The (Perceived) Quality of Agricultural Technology and its Adoption: Experimental Evidence from Uganda

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Abstract

This article presents findings from a randomized control trial to test two hypotheses on how (perceived) quality of agricultural inputs affect adoption among smallholder farmers. First, poor quality is caused by agro-input dealers' lack of knowledge on proper handling and storage. A training is expected to improve input quality and subsequent adoption. Second, information asymmetry crowds out the market for quality inputs—a classic lemons problem. Here, we implement an information clearinghouse based on crowd-sourced reviews similar to yelp.com. We find that both agro-input dealers and farmers benefit from the information clearing house, but not for the training.

Keywords: agricultural technology adoption, agricultural input quality, agro-input dealers, knowledge, information asymmetry, perceptions, information clearinghouse

JEL Codes: D82, D83, O13, O33, Q12, Q16, C93

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1 Introduction

Over the next few decades, farmers in sub-Saharan Africa will need to produce more food on less land and under increasingly difficult climatic conditions (Tilman et al., 2011). The use of climate-smart agricultural practices and improved inputs such as higher-yielding and drought-tolerant crop varieties are thought to be at least part of the solution (Evenson and Gollin, 2003). Unfortunately, the use of improved inputs and technologies across the region seems to be stagnating, or at least advancing at a slower pace than required (Suri and Udry, 2022). 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).

Several key constraints to agricultural technology adoption have been tested in the last decade. These include poor access to information (Ashraf, Giné, and Karlan, 2009), procrastination and time-inconsistent preferences (Duflo, Kremer, and Robinson, 2011), heterogeneity in the net benefits derived from the technology due to differences in infrastructure and transaction costs (Suri, 2011), missing markets for risk and credit (Karlan et al., 2014), and challenges related to learning about a new technology (Hanna, Mullainathan, and Schwartzstein, 2014).

More recently, issues related to the quality the technology (often inputs such as improved seed varieties, inorganic fertilizers, or pesticides) have emerged as a potential constraint to its adoption by smallholder farmers. Bold et al. (2017) argue that because quality is often difficult to assess by the farmers from simple visual inspection at the time of purchase, information asymmetries between sellers and buyers characterize the markets for seed and fertilizer, crowding out the market for quality inputs in Uganda, similar to what happens in Akerlof's seminal "Market for Lemons" study (Akerlof, 1970). However, subsequent research argued that it is not clear if these quality issues are due to agro-input dealers intentionally adulterating inputs, or if this is simply because they lack knowledge and skills to preserve quality (Barriga and Fiala, 2020). Furthermore, it is not even clear if these quality issues are real: While some studies argue that input quality is indeed lacking (Ashour et al., 2019), others argue that farmers' perceptions may be to blame (Michelson et al., 2021; Wossen, Abay, and Abdoulaye, 2022).

We attempt to answer some of these questions through a field experiment targeting agro-input dealers and smallholder farmers in their catchment areas in the nascent market for improved maize seed varieties (high-yielding cultivars like open-pollinated and hybrid varieties) in eastern Uganda. Agro-input dealers are very important for agricultural technology adoption in countries with large rural farmer populations living in remote areas with poor infrastructure. A reasonably dense network of semi-formal agro-input dealers provides access to technologies to rural farmers at a reasonable cost. Often, these agro-input dealers also provide services to farmers as well, in the form of agricultural advice or even credit.

At the same time, the informal nature of many of these shops means they are the weak link in the value chain for quality inputs (a risk that is likely to be smaller upstream where larger producers or importers face more scrutiny for government). Agricultural inputs such as seed or fertilizer is sometimes stored in sub-optimal conditions (eg. in direct sunlight, in moist environments,...) or handled in harmful ways (eg. stored beyond expiry date, repackaged,...). There is some evidence of this kind of quality reduction is happening in Uganda. 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 example, dealers often repack seed from larger bags packed by seed companies into smaller packages in order to offer quantities which are convenient and affordable to smallholder farmers. Important information including the expiry date and variety name can be lost during repackaging. Furthermore, seed is often repackaged in air tight polyethylene bags, which affect aeration and seed viability. Open air storage of bags can also lower the quality of seeds (Bold et al., 2017). Temperature control after the seed leaves the breeders is crucial, too (Barriga and Fiala, 2020). Inventory carryover, poor rotation of seed stock and storage in moist conditions or in direct sunlight further reduce seed quality. That is because the bio-deterioration of maize is sensitive to temperature and humidity (Curzi, Nota, and Di Falco, 2022), seed moisture affects the occurrence of storage fungi (Govender, Aveling, and Kritzinger, 2008), and many quality attributes of seed tend to degrade with storage duration time and shelf life (Hoffmann et al., 2021).

In a first hypothesis, we assume that a lack of dealer knowledge leads to deterioration in maize seed quality. Providing agro-input dealers with information on proper seed handling and storage, for instance through a training, will increase quality and subsequent adoption. Lack of information is pervasive in developing countries and often leads to sub-optimal outcomes for the rural poor. As a result, a simple piece of information can make a big difference (Duflo and Banerjee, 2011). Also in the context of agricultural technology adoption among smallholders, knowledge gaps have been identified as a key constraint, and governments around the world invest in public agricultural advisory services (Anderson and Feder, 2004). While the need for policies and interventions that strengthen input marketing capacity and infrastructure has been acknowledged decades ago (Tripp and Rohrbach, 2001), most studies target smallholder farmers with information; we are unaware of studies that look at knowledge gaps among (small) agro-input dealers.

