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Quality constraints to agricultural technology adoption

Can an information clearinghouse save the Ugandan market for seed?

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Abstract

Agricultural technologies remain under-adopted among smallholder farmers in sub-Saharan Africa. We investigate how the quality of an agricultural input affects its adoption. As the sellers of maize seed have more information about its quality than the buyers, we hypothesize that this information asymmetry leads to poor seed quality offered by agro-input dealers, resulting in under-adoption by farmers. To overcome this classic lemons technology problem, we implement a crowd-sourced information clearinghouse similar to yelp.com in the market for seed, meaning that we collect and disseminate farmers' ratings of seed quality. This intervention is tested in a randomized controlled trial among 350 agro-input dealers and 3500 smallholder maize farmers in Uganda. Midline data shows that dealers increase their efforts and improve their services in response to the clearinghouse. Treated farmers are also more likely to switch from one to another shop. There are some indications that these two mechanisms eventually lead to better maize seed quality but endline data has to be analyzed before we can draw conclusions.

1 Introduction

Smallholder farmers in sub-Saharan Africa do not sufficiently adopt agricultural technologies like high yielding seed varieties and fertilizers, even though these inputs are seen as the key to agricultural productivity (De Janvry et al., 2016). As a result, differences in agricultural yields between sub-Saharan Africa and countries in Latin America and Asia have almost doubled since 1961 (Magruder, 2018). Experts argue that the substantial growth in yields in these countries can largely be explained by increased adoption whereas the stagnation of yields in sub-Saharan Africa can mostly be explained low adoption (Morris, 2007). At the individual level, farmers who do not adopt miss out on increased yields and farm profits (Suri, 2011), and potentially on a way out of poverty and a better life. Also at the aggregate level, the lag in adoption has high costs in terms of economic development and human welfare and is holding back the reduction of rural food insecurity and poverty. That is why it is important to identify the drivers of and constraints to agricultural technology adoption.

In line with the general trend in economics, these drivers and constraints have increasingly been studied using field experiments (De Janvry et al., 2016; De Janvry, Sadoulet, and Suri, 2017). For instance, the Agricultural Technology Adoption Initiative (ATAI), a collaboration between MIT's Abdul Latif Jameel Poverty Action Lab (J-PAL) and UC Berkeley's Center for Effective Global Action (CEGA), has funded a series of field experiments to illuminate what helps and hinders adoption among smallholder farmers. The literature has identified several key constraints which include poor access to information (Ashraf, Giné, and Karlan, 2009), farmers' behavioral constraints like procrastination and time-inconsistent preferences (Duflo, Kremer, and Robinson, 2011), heterogeneity in uncertainty and the net benefits to the technology due to infrastructure and high transaction costs (Suri, 2011), missing markets for risk and credit (Karlan et al., 2014), and learning (Foster and Rosenzweig, 1995; Conley and Udry, 2010; Hanna, Mullainathan, and Schwartzstein, 2014).

This study addresses a particular constraint to technology adoption: the perceived quality of agricultural inputs in the market, which has received considerable attention from academics and policy makers recently (Bold et al., 2017; Michelson et al., 2021). To this end, we look at Ugandan *improved maize seed varieties*, which are high yielding cultivars like open-pollinated and hybrid maize varieties. Maize is an important crop in Uganda, both for home consumption and as a source of income. Yet, the uptake of improved varieties by smallholder farmers remains persistently low, despite the higher yield potential compared to traditional varieties.

Because agricultural input quality is difficult to observe, information asymmetries between sellers and buyers characterize the markets for seed and fertilizer. Bold et al. (2017) argue that the Ugandan market for improved maize seed appears similar to the market for used cars described in Akerlof's classic study (1970). In such a market where sellers have more information about the quality of the good than buyers, there is no incentive for vendors to sell good products and average quality can degrade. That is why recent studies claim that smallholder adoption of agricultural inputs, and of improved maize seed in Uganda in particular, is limited by farmers' beliefs that the inputs are of poor quality - counterfeited, adulterated, or otherwise not performing (Bold et al., 2017; Ashour et al., 2019; Barriga and Fiala, 2020). These studies provide empirical evidence of Ugandan agricultural inputs being lemons. In line with this literature, we hypothesize that the intentional and unintentional malpractices of dealers lead to poor seed quality, resulting in under-adoption by smallholder farmers. These quality issues might therefore constrain the emergence and sustainability of an efficient seed system.

To assess the importance of this potential constraint to agricultural technology adoption, we test an intervention which reduces the information asymmetry between seller and buyer by making the quality of maize seed observable. We implement a decentralized information clearinghouse that is based on crowd-sourced ratings and works through reputational mechanisms, much like yelp.com or tripadvisor.com, in the market for seed. This means that we aggregate the experiences of many users by collecting the ratings of smallholder farmers to reveal the quality of maize seed sold by each agro-input dealer. Then we disseminate these ratings back to farmers and dealers. The treatment targets the interaction between farmers and dealers who sell improved seed and play a crucial role because they form a key link between seed producers and users. This crowd-sourced information clearinghouse is tested in a randomized controlled trial (RCT) among 350 agro-input dealers and 3500 smallholder maize farmers in Uganda[1].

Midline data shows that dealers increase their efforts and improve their services in response to the clearinghouse. Treated farmers are also more likely to switch from one to another shop. There are some indications that these two mechanisms eventually lead to better maize seed quality. Heterogeneity analysis suggests that the clearinghouse works better for dealers who specialize and for dealers who face more competition. However, endline data has to be analyzed before we can confidently draw conclusions.

The paper is structured as follows: Section 2 provides some information on the background of the study, section 3 describes the experimental design. The intervention, the empirical strategy and the data are described in detail in sections 4, 5 and 6. After presenting the results in section 7, we talk about potential threats to validity. Then we discuss our findings and conclude in sections 9 and 10. Acknowledgments follow in section 11.

[1]This research received clearance from Makerere University's School of Social Sciences Research Ethics Committee (MAKSS REC 08.20.436/PR1) as well as from the International Food Policy Research Institute (IFPRI)'s Institutional Review Board (IRB) (DSGD-20-0829). The research was also registered at the Ugandan National Commission for Science and Technology (UNCST SS603ES).

2 Background

2.1 Agro-input dealers

The clearinghouse targets the interaction between the farmer and the agro-input dealer. Agro-input shops are businesses that sell inputs and equipment used in agricultural production, such as improved seed[2], fertilizers, and other agricultural technologies. These dealers play an important role in the seed system because they create a market for agricultural technologies, develop and disseminate knowledge, and sometimes perform additional tasks like providing farm credit (Hornum and Bolwig, 2021). Furthermore, they are part of an important network with connections to actors across the value chain, such as manufacturers of inputs (e.g. seed companies), government organizations (e.g. breeders) and other agribusinesses. While the importance of the dealers in the seed supply chain seems straightforward and some authors emphasize the role of private agents (De Janvry et al., 2016), there are very few studies which target these actors. As the shops form a key link between the producers and users of agricultural technologies, the activities of these dealers play an important role and quality issues may arise at their level. That is why our clearinghouse specifically targets agro-input shops and dealers.

2.2 The problem

The ability of smallholders to infer maize seed quality is severely limited. It is impossible to accurately determine quality on the basis of visual examination before purchase, as farmers can only visually inspect seed purity and the presence of mold. But also after using the seed, farmers can hardly assess quality because there are so many factors at play in agricultural production. If they experience a disappointing harvest, they cannot safely conclude that the seed material was poor because it could have also been poor soil, insufficient, late or too much rain, or own mismanagement like late planting or insufficient weeding. Misattribution occurs when farmers mistakenly ascribe bad outcomes to bad inputs, rather than to other possible causes. Learning about the true quality becomes more difficult when this misattribution is present

[2] Agro-input shops sell only *improved* seed. The alternative to improved seed is farmer saved seed which farmers harvest themselves in one crop season and save to plant it in the following season. This seed usually free of charge (if the farmer him/herself saves it) or cheap (if a neighbor, relative, someone else saves it) and not sold by agro-input shops.

(Hoel et al., 2021). Tjernström et al. (2021) agree that sub-Saharan Africa's soil heterogeneity hampers farmer learning about the returns to inputs. Also Wossen, Abay, and Abdoulaye (2022) find that farmers in developing countries routinely misperceive input quality.

As Ugandan farmers can hardly assess the quality of maize seed, we hypothesize that agro-input dealers exploit this information asymmetry, and that their malpractices lead to poor seed quality. In a context relatively similar to ours, Hoffmann et al. (2021) look at maize grain as an output in rural Kenya and find that there is no incentive for sellers to address food safety losses because they are not observable for buyers, so that there is no correlation between prices and this unobservable quality attribute.

These malpractices may be *intentional*. Agro-input dealers may sacrifice quality to increase profits, e.g. by mixing good seed with poor seed to cut costs. Mind that these dealers operate in markets with weak, under-resourced institutions and regulatory systems. There is empirical evidence of this kind of adulteration at some point in the Ugandan agricultural input supply chain. Bold et al. (2017) find that hybrid maize seed contains less than 50% authentic seeds and that 30% of nutrient is missing in fertilizer. Ashour et al. (2019) find that the average bottle of herbicide is missing 15% of the active ingredient and nearly one in three bottles contains less than 75% of the ingredient advertised. Both studies were conducted in Uganda. Recently the topic has also received considerable attention from local news channels (Kazibwe, 2021) and policy makers. A National Seed Policy report written by the Ugandan Ministry of Agriculture, Animal Industry and Fisheries states that 30-40% of seed traded in the market is counterfeit (2018). Also in our sample, 68% of farmers think that maize seed that is sold at shops is adulterated.

On the other hand, these malpractices may be *unintentional*. Poor seed handling and storage may lead to deterioration in quality. The agro-input dealer may thus sell seed of inferior quality without intending to do so. There is also some evidence of this kind of quality reduction. In a comprehensive study of the Ugandan seed supply chain, Barriga and Fiala (2020) document various issues related to handling and storage that may reduce the quality of this input. For instance, smallholder farmers often need smaller quantities than what is packaged in standard bags, and dealers thus often repackage in sub-optimal environments. Poor rotation of seed stock and storage in open bags, in moist conditions or in direct sunlight also reduce seed quality.

