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Andrew Dillon and Nicolò Tomaselli

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*DISEI, Università degli Studi di Firenze*
*Via delle Pandette 9, 50127 Firenze (Italia) www.disei.unifi.it*

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

Andrew Dillon[1] and Nicolo Tomaselli[1]

[1]Northwestern University

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**Abstract**

We study the design of auctions in a low-income country where business licenses for new markets are auctioned to private firms. The field experiment varies two auction design choices: the auction mechanism and the type of information provided to bidders. The results suggest that: i) open auctions, in which bidders implicitly share information with their peers, have up to 61 percent lower mean bid prices and up to 67 percent lower bid variance than closed auctions, in which bidders bid secretly; ii) bidding behavior is influenced by the pre-bid license information provided by the auctioneer as much as by bidders' ex-ante beliefs; and iii) auctions with real stakes reduce bids by a factor of five relative to non-incentivized auctions. These results underscore the importance of auction design for pricing innovations and the challenges inherent in creating markets in low-income countries where returns to innovations are highly uncertain.

E-mail: andrew.dillon@kellogg.northwestern.edu
E-mail: nicolo.tomaselli@kellogg.northwestern.edu

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**JEL**
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. Price elicitation 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 (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, hypothetical and real-stakes auctions are also a common price discovery mechanism 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.

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, 2024). 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 estimates the effect of alternative auction designs 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] We also vary the information provided to input dealers about market characteristics and expected demand.

The context of our VIF auctions is analogous to that of an oil lease auction, where

[1] In our English clock auction, the price of the license is increased at intervals and bidders withdraw until only one remains and pays the price of the last exit. In Second price auctions, bidders bid secretly, and the winner pays the second highest price. The BDM auction adds to the latter mechanism a randomly drawn price that winning bidders must exceed to win the license.

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 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 oil concession. Bidders learning about another bidder's test results are likely to revise their initial estimates. This is one of the main conclusion of Wilson, 1969, model where bids are based on common values. However, while the market returns to innovations such as VIFs are uncertain for each individual bidder, they are not homogeneous across bidders. Each bidder may have the same information regarding the characteristics of the license for sale, but 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 licenses.[2] Although uncertain at the time of participation in the auction, each bidder has a distinct private value of the license being sold. Private values are unlikely to be independent as ag-input dealers share wholesaler relationships and are collectively organized in a national association of ag-input dealers. Milgrom and Weber, 1982 call bid correlation *affiliation*.

We have three main research questions. First, we investigate how different auction designs affect bid levels and variance. In particular, we study if *open* auctions, where bidders are face to face and know their opponents' bids, influence bidding compared to *closed* auctions, where bids are submitted independently. Second, we study how agents use their ex-ante beliefs in combination with the pre-bid information about the license characteristics made available by the auctioneer. Finally, we take advantage of this setting to test how real-stakes (actual bidding for real licenses) influence bidding behavior in Second price auctions, where we compare non-incentivized bids with real-stakes bids.

The paper has three main results. First, auction theory predicts that in affiliated private value auctions more shared information among bidders, as observed in open auctions, increases the auctioneer revenues. This prediction, called the linkage principle (Krishna, 2003), states that an auction mechanism will generate higher expected revenues when each bidder's signals (her information and ex-ante beliefs) are more observable and better reflected in their bids.[3]

[2] 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.

[3] 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

Although a formal test is not possible within our experimental setting about this exact bidding strategy, our results are empirically consistent and in contrast to the linkage principle. Our results show a lower bidding distribution in open auctions, and consequently lower revenues with respect to closed auctions (Athey et al., 2011, Koh et al., 2007). 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 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). 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 second result provides an estimate of the value of market information on bidders' bidding behavior. In a first auction round, the experiment uses information about the potential returns of the license for *hypothetical* locations where the VIF would take place, such that bidders get only the reported information provided by the auctioneer. Then, in a second round, the auctioneer introduces reported information about the potential returns of licenses in *real* locations surrounding the bidders' usual area of operation. The results show that the average bid level is lower when bidders are provided with information regarding the actual locations. Moreover, the data indicates that bids converge and exhibit a variance that is 2 to 3.5 times less than that observed with hypothetical information. This result is significant because in the context of scaling innovations in low income countries, auction results using hypothetical information may not be useful in gauging market potential, even if low-cost. Providing information about the real locations of VIF licenses enables bidders to obtain an additional information and make more precise estimations of their private values. This is because they can now use both their ex-ante beliefs and the pre-bid information provided by the auctioneer. In our setting, bidding behavior is

analysis of the linkage principle can be found in Offerman et al., 2022.

consistent with aggregation of the multiple signals in the auction (bidder's ex-ante beliefs, other bidders' bids, and the market information) which results in bid convergence.

These two experimental results demonstrate that when bidders lack knowledge about their competitors' strategies and lack information about potential market returns in the location where the market will take place, 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. The relative ignorance about competitors' signals and the characteristics of the license impedes bidders' to form their valuation, leads to a more homogeneous bidding population, and heightened competition (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 and, consequently, make bidders' valuations more accurate.

Third, we test how real-stakes bidding influences the behavior of bidders. We find that when bids are incentivized in a real-stakes auction, average bids range between 2.45 to 4.92 times lower mean value 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. First, 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 pre-bid information provided to bidders. As more emphasis on scaling tested innovations leads to increased investment, both public and private (Kremer et al., 2021), auction design trade-offs are essential for researchers and policymakers when assessing the willingness to pay for these innovations.

