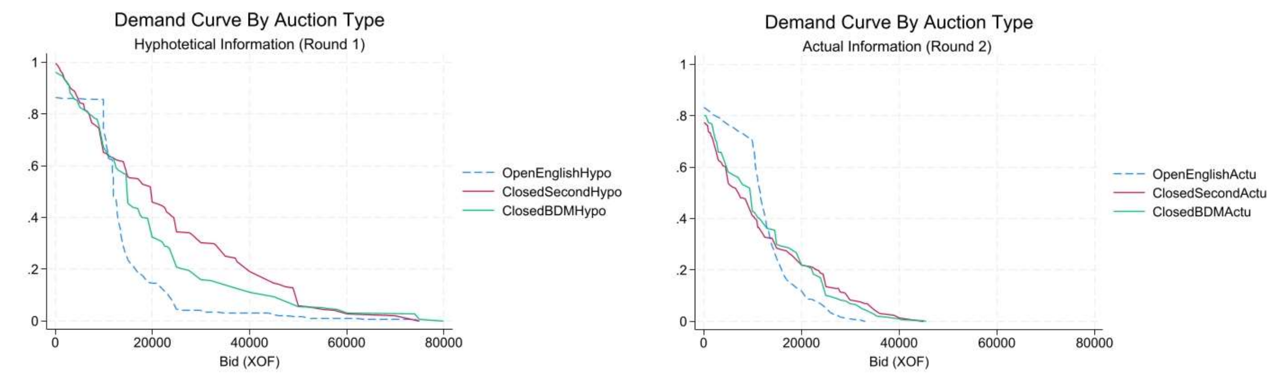
Figure 2: Demand Curves

Panel A



Note: Demand curves are plotted as the inverse of the bids cumulative distribution function (CDF). The left quadrant shows Round 1 with Hyphotetical Information (dash) versus Round 2 with Actual Information (solid). The right quadrant shows Open English Auctions (dash) versus Closed Second Price (solid red) and BDM Auctions (solid green). Graphs describe uncensored bid distributions, e.g. zeros are included.

Panel B

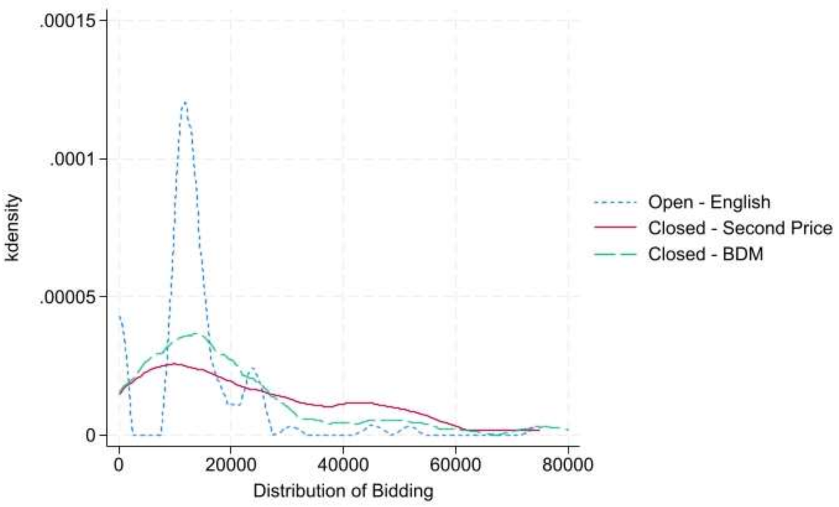


Note: Demand curves are plotted as the inverse of the bids cumulative distribution function (CDF). The left quadrant shows Round 1 with Hyphotetical Information and Open English Auctions (dash) versus Closed Second price (solid red) and BDM Auctions (solid green). The right quadrant shows Round 2 with Actual Information and Open English Auctions (dash) versus Closed Second Price (solid red) and BDM Auctions (solid green). Graphs describe uncensored bid distributions, e.g. zeros are included.

Figure 3: Bidding Distribution by Auction Mechanism and Information Type

Panel A

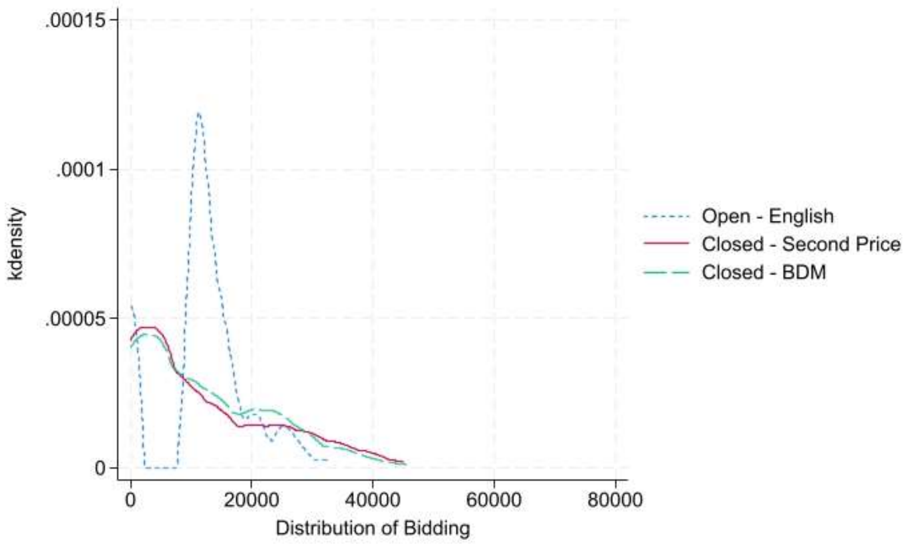
Density Estimation with Hypothetical Information



Note: Kernel density estimation for Round 1 with Hypothetical information. Bids expressed in XOF. Open mechanisms are English auctions (small dash). Closed mechanisms are Second price and BDM auctions (solid and long dash). Graphs describe uncensored bid distributions, e.g. zeros are included.

Panel B

Density Estimation with Actual Information



Note: Kernel density estimation for Round 2 with Actual information. Bids expressed in XOF. Open mechanisms are English auctions (small dash). Closed mechanisms are Second price and BDM auctions (solid and long dash). Graphs describe uncensored bid distributions, e.g. zeros are included.

Tables

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Table 1: Experimental Design, Theoretical Predictions from Milgrom and Weber (1982), and Experimental Results

	Auction Characteristics		Predicted Effects on Bids		Experimental Results on Bids		
	Shared Info (θ)	Ex-ante Beliefs (β)	Mean Net	Variance	Mean	Median	SD
Hypothesis 1: Close Mechanism + Hypothetical Information	no	no	↓	↑	22,066	17,500	17,463
Hypothesis 2: Close Mechanism + Actual Information	no	yes	↑ or ↓	↑ or ↓	14,463	11,000	10,913
Hypothesis 3: Open Mechanism + Hypothetical Information	yes	no	↑ or ↓	↓ or ↑	15,998	13,000	9,555
Hypothesis 4: Open Mechanism + Actual Information	yes	yes	↑	↓	14,655	13,000	5,074

Note: Milgrom, P. R., & Weber, R. J. (1982). A Theory of Auctions and Competitive Bidding. Econometrica, 50 (5), 1089–1122. https://doi.org/10.2307/1911865. The experimental results report censored bid distributions, e.g. zeros are excluded. Appendix B2 and B3 re-estimate specifications with full sample, including zeros. All values expressed in XOF.