The fact that seed quality can not easily be observed by farmers may also result in a lack of incentives for the agro-input dealers to invest in quality preservation. In a context 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 issues because they are not observable for buyers. Worse, agro-input dealers may sacrifice quality to cut costs and increase profits, for instance mixing improved and fresh seed with local seed or old seed. There is some evidence of this kind of adulteration 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.

In a second hypothesis, we assume that asymmetric information reduces dealers' incentives to provide quality seed. Addressing these asymmetries may lead to better quality, in turn increasing adoption. In Kenya, seed companies have started marketing their seed using novel packaging features to signal product quality and authenticity (Gharib et al., 2021). Uganda regulates 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.

In addition to incentive problems, asymmetric information can also lead to situations where farmers fail to adopt because they misperceive the quality of the inputs in the market. Michelson et al. (2021) establish that the nutrient content of fertilizer in Tanzania meets industry standards but that farmers believe that it is adulterated. 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. Note that also here, a vicious cycle emerges, where farmers that were confronted with poor seed quality may continue to perceive quality to be poor even though the quality may have been improved, and this asymmetric information in turn reduced incentives for agro-input dealers to maintain quality.

To address issues caused by asymmetric information, we implement a decentralized information clearinghouse that is based on crowd-sourced information and works through reputational mechanisms, much like yelp.com or tripadvisor.com. We ask smallholder farmers to rate agro-input dealers in their neighborhood on a number of seed quality attributes. We use this information to score and rank agro-input dealers, and we disseminate these scores back to both farmers and agro-input dealers.

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 improves their bargaining power and hence prices they receive. However, evidence is mixed: while Goyal (2010) finds that internet kiosks that provide wholesale price information significantly increase soy prices farmers received in India, Fafchamps and Minten (2012) do not find a statistically significant effect of price information delivered to farmers' mobile phones in a neighboring state. A clearinghouse that relies on crowd-sourced ratings may be more effective in increasing the quality of agricultural inputs in the market: While prices can generally be observed quite easily, assessing the performance of inputs such as seed or fertilizer is more difficult. Aggregating the experiences of many users may thus be a particularly powerful way to reveal the quality.

The objective of the clearinghouse is thus to make maize seed quality observable. However, some may argue that farmers cannot assess the quality of maize seed even after using it, because there are so many factors at play in agricultural production: if farmers 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. Tjernström et al. (2021) argue that sub-Saharan Africa's soil heterogeneity hampers farmer learning about the returns to inputs. In the limit, improved maize seed would resemble a credence good and the clearinghouse ratings of farmers would be mainly noise. Even though farmers and dealers might still change their behavior in the short run because they expect the clearinghouse to work, this effect would fade out as soon as both actors learn that the ratings are as good as random. At the same time, it seems unlikely that farmers can not learn anything from own experience. Research has shown that farmers do experiment with new technologies, but that (bayesian) learning takes time. Therefore, farmers also learn about new technologies through peer networks (Conley and Udry, 2010; Foster and Rosenzweig, 1995). The ability to combine own experience with the experience of farmers in a similar location is likely to provide a good signal about the quality of seed.

An information treatment such as a training is expected to work mainly by increasing knowledge, which when applied will lead to increased quality. An information clearinghouse is expected to work through various impact pathways. Firstly, farmers may switch from poorly rated shops to higher rated shops after ratings are revealed. Secondly, dealers could anticipate this and increase their efforts to outperform their competitors. This in turn may increase quality and agro-input dealers may want to signal this to farmers. Finally, farmers who did not buy seed before (because they were of the opinion that agro-input dealer sell poor quality seed) could start adopting improved seed when they learn that agro-input dealers generally receive good ratings. Ultimately, all this is expected to increase business at the agro-input dealer level and adoption and yields at the farmer level. Both interventions are tested in a randomized control trial (RCT) among 350 agro-input dealers and an associated 3,500 smallholder maize farmers in their catchment areas in eastern Uganda over the course of two agricultural seasons.

We find that the information clearinghouse affects outcomes for both agro-input dealers and farmers positively. Agro-input dealers that are exposed to the clearinghouse intervention receive more customers and sell more improved maize seed varieties than agro-input dealers in control areas, and the effects become stronger after two seasons. Clearinghouse treated farmers have significantly higher yields after two seasons because of increased adoption of improved seed varieties obtained from agro-input dealers. There are indications that farmers move from lower rated agro-input dealers to higher rated ones. However, most impact seems to come from agro-input dealers in the treatment area increasing effort and expanding the services that they provide to farmers. Treated shops are also more likely to be registered with the Uganda National Agro-Input and Dealers' Association (UNADA), perhaps to signal quality. Finally, we find that farmers in the treatment group are less likely to think agro-input dealers sell substandard seed, but only if we restrict attention to farmers do not have first hand experience with agro-input dealers, suggesting that the clearinghouse treatment is also effective at changing perceptions.

The training does not have a clear impact on dealers nor their customers. We find no impact on knowledge as measured by a simple quiz, even though all coefficients point in the expected direction. Interestingly, we do find that the information clearing houses increased knowledge about proper seed storage and handling. This suggests that if agro-input dealers are incentivized, they are able to find information that can help them to improve. This further suggests that providing information is most effective when there are also incentives to improve. Exploiting the factorial nature of our experimental design, we find suggestive evidence that training does increase outcomes for the subgroup of farmers that are also exposed to the information clearinghouse intervention.