Second, on auction mechanisms, our findings show bidding behavior inconsistent with the Vickrey's revenue equivalence theorem, which states that open outcry 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 group dynamics and signal aggregation in open auctions, where bidders bid together. When bidders' beliefs 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 private values (Maskin and Riley, 2000). That is, in open auctions, remaining bidders interpret bidders strategies to drop out as being more informative then their current private value causing them to also drop out of the auction. This has direct implications for pricing innovations in open auctions when bidders are risk averse and the returns to the object are uncertain.[4]

Third, with regard to the extent of information disclosure, our findings indicate that providing bidders with market information about the object for sale is not a sufficient condition to guarantee high auctioneer revenues, as otherwise modeled in standard auction theory (Eső and Szentes, 2007, Milgrom and Weber, 1982). Along with other similar evidence from empirical auctions, we do not find the standard theoretical prediction that information transparency increases auction revenues (Mithas and Jones, 2007, Dufwenberg and Gneezy, 2002). Conversely, our results indicate that less market information increased competition among bidders, raising total auction revenue. Bergemann et al., 2022 provide a theoretical model for such a prediction, demonstrating that higher bidding is possible when market information is scarce on an uncertain object for sale.[5]

## 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 interviewed in our study area reported that input dealers had never visited their village

[4] According to auction theory, the open auction could discourage bidding by the remaining bidders. However, auction theory predicts these strategies in independent-private-values auction as a response to the winner's curse problem. The mechanism we described is alternative.

[5] Within that framework, if the seller reduces the information available to each bidder regarding their own value, for instance by preventing the use of ex-ante beliefs, 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.

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 is an innovative intervention which provide a 'bundled' solution to creating agricultural input markets by easing multiple constraints at once. Through VIFs, farmers can use forward contracts to order inputs in the post-harvest period for delivery in the planting season and potentially gain access to credit. 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., forthcoming), 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 region 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 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. 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 bidder who remains after the other bidders have dropped out is declared the winner. In Second price and BDM auctions, bidders simultaneously submit bids to the auctioneer in private. Bidders are not aware of the amount bid by other bidders. In a Second price auction, the highest bidder is awarded the license and pays the price of the second highest bidder. In the BDM auction, 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. Both these mechanisms are *closed* mechanisms, since bidders bid secretly. Across the three days we conducted the lab-in-the-field, we vary the auction mechanism order each day to address order effects, see Appendix B2. In our lab-in-the-field design, bids are non-incentivized in the first and second rounds. The third round uses only the Second price mechanism where real licenses are awarded.

### 2.3 Experimental Design

Figure 1 describes the study protocol where input dealers play three rounds of auctions which differ by the auction mechanism, information provided and pricing rule. The first round consists of 18 auctions, each for a different village where a VIF will be organized. The first round was held in April 2022, and a total of 53 input dealers attended the event and bid on the 18 auctions. The second round consisted of 18 auctions, too. Round 2 was administered in January 2023, and a total of 57 input dealers attended the event and bid on the 18 auctions. While the first two rounds are conducted as lab-in-the-field experiments, the third round consists of real-stake auctions. A total of 75 auctions were held in 5 different locations. The third round was conducted 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 the first two rounds, 16 to 20 input dealers are invited each day. Each bidder participates in 6 auctions per mechanism. On each experimental day, the sampled dealers are further 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]

In advance of the auction, the auctioneer provides a *village demand reports* to bidders. We conducted 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 insight into revenue or cost shifters. See Appendix E 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.[7]

Between the first and second rounds of auctions, the information included in the village demand report changes from hypothetical to real information. In the first round, bidders have access to information about fictitious locations, so they only receive the signal included in the reported information provided by the auctioneer. In the second round, information is associated with real locations in the study area where the input dealers

[6] It should be noted that our lab in the field could be interpreted as having 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 B1 reject the hypothesis that auction sequencing may generate bias in our estimates.

[7] Bidders are assumed to have a private 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.

usually operate, so bidders can combine the demand information provided in the village demand report with their ex-ante beliefs about the profitability of that specific location.

Between the second and third rounds, the information type coming from real villages remains constant, but we vary the incentive mechanism from non-incentivized bids to real-stakes bids. The winners of the third round auctions 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, we ensure that the pre-bid demand information transmitted to the bidders, through a village demand report, is balanced between the three mechanisms. Appendix C, Panel A, shows that the three sets of six village demand reports corresponding to the pre-bid information are statistically equivalent.[8]

## 2.4 Village Input Fair Profitability

The business opportunity offered to bidders takes the form of a Village Input Fair (VIF) license where input dealers are licensed to sell their products to customers at the village fair. Two licenses are sold per village. 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 depends largely on expectations about farmers' demand and the specific business structure 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, 2024 estimate that farmers in VIF treatment groups increased demand by XOF 50,780 (USD 96.84) compared to farmers in control villages. We estimate average revenue per VIF to be XOF 577,144 (USD 1,100.7). These calculations provide suggestive evidence that, in the absence of VIFs, input dealers are foregoing potential returns thereby underestimating the profitability of rural markets