Table 2: Summary statistics and tests of equivalency by auction mechanism and information type

	(1)	(2)	(3)	(4)	(5)	(6)
	Round 1			Round 2		
	English	Second Price	BDM	English	Second Price	BDM
Mean bid (standard deviation, in thousands)	13,804 (10.4)	23,559 (18.1)	19,715 (16.8)	12,183 (7.2)	11,251 (11.8)	11,529 (10.9)
Median	12,000	20,000	15,000	12,000	7,500	10,000
Variance (in thousands)	109,131	328,642	282,574	51,592	138,623	119,255
Min	0	0	0	0	0	0
Max	75,000	75,000	80,000	33,000	45,000	45,500
N	299	289	296	338	338	335
Excluding bid ≤ Reserve P. or Zeros						
Mean bid (standard deviation, in thousands)	15,998 (9.5)	23,641 (18.1)	20,476 (16.7)	14,655 (5.1)	14,571 (11.4)	14,358 (10.3)
Median	13,000	20,000	15,000	13,000	11,000	11,500
Variance (in thousands)	91,312	327,847	277,883	25,748	131,125	107,859
Zero-bids (%)	13.7%	0.3%	3.7%	16.8%	22.8%	19.7%
Experimental Setting	Hypothetic Information / Non-incentive bid			Actual Information / Non-incentive bid		
t-test of means equality, English versus	-	t = -6.26***	t = -3.88***	-	t = 0.11	t = 0.42
t-test of means equality, Second price versus	t = 6.26***	-	t = 2.18*	t = -0.11	-	t = 0.22
Mann-Whitney test, English versus	-	z = -3.18**	z = -2.28*	-	z = 3.23**	z = 2.79**
Mann-Whitney test, Second price versus	z = 3.18**	-	z = 1.69	z = -3.23**	-	z = -0.15
Levene test English versus	-	W = 144.94***	W = 60.18***	-	W = 190.50***	W = 152.13***
Levene test Second price versus	W = 144.94***	-	W = 9.83**	W = 190.50***	-	W = 3.42

Note: Figures in parenthesis are standard deviations of the mean bid. *T*-test of means equality is for independent samples without assuming equal variances; Mann-Whitney test is for independent samples, alternative hypotheses are given by: Ho: Two groups have the same median, Ha: The probability distribution for group A is shifted to the right or to the left of that for group B; Levene test alternative hypotheses are given by: Ho: homogeneity of variance, Ha: at least two groups do not have equal variance. The symbols *, **, *** indicate significantly different values at the two-tailed $p < 0.05$ level, $p < 0.01$ level, $p < 0.001$ level, respectively. All values in XOF.

Table 3: Mean, median, standard deviation, and equivalence tests by experimental conditions (hypothesis)

Information on Bidders Signals			Information on License Characteristics: Hypothetical Location	Information on License Characteristics: Actual Location (Ex-ante Beliefs)	*T-tests of mean equality*	*Mann-Whitney test of median equality*	*Levene's test of variance homogeneity*
	Close Mechanism	Second Price	***Hypothesis 1***: Mean = 23,641 Median = 20,000 SD = 18,106	***Hypothesis 2***: Mean = 14,570 Median = 11,000 SD = 11,451	*t = 7.08****	*z = 5.70****	*W = 54.16****
		BDM	Mean =20,476 Median = 15,000 SD = 16,669	Mean = 14,358 Median = 11,500 SD = 10,386	*t = 5.21****	*z = 4.17****	*W = 20.10****
	Open Mechanism	English	***Hypothesis 3***: Mean = 15,998 Median = 13,000 SD = 9,555	***Hypothesis 4***: Mean = 14,655 Median = 13,000 SD = 5,074	*t = 2.01**	*z = 0.60*	*W = 11.99****
T-tests of mean equality							
		SP vs. Eng	*t = 6.26****	*t = -0.11*			
		BDM vs. Eng	*t = 3.88****	*t = -0.42*			
Mann-Whitney test of median equality							
		SP vs. Eng	*z = 3.18***	*z = -3.23***			
		BDM vs. Eng	*z = 2.28**	*z = -2.79***			
Levene's test of variance homogeneity							
		SP vs. Eng	*W = 144.94****	*W = 190.50****			
		BDM vs. Eng	*W = 60.18****	*W = 152.13****			

Note: T-test of means equality is for independent samples without assuming equal variances; Mann-Whitney test is for independent samples, null hypothesis is Ho: two groups have the same median; Levene test null hypothesis is Ho: homogeneity of variance. The symbols *, **, *** indicate significantly different values at the two-tailed $p < 0.05$ level, $p < 0.01$ level, $p < 0.001$ level, respectively. The table includes censored bid distributions, e.g. zeros are excluded. Appendix B3 and B4 re-estimate specifications with full sample, including zeros. All values in XOF.

Table 4: Estimation results for individual bidding by auction mechanism and information type with village demand report controls

	(1)		(2)		(3)		(4)		(5)		(6)	
	Round 1						Round 2					
	Last Price Bid		Last Price Bid		Last Price Bid		Last Price Bid		Last Price Bid		Last Price Bid	
	estimate	(s.e.)	estimate	(s.e.)	estimate	(s.e.)	estimate	(s.e.)	estimate	(s.e.)	estimate	(s.e.)
Second price	9,270***	(2,155)	9,399***	(2,166)	8,784***	(2,218)	-690	(1,192)	-523	(1,193)	-1,616	(1232)
BDM	5,766**	(1,984)	5,891**	(2,005)	4,778*	(1,911)	-879	(974)	-750	(967)	-819	(997)
Valuation report controls												
Expected profitability												
1st tercile (low)			-4,077***	(1,101)					-2,317**	(753)		
2nd tercile (middle)			-2,181*	(942)					-2,641***	(609)		
Village population (N)					54**	(20)					1	(0.1)
Fertilizers (ton)					131	(129)					5	(9)
Herbicides & insecticides (box)					4*	(2)					6	(15)
Distance to road ($)					-0.1*	(0.1)					0.1	(0.1)
Constant	14,992***	(1,299)	16,961***	(1,301)	11,634***	(1,632)	15,043***	(629)	16,586***	(729)	12,814***	(940)
Experimental Setting	Hypothetical Information / Non-incentivized bid						Actual Information / Non-incentivized bid					
Controls	No		Profitability Terciles		Information Categories		No		Profitability Terciles		Information Categories	
Zero-bids	Excluded						Excluded					
Dealer fixed-effects	Yes						Yes					
N	831		831		831		811		811		811	
rmse	12,907		12,815		12,728		7,453		7,368		7,381	

Note: Dependent variable is subject bid; Models 1 and 4 controls for Second price and BDM mechanisms, with reference to the English auction; Models 2 and 5 add controls for first and second profitability terciles, with reference to the third profitability tercile. Models 3 and 6 add controls for variables aggregated and calculated by the authors. The table includes censored bid distributions, e.g. zeros are excluded. Appendix B3 and B4 re-estimate this specification with full sample, including zeros. All values expressed in XOF.