Our study advances the literature on effective ways to reduce information asymmetries, such as who information should be targeted to and the role of reputation mechanisms in changing behaviour. For instance, Lane, Schonholzer, and Kelley (2022) show how providing information about bus safety to passengers affects the demand and supply of safer public transit, but only if there is a public signal (when bus drives know they are being tracked and this information is revealed to passengers). Our study further fits into an emerging literature that tests the effectiveness of crowd-sourced information to reduce information asymmetry and harness reputational mechanisms. Event though advances in Information and Communication Technologies (ICT) and the rise of e-commerce has led to a variety of websites that aggregate crowd-sourced reviews about businesses and most e-commerce platforms allow for consumer feedback, there is surprisingly little evidence available on the impact of this. The few rigorous studies that are available report impressive impact. Reimers and Waldfogel (2021) compare the impacts of professional critics and Amazon star ratings of books on consumer welfare and find the effect of star ratings on consumer surplus to be more than ten times the effect of traditional review outlets. Hasanain, Khan, and Rezaee (2023) implement a platform to crowdsource information about service provision quality and prices charged and reveal this information to consumers in the market for artificial insemination of livestock in Punjab, Pakistan. They find that treated farmers experience 25% higher insemination success. These effects seem largely due to existing veterinarians increasing effort in response to the intervention.

Our paper also contributes to a large literature on the effectiveness of providing training to small businesses in developing countries. Helping entrepreneurs to grow small businesses by teaching them business skills has yielded mixed results when subjected to rigorous impact evaluation methods (eg. Karlan and Valdivia, 2011; Drexler, Fischer, and Schoar, 2014; Giné and Mansuri, 2021). While these studies often suffer from methodological issues such as a lack of statistical power, it has also been argued that simply providing knowledge may be insufficient to move the needle (McKenzie and Woodruff, 2013). More promising results have emerged recently when the focus shifts from traditional training to trainings designed to instill personal initiative (Campos et al., 2017).[1] Our study similarly shows the importance of (external) motivation to make trainings more effective.

2 Experimental design

We developed two interventions (described in detail in the next section), and evaluate the impact using a randomized control trial (RCT). Interventions are randomized at the catchment area level. Catchment areas are defined relative to clusters of agro-input shops, and capture its potential customers. Generally, agro-input dealers are clustered in towns, villages, markets, trading centers and other key market sheds and so a single catchment area may be served by several agro-input shops. 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 and receive the same treatment. Grouping of agro-input dealers into catchment areas is done on the basis of geographical location.[2]

We randomize at catchment area level for three reasons. Firstly, randomizing at the level of the individual agro-input shop prompted ethical concerns. In cases where two agro-input dealers are very close to each other, treating only one of the two may lead to a competitive advantage; randomizing at catchment area level substantially reduces the risk concern. Secondly, it reduces potential spillover from treated to control agro-input dealers. Thirdly, randomizing at catchment area level allows us to measure the effect of the treatments on farmers, as all farmers in the catchment area are now exposed to agro-input dealers who all received the same treatment.

We used simulations to determine the sample sizes for this experiment. Simulating provides a flexible and intuitive way to analyze statistical power. Furthermore, instead of relying on theoretical distributions for the outcome variables that make assumptions and return analytic solutions, we run simulations that (re-)sample from real data data that was collected in previous surveys. Power simulations show that if the number of catchment areas is larger than 112, our experiments will return statistically significant

[1] Personal initiative is defined as a self-starting, future-oriented, and persistent proactive mindset.

[2] The haversine function is used to construct an adjacency matrix based on shop GPS coordinates, and dealers that are less than 5 kilometer apart are assigned to the same catchment area. The 5 kilometer threshold was selected based on a visual inspection of the map, the size of an average village and the reported distance between farmers and dealers in previous survey data.

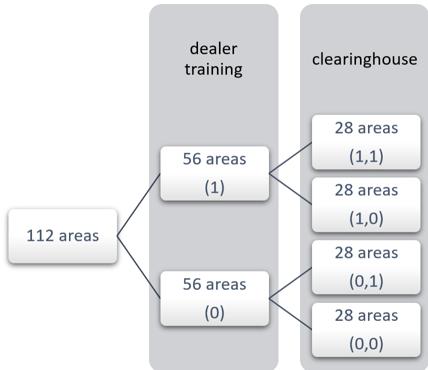

Figure 1: Factorial design

results 80% of the time on a selection of primary outcomes.[3] This corresponds to about 318 agro-input dealers. Based on further simulations to study impacts at the farmer-household level, we decide to collect information on 10 farmers per dealer, leading to a sample size of 3,180 households.[4]

The two interventions are combined in a field experiment which takes the form of a 2^2 factorial design. The resulting layout is illustrated in Figure 1. Impact is measured at both agro-input dealers and on farmers.

3 Interventions

This section provides a detailed description of the two interventions. We start with the agro-input dealer training and then explain the information clearinghouse treatment.

3.1 Agro-input dealer training

Content and training material

To determine the content of the training and to make sure it is locally anchored, we consulted experts from different Ugandan institutions and organizations like the ministry of agriculture, the seed sector and agro-input dealer associations. A series of semi-structured interviews and a workshop were organized. The experts identified common problems and malpractices by dealers, and then determined effective and realistic solutions and best practices in seed storage and handling. We then developed a training

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

[4]More detailed information can be found in the pre-analysis plan which was pre-registered at the AEA RCT registry under RCT ID 0006361.

manual to ensure standardization and a simple but visually appealing poster illustrating the most important best practices.

Training

In each treatment catchment area, all shops were selected to receive a training. Of each treated shop, both the owner and the shop manager who is in charge of day-to-day activities were invited. The owner was invited because some of the recommended techniques and practices required investments. The shop manager was invited because many of the recommendations were hands-on practices. We handed out one free portable seed moisture meter per shop as an incentive. All attendants were compensated for transport, lunch and drinks were provided. The training took place at a time of the year when dealers were not too busy. Trainings were organized in small groups, with on average about 10-15 agro-input dealers present. The trainings took place in locations that were easily reachable for agro-input dealers.