[8] 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 sequence of the auctions, while Appendix D reports the experimental scripts. At the end of the day, we compensate bidders for their participation with a lump sum transfer uncorrelated with their bidding behavior.

even for the lowest reasonable profit margins (10 percent).[9]

# 3 Theoretical Framework

## 3.1 A Model of Bidder Behavior

We introduce a Bayesian model of bidder behavior to motivate empirical predictions from our study design. Consider a seller who wants to auction a single, 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, $\theta$ 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 $\theta_b$ signal, as well as a signal $\beta$ that correspond somewhat to the common value of the license for sale.[10] Bidders signals can be affiliated. If a bidder collects more favorable information about the returns of the license for a certain location, affiliation 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 $Z = \{\beta, \theta_1, \ldots, \theta_B\}$ where $\beta$ denotes the common valuation of the state of the world and $\theta_n$ the signals of the

[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 signal to 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.

[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 $\theta$ and states of the world $\beta$ enter each bidder's valuation function $V_b$ in a non-decreasing way, such that any higher signal raises each bidder's payoff.

bidders. These variables are affiliated if the joint probability density function, or PDF, $f(z)$, 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 $\theta_1$ and $\theta_2$ 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 revenues than *closed* auctions because bidders signals are more observable. This result has been tested empirically with mixed results (for example by Athey et al., 2011, on the case of timber auctions). Second, an auctioneer can expect higher bids by providing any relevant information about the value of the object for sale.[11] In our experiment, we vary the mechanism used from open to closed, and provide village demand reports which include a demand forecast for the upcoming season from villages where licenses will be auctioned.

## 3.2 Hypotheses

We test four hypothesis based on this model. First, we use auctions that can be *open* or *closed*, affecting the bidding function through bidder's signal, $\theta$. Second, we vary the type of pre-bid information provided to bidders through the village demand reports, thereby varying expectations about both bidder's signal, $\theta$, and the state of the world, $\beta$. By interacting these parameters, we obtain four experimental conditions, leading to four hypothesis:

[11] This result on the release of information has been tested experimentally in a lab experiment (Kagel and Levin, 1986), and empirically in wholesale automobile auctions (Tadelis and Zettelmeyer, 2015).

*Hypothesis 1*: If bidders cannot observe each other bidding during the auction, and can only assess the license for sale using reported information about hypothetical locations 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 $\beta$ 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 some 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 $\beta$ 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 information coming from hypothetical locations, then the distribution of bidders' signals in vector $\theta = (\theta_1, ..., \theta_B)$ has low variance, and the state of the world $\beta$ 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 $\beta$ 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.

Table 1 summarizes the characteristic of the auctions, the theoretical predictions, and the experimental results. The experimental setting of our auctions relaxes information constraints on two margins, affecting both $\theta$ and $\beta$. Based on these predictions, the fourth hypotheses, with open mechanism and information from real villages, is expected to better aggregate information and ultimately generate greater revenues for the auctioneer. Increased information, both in $\theta$ and $\beta$, is expected to concentrate bidding and encourage higher bidding strategies.

# 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 a VIF license, which is our dependent variable. We use the last price bid by bidders in each auction — even if they do not win the license. As explanatory variable, we first include the vector of the three mechanisms. 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 villages and for those with information from real villages. We do not pool data between the first and second rounds because we have sufficient statistical power and because we are particularly interested in the relative performance of mechanisms *within* each auction round. The first and second round auction analysis examines how non-incentivized WTP is influenced by three auction mechanisms and different types of information.

In specification 1, bid $y$ for input dealer $a$ and for license $u$ represents the dependent variable; the mechanism $M$ is the explanatory variable (English auction, Second price, BDM), 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 the third round of auctions, 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 first two rounds, 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 the first and second rounds, and for each of the three auction mechanisms. Figure 2, Panel A, shows in the left quadrant the distribution function for the pooled data including both rounds of auctions. The demand curve for the first round, with information from hypothetical villages, lies consistently to the right of the demand curve for the second round, with information from real villages. The data suggests that using information from actual villages has a marginal impact on demand reduction. 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.

Graph 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 given the village demand reports from real villages, demonstrates a contraction in demand for each curve. This suggests that the negative impact on demand resulting by the use of actual information is not auction mechanism-specific.

## 5.2 Hypotheses Tested

### 5.2.1 Open vs. Closed Mechanisms and Information Sharing Among Bidders

We first report the results of hypothesis testing between open and closed auctions. Auction theory and the experimental literature on auctions generally finds that the more information bidders share, the more they express high demand for the item for sale (Offerman et al., 2022, das Varma, 2002). Accordingly, our third and fourth hypotheses posit that open mechanisms, where bidders openly share information, 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 hypothesis on higher bid levels. We find that open auctions are associated with lower bid levels compared to closed auctions. We conclude that, on average, the open auction mechanisms lower 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 auction 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 67 and 61 percent lower than in closed auctions.[12] To see this graphically, we report in Figure 3, panel A, the kernel density distribution 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 receive more information from 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 by noting that with open auctions bidders learn from the decisions of their peers in real time. First, these results could support the idea that when competitors leave an auction, those remaining in the game 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

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

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 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 auction is advantageous for car buyers, as each car buyer lowers on average about 7.5 percent of the price for 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.