Table 5: Estimation results for individual bidding by auction mechanism and information type, with dealers' controls

	(1)		(2)		(3)		(4)		(5)		(6)	
	Round 1						Round 2					
	Anybid (0/1)		Last Price Bid		Winner (0/1)		Anybid (0/1)		Last Price Bid		Winner (0/1)	
	estimate	(s.e.)	estimate	(s.e.)	estimate	(s.e.)	estimate	(s.e.)	estimate	(s.e.)	estimate	(s.e.)
Second price	0.15***	(0.03)	6,997***	(1,541)	-0.04	(0.05)	-0.06	(0.03)	89	(787)	0.03	(0.04)
BDM	0.12***	(0.03)	3,874**	(1,389)	-0.13**	(0.04)	-0.03	(0.03)	-291	(690)	-0.03	(0.04)
Input Dealer Controls												
Profit / turnover (ratio)	-0.01	(0.01)	131*	(58)	-0.00	(0.01)	n/a	-	n/a	-	n/a	-
Own transport (yes)	-0.01	(0.03)	5,739**	(1,895)	-0.04	(0.05)	-0.02	(0.03)	1,657	(917)	0.04	(0.04)
Human resources (N)	-0.01	(0.01)	407	(368)	0.02*	(0.01)	-0.03***	(0.01)	977***	(199)	0.05***	(0.01)
Bookkeeping (yes)	0.04	(0.03)	877	(1,848)	-0.11	(0.06)	-0.01	(0.03)	-1,285	(998)	-0.00	(0.04)
Wholesale (yes)	-0.05*	(0.03)	2,044	(1,700)	0.05	(0.04)	-0.14**	(0.04)	-3,045**	(1110)	-0.05	(0.05)
Village served (N)	0.01	(0.01)	142*	(57)	-0.01	(0.01)	0.01	(0.01)	-57	(68)	-0.00	(0.00)
Credit ever (yes)	0.01	(0.02)	-578	(1,572)	0.11**	(0.04)	-0.03	(0.03)	-270	(684)	-0.05	(0.03)
Participated in fair (yes)	-0.02	(0.02)	-886	(1,678)	0.03	(0.04)	-0.01	(0.03)	1,558*	(679)	0.09**	(0.03)
Years in business (N)	-0.01	(0.01)	-397***	(90)	-0.01***	(0.01)	-0.01	(0.01)	28	(50)	0.01*	(0.01)
Constant	0.89***	(0.05)	9,749***	(2,310)	0.47***	(0.07)	0.96***	(0.05)	12,619***	(1356)	0.10	(0.06)
Experimental Setting	Hypothetical Information / Non-incentivized bid						Actual Information / Non-incentivized bid					
Controls	Dealers Observables						Dealers Observables					
Zero-bids	Included		Excluded		-		Included		Excluded		-	
Regression model	Ordinary Least Squares (OLS)						Ordinary Least Squares (OLS)					
N	594		557		611		994		794		808	
rmse	0.233		14,972		0.437		0.395		9,194		0.422	
r2	0.088		0.01		0.074		0.042		0.01		0.059	

Note: Models 1 and 4 estimate the variable Anybid which is a categorical indicating non-zero and non-missing bid. Models 2 and 5 estimate the outcome variable Last Price Bid on Second price and BDM auctions, with reference to English auction. Models 3 and 6 regress the categorical variable Winner with an OLS regression. The variable Profit/Turnover is the ratio between reported Profit and Turnover. The variable Human resources is the average of the reported number of permanent staff and agents. The variable Bookkeeping takes value 1 when input dealers report to use a written bookkeeping system. The variable Wholesaler takes value 1 when dealer declares to be a wholesale instead of a retailer. The variable Village served describes the number of villages that input dealers report to be usually serving. The variable Credit ever takes value 1 when input dealers report having received credit at least once. The variable Participated in Fair takes value 1 when input dealers report having already taken part of village input fairs. The variable Years in business describes the reported number of years of activities of the enterprise. The table includes uncensored bid distributions in Models 1 and 4 and censored otherwise. All values in XOF.

Table 6: Estimation results for individual bidding per incentive rule

	(1)		(2)	
	Last Price Bid		Last Price Bid	
	estimate	(s.e.)	estimate	(s.e.)
Real-stakes bids	-14,527***	(1,949)	-12,398***	(1,120)
Valuation Report Controls				
Village population (N)	0.1	(0.1)		
Fertilizers (ton)	33	(18)		
Herbicides & insecticides (box)	-12	(24)		
Distance to road ($)	-0.1	(0.1)		
Input Dealer Controls				
Own Transport (yes)			1,217	(1,363)
Human Resources (N)			650	(302)
Bookkeeping (yes)			-2,753	(1,429)
Wholesale (yes)			1,216	(1,940)
Village served (N)			-80	(91)
Credit ever (yes)			-571	(789)
Participated in fair (yes)			1,012	(1,298)
Years in business (N)			-65	(70)
Constant	11,722***	(1,514)	14,667**	(2,656)
Controls	Information Categories		No	
Zero-bids	Excluded		Excluded	
Dealer fixed-effects	Yes		No	
Village fixed-effects	No		Yes	
N	305		297	
rmse	6,883		10,506	

Note: Dependent variable is subject's bid, the coefficient is estimated with reference to non-incentivized bids. Models 1 controls for variables included in the cards, aggregated by nature, and calculated by the authors. Model 2 controls for input dealers characteristics collected the day of the experiment. All values in XOF.

Appendix A – Descriptive statistics of input dealers' observable demographics characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variable	Turnover ($/month)	Profit ($/month)	Own Transport (N)	Staff (N)	Wholesale (yes)	Village Served (N)	Credit Ever (yes)	Input Fair Experience (yes)	Experience (years)
Median	358	64	1	0	0	5.5	0	0	9
Mean	934	181	0.78	0.53	0.35	8.73	0.42	0.48	10.40
S.d.	2,036	486	0.41	1.13	0.48	7.78	0.49	0.50	7.71
Min	0	0	0	0	0	1	0	0	2
Max	9,548	3,183	1	6	1	31.50	1	1	38
N	43	43	151	151	43	40	151	145	43

Note: The variable Staff describes the number of permanent staff, paid every month by the employer, and agents, paid on commission, and interns and apprentices working in the enterprise; the variable Wholesale takes value one when the enterprise is described by the entrepreneur as wholesale trade, zero if it is retail trade; the variable Village Served describes the number of villages that an enterprise serves on average during one agricultural season; the variables Credit Ever gets value one when the entrepreneur declares having already obtained formal or informal business credit; the variable Input Fair Experience gets value one when the entrepreneur declares having already participated in a Village Input Fair; the variable Experience describes the number of years the enterprise has been operating in Mali.