The trainers explained the correct handling and storage practices for improved maize seed and used the poster and an example seed bag for illustration. Afterwards the dealers rehearsed the more challenging practices like measuring moisture using a moisture meter. At the end of the training, they were asked to answer a couple of multiple choice questions. The dealers were told at the beginning of the training that receiving a moisture meter was conditional on passing this test, which might have motivated them to pay closer attention. They also received the poster as a handout which could be hung in their store.

The trainings took one day and were organized in May 2021, late enough so that dealers were not busy with selling for the first agricultural season but early enough so that they could use the newly learned practices on the seed of the second agricultural season. A timeline is illustrated in Figure 2. The trainings were organized together with the Uganda National Agro-input Dealer Association (UNADA), the national organization for agro-inputs in Uganda.

3.2 Information clearinghouse

Collection and computation of ratings

At the time of baseline data collection from smallholder farmers, we asked them to rate agro-input dealers in their proximity on a number of characteristics. Enumerators were guided by an application on a tablet computer that iterated through all the agro-input dealers in the catchment area. For each dealer, we provided the common names that are used to refer to the shop, a description of where the store was located, and a picture of the store front (obtained during the agro-input dealer census—see Section 5.1). We further asked if farmers knew the dealer. We then asked farmers to rate them using the questions which are outlined in Table 1. For example, we asked farmers to rate the maize seed that an agro-input shop sells on a scale of one to five stars on germination. Ratings were always collected after harvest, when smallholders were able

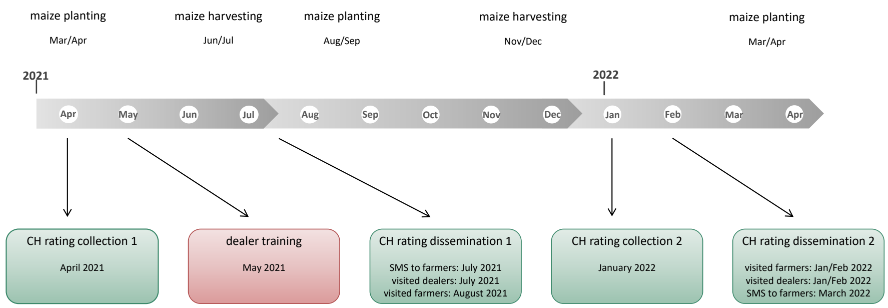

Figure 2: Timeline

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 for a timeline of the interventions.

It may be argued that by asking farmers to rate dealers, one also makes farmers aware of the existence of all dealers in the area, and that this awareness effect may potentially confound the clearinghouse effect. In the control group, we thus also iterated through dealers in the catchment areas, to make control farmers similarly aware of the existence of dealers in their vicinity. However, control farmers were not asked to rate dealers as the process of rating a dealer's seed could make quality more salient, which we consider to be an important impact pathway in the treatment.

Based on the answers of all farmers about all dealers in a catchment area, we computed the ratings for each agro-input shop. These ratings were translated into words and stars for dissemination, such that they are comprehensible for farmers and dealers who are not used to interpreting numbers. More details about the rating computations can be found in appendix A.2.

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, such 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.

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

Text messages We sent farmers one text message (Short Message Service - SMS) 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. Table 20 in the appendix provides 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. To separate this knowledge effect from the effect emanating from the information clearing house, we also disseminate control dealer information. An additional advantage is that it is harder for farmers to identify if they are being treated or not, reducing the likelihood of experimenter demand effects (Bulte et al., 2014).

In person The enumerators also re-visited the farmers in our sample. For this purpose, we designed a visually appealing dissemination application (shown to farmers on tablet computers) which cycles through all dealers in the catchment area of each farmer and states: "We wanted to let you know that customers from [name of the shop] 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. The application also showed the stars associated with the score. Again, we also cycled through dealers in control areas without providing ratings, but just indicating to farmers that these agro-dealers are operating in their area.

As was the case for the collection of ratings at baseline, the application provides

Figure 3: SeedAdvisor certificate

different names under which the shop is known, a description of where the store was located, and a picture of the store front to make sure farmers associate the score to the correct shop.

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. We encouraged agro-input dealers to display the ratings in the shop, similar to a "certificate of excellence" from TripAdvisor.

The back of the report shows more detailed information. In addition to the dealer's general rating, it shows the separate ratings that the seed of the agro-input dealer received on the different attributes (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 provide an important incentive to improve.

The intervention was repeated in the course of 2022; see Figure 2. We expect dealers to be more likely to change their behavior 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.

4 Empirical strategy

Due to the random assignment to treatment and control groups, comparing outcome variable means of treated and control participants provides unbiased estimates of the effects of the interventions. Note that impact will be judged by looking at outcomes 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 both interventions:

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

where for dealer level outcomes, Y_{ij} is the outcome variable for dealer i in catchment area j at mid- or endline, Y_{0ij} is the corresponding outcome at baseline, T_j is a dummy for the treatment status of catchment area j, X_{ij} is a vector of controls for the orthogonal treatments in the factorial design (demeaned and interacted with the main treatment effect, see Lin, 2013; Muralidharan, Romero, and Wüthrich, 2019), and ε_{ij} an error term that is potentially correlated withing catchment areas. The coefficient β is the estimated average treatment effect. For farmer level outcomes a similar equation is estimated, where Y_{ij} is now the outcome variable for farmer i in catchment area j at mid- or endline, ε_{ij} is an error term that is potentially correlates within catchment areas, and all other terms are defined as above.