### 5.2.2 Pre-bid Information, Village Demand Reports, 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.[13] To test the hypothesis that ex-ante beliefs and village demand reports influence bidders' valuations, we need to compare the first and second round of auctions. Both Table 2 and Table 3 report descriptive statistics showing that

[13] 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.

in the first round with village demand reports with information from hypothetical villages, the variance of the bids ranges between XOF 109,131 thousands and XOF 328,642 thousands, while the same value in the second round with village demand reports with information from real villages drops to a range between XOF 51,592 thousands and XOF 138,623 thousands. In the second round, the variance ranges between 53 and 57 percent less than in the first round. 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 village demand reports include information from real villages. 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 by the auctioneer in the second round on village demand reports for real locations is common knowledge. 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 provide an additional signal to bidders, which affect their valuations in different ways. Conversely, in the first round 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 and tend on average to generate higher expectations which in turn result in higher monetary bids (as predicted by Ganuza, 2004).

Empirical work similarly concludes that providing imperfect information about the license for sale may end up increasing demand, bid dispersion, and auction revenues. Mithas and Jones, 2007, specifically introduce the notion of informational transparency in auctions and test its welfare implications using a large electronic auction dataset. Their model predicts that the auctioneer's surplus increases when less information is shared with bidders. They confirm this hypothesis empirically and also find that the use of rank bidding formats has a positive marginal effect on bidders' bid levels.

### 5.3 Determinants of WTP

Table 4, columns 2 and 5, presents the results of our WTP estimates. The results show that when using pre-bid information from village demand report with hypothetical villages, bidders' demand is elastic to the demand forecast included in the village demand reports. We include tercile fixed effects indicating different expected license profitability levels. 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 bides are highly correlated with pre-bid information in the hypothetical villages.

This result shows that a license with higher expected market returns is correlated with higher WTP. By introducing village demand reports with information from real villages, in the second round of auctions, we get a similar result although less precisely estimated. This may seem counter-intuitive if we assume that input dealers can use ex-ante beliefs in the second round. 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 expected profitability decreases.

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. While these controls have the expected signs and are statistically significant in the first auction round with hypothetical villages, they lose their significance in the second round when village demand reports include information from real villages. It seems reasonable to conclude that the detailed and location-specific information provided to bidders affects their WTP only when it is the sole information available to them, as is the case in round one.

Finally, in Table 5, we exploit the observable characteristics of the input dealers that we collected on each day of the experiment. Here we use OLS models, introducing the categorical variable describing whether a bidder bid any positive value and whether she is a *winner* of the auction. The *anybid* variable qualify non-compliant bidders, i.e., those who, even if present at the auction, decided to bid zero. The experiment does not allow disentangling which of these zero bids are true WTP, which are censored values that could have been negative bids, and which are just protest bidding (Strazzera et al., 2003).

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 successful 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

Our experimental design allows for comparison between different pricing rules. In the third round of auctions, when bids are real-stakes, average bids have a lower mean value and lower variance than non-incentive bids in rounds one and two. 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.[14]

Table 6 reports the estimation results. This time we are not comparing between auction mechanisms, since only Second price auctions were administered in the final round. We pool data from the second and third rounds of auctions 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.[15] During the third round 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 and comprehensible by them.

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 Mali demonstrate that both the bid levels and the bid variance are higher in non-incentivized bids in comparison to real-stakes bids.

[14]See Appendix G. These effect size are in line with other available experimental and empirical evidence (List, 2001, Blumenschein et al., 1997).

[15]Appendix H reports the coefficient estimates using the same specification that we used in Table 4, with independent samples for round 2 and 3.

## 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 imply higher bid levels. Open auctions show lower mean bid levels between -34 and -75 percent with respect to closed auctions. The results indicate that signals' aggregation makes lower bids more likely.

Our analysis suggests that the withdrawal of competing bidders from an open auction reduces bids submitted by the remaining bidders. This is because dropping bidders signal low expectations for the market returns of the auctioned license. We consider that our context is distinct from Milgrom and Weber's theoretical approach which assumes risk neutrality of bidders. In our case, potential bidders are uncertain about both the profitability of the business opportunity and their own ability to take advantage of the opportunity. They are also more likely risk averse in our low-income country context.

The experiment also shows the behavioral responses of bidders when they are presented with market information about the license in the form of village demand reports issued from either hypothetical or real villages. For licenses auctioned for existing villages, market information does not substantially change bidder valuations for the license, suggesting that our bidders have strong ex-ante beliefs about market returns in the study area.

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 evidence on the correlation between real-stakes and non-incentivized bids (List and Gallet, 2001, List and Shogren, 1998).

This paper shows how auctions can support scaling market innovations in low income countries. 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 from a supply-side perspective. The bid amounts elicited in the auctions provide a definitive reflection of the private sector WTP for exploiting the new business opportunities and the potential for private sector scaling strategies.[16]

[16] In our first seasons of scaling VIFs, auctions generated between 50 and 60 percent of the marginal

Auctions also support allocative efficiency when scaling with large groups of potential actors. We have used auctions to identify input dealers with the highest motivation to participate in fairs. The auctions described in this paper effectively induce private suppliers to consider market opportunities, thereby allowing firms to invest in advance, purchasing a license. Future research will focus on whether auction winners increase their profits and grow their businesses in response to expanded market access.

costs of implementing VIFs.