Appendix B - Robustness checks

We consider and address potential issues that can arise in the experimental auctions we have designed. These include sequential learning, order effects, and zero censoring.

Sequential Auctions – There is a trade-off between obtaining more information, the time spent by bidders in the experiment and its complexity. A concern in our setting is that prices are posted after each auction. The outcome of one auction may convey additional, albeit imperfect, information about some relevant elements of the environment. This may introduce a strategic link between the elements of the auction sequence, which could affect bidder participation and strategies (Corazzini et al., 2019, Jeitschko, 1998).

A categorical variable is generated which defines the first three auctions played by bidders for each group of auctions played with each mechanism. The variable defines whether bidders are playing the first triplet or the second triplet of auctions. We then use this dummy as explanatory variable and test the hypothesis that the bid levels in the first triplet of auctions are not statistically different from the bids in the second triplet. Failing to reject this hypothesis indicates that there is no systematic pattern in different segments of the sequence for each mechanism.

$$y = \alpha + \beta Triplet + Controls + \epsilon_{au} \tag{3}$$

For both the first and second rounds, we are able to reject the hypothesis that bidding levels in the first auction triplet are statistically different from those in the second triplet. Results are reported in Appendix B1 below.

Order Effects – Attention must be paid to order effects, in particular when eliciting bids in multiple auction sessions. Appendix B2 presents the order in which the three auction mechanisms were presented to bidders on each of the days of the experiment. Each bidder participated in only one auction day. All bidders bid on the same 18 villages. Three segments of villages were defined. Villages numbered 1 to 6 were auctioned using the Second Price auction protocol. Villages numbered 7 to 12 with the BDM auction protocol. Villages numbered 13 to 18 with the English auction protocol. The order of the three segments changed every day as depicted in Appendix B2.

Zero Censoring – Auction bids are often censored from low to zero. In principle, auction experiments can be constructed to allow negative bids, but in practice this is uncommon (Canavari et al., 2019). The experimenter cannot distinguish which offers are authentically zero, which are censored but might be negative. We address this issue by isolating the zero bids and running regressions with and without the censored data. Our preferred specification in Table 4 reports estimation results excluding the censored zero bids. We re-estimate the specification including zeros. The results reported in Appendix B3 show that the signs and magnitudes of the coefficients are statistically similar to those reported in Table 4. To confirm this trend, we re-estimate the same specification including zeros, but using a Tobit model. Results are reported in Appendix B4 and confirm that our results are robust to the inclusion of censored zero-bids, with the exception of the estimates for Second price auction that become slightly significant for Round 2.

Appendix B1 - Robustness Check for Sequential Auction

	(1)		(2)	
	Round 1		Round 2	
	Last Price Bid		Last Price Bid	
	estimate	(s.e.)	estimate	(s.e.)
Sequence				
Triplet (2^{nd})	919	(749)	1,120	(579)
Auction Controls				
Second Price	9,264***	(2,156)	-651	(1,197)
BDM	5,757**	(1,986)	-869	(975)
Constant	14,541***	(1,403)	14,461***	(749)
Zero bids	Excluded			
Dealers Fixed Effects	Yes			
N	831		811	
rmse	12,907		7,437	

Note: Dependent variable is subject bid. Dummy variable Triplet takes value 1 for second triplet.

Appendix B2 - Treatment Order on Each Experiment Day

Order of Submission of the Auction Mechanisms in Round 1 and Round 2

Round 1: With 64 input dealers (16 each day) on April 2022

	Auction Sequencing		
Day	*First Through Sixth*	*Seventh Through Twelfth*	*Thirteenth Through Eighteenth*
1	Second Price	BDM	English
2	BDM	Second Price	English
3	English	Second Price	BDM
4	BDM	English	Second Price

Round 2: With 60 input dealers (20 each day) on January 2023

	Auction Sequencing		
Day	*First Through Sixth*	*Seventh Through Twelfth*	*Thirteenth Through Eighteenth*
1	Second Price	BDM	English
2	BDM	Second Price	English
3	English	BDM	Second Price

Note: On each day of the experiment, a different group of input dealers was invited. For Round 1, 16 input retailers were invited each day, for a total of 64 input retailers. For Round 2, 20 input dealers were invited, for a total of 60 input dealers.

Appendix B3: Re-estimation results for individual bidding by auction mechanism and information type with valuation report controls, including zeros

	(1)		(2)		(3)		(4)		(5)		(6)	
	Round 1						Round 2					
	Last Price Bid		Last Price Bid		Last Price Bid		Last Price Bid		Last Price Bid		Last Price Bid	
	estimate	(s.e.)	estimate	(s.e.)	estimate	(s.e.)	estimate	(s.e.)	estimate	(s.e.)	estimate	(s.e.)
Second price	10,892***	(2,124)	10,889***	(2,129)	10169***	(2195)	-989	(1,158)	-985	(1,162)	-1901	(1161)
BDM	6,639**	(1,909)	6,691**	(1,925)	5173**	(1780)	-728	(952)	-715	(954)	-541	(955)
Valuation report controls												
Expected profitability												
1st tercile (low)			-4,944***	(1,037)					-2,605***	(643)		
2nd tercile (middle)			-2,885**	(870)					-2,013***	(553)		
Village population (N)					49*	(20)					1*	(0.1)
Fertilizers (ton)					184	(126)					14	(8)
Herbicides & insecticides (box)					6**	(2)					10	(14)
Distance to road ($)					-0.1*	(0.1)					-0.1	(0.1)
Constant	13,188***	(1,203)	15,802***	(1,176)	9,822***	(1,498)	12,227***	(649)	13,755***	(698)	9,524***	(854)
Experimental Setting	Hypothetical Information / Non-incentivized bid						Actual Information / Non-incentivized bid					
Controls	No controls		Profitability Terciles		Information Categories		No controls		Profitability Terciles		Information Categories	
Regression Model	Ordinary Least Squares (OLS)						Ordinary Least Squares (OLS)					
Zero-bids	Included						Included					
Dealer fixed-effects	Yes		Yes		Yes		Yes		Yes		Yes	
N	884		884		884		1,011		1,011		1,011	
rmse	13,205		13,064		12,985		7,745		7,671		7,676	

Note: Dependent variable is subject bid; Models 1 and 4 controls for the Second price and BDM auction mechanism, with reference to the English auction; Models 2 and 5 add controls for the first and second Profitability Tercile, with reference to the third Profitability Tercile. Models 3 and 6 add controls for variables aggregated and calculated by the authors. All values in XOF.