Because we randomize at catchment area level, we use cluster-robust variance-covariance matrices that cluster standard errors at this level. For outcomes at the farmer level where we have almost 3,500 observations in 130 clusters, the original form of the sandwich estimator (Liang and Zeger, 1986) which does not make any small-sample correction, is used. For outcomes at the agro-input dealer level where we have almost 350 observations in 130 clusters, we approximate the leave-one-cluster-out jack-knife variance estimator (Bell and McCaffrey, 2002).

We account for multiple hypothesis testing by aggregating different outcomes within each domain into summary indices, following Anderson (2008).[5] However, interpreting these overall impacts can be difficult while effects on individual outcomes show us which variables drive the results and inform us about the different impact channels. That is why we also report the treatment effects on individual variables even though they have to be interpreted with care.

[5]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.

5 Data

5.1 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. We found 348 dealers, sufficient to detect treatment effects according to our power simulations; see section 2.

After the census, these agro-input shops were assigned to 130 catchment areas (for details, see Section 2, Footnote 2 in particular). We find that 1 to 18 dealers operate in an area, with a mean of 2.7. To connect shops to customers, we asked dealers the name of the villages where most of their customers come from. Then enumerators were instructed to randomly sample ten households that grow maize in these villages. Consequently, about 3,500 smallholder maize farmers were sampled, sufficient to detect treatment effects for the outcomes used in our power simulations (see Section 2).

Baseline data was collected from dealers in September and October 2020 and from farmers in April 2021. Midline data from both farmers and dealers was collected in January and February 2022, and endline data from farmers and dealers was collected in July and August 2022.

5.2 Descriptive statistics

This subsection describes the baseline sample. Information about the average agro-input shop can be found in Table 2. When enumerators approached a shop, they tried to interview the person who is most knowledgeable about the day to day operations, which was usually the shop manager. 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 also 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. Others have many customers, are located in towns and specialize 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 information that would allow us to assess 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 that agro-input dealers 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 over the course of the last season.

We also purchased a bag of maize seed. However, only 232 of the 348 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. It is recommended to keep moisture below 13%. While 68% of seed bags show a packaging date, only 18% show an expiry date, and 8% show a certification sticker.

Table 3 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. 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 at about 500 kilograms per acre.

5.3 Orthogonality tests of randomization balance

To test if treatment and control groups are comparable in terms of a set of baseline characteristics we include standard orthogonality tables with pre-registered variables for both dealers and farmers (Tables 2 and 3 respectively). Some of these characteristics are unlikely to be affected by the intervention, while others are picked from the outcome variables we will use to measure the impact of our interventions and explore impact pathways in the next sections.

For outcomes at the agro-input dealer level reported in Table 2, we find that from a total of 16 comparisons, only one is significant at the 5 percent level for the agro-input dealer training. For the clearing house treatment, we find two significant differences, both at the 10 percent level. This is consistent with a balanced sample. For outcomes at the farmer level, out of 32 comparisons, none is statistically significant.

6 Results

This section presents results on the impact of the agro-input dealer training and the information clearinghouse treatments. We report impact at the agro-input dealer level as well as at the level of the farmers that reside in catchment areas of the agro-input dealers. Furthermore, we separately present impact one agricultural season after the

Table 2: Descriptive statistics and orthogonality tests at dealer level

	mean	training	CH
Respondent's age in years	32.43	0.56	-2.24^{+}
	(11.49)	(1.19)	(1.21)
Respondent is male	0.59	0.02	-0.01
	(0.49)	(0.06)	(0.06)
Respondent finished primary education	0.92	0.01	-0.01
	(0.27)	(0.03)	(0.03)
Respondent owns shop	0.55	0.03	0.02
	(0.50)	(0.06)	(0.06)
Respondent received training on maize seed handling	0.53	0.05	0.12^{+}
	(0.50)	(0.07)	(0.07)
Respondent knows how to store seed after repackaging	0.27	0.07	0.08
	(0.44)	(0.06)	(0.06)
Shop's distance to nearest tarmac road in km	6.56	-0.92	-1.58
	(10.39)	(2.21)	(2.24)
Shop only sells farm inputs	0.74	-0.09	0.03
	(0.44)	(0.07)	(0.06)
Years since shop establishment	5.34	-0.09	0.21
	(6.30)	(0.77)	(0.78)
Number of customers per day	41.49	11.35	6.43
	(46.49)	(7.16)	(6.72)
Quantity of maize seed sold in kg	695.50	201.06	176.31
	(1497.18)	(252.97)	(235.92)
Amount of maize seed lost/wasted last season in kg	3.50	1.99	2.40
	(18.65)	(2.47)	(2.30)
Shop has problem with pests	0.65	-0.01	-0.03
	(0.48)	(0.06)	(0.06)
Shop stores maize seed in open containers	0.16	0.00	0.08
	(0.36)	(0.05)	(0.05)
Shop received seed related complaint from customer	0.64	-0.11*	0.07
	(0.48)	(0.05)	(0.05)
Moisture in bag of maize seed in percent	13.56	0.25	-0.18
	(1.44)	(0.25)	(0.26)

Note: 1st column reports sample means at baseline and standard deviations below; 2nd-3rd column reports differences between treatment and control groups and standard errors below; they are clustered at the level of randomization; **, * and + denote significance at the 1, 5 and 10 percent levels.