These intentional and unintentional malpractices at the dealer level may lead to poor agricultural input quality. Purchasing poor inputs will lead to disappointing experiences at the farmer level. This will reduce their willingness to pay. For instance, Gharib et al. (2021) find that concerns about seed quality reduce farmers' willingness to invest in seeds, as farmers are willing to pay 15% more for bags directly from the seed company than for bags from local retailers. That is why we hypothesize that smallholder farmers' seed adoption is low because they perceive the quality of these inputs sold at agro-input dealers to be poor.

2.3 The potential solution

This classic lemons technology problem can be solved by reducing information asymmetries between the two parties. In Kenya, seed companies have started marketing their seed using novel packaging features to signal product quality and authenticity (Gharib et al., 2021). Uganda does regulate seed quality by means of certifications and standards, but they provide farmers with a relatively weak and unreliable indication of quality. We bought seed bags from agro-input dealers in our sample, and only 8% of them have a certification sticker from an inspection agency. Alternatives such as electronic verification systems have also been experimented with, but the cost of implementation has proven challenging, and they depend on the reliability of the underlying seed certification system.

That is why we test an alternative, decentralized clearinghouse that is based on crowd-sourced information and works through reputational mechanisms, much like yelp.com or tripadvisor.com. Studies in other contexts have shown that new crowd-based sources of pre-purchase information can be particularly useful. For instance, Reimers and Waldfogel (2021) compare the impacts of professional critics and Amazon star ratings of books on consumer welfare. The aggregate effect of star ratings on consumer surplus is more than ten times the effect of traditional review outlets.

Information clearinghouse mechanisms in developing countries have been studied to some extent, but mostly to address market price information asymmetries between smallholder farmers and middlemen. Assuming that middlemen are better informed about prevailing prices in the market than farmers, theory suggests that providing farmers with price information increases their bargaining power. However, evidence is mixed: while Goyal (2010) finds that internet kiosks that provide wholesale price information significantly increase soy prices in India, Fafchamps and Minten (2012) do not find a statistically significant effect of market information delivered to farmers' mobile phones in a neighboring state.

A clearinghouse that relies on crowd-sourced ratings may be more effective in increasing seed quality in the market. While prices can generally be observed reasonably easy, assessing an experience or credence good such as seed is much more difficult. Aggregating the experiences of many users may thus be a particularly powerful way to reveal the quality of the product.

A study by Hasanain, Khan, and Rezaee (2019), who set up a rating system for public veterinary services in Pakistan, is probably the closest to ours. They find that farmers who use the clearinghouse enjoy a 25% higher success rate of artificial insemination. Their research suggests that this is mostly due to increased veterinarian effort, as few farmers seem to be switching from veterinaries that receive poor ratings to veterinaries that receive good ratings. In Hasanain, Khan, and Rezaee's study, veterinaries provide their services directly, without an intermediary. If producers do not sell to customers directly, so that more entities and transactions are involved, there is even more scope for information asymmetries. That is why reducing asymmetric information can be even more important in markets with intermediaries like agro-input dealers.

Hence a crowd-sourced information clearinghouse can be an important institutional innovation to solve the problem of asymmetric information in the market for agricultural inputs and may affect both intentional and non-intentional quality reductions by reducing malpractices at the agro-input dealer level. We hypothesize that it improves smallholder farmers' perception and adoption of agricultural inputs. It may be preferable to alternative strategies due to its likely lower cost, self-sustaining nature and scaleability, and helps to overcome problems such as insufficient public investment in regulatory systems, regulatory enforcement, and market surveillance.

An information clearinghouse could work through different impact pathways which are illustrated in figure 1. Firstly, farmers who did not buy (or who bought only a little) seed before may start adopting (or start adopting more) improved seed when they realize that an agro-input dealer in their vicinity has a good rating, meaning that the quality of the seed sold there is better than expected. The literature indicates that this pathway of improving the perception of quality without actually improving quality could be very relevant. Michelson et al. (2021) establish that the nutrient content of fertilizer in Tanzania is good and meets industry standards but that farmers believe that it is adulterated. One would simply need to correct farmers' beliefs which are inconsistent with the reality to increase adoption. Also Wossen, Abay, and Abdoulaye (2022) show that farmers in developing countries routinely misperceive input quality and that rectifying this misperception may improve farmers' investment choices and productivity outcomes.

Secondly, farmers could switch from low rated shops to higher rated shops after learning that their usually chosen agro-input dealer received a poor rating. Alternatively, farmers may pressure their usual dealers to increase efforts. Dealers could also start improving on their own (i.e. without the pressure of farmers) after they have learned that their seed is rated poorly and want to improve their products. Lastly, dealers could also increase their efforts after seeing that they were rated well and feel motivated and satisfied due to this reward. All these scenarios lead to seed of better quality, farmers purchasing better seed which improves their experiences by reducing risk and increasing profitability and later their perception of seed. Ultimately, this is expected to lead to increased adoption of improved maize seed. In the long run, the improved reputation of agro-input dealers could also boost seed producers' trust in them, which could lead to better support etc.

2.4 Maize seed as an experience or credence good

If farmers could observe the quality of seed perfectly after using it once, i.e. after one agricultural season, there would be no need for a clearinghouse as Ugandan farmers plant maize twice a year and could infer relatively fast which agro-input dealer provides good quality. If farmers could not observe the quality of maize seed at all, also not after adopting it, there would also be no use of a clearinghouse, as their ratings would be useless.

While farmers' ability to infer seed quality is limited as described above in subsection 2.2, they can infer maize seed quality to some extend. Shortly after planting, farmers can observe germination rates, i.e. the proportion of seeds that germinate, and later how fast the seed matures. Some seed may also be more susceptible to pests and diseases, while other seed may be particularly tolerant in terms of drought. After harvest, the farmer can observe the yield. All these attributes of seed quality can be judged to some extent after one agricultural season.

In conclusion, improved maize seed lies somewhere on the continuum between experience goods and credence goods. While a farmer cannot safely infer quality from only his or her experience, the aggregation of the experiences of many users may be a powerful way to reveal the quality of the

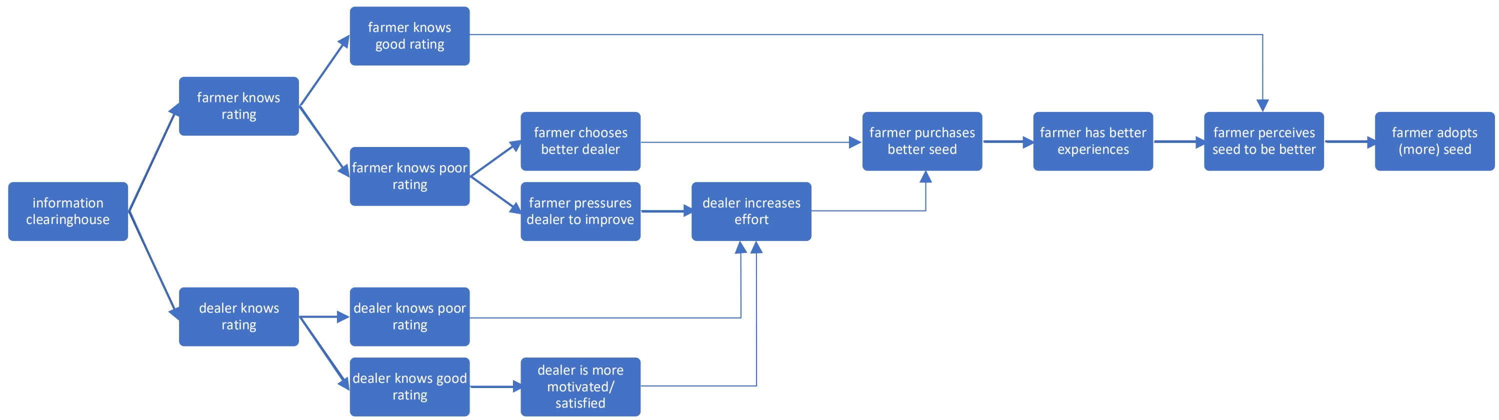

Figure 1: Theory of change

product. Even if a farmer observes impressive yield and correctly infers that the quality of the seed they used is good, he or she perceives this as only one source, as only one observation. The extension literature shows that a smallholder is more likely to trust that information if it comes from more than one source, e.g. from a clearinghouse rating that is computed based on multiple opinions.

3 Experimental design

3.1 Level of randomization

To evaluate the impact of the clearinghouse, we conduct an RCT. We randomize at the level of the *catchment area*. A catchment area is defined as the area that is served by an agro-input dealer, as the area where this shop's customers live. Dealers were listed during our census of all shops in 11 districts in southeastern Uganda. If the catchment areas of two or more shops overlap because these dealers operate in the same town, street or right next to each other, they are assigned to the same catchment area. This is done on the basis of geographical location. Using GPS coordinates of the dealers, the haversine function is used to construct an adjacency matrix, and dealers that are less than 5 kilometer apart are assigned to the same catchment area. The 5 kilometer threshold was selected based on visual inspection of the map, the size of an average village and reported distance between farmers and dealers.

We randomize at catchment area level for three reasons. Firstly, because randomizing at the level of the individual agro-input shop prompted ethical concerns and it is important to think about the ethics of experimentation, especially when the participants are vulnerable Deaton (2020). Often, dealers are clustered in towns, villages, markets, trading centers and other key market sheds. Two or more dealers may operate in the same neighborhood, or in the same street or even right next to each other. If we would randomize at shop level, one dealer may get assigned to the clearinghouse treatment group and receive a good rating, while his or her neighbor gets assigned to the clearinghouse control group and does not get the chance to receive any rating. Farmers may prefer the dealer with the rating, even though the seed quality of the control dealer may be similar or even better. The rating would in this case lead to a competitive advantage for the treated dealer, but the reverse may also be true if the treated dealer gets a poor rating.