# References


Asante, S., Andam, K. S., Simons, A. M., Amprofi, F. A., Osei-Assibey, E., Iddrisu, A., & Blohowiak, S. (2021). Agricultural input markets in Ghana: A descriptive assessment of input dealers in eight districts. https://doi.org/10.2499/p15738coll2.134481

Ashraf, N., Berry, J., & Shapiro, J. M. (2010). Can higher prices stimulate product use? evidence from a field experiment in zambia. *American Economic Review*, *100*(5), 2383–2413. https://doi.org/10.1257/aer.100.5.2383

Athey, S., Levin, J., & Seira, E. (2011). Comparing open and Sealed Bid Auctions: Evidence from Timber Auctions. *The Quarterly Journal of Economics*, *126*(1), 207–257. https://doi.org/10.1093/qje/qjq001

Bergemann, D., Brooks, B., & Morris, S. (2019). Revenue guarantee equivalence. *American Economic Review*, *109*(5), 1911–29. https://doi.org/10.1257/aer.20180773

Bergemann, D., Heumann, T., Morris, S., Sorokin, C., & Winter, E. (2022). Optimal information disclosure in classic auctions. *American Economic Review: Insights*, *4*(3), 371–88. https://doi.org/10.1257/aeri.20210504

Berry, J., Fischer, G., & Guiteras, R. (2020). Eliciting and Utilizing Willingness to Pay: Evidence from Field Trials in Northern Ghana. *Journal of Political Economy*, *128*(4), 1436–1473. https://doi.org/10.1086/705374

Blumenschein, K., Johannesson, M., Blomquist, G. C., Liljas, B., & O'Conor, R. M. (1997). Hypothetical versus real payments in Vickrey auctions. *Economics Letters*, *56*(2), 177–180. https://doi.org/10.1016/S0165-1765(97)81897-6

Canavari, M., Drichoutis, A. C., Lusk, J. L., & Nayga, J., Rodolfo M. (2019). How to run an experimental auction: a review of recent advances. *European Review of Agricultural Economics*, *46*(5), 862–922. https://doi.org/10.1093/erae/jbz038

Cohen, J., & Dupas, P. (2010). Free Distribution or Cost-Sharing? Evidence from a Randomized Malaria Prevention Experiment*. *The Quarterly Journal of Economics*, *125*(1), 1–45. https://doi.org/10.1162/qjec.2010.125.1.1

Corazzini, L., Galavotti, S., & Valbonesi, P. (2019). An experimental study on sequential auctions with privately known capacities. *Games and Economic Behavior*, *117*, 289–315. https://doi.org/10.1016/j.geb.2019.06.005

Corrigan, J. R., & Rousu, M. C. (2006). Posted Prices and Bid Affiliation: Evidence from Experimental Auctions. *American Journal of Agricultural Economics*, *88*(4), 1078–1090. https://doi.org/10.1111/j.1467-8276.2006.00917.x

Dar, M. H., de Janvry, A., Emerick, K., Sadoulet, E., & Wiseman, E. (2024). Private input suppliers as information agents for technology adoption in agriculture. *American Economic Journal: Applied Economics*, *16*(2), 219–48. https://doi.org/10.1257/app.20220037

das Varma, G. (2002). Standard auctions with identity-dependent externalities. *The RAND Journal of Economics*, *33*(4), 689–708. Retrieved June 23, 2024, from http://www.jstor.org/stable/3087481

Delavande, A. (2023). Expectations in development economics. In R. Bachmann, G. Topa, & W. van der Klaauw (Eds.), *Handbook of economic expectations* (pp. 261–291). Academic Press. https://doi.org/https://doi.org/10.1016/B978-0-12-822927-9.00016-1

Delgado, M. R., Schotter, A., Ozbay, E. Y., & Phelps, E. A. (2008). Understanding overbidding: Using the neural circuitry of reward to design economic auctions. *Science*, *321*(5897), 1849–1852. https://doi.org/10.1126/science.1158860

Devenow, A., & Welch, I. (1996). Rational herding in financial economics. *European Economic Review*, *40*(3), 603–615. https://doi.org/https://doi.org/10.1016/0014-2921(95)00073-9

Dillon, A., Michelson, H., Lybbert, T., & Rudder, J. (forthcoming). Agricultural input markets in sub-saharan africa: Theory and evidence from the (underappreciated) supply-side. *Annual Review of Resource Economics*.

Dillon, A., & Tomaselli, N. (2024). Making markets: Experiments in agricultural input market formation. *SSRN Electron. J.* https://doi.org/http://dx.doi.org/10.2139/ssrn.4934116

Dufwenberg, M., & Gneezy, U. (2002). Information disclosure in auctions: An experiment. *Journal of Economic Behavior  Organization*, *48*(4), 431–444. https://doi.org/https://doi.org/10.1016/S0167-2681(01)00235-9

Engelbrecht-Wiggans, R., & Weber, R. J. (1983). A sequential auction involving asymmetrically-informed bidders. *International Journal of Game Theory*, *12*(2), 123–127. https://doi.org/10.1007/BF01774302

Eső, P., & Szentes, B. (2007). Optimal information disclosure in auctions and the handicap auction. *The Review of Economic Studies*, *74*(3), 705–731. https://doi.org/10.1111/j.1467-937X.2007.00442.x