Appendix B4: Re-estimation results for individual bidding by auction mechanism and information type with valuation report controls, Tobit estimation

	(1)		(2)		(3)		(4)		(5)		(6)	
	Round 1						Round 2					
	Last Price Bid		Last Price Bid		Last Price Bid		Last Price Bid		Last Price Bid		Last Price Bid	
	estimate	(s.e.)	estimate	(s.e.)	estimate	(s.e.)	estimate	(s.e.)	estimate	(s.e.)	estimate	(s.e.)
Second price	11,858***	(1,199)	11,885***	(1,184)	11,074***	(1,245)	-1,653*	(746)	-1,603*	(738)	-2,580**	(884)
BDM	7,491***	(1,190)	7,569***	(1,176)	6,009***	(1,305)	-1,196	(745)	-1,147	(738)	-840	(771)
Valuation report controls												
Expected profitability												
1st tercile (low)			-5,469***	(1,172)					-3,081***	(739)		
2nd tercile (middle)			-3,186**	(1,170)					-1,872*	(736)		
Village population (N)					56**	(21)					1	(0.1)
Fertilizers (ton)					187	(162)					20	(10)
Herbicides & insecticides (box)					6**	(2)					12	(17)
Distance to road ($)					-0.1**	(0.1)					-0.1	(0.1)
Constant	12,031***	(1,350)	14,899***	(1,507)	8,234***	(1,729)	11,286***	(1,163)	12,909	(1,231)	7,935***	(1,451)
Experimental Setting	Hypothetical Information / Non-incentivized bid						Actual Information / Non-incentivized bid					
Controls	No controls		Profitability Terciles		Information Categories		No controls		Profitability Terciles		Information Categories	
Regression Model	Tobit						Tobit					
Zero-bids	Included						Included					
Dealer fixed-effects	Yes		Yes		Yes		Yes		Yes		Yes	
N	884		884		884		1011		1011		1011	
sigma_u	7,647***		7,714***		7,701***		7,841***		7,825***		7,831***	
sigma_e	14,263***		14,083***		13,981***		9,366***		9,266***		9,260***	

Note: Dependent variable is subject bid; Models 1 and 4 controls for the Second price and BDM auction mechanism, with reference to the English auction; Models 2 and 5 add controls for the first and second Profitability Tercile, with reference to the third Profitability Tercile. Models 3 and 6 add controls for variables aggregated and calculated by the authors. All values in XOF.

Appendix C - Examples of village demand reports for Round 1 (Panel A) and Round 2 (Panel B)

Panel A

GROUPE D'INTERMEDIATION FINANCIERE POUR LE DEVELOPPEMENT AGRICOLE AU MALI
GIFDA
Accés des producteurs aux intrants agricoles

Village 1: A'gata

Hypothetical Village Name

Chef du village: Ahmad Baba al Massufi

Position géographique

Sur le chemin de	**Koumantou**
Km séparant le village de la route goudronnée	**0 km**
Ville la plus proche	**Bougouni**
Présence de fleuve	**Non**

Population et agriculture

Nombre de ménages vivant dans le village	**55 ménages**
Estimation du nombre de producteurs dans le village	**60 producteurs**
Présence de coopératives, de groupes d'épargne ou d'autres associations d'agriculteurs.	**Il y a des coopératives**
Principales cultures pratiquées	**Mais, Coton, Sorghum**

La foire à entrants

Nombre de stands disponibles à la foire GIFDA	**2 stands disponibles**
Période d'organisation de la foire	**Mois de mai 2022**
Opportunité de crédit offerte aux producteurs	**Les producteurs peuvent négocier du crédit**

Estimation des besoins

Urée **21 sacs**	NPK **41 sacs**	DAP **12 sacs**
Fertinova **15 sacs**	Organova **-**	Pesticides **70 cartons**
Insecticides **345 cartons**	Fongicides **-**	Semences **10 kg**

Panel B

GROUPE D'INTERMEDIATION FINANCIERE POUR LE DEVELOPPEMENT AGRICOLE AU MALI
GIFDA
Accés des producteurs aux intrants agricoles

Village 1: BANKO-ZANFINA

Actual Village Name

Koumantou

Position géographique

Distance au chef lieu de la commune	12 km
Km séparant le village de la route goudronnée	12 km
Ville la plus proche	Bougouni

Population et agriculture

Population du village	2919 habitants
Première culture principale du village	Cotton
Deuxième culture principale du village	Mais
Troisième culture principale du village	Mil/sorgho

La foire à entrants

Nombre de stands disponibles à la foire GIFDA	2 stands disponibles
Période d'organisation de la foire	Mois de Fevrier 2023 (livraison en Juin)
Opportunité de crédit offerte aux producteurs	Les producteurs peuvent négocier du crédit

Estimation des besoins

Urée 331 sacs de 50 kg	NPK 200 sacs de 50 kg	DAP 501 sacs de 50 kg
Autre engrais chimiques -	Fertinova -	Herbicides 40 cartons
Insecticides 30 cartons	Fongicides 180 kg	Semences 200 kg

Appendix D – Village demand reports attributes and test of equivalency by auction mechanism (panel A) and terciles (panel B)

	Panel A	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
		Farmers (N)	Population (N)	Urée (ton)	NPK (ton)	DAP (ton)	Fertinova (ton)	Herbicide (box)	Insecticide (box)	Seed (ton)	Distance to paved way (km)	Presence of river (yes)
	Experimental Setting: Field Lab with Hypothetical Villages (Round 1)											
T-test	Second price vs. English	*t* = -0.91	n/a	*t* = -0.51	*t* = -1.13	*t* = -1.34	*t* = -0.32	*t* = 0.71	*t* = -0.89	*t* = 0.65	*t* = 0.30	*t* = -1.11
T-test	Second price vs. BDM	*t* = -0.92	n/a	*t* = -0.93	*t* = -0.52	*t* = 0.01	*t* = -1.75	*t* = -0.73	*t* = 0.82	*t* = -1.01	*t* = -1.86	*t* = -0.54
T-test	English vs. BDM	*t* = -0.08	n/a	*t* = -0.69	*t* = 1.59	*t* = 1.41	*t* = -1.71	*t* = -1.44	*t* = 1.27	*t* = -2.07	*t* = -4.25**	*t* = 0.54
	Experimental Setting: Field Lab with Real Villages (Round 2)											
T-test	Second price vs. English	n/a	*t* = -1.99	*t* = -0.06	*t* = -1.22	*t* = -0.60	*t* = -0.19	*t* = -0.34	*t* = -0.49	*t* = 2.06	*t* = -0.77	n/a
T-test	Second price vs. BDM	n/a	*t* = -3.24**	*t* = -0.12	*t* = 1.17	*t* = -0.41	*t* = -0.88	*t* = -0.86	*t* = -0.16	*t* = 1.70	*t* = 041	n/a
T-test	English vs. BDM	n/a	*t* = -0.85	*t* = -0.07	*t* = 2.08	*t* = 0.12	*t* = -0.85	*t* = -0.57	*t* = 0.34	*t* = -0.19	*t* = 1.05	n/a