Randomizing at catchment area level reduces the risk of harming someone with our experiment. Secondly, it erases any spillover concerns. Otherwise treated dealers could inform control dealers nearby that they will be rated soon, which would contaminate the control group. Thirdly, randomizing at area level allows us to measure the effect of the clearinghouse on farmers. If we would randomize at shop level, one dealer may be rated but his or her neighbor may not. Some farmers would then have access to treated and control dealers, so that it would be difficult to distinguish treatment and control farmers. If we want to know if the clearinghouse leads to e.g. increased improved maize seed adoption among farmers, we need to be able to connect each farmer unambiguously to treatment or control. We ensure this by randomizing at the area level because then all dealers within an area are rated (or not) and all farmers within that area are potential customers of only dealers who are rated (or not). For these reasons we opted to randomize at the catchment area at the expense of statistical power, and collect data from a large sample to compensate for that.

3.2 Power analysis simulations

We used simulations to determine the sample sizes for experiment. Simulating provides a flexible and intuitive way to analyze power. Furthermore, instead of relying on theoretical distributions for the outcome variables that take assumptions and return analytic solutions, simulations can sample from real data. Here, we use data from 78 agro-input dealers and 1,529 smallholder farmers in the catchment areas of these dealers that were collected in three districts in eastern Uganda in July 2019[3].

We analyze power for outcomes at the agro-input dealer level and at the farmer level. To determine the sample size (defined in terms of the number of catchment areas), the algorithm iterates over different candidate sample sizes. For each candidate sample size, a random sample with replacement is drawn from the data. This sample is used to run a number of simulations of the experiment. Then we determine how often, out of the total number of simulations, we are able to detect the effect at the 5% significance level. This gives us the power associated with that particular candidate sample size.

Once we determined the minimum number of catchment areas (and corresponding dealers) that are necessary to detect effects at the level of the

[3]These surveys were part of a study of the maize value chain and can be found here.

agro-input dealer, we fix the number of areas and then determine the number of farmers we need to sample per dealer to the identify impact of the interventions on that level. As we allocate a fixed number of farmers to each dealer, we have slightly differing numbers of farmers in the different treatment groups, as the randomization happens at the catchment area level. While this may reduce power somewhat, it does not bias impact estimates. We iterate over different candidate sample sizes of farmers per dealer. The resulting sample in each iteration is used to run a number of simulations of the experiment. We again determine how often, out of the total number of simulations, we were able to detect the effect at the 5% significance level, which will give us the power associated to that iteration.

We find that if the number of catchment areas is larger than 112, our experiments will return statistically significant results 80% of the time. This corresponds to about 318 agro-input dealers. Based on further simulations, we decided to collect information on 10 farmers per dealer, leading to a sample size of 3,200 households. More detailed information can be found in our pre-analysis plan.

4 Intervention

4.1 Collection of ratings

Right after we collected baseline data from smallholder farmers, we asked them to rate dealers in their proximity on a number of characteristics. Names, locations, descriptions and photos of the shops were preloaded onto the tablet computers used for data collection and the relevant dealers and questions showed up automatically.

Farmers' responses to the questions which are outlined in table 1 constitute the ratings. They were collected *after* harvest, when smallholders were able to assess seed quality based on observing germination and yield, the resistance against droughts, pests and diseases, and how fast the seed matures, see figure 2.

4.2 Computation of ratings

Based on the answers of all farmers in a catchment area, we computed the ratings for each agro-input shop. These ratings were translated into words

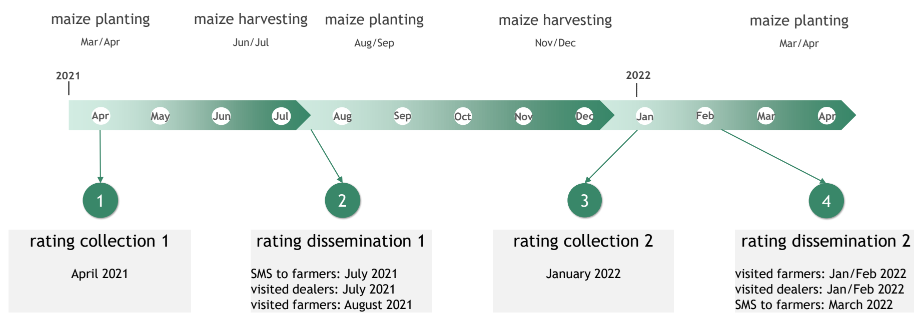

Figure 2: Timeline of intervention

Table 1: Questions for farmers to rate dealers

	min	max
Do you know this *shop name* or *dealer name*, sometimes called *nickname*, located in *market name*? The place can be described as *description*.	no	yes
Please rate this agro-input shop on:		
Quality and authenticity of seed	1 star	5 stars
Please rate the maize seed that this agro-input shop sells on:		
General quality	1 star	5 stars
Yield as advertised	1 star	5 stars
Drought tolerance as advertised	1 star	5 stars
Pest/disease tolerance as advertised	1 star	5 stars
Speed of maturing as advertised	1 star	5 stars
Germination	1 star	5 stars

and stars, so that they are easily understandable for farmers and dealers who are not used to interpreting numbers. More details about the rating computations can be found in appendix A.1.

4.3 Dissemination of ratings to farmers

For the success of the clearinghouse it is crucial to disseminate the agro-input dealer ratings *before* farmers start buying seed for the next agricultural season, so that they can use this information when choosing whether and where to purchase inputs, see figure 2. Ratings were disseminated to farmers in person and by means of text messages.

4.3.1 Text messages

We sent farmers one text message per dealer in their proximity. This message was translated into three local languages - Lusoga, Lugwere, Samia - chosen at the sub-county level to increase specificity. Please see table 2 for more details about these messages.

Also in control catchment areas, farmers received text messages with the names of dealers in their proximity, so that they were aware of the presence of these dealers. Dillon, Aker, and Blumenstock (2020) demonstrate the importance of these control messages. They introduced a "Yellow Pages" phone directory with contact information for local enterprises in central Tanzania. They find that enterprises randomly assigned to be listed in the directory receive more business calls, make greater use of mobile money, and are more likely to employ workers. As we are not interested in this kind of knowledge effect, i.e. farmers knowing which dealers operate in their proximity, we also disseminate control dealer information, so that we are able to measure the pure clearinghouse effect of making unobservable seed quality observable. An additional advantage is that control farmers will also believe that they are somehow treated, so that treated and control farmers will adjust their behavior similarly (Bulte et al., 2014) and effort responses will not explain the treatment effect, if we find one.

4.3.2 In person

The enumerators also re-visited all farmers in our sample. For this purpose, we designed a visually appealing dissemination app which cycles through all

Table 2: Text messages to disseminate ratings to farmers

treatment SMS	Hello from AgroAdvisor! Did you know that customers from *shop name* rate the quality of maize seed sold there as okay/good/very good/excellent?
control SMS	Hello from AgroAdvisor! Did you know that you can get quality maize seed in your area from *shop name*?

dealers in the proximity of each farmer and states: "We wanted to let you know that customers from *shop name* rate the quality of maize seed sold there as okay/good/very good/excellent! The quality of the maize seed that this agro-input shop sells got a score of *score* out of 5!" in treated catchment areas. Then the enumerator showed the stars associated with the score.

To ensure that control farmers were aware of the existence of dealers in their proximity, i.e. to separate the "knowledge effect" from the clearinghouse effect, we also cycled through dealers in control areas and asked a couple of questions e.g. "Do you know this *shop name*?". This way, control farmers feel as treated as treatment farmers, which can be of importance (Bulte et al., 2014).

4.4 Dissemination of ratings to dealers

Agro-input dealers received their ratings by means of a report on laminated paper which was delivered to their shops. The front shows a visually appealing certificate with a logo and the own general rating, see figure 3. It can be used to display the ratings in the shop, similar to a "certificate of excellence" of TripAdvisor.

The back of the report shows more detailed information. In addition to the dealer's general rating, it shows the dealer's specific ratings (overall quality, yield, drought and disease resistance, speed of maturing, and germination) and the average ratings of other agro-input dealers in the same catchment area in a table, visualized by stars. This shows dealers their relative position in the area and could stimulate competition. Dealers were not

Figure 3: SeedAdvisor certificate

informed about the individual ratings of their competitors, they only learned about the catchment area averages.

The intervention was repeated in the course of 2022, see figure 2. We expect dealers to be more likely to change their behavior, i.e. increase their efforts, if they know that the clearinghouse will remain in place for some time, so that they will be scored again. It could also increase farmers' trust in the ratings.

5 Empirical strategy

5.1 Specification

Due to the random assignment to treatment and control groups, simply comparing outcome variable means of treated and control participants provides unbiased estimates of the effect of the clearinghouse intervention on the outcomes of interest. Note that impact will be judged by looking at outcomes both at the agro-input dealer level as well as at the farmer level. To increase power, we condition the estimates on baseline values of the outcome variables. We estimate the following specification using Ordinary Least-Squares to get the average treatment effects of the clearinghouse intervention:

$$Y_{1ij} = \alpha + \beta T_j + \delta Y_{0ij} + \varepsilon_{ij} \tag{1}$$

where Y_{1ij} is the outcome variable for input dealer or farmer i in catchment area j at endline, Y_{0ij} is the corresponding outcome at baseline, T_j is a dummy for the treatment status of catchment area j, and ε_{ij} is an input dealer- or farmer-specific error term. The coefficient β is our estimated average treatment effect.

For continuous variables, trimmed values are used to reduce the influence of outliers. Inverse hyperbolic sine transforms are used if variables are skewed. Outcomes for which 95% of observations have the same value within the relevant sample are omitted from the analysis and not included in any indicators or hypothesis tests.

5.2 Multiple hypothesis testing

We evaluate the effect of the clearinghouse intervention and investigate its impact channels by considering a range of different outcome variables. Testing hypotheses regarding multiple outcomes calls for special techniques because the probability of rejecting a true null hypothesis for at least one outcome is larger than the significance level used for each test (Kling and Liebman, 2004).