Ganuza, J.-J. (2004). Ignorance promotes competition: An auction model with endogenous private valuations. *The RAND Journal of Economics*, *35*(3), 583–598. Retrieved December 4, 2024, from http://www.jstor.org/stable/1593709

Georganas, S., Levin, D., & McGee, P. (2017). Optimistic irrationality and overbidding in private value auctions. *Experimental Economics*, *20*(4), 772–792. https://doi.org/10.1007/s10683-017-9510-y

Hendricks, K., & Porter, R. H. (1988). An Empirical Study of an Auction with Asymmetric Information. *American Economic Review*, *78*(5), 865–883. https://ideas.repec.org/a/aea/aecrev/v78y1988i5p865-83.html

Hu, A., Offerman, T., & Onderstal, S. (2011). Fighting collusion in auctions: An experimental investigation [Special Issue: Experiments in Industrial Organization]. *International Journal of Industrial Organization*, *29*(1), 84–96. https://doi.org/10.1016/j.ijindorg.2009.06.003

Irwin, J. R., McClelland, G. H., & Schulze, W. D. (1992). Hypothetical and real consequences in experimental auctions for insurance against low-probability risks. *Journal of Behavioral Decision Making*, *5*(2), 107–116. https://doi.org/10.1002/bdm.3960050203

ISTAT. (2019). *Enquête Harmonisée sur le Conditions de Vie des Ménages 2018-2019*. World Bank, Development Data Group. https://doi.org/10.48529/90E9-4E91

Jeitschko, T. D. (1998). Learning in Sequential Auctions. *Southern Economic Journal*, *65*(1), 98–112. https://doi.org/10.2307/1061354

Just, D. R., & Hanks, A. S. (2015). The hidden cost of regulation: Emotional responses to command and control. *American Journal of Agricultural Economics*, *97*(5), 1385–1399. Retrieved June 13, 2024, from http://www.jstor.org/stable/24477211

Kagel, J. H., Harstad, R. M., & Levin, D. (1987). Information Impact and Allocation Rules in Auctions with Affiliated Private Values: A Laboratory Study. *Econometrica*, *55*(6), 1275–1304. https://doi.org/10.2307/1913557

Kagel, J. H., & Levin, D. (1986). The winner's curse and public information in common value auctions. *The American Economic Review*, *76*(5), 894–920. Retrieved June 21, 2024, from http://www.jstor.org/stable/1816459

Koh, W. T. H., Mariano, R. S., & Tse, Y. K. (2007). Open vs. sealed-bid auctions: Testing for revenue equivalence under Singapore's vehicle quota system. *Applied Economics*, *39*(1), 125–134. https://doi.org/10.1080/00036840500427916

Kremer, M., Gallant, S., Rostapshova, O., & Thomas, M. (2021). Is development a good investment? which innovations scale? evidence on social investing from usaid's development innovation ventures. chrome-extension://efaidnbmnnnibpcajpcglclefindmkaj/https://michaelkremer.economics.uchicago.edu/files/2022/04/SROR-21.11.04_clean-2.pdf

Krishna, V. (2003, January 1). 7 - The revenue ranking ("Linkage") principle. In V. Krishna (Ed.), *Auction Theory* (pp. 103–110). Academic Press. https://doi.org/10.1016/B978-012426297-3.50033-3

List, J. A. (2001). Do Explicit Warnings Eliminate the Hypothetical Bias in Elicitation Procedures? Evidence from Field Auctions for Sportscards. *American Economic Review*, *91*(5), 1498–1507. https://doi.org/10.1257/aer.91.5.1498

List, J. A. (2022). *The voltage effect: How to make good ideas great and great ideas scale*. Crown Currency.

List, J. A., & Gallet, C. A. (2001). What Experimental Protocol Influence Disparities Between Actual and Hypothetical Stated Values? *Environmental and Resource Economics*, *20*(3), 241–254. https://doi.org/10.1023/A:1012791822804

List, J. A., & Shogren, J. F. (1998). Calibration of the difference between actual and hypothetical valuations in a field experiment. *Journal of Economic Behavior & Organization*, *37*(2), 193–205. https://doi.org/10.1016/S0167-2681(98)00084-5

Maskin, E., & Riley, J. (2000). Asymmetric Auctions. *The Review of Economic Studies*, *67*(3), 413–438. https://doi.org/10.1111/1467-937X.00137

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

Mithas, S., & Jones, J. L. (2007). Do Auction Parameters Affect Buyer Surplus in E-Auctions for Procurement? *Production & Operations Management*, *16*(4), 455–470. Retrieved October 23, 2023, from https://doi.org/10.1111/j.1937-5956.2007.tb00272.x

Offerman, T., Romagnoli, G., & Ziegler, A. (2022). Why are open ascending auctions popular? the role of information aggregation and behavioral biases. *Quantitative Economics*, *13*(2), 787–823. https://doi.org/https://doi.org/10.3982/QE1692

Pons-Novell, J. (2003). Strategic bias, herding behaviour and economic forecasts. *Journal of Forecasting*, *22*(1), 67–77. https://doi.org/https://doi.org/10.1002/for.860