	Panel B	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Experimental Setting: Field Lab with Hypothetical Villages (Round 1)											
Mean	1st Tercile	42	n/a	0.66	0.81	0.42	0.32	31.83	145.50	0.96	8.17	1.00
Mean	2nd Tercile	60.5	n/a	0.96	1.45	0.80	0.37	65.16	136.83	1.26	3.67	0.00
Mean	3rd Tercile	79	n/a	2.61	3.22	1.80	0.72	109.66	403.5	4.42	8.33	0.50
	Experimental Setting: Field Lab with Real Villages (Round 2)											
Mean	1st Tercile	n/a	1264	8.92	3.33	15.17	0.83	23.33	9.83	1.76	20.6	n/a
Mean	2nd Tercile	n/a	1777	28.03	7.92	43.14	2.41	33.16	18.50	0.54	9.5	n/a
Mean	3rd Tercile	n/a	1867	45.00	15.00	67.92	18.75	33.83	37.33	4.34	31.5	n/a

Note: Panel A includes results of t-tests between auction mechanisms. Panel B includes means grouped by tercile of expected demand. The variable Farmer describes the number of producers in the village where the fair would take place. Population describes the number of dwellers in each village (based on RGPH, 2009). The variables Urée, NPK, DAP, and Fertinova, describe the tons of fertilizers demanded by the farmers, as expressed in the cards. The variables Herbicides and Insecticide describe the number of boxes of crop protection products demanded by the farmers, as expressed in the cards. The variable Seeds describes the tons of seeds demanded by the farmers, as expressed in the cards. The variable Distance to paved way describes the distance between the village where the fair would take place and the nearest paved way, as expressed in the cards. The variable Presence of river is a dummy describing whether there's a river near the village where the fair will take place, as expressed in the cards.

Appendix E - Experimental Auction Scripts

English Ascending Auctions

READ THE SCRIPT EXACTLY AS IT IS WRITTEN. DON'T SAY ANYTHING THAT ISN'T IN THE SCRIPT.

INTRODUCTION

Thank you for taking part in today's auction exercise, which will help us understand how to organize an auction where participants can win a stand to sell agricultural inputs at a village input fair. Today we won't actually be auctioning off stands for an input fair, but we will be testing and getting your feedback on the best way to go about it. You have to participate as if you wanted to buy a real stand for the village input fair. This means you should only bid on the amount you're able and willing to pay for a spot at a real input fair. In the real auction, if you had won, your prize would have been a place at the input fair. Today, instead of actual winnings, we're going to estimate what the winners would have earned if they'd won the auction and sold their products at the fair. You won't have to pay any money today, and you won't win anything. Do you have any questions? Note: Answer all questions that are asked.

INSTRUCTIONS

Here are the rules for today's auction

- Each of you has the opportunity to bid for a place at a hypothetical input fair.
- We'll be auctioning places at hypothetical input fairs in 6 villages, and you can make your best bid to win a place in each of them. There are two stalls available in each village's input fair. We'll identify the winners of these two places based on a set of rules that I'll explain in a few minutes.
- Each agro input dealer will receive a village information sheet containing information that can help you decide on the auction amount for that village. Everyone will receive the same sheet, and you'll bid different amounts for the opportunity to have an input fair location in the same village.
- The village information sheet contains the name of the village where the input fair will be held, its location, population size and number of farmers. It also contains information on what the demand for inputs might be for all farmers in the village. This forecast of needs was confirmed by calling key contacts in the village.
- You must accept the amount you wish to bid to secure your place at the input fair. If you do not wish to sell at the input fair, you must communicate this and leave the auction.

• You're competing with the other input vendors in the room for a place.

Here's how you can offer your best price for a spot at the input fair in each village:

• First, I'll give you the village information sheet, which you can use to determine the maximum you're willing and able to pay to participate in the village fair.

• I'll announce aloud the price at which you can buy one of the two places available at the input fair. If this price is too high for you, i.e. you are not prepared to pay this price to participate in the fair, you must raise your hand to abandon the bidding for this village. Your decision to leave this auction round is final.

• Once you've left the turn, please get up and move to the side of the room, so that those remaining can continue the auction for this village.

• If you're willing and able to pay this price to take part in the fair, you don't have to do anything and can continue.

• I'll wait a minute for you to make a decision and give you a five-second warning. Then I'll announce a new, higher price.

• Once again, if this new price is too high for you, you must raise your hand to leave the auction. Otherwise, if you are willing and able to pay this price, do nothing and continue the auction.

• That way, I'll keep announcing higher prices one by one, and every time someone wants to give up, they have to raise their hand and step aside.

• The auction ends when only two people remain in the auction. These two people are the winners of the game.

• Normally, if this were a real auction, the winners would have to pay the price I announced last time. Today we're running a practice auction, so you don't have to pay any money, nor will you win a place in the input fair.

• We'll now calculate each winner's income, opening the envelope to see how much they could have earned at the input fair.

• The auction is now over.

Do you have any questions about this process? Note: answer all questions that are asked.

AUCTION SALE

We're now going to start the auction. There will be 6 villages in today's auction, where each round will be for places at an input fair in a different village. You can participate and offer your best price in all 6 villages.

Note: Distribute information sheets on the first village to all input dealers. A member of the IPA or GIFDA team should note the details of the auction in the "auction tracking sheet" as the auction progresses.

• We are now starting the auction for two input fair places in the village of [village name]. The expected income from one at the fair in this village is sealed in this envelope [show envelope with income], which I will open only after the winner has been announced.

• The starting price for a place at this village's input fair is 10,000 FCFA. Please remember to accept only the amount you are willing and able to pay.

• If this price is too high for you, and you wish to leave this round, please raise your hand now and stand up and move to the side of the room.

• I'll give you a little time to make your decision. This is your last chance to give up this trick.

• Now, all of you who haven't raised your hands are ready to pay 11,000 CFA for a seat. I'm now raising the price to 12,000 CFA [or an increase of 1,000 FCFA].

Repeat steps (3) and (4).

Increase the price by 1,000 FCFA each time, until there are only two participants left.

• Since there are only two participants left, these two people are the winners of the input fair booths in [name of village]. The winning bid is [last amount announced].

* If you're in a scenario where there are three participants left (let's say at 14,000 FCFA), you increase the price by 1,000 FCFA (let's say 15,000 FCFA) and there are only one or no participants left at that price, you must start reducing the price by 100 FCFA until there are only two participants left (14,900 FCFA, then 14,800 FCFA and so on). This is the only scenario where a participant's decision to drop out is not final. In this scenario, you need to invite the last three participants to continue bidding as you lower the price, until there are just two winners.

• We're now going to find out how much these winners would have made if the fair had been real. The estimated income from the sale of agricultural inputs at this village fair is [amount mentioned in envelope].