That is why we account for multiple hypothesis testing by aggregating families of outcomes into groups, an approach followed by O'Brien (1984) and Kling and Liebman (2004). We use a method by Anderson (2008) and aggregate different outcomes within each domain into single summary indices. Each index is computed as a weighted mean of the standardized values of the outcome variables. The weights of this efficient generalized least squares estimator are calculated to maximize the amount of information captured in the index by giving less weight to outcomes that are highly correlated with each other.

Combining outcomes in indices is a common strategy against over-rejection of the null hypothesis due to multiple inference. This approach is useful to see whether a treatment has a positive overall impact. For instance, it is interesting to group primary outcome variables at the agro-input dealer level to see if the clearinghouse treatment generally has a positive impact on dealers. However, interpreting these effects can be difficult. Furthermore, we remain interested in individual outcomes because they inform us about the different channels of impact. It is interesting to see whether e.g. the seed handling practices, efforts and services of dealers improved at midline due to the clearinghouse, even though the overall index of primary dealer outcomes might not have significantly changed, yet. That is why, in addition to reporting the treatment effects on these indices, we will report the treatment effects on individual outcome variables.

6 Data

6.1 Sample

Our sample consists of agro-input dealers and smallholder maize farmers who live in the catchment areas of these dealers. The dealer sample was obtained by listing all input shops in 11 districts in southeastern Uganda, which roughly corresponds to the Busoga kingdom, during a census. It consists of 348 dealers, sufficient to detect treatment effects according to our power simulations in subsection 3.2.

After the census, agro-input dealers were assigned to catchment areas. The 348 shops in Busoga were assigned to 130 catchment areas, see subsection 3.1. 1 to 18 dealers operate in an area, with a mean of 2.7. A computer algorithm used this list of catchment areas for the allocation of the treatment because randomization happened at area level.

To connect agro-input shops and villages, we asked every dealer where most of his or her customers came from. Then enumerators were instructed to randomly sample ten households that grow maize in these villages. Consequently, about 3500 smallholder maize farmers were sampled, sufficient to detect treatment effects according to our power simulations.

For some outcome variables, e.g. seed spacing or rate, details at the plot level are needed. However, farmers often have more than one field. As outcomes on different plots from the same farmer are likely to be strongly correlated, it is not cost effective to ask questions about all fields. An unbiased estimate of the outcome at the household level can be obtained by randomly selecting one plot. To do so, we ask enumerators to first list all fields, with names farmers use to refer to these plots (e.g. home plot, plot near the sugar cane factory). The Computer-Assisted Personal Interviews software then randomly selects one plot for which detailed questions are asked.

We measure the outcomes of interest before and after the intervention, so that we can condition the treatment effect estimates on baseline values of the outcome variables to increase power. Baseline data was collected from dealers in September and October 2020 and from farmers in April 2021. Midline data was collected in January and in February 2022, and endline data will be collected in July and August 2022.

6.2 Descriptive statistics

This subsection describes the baseline sample. Information about the average *agro-input shop* can be found in table 3. When enumerators approached a shop to interview the dealer, they tried to talk to the person who is most knowledgeable about the day to day operations of the business, inventories, sales, and so on. The average respondent is 32 years old. 60% are male and more than 90% finished primary education. In 55% of the cases, the respondent is the owner of the shop.

We see substantial heterogeneity among agro-input shops. Some are small informal stores which are located in rural areas and sell maize seed only during the planting season while they usually sell other products. Others have many customers, are efficient, located in towns and specialized in inputs and equipment used in agricultural production. The average shop was established 5 years ago and is located 7 kilometers from the nearest tarmac road. It has 41 customers per day. 74% are specialized shops which only sell farm inputs.

We also collected a variety of variables related to the quality of maize seed sold at these agro-input shops. Enumerators asked if they could inspect the area where seed is stored and noted that there is quite some room for improvement. 65% of shops have problems with pests like rats or insects and 16% store maize seed in open containers. When we asked dealers about the services they provide, around half reported to offer credit and extension or training. On the other hand, 2 in 3 shops received a complaint about seed they sold from a customer since last season.

We also purchased a bag of maize seed. However, only 232 shops in our sample had seed in stock at the time of the baseline interview. We measured the moisture in the bag and found that it was 13.6% on average, with a minimum of 10.3 and a maximum of 17.4. Note that seed moisture content determines whether molds and storage pests thrive, so that moisture should stay below 13%. While 68% of seed bags show a packaging date, only 18% show an expiry date, and 8% show a certification sticker.

Table 4 reports means in the *farmer* sample. When approaching a household, enumerators were instructed to interview the person who is most knowledgeable about maize farming. However, a set of questions deals with the household head, who could be or could not be the respondent. 78% of household heads in our sample are male, 51% have finished primary education. The average household head is 49 years old.

On average, 9 people belong to one household and share 3 rooms. The homestead is located 4 kilometers from the nearest agro-input shop and 9 kilometers from the nearest tarmac road. The average farmer started growing maize 23 years ago and has 3 acres of land for crop production.

Half of the farmers in our sample adopted improved maize seed on at least one of their fields last season. Of these adopting farmers, 2 out of 3 bought seed at an agro-input shop. Baseline data also shows that quality is an important factor when farmers decide whether and where to buy maize seed. When we asked farmers for the most important reason why they bought seed at an agro-input shop last season, seed there being of very good quality was the most frequent answer with 58%. On the other hand, when we asked farmers for the most important reason why they did not buy seed at an agro-input shop last season, quality concerns were the second most frequent answer (after the shop being too expensive).

Only 25% applied chemical fertilizers like Di-Ammonium Phosphate (DAP) or Nitrogen, Phosphorus, and Potassium (NPK) on a randomly selected maize field. Productivity is low with 500 kilograms per acre. Interestingly, farmers who adopted improved maize seed harvested 589 kilograms (worth 413 000 Ugandan shillings (UGX)) per acre on average, whereas farmers who did not harvested 424 kilograms (worth 299 000 UGX) per acre, meaning that adopting farmers had 39% more yield (worth 114 000 UGX) per acre. However, farmers who adopted report to have spent on average 32 000 UGX per acre on seed material, farmers who did not 1 000 UGX per acre. This results in a difference of 31 000 UGX per acre in seed costs, meaning that adopting farmers almost quadrupled their investment.

6.3 Randomization balance

To test if treatment and control groups are comparable in terms of a set of baseline characteristics, i.e. to test for balance at baseline, we include standard orthogonality tables with pre-registered variables. Some of these characteristics are unlikely to be affected by the intervention, while others are picked from the primary and secondary outcomes. In table 4, we test balance at the level of the farmer. Tests of balance at the level of the agro-input dealer are reported in table 3.

Sample averages with standard deviations in brackets below are reported in the first column. In the second column, we report the difference between dealers or farmers in catchment areas that will be and those that will not exposed to the clearinghouse treatment. When comparing these catchment areas, we find that none of the pre-registered baseline characteristics is significantly different between treated and control dealers and farmers.

7 Results

This section contains the results of analyzing the data in order to evaluate the impact of the clearinghouse intervention. We investigate a set of primary outcomes and various secondary outcomes to explore the effects in more detail, to identify steps along the causal chain and understand the mechanisms at work. As farmers and agro-input dealers are targeted by the intervention, we will assess changes in outcomes at both levels. Note that all outcome variables have been registered in a pre-analysis plan which can be found on the American Economic Association (AEA)'s registry for RCTs. Additionally, we completed the entire econometric analysis on simulated data in a mock report[4] and added it to the AEA registry before midline data was collected. Mock reports serve to tie the hands of researcher, reducing the freedom in choosing which specifications and variables to select when testing hypotheses. Humphreys, De la Sierra, and Van der Windt (2013) argue that mock reports can reduce intentional and unintentional fishing, and make published research more reliable. All documents, codes, and data related to this project are under revision control and publicly accessible via GitHub which provides time-stamped recordings of all changes made over the course of the project.

In the tables showing the results, the first column reports sample means with standard deviations below in brackets. The second column reports the differences between treatment and control groups using ANCOVA models which control for the baseline value of the outcome, i.e. the average treatment

[4]This mock analysis is contained in an R script, which is run from within the LyX or LaTeX typesetting software using the knitr engine.

Table 3: Orthogonality tests of randomization balance at dealer level

	mean	clearing house
Respondent's age (in years)	32.43	-0.04
	(11.49)	(2.66)
Respondent is male	0.59	0.05
	(0.49)	(0.13)
Respondent finished primary education	0.92	-0.08
	(0.27)	(0.06)
Respondent owns shop	0.55	0.08
	(0.50)	(0.13)
Respondent received training on maize seed handling/storage	0.53	0.01
	(0.50)	(0.14)
Respondent knows how seed should be stored after repackaging	0.27	0.10
	(0.44)	(0.13)
Shop's distance to nearest tarmac road (in km)	6.56	0.90
	(10.39)	(3.36)
Shop only sells farm inputs	0.74	-0.14
	(0.44)	(0.12)
Years since shop establishment	5.34	0.21
	(6.30)	(1.59)
Number of customers per day	41.49	-3.57
	(46.49)	(8.80)
Amount of maize seed sold during last season (in kg)	910.88	131.99
	(2683.24)	(405.97)
Amount of maize seed lost/wasted during last season (in kg)	3.50	-1.87
	(18.65)	(3.82)
Shop has problem with pests	0.65	-0.04
	(0.48)	(0.11)
Shop stores maize seed in open containers	0.16	0.02
	(0.36)	(0.11)
Shop provides seed on credit	0.59	0.07
	(0.49)	(0.10)
Shop received seed related complaint from customer	0.64	0.08
	(0.48)	(0.08)
Moisture in random seed bag (in percent)	13.58	0.27
	(1.52)	(0.36)
Random seed bag shows packaging date	0.68	0.16
	(0.47)	(0.15)

Note: First column reports sample means (and standard deviations below); **, * and + denote significance at the 1, 5 and 10 percent levels. Reported standard errors are clustered at the level of randomization (catchment area).