Strazzera, E., Scarpa, R., Calia, P., Garrod, G. D., & Willis, K. G. (2003). Modelling zero values and protest responses in contingent valuation surveys. *Applied Economics*, *35*(2), 133–138. https://doi.org/10.1080/0003684022000015900

Suri, T., & Udry, C. (2022). Agricultural Technology in Africa. *Journal of Economic Perspectives*, *36*(1), 33–56. https://doi.org/10.1257/jep.36.1.33

Tadelis, S., & Zettelmeyer, F. (2015). Information disclosure as a matching mechanism: Theory and evidence from a field experiment. *American Economic Review*, *105*(2), 886–905. https://doi.org/10.1257/aer.20110753

Vickrey, W. (1961). Counterspeculation, auctions, and competitive sealed tenders. *The Journal of Finance*, *16*(1), 8–37. https://doi.org/https://doi.org/10.1111/j.1540-6261.1961.tb02789.x

Wilson, R. B. (1969). Communications to the Editor—Competitive Bidding with Disparate Information. *Management Science*, *15*(7), 446–452. https://doi.org/10.1287/mnsc.15.7.446

## Figures

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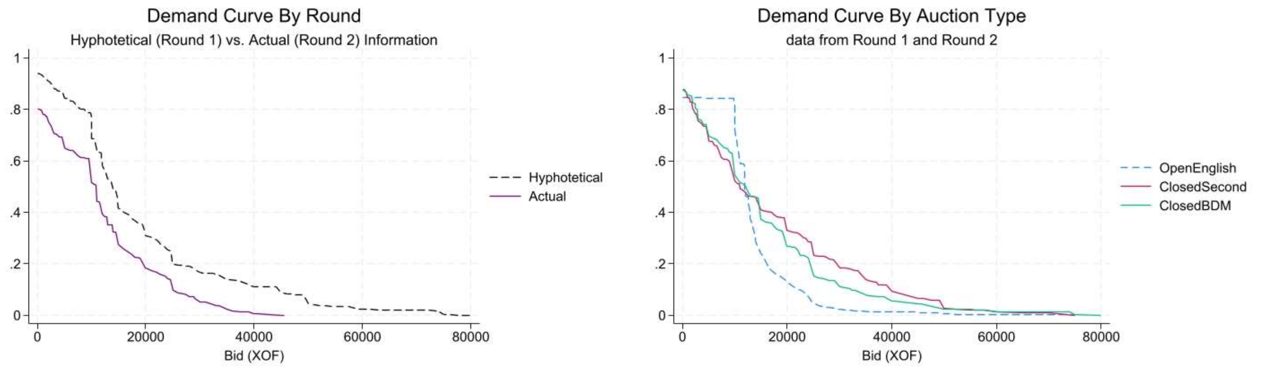
Figure 1: Lab in the Field Protocol

| | Round 1 | Round 2 | Round 3 |
|---|---|---|---|
| Information | Hypothetical information | Actual information | Actual information |
| Auction Type | English<br>Second price<br>BDM | English<br>Second price<br>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.