Table 3: Descriptive statistics and orthogonality tests at farmer level

	mean	training	CH
Household head's age in years	48.62	-0.08	-0.24
	(13.38)	(0.56)	(0.56)
Household head is male	0.78	-0.02	0.03
	(0.42)	(0.03)	(0.03)
Household head finished primary education	0.51	0.00	0.04
	(0.50)	(0.03)	(0.03)
Homestead's distance to nearest tarmac road in km	9.39	0.33	-1.23
	(10.81)	(1.69)	(1.71)
Homestead's distance to nearest agro-input shop in km	3.78	-0.11	0.11
	(4.79)	(0.37)	(0.37)
Number of people in household (incl. respondent)	8.70	-0.16	-0.09
	(3.98)	(0.18)	(0.18)
Number of rooms in house	3.49	-0.01	0.02
	(1.45)	(0.09)	(0.09)
Farmer's land for crop production in acres	3.35	0.07	0.00
	(4.32)	(0.21)	(0.22)
Years since farmer started growing maize	23.09	0.61	-0.55
	(13.14)	(0.55)	(0.58)
Yield in kg/acre	443.01	27.15^{+}	-6.14
	(304.99)	(13.71)	(13.52)
Farmer used quality maize seed on any plot	0.49	0.02	0.01
	(0.50)	(0.02)	(0.02)
Farmer bought this seed at agro-input shop	0.32	-0.01	0.01
	(0.47)	(0.02)	(0.02)
Amount of this seed farmer bought at agro-input shop in kg	9.52	0.16	-0.34
	(6.92)	(0.53)	(0.53)
Farmer thinks maize seed at agro-input shops is adulterated	0.68	0.01	0.00
	(0.46)	(0.03)	(0.03)
Farmer used DAP/NPK	0.25	0.04	0.02
	(0.43)	(0.03)	(0.04)
Farmer used organic manure	0.07	-0.01	0.01
	(0.26)	(0.01)	(0.01)

Note: 1st column reports sample means at baseline and standard deviations below; 2nd-3rd column reports differences between treatment and control groups and standard errors below; they are clustered at the level of randomization; **, * and + denote significance at the 1, 5 and 10 percent levels.

intervention (referred to as impact at midline) and two seasons after the intervention (referred to as impact at endline).

We take transparency and replicability serious. All outcome variables have been registered in a pre-analysis plan which can be found in the American Economic Association (AEA)'s registry for RCTs. In addition to the pre-analysis plan, we completed the entire econometric analysis on simulated data in a mock report and added it to the AEA registry before midline data was collected.[6] These mock reports are essentially dynamic documents that integrate all the code within the document. As such, when midlne and endline data becomes available, we simply had to replace the simulated with real data.[7] All documents, code, and data are under revision control and publicly accessible via GitHub which provides time-stamped records of all changes made over the course of the project.[8]

Exact variables definitions are provided in the results section below. In terms of variable construction, we follow some (preregistered) overall principles. For continuous variables, trimmed values are used to reduce the influence of outliers. In particular, we trim 1 % of each side of the distribution for agro-input dealer level outcomes and we trim 2.5% of each side of the distribution for farmer level outcomes. Inverse hyperbolic sine transforms are used if variables are skewed, with skewness being defined as the adjusted Fisher-Pearson coefficient of skewness exceeding 1.96. Outcomes for which 95 percent of observations have the same value within the relevant sample will be omitted from the analysis.

Results tables have a common layout. The first column (1) provides sample means (with standard deviations in brackets below). This is mainly to get an idea of effect sizes and so we always provide averages in levels, even though we may use inverse hyperbolic sine transforms when we compare differences between treatment and control groups. In the second column, we provide the average treatment effect for the dealer training at midline, while the third column reports the average treatment effect for the clearinghouse treatment at midline. We also report the number of observations that

[6]Mock reports serve to further tie the hands of researchers, reducing their 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.

[7]We use the knitr engine to integrate R code in LaTeX (Xie, 2017).

[8]Presentation of results in this paper differs somewhat from the way it was pre-registered and how it was presented in the mock reports (and midline report, endline report and previous versions of this manuscript). In the pre-registered report, the structure of the presentation of the results was mainly focusing on reducing researcher degrees of freedom and committing to decision rules to determine if the interventions worked or not. As such, we had a table of key outcomes along the entire causal chain (combined in an index) to assess overall treatment impact. Other tables then went into detail (for instance focusing on a particular seed type sold by an agro-input dealer or a particular plot cultivated by a farmer). In this paper, we reorganized the reporting to better match a structure where we first look at impact on outcomes downstream of the causal chain and then look at impact on intermediate outcomes to explore potential mechanisms. While this change did have an impact on some of the indices that we define, the results in terms of overall conclusions did remain the same. An analysis that follows the preregistered structure can be found through the project history in GitHub, for instance here.

were used for the outcome at midline in column four. The fifth and sixth column reports average treatment effects for the dealer training and the clearinghouse treatment respectively, but now at endline (after two seasons). Also here, we report the number of observations that was used in the estimation. As mentioned in Section 4, we account for multiple hypothesis testing by aggregating different outcomes within a family into overall summary indices, following Anderson (2008). Results for these indices are reported at the bottom of the tables.[9]