Table 4: Orthogonality tests of randomization balance at farmer level

	mean	clearing house
Household head's age (in years)	48.62	0.20
	(13.38)	(1.21)
Household head is male	0.78	-0.01
	(0.42)	(0.05)
Household head finished primary education	0.51	0.00
	(0.50)	(0.05)
Homestead's distance to nearest tarmac road (in km)	9.39	1.66
	(10.81)	(2.97)
Homestead's distance to nearest agro-input shop (in km)	3.78	0.29
	(4.79)	(1.04)
Number of people in household (incl. respondent)	8.70	0.04
	(3.98)	(0.33)
Number of rooms in house	3.49	-0.08
	(1.45)	(0.16)
Farmer's land for crop production (in acres)	3.35	-0.05
	(4.32)	(0.37)
Years since farmer started growing maize	23.09	0.76
	(13.14)	(0.96)
Yield (in kg/acre)	499.52	-52.81
	(771.17)	(45.53)
Farmer sold maize	0.51	-0.03
	(0.50)	(0.06)
Farmer used improved maize seed for any field last season	0.49	-0.03
	(0.50)	(0.04)
Farmer bought this seed at agro-input shop	0.32	0.00
	(0.47)	(0.04)
Amount of improved maize seed bought from agro-input shop (in kg)	3.53	-0.78
	(9.20)	(1.07)
Farmers thinks seed at agro-inputs shop is counterfeit	0.68	-0.04
	(0.46)	(0.08)
Farmer used DAP/NPK	0.25	0.02
	(0.43)	(0.06)
Farmer used organic manure	0.07	-0.02
	(0.26)	(0.02)
Farmer's rating of planted maize seed on quality	3.39	-0.06
	(1.03)	(0.11)

Note: First column reports sample means (and standard deviations below); **, * and + denote significance at the 1, 5 and 10 percent level. Reported standard errors are clustered at the level of randomization (catchment area).

effect of the clearinghouse, see section 5. The standard errors in brackets below are clustered at catchment area level, the level of randomization. The third column shows the number of observations. We report one overall index, which has been constructed following Anderson (2008), per outcome family and table. † indicates that a variable has been included in this index. If an outcome variable is not included in the index, the explanation for this can be found in appendix A.2. In the tables, the abbreviation IHS stands for Inverse Hyperbolic Sine, a transformation that is used if variables are skewed.

7.1 Primary outcome variables

7.1.1 Agro-input dealer

The average treatment effects on primary outcomes at agro-input dealer level are reported in table 5. The index of capital-intensive practices contains different shop attributes which are associated with seed handling and storage but come along with an investment. Examples of these attributes are the quality of the roof, walls, and ventilation of the shop, and whether or not there are any official inspection, training or registration certificates displayed in the store. All this was observed by our enumerators who inspected the area where seed was stored. But also questions like what is usually done with expired seed, e.g. is it sold, thrown away or mixed with other seed, are included in this index. On the other hand, the index of labor-intensive seed handling consists of practices that are not expensive or even for free. Examples include whether seed is stored in a dedicated area, on an appropriate surface and in appropriate lighting, or in open bags or containers. Other variables that are not necessarily related to an investment like the cleanness and professionality of the shop, and whether there are problems with rats, insects or other pests also contribute to this index. The index of all seed handling practices contains both sets of variables. The index of efforts and services measures a range of outcomes related to the customer friendliness of the shop, e.g. whether the dealer offers explanations, recommendations, extension or training, discounts, credit, different payment modalities but also what the smallest package of seed is and a question related to customers complaints.

Most estimates go in the expected direction. For instance, we find that treated dealers sell 200 kilograms more maize seed, corresponding to a 20% increase over the mean. However, the coefficients have not been estimated precisely enough to yield a significant effect at conventional significance levels.

7.1.2 Farmer

Table 6 reports the effects of the clearinghouse intervention on a set of key outcomes at the farmer level. For the index of efforts and services provided by the dealer, farmers were asked whether a shop nearby offers refund or insurance if there is a problem, credit, training or advice on how to use seed, delivery, after-sales service, accepts different payment methods and sells small quantities. The answers are aggregated at shop level and then the index is computed at farmer level. The index of farmer's practices on a randomly selected maize field contains questions related to the number and spacing of seeds, weeding, timing of planting, re-sowing, and the use of organic manure, DAP, NPK, Urea, pesticides, herbicides and fungicides etc.

Again, we find that most estimates go in the expected direction. In the treatment group, farmers are more likely to adopt improved maize seed and less likely to think seed from input shops is adulterated. However, most of the coefficients are not significant. We do find that treated farmers are significantly more likely to indicate that the shop they bought maize seed from for the last season was not the same shop they bought seed from for the previous season(s). Compared to the control group, treated farmers are 5 percentage points more likely to have switched to a different agro-input shop. Note that we expected farmers to switch from low rated shops to higher rated shops, as illustrated in figure 1.

7.2 Secondary outcome variables

7.2.1 Agro-input dealer

As a first set of secondary outcomes at the dealer level, we construct *indices* which aggregate different outcomes according to Anderson (2008). The results are reported in table 7. An index of motivation and satisfaction summarizes the answers to questions like whether dealers see themselves working as dealers in the future, whether they think their job makes a positive difference, how likely they are to recommend working as dealers, or how happy they feel when they come to work. For the index of self-ratings, dealers were asked to rate themselves on location, price, product quality, stock, and reputation. For the index of efforts and services, farmers were asked whether

Table 5: Average treatment effects on primary outcomes at dealer level

	mean	clearing house	obs.
Quantity sold of 4 maize varieties (in kg)†	979.738	203.417	292
	(1620.296)	(198.567)	
Avg. sales price of 4 maize varieties (in UGX/kg)	4537.728	35.207	275
	(871.743)	(265.212)	
Revenue from 4 maize varieties (in mill. UGX) (IHS)†	1.494	0.217	292
	(1.076)	(0.201)	
Number of customers buying maize seed per day (IHS)†	3.230	0.206	294
	(0.824)	(0.207)	
Moisture in random seed bag (in percent)†	12.948	0.163	135
	(0.848)	(0.335)	
Index of **capital-intensive** seed handling practices†	0.021	-0.026	270
	(0.493)	(0.136)	
Index of **labor-intensive** seed handling practices†	0.005	0.135	285
	(0.457)	(0.111)	
Index of **all** seed handling practices	0.013	0.039	251
	(0.360)	(0.103)	
Index of efforts and services†	-0.007	0.165	243
	(0.413)	(0.110)	
Overall index	0.132	0.100	82
	(0.493)	(0.374)	

Note: 1st column reports sample means and standard deviations below in brackets; 2nd column reports differences between treatment and control groups and standard errors below in brackets; they are clustered at the level of randomization; 3rd column reports number of observations; **, * and + denote significance at the 1, 5 and 10 percent levels; † indicates that the variable is included in the overall index.

Table 6: Average treatment effects on primary outcomes at farmer level

	mean	clearing house	obs.
Farmer used improved maize seed for any field†	0.609	0.029	3206
	(0.488)	(0.033)	
Farmer bought this seed at agro-input shop†	0.429	0.028	3145
	(0.495)	(0.039)	
Amount of this seed bought at shop (in kg) (IHS)†	1.025	0.045	3025
	(1.284)	(0.099)	
Index of shop's services and efforts	-0.022	0.033	312
	(0.597)	(0.171)	
Farmer switched to different agro-input shop	0.167	0.052^{+}	3470
	(0.373)	(0.029)	
Farmer thinks seed at agro-input shops is counterfeit†	0.506	-0.033	2113
	(0.500)	(0.062)	
Index of practices on randomly selected maize field†	0.008	-0.035	2929
	(0.400)	(0.043)	
Farmer planted local land race maize seed on this field†	0.390	0.017	2954
	(0.488)	(0.043)	
Overall index	0.032	0.034	1686
	(0.598)	(0.079)	

Note: 1st column reports sample means and standard deviations below in brackets; 2nd column reports differences between treatment and control groups and standard errors below in brackets; they are clustered at the level of randomization; 3rd column reports number of observations; **, * and + denote significance at the 1, 5 and 10 percent levels; † indicates that the variable is included in the overall index.

Table 7: Average treatment effects on secondary outcomes at dealer level: Indices

	mean	clearing house	obs.
Index of motivation and satisfaction	0.000	-0.071	306
	(0.674)	(0.187)	
Index of self-ratings	0.000	0.144	306
	(0.626)	(0.159)	
Index of efforts and services according to farmers	0.001	0.232*	259
	(0.552)	(0.086)	
Index of knowledge about seed storage	0.000	0.116	306
	(0.511)	(0.129)	
Index of knowledge about seed	0.000	-0.031	306
	(0.530)	(0.121)	

Note: 1st column reports sample means and standard deviations below in brackets; 2nd column reports differences between treatment and control groups and standard errors below in brackets; they are clustered at the level of randomization; 3rd column reports number of observations; **, * and + denote significance at the 1, 5 and 10 percent levels; † indicates that the variable is included in the overall index.

a shop offers services like refunds or credits as described above. Here the answers to those questions are aggregated at the dealer level and then the index is computed. To investigate changes in skills and knowledge, we construct two more indices. The index of knowledge particularly related to seed storage is based on answers to questions about seed viability, repackaging, and the optimal location to store seed. For the index of knowledge about seed, dealers were asked about the yield benefits of improved maize seed and which variety they would recommend if a farmer needs fast maturing seed or complains about poor soil or little rain.

Farmers report that dealers in treated catchment areas invest significantly more effort and provide significantly better services. Also, given that any Anderson (2008) index ranges from minus one to one with a mean of zero, a coefficient of 0.23 is quite substantial. Note that again, this is what we predicted to happen, see figure 1. We expected dealers to increase their efforts due to pressure by farmers, their own ambitions or increased motivation. For the other indices, we do not find any measurable impact.