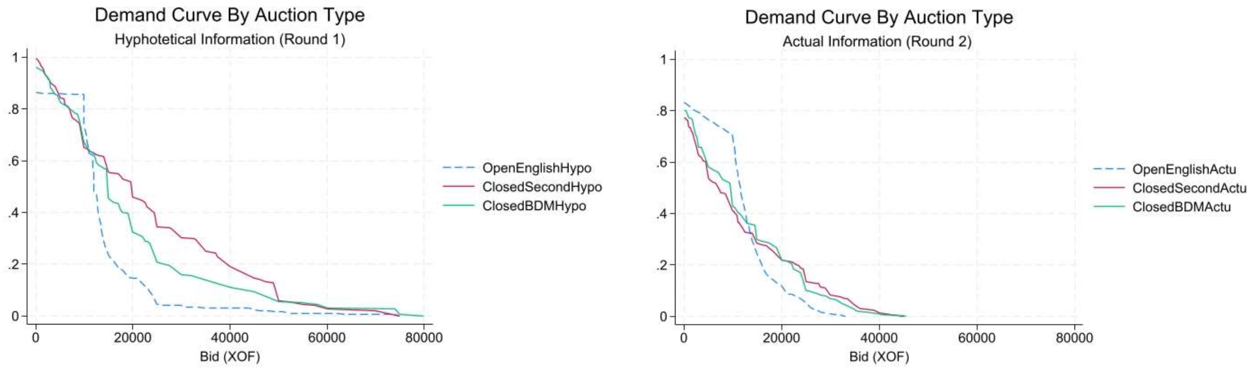
Figure 1: Demand Curves

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

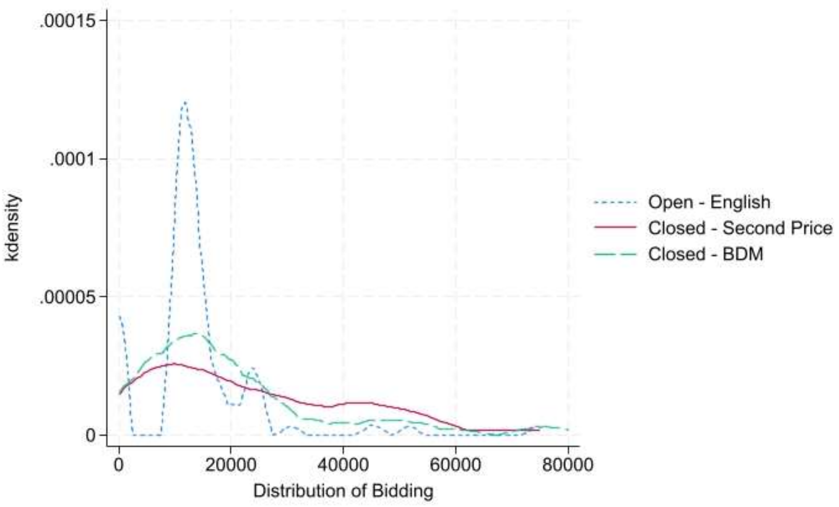



Note: Demand curves are plotted as the inverse of the bids cumulative distribution function (CDF). The left quadrant shows Round 1 with Hyphotetical Information and Open English Auctions (dash) versus Closed Second price (solid red) and BDM Auctions (solid green). The right quadrant shows Round 2 with 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 2: Bidding Distribution by Auction Mechanism and Information Type

Panel A

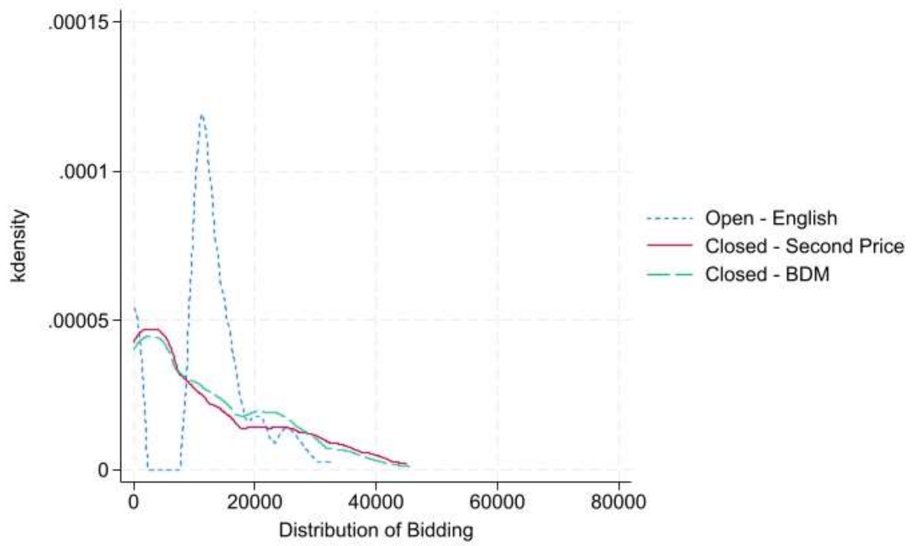
Density Estimation with Hypothetical Information




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

—

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) | Prior 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 | *T-tests of mean equality* | *Mann-Whitney test of median equality* | *Levene's test of variance homogeneity* |
|---|---|---|---|---|---|---|---|
| | Close Mechanism | Second Price | ***Hypothesis 1***:<br>Mean = 23,641<br>Median = 20,000<br>SD = 18,106 | ***Hypothesis 2***:<br>Mean = 14,570<br>Median = 11,000<br>SD = 11,451 | *t = 7.08**** | *z = 5.70**** | *W = 54.16**** |
| | | BDM | Mean =20,476<br>Median = 15,000<br>SD = 16,669 | Mean = 14,358<br>Median = 11,500<br>SD = 10,386 | *t = 5.21**** | *z = 4.17**** | *W = 20.10**** |
| | Open Mechanism | English | ***Hypothesis 3***:<br>Mean = 15,998<br>Median = 13,000<br>SD = 9,555 | ***Hypothesis 4***:<br>Mean = 14,655<br>Median = 13,000<br>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, and which are actually protest bids (Just and Hanks, 2015). 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 – 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 |
| | 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 |
| | 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 |
| | 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 |
| | 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 |
| | 2nd Tercile | 60.5 | n/a | 0.96 | 1.45 | 0.80 | 0.37 | 65.16 | 136.83 | 1.26 | 3.67 | 0.00 |
| | 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 |
| | 2nd Tercile | n/a | 1777 | 28.03 | 7.92 | 43.14 | 2.41 | 33.16 | 18.50 | 0.54 | 9.5 | n/a |
| | 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 D - 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 E - Examples of village demand reports for first round (Panel A) and second round (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

**Chef du village: Ahmad Baba al Massufi**

Fictitious Village Name

### 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<br>**21 sacs** | NPK<br>**41 sacs** | DAP<br>**12 sacs** |
| Fertinova<br>**15 sacs** | Organova<br>**-** | Pesticides<br>**70 cartons** |
| Insecticides<br>**345 cartons** | Fongicides<br>**-** | Semences<br>**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<br>331 sacs de 50 kg | NPK<br>200 sacs de 50 kg | DAP<br>501 sacs de 50 kg |
| Autre engrais chimiques<br>- | Fertinova<br>- | Herbicides<br>40 cartons |
| Insecticides<br>30 cartons | Fongicides<br>180 kg | Semences<br>200 kg |

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 | | | | | | | | |
| 1st tercile | -3,421* | (1,474) | | | -337 | (267) | | |
| 2nd 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.