• The auction for this village is now closed. We will now start a new auction for the next village. I ask you all to take your seats as you were originally seated.

Repeat steps (1) to (6) for the next village. The starting bid will always be 10,000 FCFA.

Once the auction is over for all villages, invite everyone to give you feedback based on the questions posed in the document "Post-auction focus group questions."

Auction Second Price

READ THE SCRIPT EXACTLY AS IT IS WRITTEN. DON'T SAY ANYTHING THAT ISN'T IN THE SCRIPT.

INTRODUCTION

Thank you for taking part in today's auction exercise, which will help us understand how to organize an auction where participants can get a place to sell agricultural inputs at a village input fair. Today, we won't actually be auctioning places at the input fair, but we will be testing to get your feedback on the best way to proceed. You must participate as if you were offered a real place at the village input fair. This means you should only offer as much as you're able and willing to pay for a place at a real input fair. In a real auction, if you had won, your prize would have been a place at the input fair. Today, instead of a win, we're going to estimate the income the winners would have made if they'd won the auction and sold their products at the fair. You won't have to pay any money today, and you won't win anything. Do you have any questions? Note: Answer all questions that are asked.

INSTRUCTIONS

Here are the rules for today's practice auction

- Each of you has the opportunity to bid for a place at an input fair.
- We'll be auctioning places at hypothetical input fairs in 6 villages, and you can bid to win a place in each of them. There are two places available in each village's input fair. We'll identify the winners of these two places based on a set of rules that I'll explain in a few minutes.
- Each participant will receive a village information sheet containing useful information to help them decide how much to bid for that village. Everyone will receive the same sheet, and you will bid your best price for the opportunity to have an input fair space in the same village.
- The village information sheet contains, among other things, the name of the village where the input fair will be held, its location, population size and number of farmers. It also contains information on input demand for all farmers in the village. This demand forecast was confirmed by calling key contacts in the village.
- You can make your best offer to secure a place at the input fair. If you don't want to take part in the input fair, i.e. you're not interested in the village, you should offer 0 FCFA.
- You're competing with the other input vendors in the room for a place.

Here's how you can bid for a place at the input fair in each village:

• First, I'll give you the village information sheet, which you can use to determine your best offer that you're willing and able to pay to participate in the fair for that village.

• Fill in the "quotation form" with the best price you are willing to pay to participate in this village's input fair and give me your quotation form. Please note that you may be able to pay less than this. Take your time, as you won't be able to change your offer after submission.

• The winner of the auction will be determined in two stages:

• First, all bids submitted will be ranked from highest to lowest, and the two highest bids will be identified. These are the auction winners.

• Next, we'll identify the lower of the two winning bids. The auction winners will then both pay this lower amount. If both winners have made the same bid, they will pay this amount.

Do you have any questions about this process? Note: please answer all questions.

I'm now going to ask you a few questions to make sure you've understood. Please raise your hand if you know the answer.

i. Suppose you bid 20,000 FCFA and you win the auction with another person who bid 15,000 FCFA. How much do you have to pay to get a place at the fair? Note: If the respondent doesn't give the right answer, ask someone else. Explain the rules again if necessary.

ii. Suppose you bid 18,000 FCFA and you win the auction with another person who bid 22,500 FCFA. How much do you have to pay to get a place at the fair? Note: If the respondent doesn't give the right answer, ask someone else. Explain the rules again if necessary.

AUCTION SALE

We're now going to start the auction. There will be 6 rounds in today's auction, where each round will be for a place in an input fair in a different village. You can participate and bid for all 6 villages.

Note: Distribute village information sheets and tender forms for village 1 to all input sellers. 1. We are now inviting bids for two input fair places in the village of [name of village]. The expected income from a place at the fair in this village is in this envelope [show envelope with income]. I will open the envelope after the winner is announced at the end of the auction.

2 On your bid form, please indicate the amount you are prepared to offer for a place at the [name of village] village input fair.

3 Remember the rules for winning the auction:

• To win, you must be among the top two bidders.

• If you win, you'll have to pay the lower of the two best offers.

4. If you wish to revise your bid that you have written on your form, please do so now. We will collect your bid forms when you are ready.

Collect the forms. Rank them to identify the two best offers.

5. The two best bids for this village are : [name of highest bidder 1] who bid [bid amount] and [name of highest bidder 2] who bid [bid amount]! Congratulations, you've won this round of bidding!

6 If this were a real auction, you would both have paid the second-best price of [auction amount].

7 We're now going to find out how much sales these winning bids would have made if the fair had been real. The estimated income from the sale of agricultural inputs at this village fair is [amount mentioned in envelope].

8 The auction for this village is now closed. We will now launch a new auction for the next village.

Repeat steps (1) to (6) for the next village.

Once the auctions are over for all villages, invite everyone to give you their comments based on the questions in the "Post-auction focus group questions" section.

BDM Auctions

READ THE SCRIPT EXACTLY AS IT IS WRITTEN. DON'T SAY ANYTHING THAT ISN'T IN THE SCRIPT.

INTRODUCTION

Thank you for taking part in today's auction exercise, which will help us understand how to organize an auction where participants can win a slot to sell agricultural inputs at a village input fair. Today we won't actually be auctioning off slots for the input fair, but we will be testing and getting your feedback on the best way to go about it. You should participate as if you were bidding on a real village input fair slot. This means that you should only bid on the amount you are able and willing to pay for a location at a real input fair. In the real auction, if you had won, your gain would have been a slot in the input fair. Today, instead of a gain, we'll estimate the sales you would have made if you had won the auction and sold your products at the fair. You won't have to pay any money today, and you won't earn anything. Do you have any questions? Note: Answer all questions that are asked.

INSTRUCTIONS

Here are the rules for today's practice auction

• Each of you has the opportunity to bid for a place in a simulated input fair.

• We'll be auctioning places at input fairs in 6 villages, and you can bid your best price to win a place in each of them. There are two places available in each village. We'll identify the place winners based on a set of rules that I'll explain in a few minutes.

• Each agro input dealer will receive a village information sheet containing useful information that will enable him to decide how much to bid for the village. Everyone receives the same sheet, and you make your best bid for a place at the village fair.

• The village information sheet contains, among other things, the name of the village where the input fair will be held, its location, population size and number of farmers. It also contains information on what the demand for inputs might be for all farmers in the village. This demand forecast was confirmed by calling key contacts in the village.

• You can offer any amount to secure your place at the input fair. If you do not wish to participate in the input fair, you must propose 0 FCFA.

• You're competing with the other input vendors in the room for the two available slots.

Here's how you can enter to win a place at the input fair for each of the villages:

• First, I'll send you the village information sheet, which you can use to determine the best price you're willing to pay to participate in the fair for that village.

• Fill in the "offer form" we've given you, indicating the best price you're willing to pay to participate in this village's input fair. Be as sincere and precise as possible. We'll collect the offer forms if you're finished. Take your time, as you won't be able to change your offer after submission.