We also consider outcomes associated with particular seed types, e.g. their stock and turn over. The next set of variables is related to *Longe 10H*, a popular hybrid maize variety which is sold in the area. The results can be found in table 14 in appendix A.3. We do not find any significant effect. The same questions were asked for *Longe 5*, the most commonly traded open-pollinated maize variety. Table 15 in appendix A.3 shows that we cannot estimate any measurable effect.

We also collect information related to *memberships, licenses, and inspections*. The clearinghouse could lead dealers to voluntarily expose themselves to increased scrutiny to signal farmers that they deliver quality products. That is why we ask whether the shop is a member of Uganda National Agro-Input Dealers' Association (UNADA) or any other professional association, whether it has a trading license, and some questions related to inspection. Table 16 in appendix A.3 reports that we do not find any treatment effect.

Furthermore, enumerators purchased a random *bag of maize seed*, so that we could note a number of features and measure moisture. Mind that they were not able to buy seed in every shop and that the comparisons are made under the condition that a bag was bought. Table 8 provides the results. We see that bags which were purchased from treated agro-input dealers are 0.29 percentage points more likely to show a packaging date and that this difference is significant at the 10% level. This could be an indication of better seed quality in the clearinghouse treatment group, as seed is less likely to have been repackaged if this date is visible on the bag. The remaining coefficients are insignificant. Finally, table 17 reports the effects of the clearinghouse on a family of *other* secondary outcomes. We do not find any significant impact and include this table in appendix A.3.

7.2.2 Farmer

To explore impact pathways at the level of the farmer, we often consider outcomes at the plot level. In table 18 in appendix A.3 we look at the *adoption of improved maize seed*. The clearinghouse did not affect any variable of this family, yet.

In table 9, we zoom in on the particular *maize seed that farmers used* on a randomly selected field, and investigate farmers' quality perceptions. For the rating index, farmers were asked to rate this seed in terms of general quality, yield, drought, pest and disease tolerance, early maturity, (output) market price and demand, (input) price, availability, and germination rate. We see that farmers in the treatment group rate seed they used significantly better, meaning that their quality perceptions changed due to the treatment.

Table 8: Average treatment effects on secondary outcomes at dealer level: Bag of maize seed

	mean	clearing house	obs.
Seed bag shows packaging date†	0.855	0.290^{+}	144
	(0.353)	(0.141)	
Shelf-life†	159.524	-77.316	102
	(94.440)	(44.925)	
Seed bag shows lot number†	0.642	0.096	144
	(0.481)	(0.202)	
Overall index	-0.002	0.576	102
	(0.652)	(0.375)	

Note: 1st column reports sample means and standard deviations below in brackets; 2nd column reports differences between treatment and control groups and standard errors below in brackets; they are clustered at the level of randomization; 3rd column reports number of observations; **, * and + denote significance at the 1, 5 and 10 percent levels; † indicates that the variable is included in the overall index.

Note that we cannot compare farmers' ratings of the maize seed at agro-input shops, yet, which is the main focus of this study, as control farmers did so far not rate dealers because rating is part of the treatment. Considering that 42% of the seed farmers used on the random field was bought at an agro-input shop, see table 18, this coefficient could be an indication that farmers' perception of seed at shops also changed due to the clearinghouse treatment. When we have collected the ratings from the entire sample at endline, we will be able to see whether this is in fact the case. All coefficients in this table go into the expected direction, so that also the overall index changed significantly.

We further look at *production and disposal* related outcomes, like yield and revenue from the randomly selected maize field.[5] Table 19 in appendix A.3 shows that we do not find a significant impact.

[5]Note that inter-cropping was not taken into account when calculating these numbers because if maize is inter-cropped, it is almost always the main crop, so that there are equal numbers of maize crops on inter-cropped and not inter-cropped plots.

Table 9: Average treatment effects on secondary outcomes at farmer level: Seed used on randomly selected maize field

	mean	clearing house	obs.
Index of seed quality ratings†	0.005	0.120^{+}	2317
	(0.483)	(0.063)	
Farmer was satisfied with quality of seed†	0.707	0.020	3217
	(0.455)	(0.057)	
Farmer would use seed again†	0.733	0.023	3217
	(0.443)	(0.037)	
Amount of seed (in kg)†	6.857	-0.294	2909
	(4.761)	(0.439)	
Price of seed (in UGX/kg)†	2211.631	63.390	2982
	(3028.716)	(207.265)	
Cost of seed (in UGX) (IHS)	4.571	0.375	2848
	(5.312)	(0.474)	
Overall index	0.013	0.112*	1985
	(0.574)	(0.054)	

Note: 1st column reports sample means and standard deviations below in brackets; 2nd column reports differences between treatment and control groups and standard errors below in brackets; they are clustered at the level of randomization; 3rd column reports number of observations; **, * and + denote significance at the 1, 5 and 10 percent levels; † indicates that the variable is included in the overall index.

7.3 Heterogeneity analyses

7.3.1 Specialized agro-input shops

When we asked agro-input dealers during baseline data collection whether their shop only sells farm inputs, 74% answered with yes, while 26% reported to also sell other products. The results of rerunning the analysis for specialized shops only can be found in table 10. Treated specialized shops earn significantly more revenue from selling maize seed than specialized shops in the control group, whereas we previously did not find any treatment effect on primary outcomes at dealer level. Revenue could have increased because the clearinghouse's effect on efforts and services is larger for this subset of dealers, according to farmers. For these specialized shops, the treatment also reduced the shelf-life of stored seed significantly. A seed bag's shelf-life is an important indication of its quality. Treated specialized dealers stock seed which is on average 79 days younger than seed stocked by control dealers, while the mean is 150 days. Treated specialized dealers also sell significantly more Longe 10H. All this could explain why specialized shops in treated catchment areas enjoy a higher revenue than specialized shops in control areas and indicates that the clearinghouse has a stronger impact on specialized agro-input dealers. An explanation could be that dealers who only sell inputs and equipment used in agricultural production take the maize seed ratings more serious because they concern their only business, while shops which also sell other products face less risk due to risk spreading.

7.3.2 More competitive catchment areas

The sample contains 46 catchment areas with only one dealer. Excluding these smallest clusters leaves us with 302 shops and 3020 farmers in 84 areas. Table 11 reports that within this subset of more competitive areas, the clearinghouse has a slightly larger effect on the switching of farmers to different agro-input shops. According to farmers, the difference in efforts and services between treatment and control group is larger in these areas and significant at the 1% level. For areas with more than one dealer, the difference in likelihood of packaging dates being visible on maize seed bags is also larger than for the full sample. Together, this could indicate that the clearinghouse works better in areas with several shops and that our results for the entire sample are driven by these dealers. This stands to reason because in areas with only one shop, it is less easy for farmers to switch and dealers could

Table 10: Average treatment effects on primary outcomes at dealer level: Specialized agro-input shops only

	mean	clearing house	obs.
Quantity sold of 4 maize varieties (in kg)†	1129.734	365.235	217
	(1747.230)	(241.027)	
Avg. sales price of 4 maize varieties (in UGX/kg)	4549.697	14.458	207
	(835.944)	(322.524)	
Revenue from 4 maize varieties (in mill. UGX) (IHS)†	1.649	0.397+	217
	(1.086)	(0.210)	
Number of customers buying maize seed per day (IHS)†	3.298	0.224	218
	(0.823)	(0.270)	
Moisture in random seed bag (in percent)†	12.922	0.239	109
	(0.826)	(0.378)	
Index of **capital-intensive** seed handling practices†	0.019	-0.045	203
	(0.479)	(0.168)	
Index of **labor-intensive** seed handling practices†	0.001	0.072	221
	(0.438)	(0.099)	
Index of **all** seed handling practices	0.008	0.011	197
	(0.346)	(0.119)	
Index of efforts and services†	-0.016	0.189	180
	(0.403)	(0.148)	
Overall index	0.133	0.016	72
	(0.476)	(0.433)	

Note: 1st column reports sample means and standard deviations below in brackets; 2nd column reports differences between treatment and control groups and standard errors below in brackets; they are clustered at the level of randomization; 3rd column reports number of observations; **, * and + denote significance at the 1, 5 and 10 percent levels; † indicates that the variable is included in the overall index.

be less inclined to increase their efforts if there is no threat of competition nearby.

7.3.3 Shops that were rated

In the first round, 8% of dealers in the clearinghouse treatment group were not rated by a single farmer, e.g. because no farmer in our sample knew them, so we exclude these shops and rerun the analysis. For this sub-sample, the difference between treated and control dealers in terms of efforts and services is larger and significant at the 1% level. As shown in table 12, we also find a significant impact on the overall index summarizing variables related to the bag of maize seed. This result is driven by the shelf-life variable, an important indication of seed quality. In conclusion, the impact of the clearinghouse seems stronger for shops that were actually rated than for those who were supposed to be but not actually rated, which is what one would expect.

8 Threat to validity

When we revisited agro-input dealers and farmers for midline data collection, we were not able to find all respondents. Table 13 reports attrition levels in the treatment and comparison groups. Despite our efforts to minimize attrition, we failed to collect data from 2% of farmers and 12% of dealers who were part of the original sample. We also test if non-response is related to the clearinghouse treatment status. To be more precise, we regress the likelihood of leaving the sample on the treatment indicator and report the p-values in table 13. We find that control dealers are significantly more likely to leave the sample.