6.1 Impact on agro-input dealers

We start by testing if the interventions have an impact on general business operations of agro-input dealers (Table 4). Outcomes that can be classified under this heading include sales volume, prices, and revenue. A measure of sales volume was constructed by asking total quantities that were sold during the course of the previous season. We restrict attention to the four most popular improved seed varieties, two of which are hybrid seed varieties (Longe 7H and Longe 10H) and two of which are Open Pollinated Varieties (Longe 4 and Longe 5). Total sales is then simply the sum of quantities sold of these four varieties. As can be seen in column 1 of Table 4, the average agro-input dealer sold about 700 kilograms of improved seed. We also asked agro-input dealers about the sales price at the start of the season for each of these four seed types and again calculate the simple average at the dealer level. Table 4 shows that at baseline the average price for one kilogram of improved maize seed was about 4,300 ugandan shillings (or about USD 1.2). We then calculate revenue derived from sales of improved seed varieties (expressed in millions of Ugandan shillings) by first multiplying prices by quantities and then summing for the four seed types. For each of the four seed types, we then multiply the reported price with the reported quantities sold and sum over the four seed types to obtain total revenue. Average revenue is about UGX 2.9 million (or about USD 800). We also include the number of customers that come to buy seed on an average day at the start of the previous season, as well as the number of improved seed varieties that the agro-input dealer had in stock. At baseline, we find the average ago-input dealer receives 20 customers per day, and has almost three different improved maize seed varieties in stock. The variables in this family of outcomes are combined in an index to assess overall impact of the two interventions on agro-input dealer business operations.

Table 4 shows that we do not find an impact of the agro-input dealer training on agro-input dealer business outcomes. Both at midline (column 2) and at endline (column 5), the index is not significantly different from zero. Looking at the individual outcomes, there is no consistent pattern. At midline, we find a negative impact of the agro-input dealer training on the average sales price of improved maize varieties. At endline, we find some evidence that the training reduced amounts sold, and this is also

[9] In the regressions with these overall indices, we do not control for the baseline values because this would imply having the result only for dealers and farmers who have no missing values for any of the variables constituting these indices at mid-/endline and at baseline, severely reducing statistical power.

reflected in lower revenue.

We do find a positive impact for the clearinghouse intervention on agro-input dealer operations. At midline, the overall index (in column 3) is significantly higher among dealers that were in the information clearinghouse treatment group. Looking at individual outcomes, we see that dealers in the treatment group sold more maize seed at a higher price, albeit not significantly so. However, the combination of this does lead to revenues that are almost 20 percent higher (and this difference is significant at the 10 percent level).[10] At endline, the positive effects of the clearinghouse intervention seems to become stronger, with the overall index now becoming significant at the 1 percent level. The effect seems to be driven by a 31 percent increase in the number of customers that a treated shop attracts, which translates into an extra 6 customers.

While Table 4 looks at overall business impact based on four most commonly used improved seed varieties, Tables 5 and 6 focus on the effect of the interventions on business related to a particular seed. We look at the most recently released hybrid seed variety (Longe 10H) in Table 5 and the most recent OPV variety (Longe 5) in Table 6.

In line with Table 4, we start by looking at sales volumes, prices, and revenue for the particular seeds. At baseline, agro-input dealers sold almost 400 kilograms of the OPV versus about 300 kilograms of the hybrid seed, the latter being significantly more expensive than the OPV. We also focus on outcomes related to stock management. For instance, one problem affecting seed quality is stale seed. We asked agro-input dealers how much of the particular seed that they sold was carried over from the previous season. Many agro-input dealers reported that they did not carry over seed. Furthermore, we asked agro-input dealers to estimate how much of their stock was procured directly from seed companies in the same season. For both seed, this is slightly more than what was reported to be sold. We expect that out treatments will reduce amounts of seed carried over and increase fresh seed procured from seed companies. We also asked agro-input dealers to provide an estimate of how much of the seed stock was wasted or lost during the season, and how often they ran out of stock for the particular seed. At baseline, losses seem limited while stockouts do occur. We expect the interventions to reduce both losses and stockouts.

For Longe 10H, we do not find significant effects of the training nor clearinghouse treatment at midline. However, at endline, for the information clearing, house individual outcomes all go in the expected direction, and when the effects are combined in an index, the effect becomes positive and significant at the one percent level. Results are very similar for Longe 5.

One step further down up the impact chain, increased sales are driven by an increase in (perceived) quality of agricultural inputs. Unfortunately, the quality of seed is hard to assess, which is one of the key reasons why information asymmetries exist and the clearinghouse intervention was implemented. Nevertheless, to get an idea of the quality of seed sold, we bought a bag of seed at each dealer and inspected it on a number of

[10]For reasonable large values, regression coefficients for regressions involving a dependent variable that has been transformed using the inverse hyperbolic sine can be interpreted as elasticities (Bellemare and Wichman, 2020).

Table 4: Effects agro-input dealer operations

	baseline	*midline*			*endline*		
	mean	training	CH	obs.	training	CH	obs.
Quantity of maize seed sold in kg§†	695.503	-0.092	0.284	292	-0.597*	0.747*	334
	(1497.183)	(0.220)	(0.227)		(0.289)	(0.307)	
Sales price of maize seed in UGX/kg†	4273.897	-192.784^{+}	99.272	275	-33.867	145.861	264
	(955.073)	(114.934)	(113.292)		(143.152)	(138.816)	
Revenue from maize seed in mln UGX§†	2.890	-0.069	0.185^{+}	292	-0.227^{+}	0.143	286
	(6.286)	(0.104)	(0.108)		(0.118)	(0.118)	
Number of maize seed customers per day§†	19.764	-0.056	0.127	294	-0.190	0.310**	288
	(20.689)	(0.098)	(0.101)		(0.116)	(0.112)	
Number of maize varieties in stock†	2.834	0.042	0.245	295	-0.216	0.221	292
	(1.589)	(0.266)	(0.245)		(0.234)	(0.220)	
Overall index	0.031	-0.130	0.197*	274	-0.114	0.226**	269
	(0.610)	(0.095)	(0.092)		(0.077)	(0.077)	
Max. number of obs.				306			297

Note: 1st column reports baseline means and standard deviations below; 2nd, 3rd, 5th and 6th column reports differences between treatment and control groups and standard errors below; they are clustered at the level of randomization; 4th and 7th 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; larger indices indicate more desirable outcomes.
§Due to the skewness of this variable, the regression was run after an Inverse Hyperbolic Sine transformation. Coefficient estimates can therefore be interpreted as percentage changes. The baseline mean column shows the untransformed variable.