• The winner of the auction will be determined as follows:

First, all bids will be ranked from highest to lowest, and the top two bidders will be identified. Next, the highest bidder will win a prize of a bucket, between 10,000 FCFA and 25,000 FCFA :

◦ If the price drawn from the bucket is equal to or lower than the two highest bids, these participants win the auction and pay the price drawn;

◦ If the price from the bucket is higher than the two best bids, there will be no winners.

Do you have any questions about this process? Note: answer all questions that are asked. I'm now going to ask you a few questions to make sure you've understood. Please raise your hand if you know the answer.

I. Suppose you offer a price of 10,000 FCFA and the price of the bucket is 10,500 FCFA. Do you get a place at the input fair? Note: If the respondent doesn't give the right answer, ask someone else. Explain the rules again if necessary.

II. Suppose you offer a price of 22,500 FCFA and the price of the bucket is 18,000 FCFA. Will you get a place at the input fair? What price will you pay? Note: If the respondent doesn't give the right answer, ask someone else. Explain the rules again if necessary.

III. Suppose the price you quoted is equal to the price of the bucket. Do you get a place at the input fair? Note: If the respondent doesn't give the right answer, ask someone else. Explain the rules again if necessary.

AUCTION SALE

We're now going to start the auction. There will be 6 rounds in today's auction, where each round will be for slots in an input fair in a different village. You can participate and bid in all 6 rounds.

Note: Distribute village information sheets and tender forms for village 1 to all input sellers. We are now inviting bids for two places at the input fair in the village of [name of village]. The expected income from participation in this fair in this village is in this envelope [show envelope with income]. I will open the envelope and announce the amount at the end of the auction.

2 On your bid form, please indicate your best offer for a place at the [name of village] village input fair.

3 Remember the rules for winning the auction:

• To win, you must be among the first two bidders.

• Next, the price you offer must be greater than or equal to the price drawn from the bucket. The bucket contains prizes ranging from 10,000 to 25,000 FCFA. If you win, you'll have to pay the prize from the bucket.

4. if you wish to revise the offer you have written on your form, please do so now. We will now collect your offers, if you are ready.

Collect the forms. Rank them to identify the two best offers.

5 The first two bidders for this village are [name of first bidder] who offered [bid amount] and [name of second bidder] who offered [bid amount]!

6 I will now invite [name of highest bidder] to draw a prize from the bucket. Hold the bucket above the highest bidder's eye level and ask him to take a piece of paper without looking. Look at the price from the bucket. A GIFDA or IPA team member should record the bucket price and the two winning bid prices on the "bid tracking sheet."

7. the price per bucket is [price per bucket].

8. [If the winner's bid is greater than or equal to the bucket price]: The winner's bid price, [bid amount] is greater than/equal to the bucket price [bucket amount]. Congratulations, you've won this round of bidding. If this were a real auction, you would now have paid the bucket price [bucket amount] to secure your place at the fair. [If the winner's bid is lower than the bucket price]: The winner's bid price, [bid amount] is lower than the bucket price [bucket amount]. Sorry, you lost this round of bidding. Repeat step (8) for the second highest bidder.

9 We're now going to find out how much the winners would have made if the fair had been real. The estimated income from the sale of agricultural inputs at the [name of village] village fair is [amount mentioned in envelope].

10 The auction for the village of [village name] is over. We will now launch a new auction for the next village.

Repeat steps (1) to (10) for the next village.

Once the auctions are over for all villages, invite everyone to give you their comments based on the questions in the "Post-auction focus group questions" section.

Appendix F – Bidding variance by bidder and auction mechanism

Panel A

	(1)	
Dependent Variable	Variance	
	estimate	(s.e.)
Second price (in thousands)	92,573**	(33,221)
BDM (in thousands)	101,864*	(38,303)
Constant (in thousands)	75,373***	(20,266)
Experimental Setting	Hypothetical Information – Round 1	
Controls	No controls	
Regression model	OLS	
Dealers fixed effects	Yes	
N	936	
rmse (in thousands)	147,807	

Note: All values in XOF.

Panel B

	(1)	
Dependent Variable	Variance	
	estimate	(s.e.)
Second price (in thousands)	13,844	(9,797)
BDM (in thousands)	19,618	(9,958)
Constant (in thousands)	38,860***	(5,910)
Experimental Setting	Actual Information – Round 2	
Controls	No controls	
Regression model	OLS	
Dealers fixed effects	Yes	
N	1,026	
rmse (in thousands)	41,089	

Note: All values in XOF.

Appendix G: Summary statistics for individual bidding per incentive rule, non-incentivized and real-stakes bids

	(1)	(2)
	Round 2	Round 3
	Second Price	Second Price
Average bid (standard deviation)	11,251 (11,773)	2,284 (3,982)
Median	7,500	0
Variance (in thousands)	138,623	15,861
Min	0	0
Max	45,000	30,000
N	338	716
Excluding Zero-bids		
Average bid (standard deviation)	14,571 (11,451)	4,647 (4,615)
Median	11,000	3,000
Variance	131,125	21,300
Zero-bids (%)	23%	51%
Information Setting	Actual Information	
Price Rule	Non-incentivized bid	Real-stakes

Note: All values in XOF.

Appendix H: Estimation results for individual bidding per incentive rule, non-incentivized and real-stakes bid

	(1)		(2)		(3)		(4)	
	Round 2				Round 3			
	Last Price Bid		Last Price Bid		Last Price Bid		Last Price Bid	
	estimate	(s.e.)	estimate	(s.e.)	estimate	(s.e.)	estimate	(s.e.)
Expected profitability								
1^{st} tercile	-3,421*	(1,474)			-337	(267)		
2^{nd} tercile	-2,546*	(1,181)			- 216	(345)		
Village population (N)			1	(1)			-0.0	(0.08)
Fertilizers (ton)			35	(21)			-1.8	(1.6)
Herbicides & insecticides (box)			-19	(27)			2.2	(1.9)
Distance to paved way ($)			-0.1	(0.1)			0.1	(0.1)
Constant	16,609***	(862)	10,933***	(1,867)	4,820***	(181)	4,447***	(131)
Experimental Setting	Actual Info / Non-incentivized bid		Actual Info / Non-incentivized bid		Actual Info / Real-stakes bid		Actual Info / Real-stakes bid	
Controls	Profitability Terciles		Information Categories		Profitability Terciles		Information Categories	
Zero Bids	Excluded		Excluded		Excluded		Excluded	
Dealer fixed-effects	Yes		Yes		Yes		Yes	
N	261		261		352		352	
rmse	6,881		6858		1187		1167	
r2	0.01		0.01		0.011		0.049	

Note: Dependent variable is subject's bid; Models 1 and 3 controls for the first and second profitability tercile, with reference to the third profitability tercile. Models 2 and 4 add controls for variables included in the valuation reports, aggregated by nature, and calculated by the authors. The table includes censored bid distributions, e.g. zeros are excluded. All values expressed in XOF.