Whether our estimates are biased or not depends on whether this attrition is random or not. For instance, it is plausible that enumerators invested less effort when searching control dealers because they did not have to deliver their SeedAdvisor certificates. Carrying this certificate might have made them more persistent when looking for a shop because they did not want to return to their supervisor without having delivered that paper. Moreover, the certificate might have helped enumerators to find the treated dealers because they were able to show the names to neighbors etc. (instead of just asking) who in turn helped finding them. In that case, a larger number of random dealers left the control sample, meaning that the dealers who were

Table 11: Average treatment effects on primary outcomes at farmer level: More competitive catchment areas only

	mean	clearing house	obs.
Farmer used improved maize seed for any field†	0.612	0.030	2774
	(0.487)	(0.036)	
Farmer bought this seed at agro-input shop†	0.433	0.025	2717
	(0.496)	(0.043)	
Amount of this seed bought at shop (in kg) (IHS)†	1.036	0.024	2614
	(1.290)	(0.109)	
Index of shop's services and efforts	-0.018	0.032	291
	(0.594)	(0.178)	
Farmer switched to different agro-input shop	0.172	0.057^{+}	3020
	(0.377)	(0.032)	
Farmer thinks seed at agro-input shops is counterfeit†	0.497	0.011	1818
	(0.500)	(0.063)	
Index of practices on randomly selected maize field†	0.009	-0.044	2519
	(0.397)	(0.045)	
Farmer planted local land race maize seed on this field†	0.388	0.051	2541
	(0.487)	(0.045)	
Overall index	0.030	-0.004	1433
	(0.599)	(0.084)	

Note: 1st column reports sample means and standard deviations below in brackets; 2nd column reports differences between treatment and control groups and standard errors below in brackets; they are clustered at the level of randomization; 3rd column reports number of observations; **, * and + denote significance at the 1, 5 and 10 percent levels; † indicates that the variable is included in the overall index.

Table 12: Average treatment effects on secondary outcomes at dealer level: Seed bag: Shops that were rated only

	mean	clearing house	obs.
Seed bag shows packaging date†	0.871	0.278+	138
	(0.337)	(0.146)	
Shelf-life†	155.710	-94.292*	97
	(92.534)	(32.857)	
Seed bag shows lot number†	0.653	0.091	138
	(0.477)	(0.206)	
Overall index	-0.001	0.635+	97
	(0.643)	(0.320)	

Note: 1st column reports sample means and standard deviations below in brackets; 2nd column reports differences between treatment and control groups and standard errors below in brackets; they are clustered at the level of randomization; 3rd column reports number of observations; **, * and + denote significance at the 1, 5 and 10 percent levels; † indicates that the variable is included in the overall index.

Table 13: Attrition levels in treatment and control groups

	all	clearing house	control
Number of dealers who left the sample	42	14	28
Total number of dealers	348	193	155
Percentage of dealers who left the sample	12.07%	7.25%	18.06%
Significant difference? (p-value)		0.03	
Number of farmers who left the sample	63	36	27
Total number of farmers	3470	1931	1539
Percentage of farmers who left the sample	1.82%	1.86%	1.75%
Significant difference? (p-value)		0.83	

not found are not different from the ones that were found. The sub-sample of dealers that remained in the control group would then be representative for the entire control group, hence our estimates would be unbiased. Attrition would only reduce power.

On the other hand, a non-random subset of agro-input dealers might have left the sample, meaning that attritors and non-attritors differ significantly, which could bias our results. It is for instance plausible that the worst performing shops in the clearinghouse control group went bankrupt. Our clearinghouse treatment might have prevented bankruptcy and helped dealers to stay in the market because it served as some kind of advertisement if the rating was good. When attrition bias is likely to be negative and treatment effects are expected to be positive, the unadjusted selection-contaminated estimates provide *lower* bounds for the true treatment effect (Angrist, Bettinger, and Kremer, 2006; Duflo, Glennerster, and Kremer, 2007). One could exploit statistical techniques to estimate *upper* bounds which are robust to non-random attrition, e.g. the non-parametric approaches by Manski (1989) or Lee (2002). However, we refrain from doing so at this point because our ordinary estimates are lower bounds for the true effect and therefore the most conservative estimates. If, after increasing our efforts to find every dealer during endline data collection, attrition remains correlated with the treatment status, we will estimate the upper bounds.

9 Discussion

When farmers were asked why they bought maize seed at a particular agro-input shop, a couple of clearinghouse treated farmers named the shop's high SeedAdvisor rating as the most important reason during the midline interview. Also the results of our analyses show that several outcome variables change in response to the clearinghouse treatment, and behave the way the theory of change in figure 1 predicted. These changes, even though often not robust to multiple hypothesis testing, can be interpreted as first indications of an impact. Note that the reported unadjusted estimates are likely to be rather conservative lower bounds for the true effect as attrition bias is negative and the treatment effect is positive. Also note that at this point in time, ratings have been disseminated only once, and that changing farmer and dealer behavior is likely to take some time. If the clearinghouse triggers farmers to choose better dealers and dealers to increase their efforts, so that farmers purchase better seed, then it still takes another agricultural season for farmers to have better experiences, perceive seed to be better and ultimately increase improved maize seed adoption. Endline data will show whether the clearinghouse has a substantial impact.

Because the objective of the clearinghouse is to make maize seed quality observable, its functioning could be endangered if farmers' ratings do not actually measure seed quality but e.g. the personal relationship between a farmer and a dealer. That is why we test whether the ratings are correlated with seed quality. Even though objectively measuring seed quality is challenging and DNA fingerprinting is the only reliable way to detect varietal purity, we were able to check whether ratings are correlated with other objective indications of seed quality.[6] We find that specialized agro-input shops which only sell farm inputs have higher ratings. Dealers who did not receive any customer complaint about seed they sold since last season have higher ratings than dealers who did. Furthermore, farmers did not only rate the seed of agro-input shops but also the seed they used on a randomly selected maize field, using the same questions. We find that an index of these seed ratings is positively correlated with farmers' yield. All this shows that the clearinghouse ratings do measure maize seed quality to some extend.

Another danger to the functioning of the clearinghouse could be agro-input dealers who start to influence ratings in a dishonest manner, e.g. by faking ratings or by bribing farmers. Note that during this trial, rating and rated participants were connected by asking dealers where their customers come from, and collecting ratings from ten random farmers in that village. Dealers would need to understand our experimental design in order to know which farmer they would need to influence. That is why it is almost impossible that dealers cheat during this trial. However, if the clearinghouse intervention would be scaled up, these kind of challenges would need to be addressed. However, the objective of this paper is to test whether a prediction of the theory occurs in practice, namely whether making seed quality observable improves quality and ultimately adoption, and not to provide a policy intervention, sophisticated enough to be applied without further considerations.

[6] Note that this was only done for treated shops because control shops had not been rated at baseline, yet.

10 Conclusion

Even though agricultural technologies like high yielding seed varieties and fertilizers are seen as the key to agricultural productivity, the adoption by smallholders remains persistently low in sub-Saharan Africa, which hinders poverty alleviation at the individual and aggregate level. We study a particular constraint to technology adoption: the perceived quality of agricultural inputs like improved maize seed. We hypothesize that the intentional and unintentional malpractices of agro-input dealers lead to poor seed quality, resulting in under-adoption by farmers.

To assess the importance of this potential constraint to agricultural technology adoption, we test an intervention which reduces the information asymmetry between seller and buyer by making the quality of maize seed observable. To this end, we implement an information clearinghouse that is based on crowd-sourced ratings in the market for seed. This clearinghouse is tested in a randomized controlled trial among 350 agro-input dealers and 3500 smallholder maize farmers in Uganda.

The analysis of midline data shows first indications of an impact. Heterogeneity analysis suggests that the information clearinghouse works better for agro-input dealers who only sell farm inputs and who were actually rated by farmers. The intervention also has a larger effect in areas with more competition. However, endline data has to be analyzed before we can draw final conclusions.

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A Appendix

A.1 Details about rating computations

What to do if a treated dealer does not receive a single rating? If a shop in a treated catchment area is not rated by a single farmer, e.g. because no farmer in our sample knows him or her, we could fill in the catchment area mean as his or her rating. However, this is not as innocent as it seems because it is likely that the lack of ratings is not random. Poor quality dealers have less customers, so their likelihood to get rated is lower. Giving them average catchment area ratings inflates the ratings of these low quality dealers. Instead, we simply told farmers that we do not have information about this shop (implicitly informing the farmer that it exists). 16 of 193 treated dealers were not rated by a single farmer in the first round.

Should more ratings lead to better ratings? Some shops were not rated by any smallholder in the first round, while others were rated by up to 22 smallholders. If dealer A is rated by 10 farmers and gets rating 3,5 and dealer B is rated by 1 farmer and gets rating 3,6, we treat dealer B as the better dealer. Even though receiving many (few) ratings can be related to good (poor) quality (the lack of ratings could be nonrandom, see previous paragraph), there could be other reasons why dealers are rated by many (few) farmers. Furthermore, giving higher ratings to better-known dealers could harm new dealers entering the market and dealers who are discriminated, e.g. due to their gender. Also on TripAdvisor, having more reviews than a rival hotel does not lead to a better rating.

Should ratings depend on catchment area dealer performance? The following examples show that ratings should not depend on catchment area averages. In an area with poor quality dealers in which one dealer is a bit better than the rest but still poor, we do not want this dealer to be rated well (i.e. expose farmers to poor quality dealers). Similarly, in an area with good dealers in which one dealer is a bit worse than the rest but still good, we do not want this dealer to be rated poorly (which would be unfair towards him or her). On the other hand, less than 9% of shops received a rating below 3 out of 5, so we would throw away valuable data if we would only disseminate good scores without any variation. Therefore, we take the distribution of ratings into account by using quintiles. Consequently, less dealers receive rating 4 or 5, more dealers receive rating 1 or 2. This could strengthen the effect of the treatment on dealer effort. If dealers get ratings 1 or 2 instead of 4 or 5, they could feel more inclined to improve their scores. Consequently, also the effect on seed quality itself could be larger. However, the clearinghouse should also have a signaling effect, which might be weaker if more dealers are rated 1 or 2 instead of 4 or 5 (dealers would seem to be of worse quality to farmers). Therefore, we chose words with a positive connotation as the quintile names for rating dissemination. As most dealers received a good or very good rating before taking the distribution into account, we ensure that even a 2 is still communicated as "good" to farmers to not weaken the signaling effect. That is why the first quintile is translated to "okay" and gets one star, the second one is named "good" and receives two stars, the third quintile is "very good" and gets three stars, the fourth and fifth one are "excellent" and awarded with four and five stars. This way of considering the distribution of the original ratings when choosing the names also helps us to disseminate ratings as truthfully, purely and as closely to reality as possible.

Are female dealers rated worse than male dealers? Because we found significant differences between the ratings of female (41% of dealers) and male agro-input dealers (59% of dealers) after controlling for some potentially confounding variables like education and for several indications of quality, we have no reason to believe that these differences in perception can be explained by differences in real quality. Instead, it is likely that women are perceived to be worse due to discrimination (De, Miehe, and Van Campenhout, 2022), so that we adjusted the ratings of female dealers accordingly to prevent that they are harmed by our intervention. We regressed all seed quality attributes on the gender dummy and added the resulting coefficients to the initial ratings of female dealers.

A.2 Explanations for not including variables in overall indices

Primary outcomes at dealer level The average sales price of 4 improved maize varieties last season is not included because the impact of the treatments on this outcome is ambiguous (increased adoption could e.g. increase demand and hence prices but dealers could also lower prices to be more customer friendly). The index of all seed handling and storage practices is not included because it is a function of the index of capital-intensive practices and the index of labor-intensive practices, which are both included in the index.

Primary outcomes at farmer level The index of services of shops nearby according to farmers is not included because the regression with the overall index controls for the baseline value and many observations of this service index are missing at baseline. Whether the farmer switched to a different agro-input shop or not was not asked at baseline, and is not included for the same reason.

Secondary outcomes at dealer level: Longe 10H and Longe 5 The transformed sales price of Longe 10H per kg at beginning of last season (IHS) is not included because the impact of the treatments on this outcome is ambiguous (increased adoption could e.g. increase demand and hence prices but dealers could also lower prices to be more customer friendly). The transformed amount of Longe 10H lost or wasted last season (IHS) is not included because many observations are missing at baseline. The number of times the shop ran out of Longe 10H last season is not included because the impact of the treatments on this outcome is ambiguous (increased adoption could e.g. increase demand and hence this number but dealers could also take better care of stock to be more customer friendly, hence decrease it). Furthermore, this number mostly depends on parameters further up the value chain. These explanations are also relevant for outcomes related to Longe 5.

Secondary outcomes at dealer level: Memberships, licenses, and inspections The transformed number of times the shop was inspected by DAO, MAAIF or UNADA last year (IHS) is not included because the impact of the treatment on this outcome is ambiguous (e.g. more dealers could ask to be inspected to receive a certificate and signal quality which would increase the number but the treatments could also improve quality which could make inspections less necessary and common).

Secondary outcomes at dealer level: Other The number of maize varieties in stock last season is not included because it is a function of the number of hybrid varieties and the number of open-pollinated varieties which are both included in the index.

Secondary outcomes at farmer level: Adoption on randomly selected maize field Whether the farmer planted hybrid or open-pollinated seed on this field is not included because it is a function of whether the farmer planted hybrid maize seed and whether the farmer planted open-pollinated maize seed, which are both included in the index.

Secondary outcomes at farmer level: Seed used on randomly selected maize field The transformed cost of seed farmer used on this field last season is not included because it is a function of the amount of seed and the price of seed, which are both included in the index.

Secondary outcomes at farmer level: Production and disposal on randomly selected maize field Production from this field last season is not included because it is included in the yield, which is included in the index. Whether the farmer harvested as much maize as expected from this field last season and whether he or she did not harvest as much maize as expected due to own mismanagement and the transformed amount kept as seed are only included in the regressions that do not control for the baseline values because we did not ask these questions at baseline.

A.3 More results

Table 14: Average treatment effects on secondary outcomes at dealer level: Longe 10H

	mean	clearing house	obs.
Amount carried over from previous season (in kg) (IHS)†	0.698	0.053	262
	(1.550)	(0.459)	
Amount bought by shop from provider (in kg) (IHS)†	6.023	0.365	257
	(1.357)	(0.338)	
Cost (in UGX/kg)†	5100.973	59.758	180
	(898.767)	(269.380)	
Quantity sold (in kg) (IHS)†	5.934	0.373	256
	(1.311)	(0.331)	
Sales price (in UGX/kg) (IHS)	9.415	0.024	194
	(0.156)	(0.047)	
Amount lost/wasted (in kg) (IHS)	0.169	-0.392	133
	(0.693)	(0.412)	
Number of times per month shop ran out	1.931	0.447	112
	(1.782)	(0.790)	
Overall index	-0.002	0.028	169
	(0.517)	(0.156)	

Note: 1st column reports sample means and standard deviations below in brackets; 2nd column reports differences between treatment and control groups and standard errors below in brackets; they are clustered at the level of randomization; 3rd column reports number of observations; **, * and + denote significance at the 1, 5 and 10 percent levels; † indicates that the variable is included in the overall index.

Table 15: Average treatment effects on secondary outcomes at dealer level: Longe 5

	mean	clearing house	obs.
Amount carried over from previous season (in kg) (IHS)†	0.895	-0.066	270
	(1.807)	(0.522)	
Amount bought by shop from provider (in kg) (IHS)†	6.116	0.279	262
	(1.438)	(0.378)	
Cost (in UGX/kg)†	2518.061	-106.767	231
	(318.852)	(109.457)	
Quantity sold (in kg) (IHS)†	6.015	0.363	261
	(1.446)	(0.364)	
Sales price (in UGX/kg) (IHS)	8.747	-0.035	249
	(0.128)	(0.037)	
Amount lost/wasted (in kg) (IHS)	0.357	0.069	167
	(1.025)	(0.445)	
Number of times per month shop ran out	0.876	0.211	248
	(1.504)	(0.398)	
Overall index	0.011	-0.097	218
	(0.481)	(0.116)	

Note: 1st column reports sample means and standard deviations below in brackets; 2nd column reports differences between treatment and control groups and standard errors below in brackets; they are clustered at the level of randomization; 3rd column reports number of observations; **, * and + denote significance at the 1, 5 and 10 percent levels; † indicates that the variable is included in the overall index.

Table 16: Average treatment effects on secondary outcomes at dealer level: Memberships, licenses, and inspections

	mean	clearing house	obs.
Shop is registered with UNADA†	0.397	0.042	252
	(0.490)	(0.128)	
Shop has trading license issued by local government†	0.831	-0.102	288
	(0.375)	(0.100)	
Shop is member of other professional association†	0.265	0.142	268
	(0.442)	(0.114)	
Number of times shop was inspected last year (IHS)	1.347	-0.733	293
	(1.782)	(0.542)	
Shop received warning after inspection†	0.396	0.042	291
	(0.490)	(0.120)	
Shop's products were confiscated after inspection†	0.129	-0.020	293
	(0.335)	(0.084)	
Overall index	-0.020	-0.061	228
	(0.498)	(0.152)	

Note: 1st column reports sample means and standard deviations below in brackets; 2nd column reports differences between treatment and control groups and standard errors below in brackets; they are clustered at the level of randomization; 3rd column reports number of observations; **, * and + denote significance at the 1, 5 and 10 percent levels; † indicates that the variable is included in the overall index.

Table 17: Average treatment effects on secondary outcomes at dealer level: Other

	mean	clearing house	obs.
Number of maize varieties in stock	3.736	0.241	295
	(1.665)	(0.350)	
Number of **hybrid** maize varieties in stock†	2.397	-0.021	301
	(1.352)	(0.325)	
Number of **open-pollinated** maize varieties in stock†	1.374	-0.168	301
	(0.775)	(0.204)	
Shop has equipment to monitor seed moisture	0.369	-0.007	306
	(0.483)	(0.039)	
Overall index	-0.008	-0.142	296
	(0.790)	(0.195)	

Note: 1st column reports sample means and standard deviations below in brackets; 2nd column reports differences between treatment and control groups and standard errors below in brackets; they are clustered at the level of randomization; 3rd column reports number of observations; **, * and + denote significance at the 1, 5 and 10 percent levels; † indicates that the variable is included in the overall index.

Table 18: Average treatment effects on secondary outcomes at farmer level: Adoption on randomly selected maize field

	mean	clearing house	obs.
Farmer planted hybrid seed†	0.312	-0.015	2654
	(0.463)	(0.046)	
Farmer planted open-pollinated seed†	0.273	0.003	2654
	(0.446)	(0.055)	
Farmer planted farmer saved seed†	0.518	-0.020	3153
	(0.500)	(0.040)	
Farmer planted seed from agro-input shop†	0.422	0.020	3153
	(0.494)	(0.045)	
Farmer planted hybrid or o.-p. seed	0.544	0.001	2954
	(0.498)	(0.042)	
Overall index	0.005	-0.013	2604
	(0.518)	(0.046)	

Note: 1st column reports sample means and standard deviations below in brackets; 2nd column reports differences between treatment and control groups and standard errors below in brackets; they are clustered at the level of randomization; 3rd column reports number of observations; **, * and + denote significance at the 1, 5 and 10 percent levels; † indicates that the variable is included in the overall index.

Table 19: Average treatment effects on secondary outcomes at farmer level: Production and disposal on randomly selected maize field

	mean	clearing house	obs.
Production last season (in kg)	300.256	-5.026	2884
	(277.792)	(37.022)	
Yield (in kg/acre) (production/area)†	335.023	-4.379	2878
	(260.714)	(43.859)	
Farmer harvested as much maize as expected	0.154	-0.027	3200
	(0.361)	(0.047)	
Farmer did not harvest as much due to own mismanagement	0.102	-0.005	2981
	(0.303)	(0.039)	
Amount of maize sold (in kg) (IHS)†	1.612	-0.118	3063
	(2.665)	(0.241)	
Revenue (in UGX) (IHS)†	3.331	-0.069	3058
	(5.507)	(0.489)	
Amount kept as seed (in kg) (IHS)	1.774	-0.042	2931
	(1.654)	(0.149)	
Overall index	-0.015	-0.018	2742
	(0.806)	(0.112)	

Note: 1st column reports sample means and standard deviations below in brackets; 2nd column reports differences between treatment and control groups and standard errors below in brackets; they are clustered at the level of randomization; 3rd column reports number of observations; **, * and + denote significance at the 1, 5 and 10 percent levels; † indicates that the variable is included in the overall index.

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