Table 5: Effects on dealer operations: Longe 10H

	baseline	*midline*			*endline*		
	mean	training	CH	obs.	training	CH	obs.
Quantity sold in kg§†	288.384	0.050	0.236	256	-0.205	0.352	242
	(727.049)	(0.206)	(0.204)		(0.231)	(0.239)	
Sales price in UGX/kg§†	9.417	-0.025	-0.013	194	-0.019	0.010	187
	(0.145)	(0.026)	(0.026)		(0.030)	(0.029)	
Revenue in mln UGX§†	1.625	0.008	0.130	255	-0.106	0.173	241
	(3.839)	(0.119)	(0.123)		(0.130)	(0.136)	
Amount carried forward in kg§†	2.679	-0.186	0.090	262	-0.012	-0.034	250
	(12.137)	(0.212)	(0.215)		(0.138)	(0.134)	
Amount shop bought from provider in kg§†	294.672	0.118	0.206	257	-0.022	0.283	243
	(741.810)	(0.218)	(0.213)		(0.250)	(0.253)	
Amount lost/wasted in kg§†	0.036	-0.001	0.019	257	-0.058	-0.038	243
	(0.405)	(0.093)	(0.097)		(0.037)	(0.041)	
Number of times per month shop ran out§†	1.039	-0.236^{+}	-0.045	192	-0.180	-0.205	185
	(1.575)	(0.129)	(0.133)		(0.128)	(0.136)	
Overall index	0.080	0.030	0.029	244	0.021	0.217**	233
	(0.437)	(0.067)	(0.070)		(0.052)	(0.057)	
Max. number of obs.[1]				268			254

Note: 1st column reports baseline means and standard deviations below; 2nd, 3rd, 5th and 6th column reports differences between treatment and control groups and standard errors below; they are clustered at the level of randomization; 4th and 7th 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; larger indices indicate more desirable outcomes.
§Due to the skewness of this variable, the regression was run after an Inverse Hyperbolic Sine transformation. Coefficient estimates can therefore be interpreted as percentage changes. The baseline mean column shows the untransformed variable.
[1]The comparisons were only made for shops which had Longe 10H in stock at mid- or endline.

Table 6: Effects on dealer operations: Longe 5

	baseline	*midline*			*endline*		
	mean	training	CH	obs.	training	CH	obs.
Quantity sold in kg§†	389.492	-0.040	0.304	261	-0.215	0.316	259
	(716.556)	(0.222)	(0.216)		(0.234)	(0.230)	
Sales price in UGX/kg§†	8.730	0.017	-0.015	249	-0.002	0.013	241
	(0.110)	(0.016)	(0.016)		(0.022)	(0.022)	
Revenue in mln UGX§†	1.193	0.019	0.111	261	-0.080	0.114	258
	(2.175)	(0.099)	(0.096)		(0.100)	(0.105)	
Amount carried forward in kg§†	4.312	0.247	-0.092	270	-0.095	-0.004	263
	(19.088)	(0.324)	(0.306)		(0.148)	(0.155)	
Amount shop bought from provider in kg§†	431.451	-0.005	0.253	262	-0.179	0.289	260
	(803.696)	(0.221)	(0.215)		(0.232)	(0.235)	
Amount lost/wasted in kg§†	1.756	-0.150	0.031	266	-0.055	-0.033	261
	(10.173)	(0.128)	(0.128)		(0.055)	(0.058)	
Number of times per month shop ran out§†	0.839	0.053	0.086	248	0.094	-0.054	237
	(1.509)	(0.100)	(0.101)		(0.120)	(0.126)	
Overall index	0.039	0.037	0.012	256	-0.038	0.152*	252
	(0.401)	(0.068)	(0.062)		(0.058)	(0.058)	
Max. number of obs.[1]				275			269

Note: 1st column reports baseline means and standard deviations below; 2nd, 3rd, 5th and 6th column reports differences between treatment and control groups and standard errors below; they are clustered at the level of randomization; 4th and 7th 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; larger indices indicate more desirable outcomes.

§Due to the skewness of this variable, the regression was run after an Inverse Hyperbolic Sine transformation. Coefficient estimates can therefore be interpreted as percentage changes. The baseline mean column shows the untransformed variable.

[1]The comparisons were only made for shops which had Longe 5 in stock at mid- or endline.

attributes. First, we measured the moisture content of the seed. Table 7 shows that mean moisture at baseline was good. We see that the clearinghouse treatment reduced moisture as expected, but the parameter is estimated imprecisely (partly due to the small dataset as we were not able to source seed from all agro-input dealers).

We further look at the integrity of the package and whether it shows important information such as the packaging date and the lot number. We do not find that the clearinghouse treatment nor the agro-input dealer training affected quality proxies of the seed that agro-input dealers sell.

6.2 Impact on smallholder farmers

We first look at production related outcomes for farmers that live in catchment areas of agro-input dealers involved in our study (reported in Table 8). We start by looking at overall production, total area of maize planted, and production scaled by plot size (yield). We also look at market participation (amounts sold, sales price and total revenue from maize sales) and how much grain farmers save for seed for use in the next season. While we expect positive effects on harvest and sales, we expect that the intervention reduces the likelihood that farmers recycle grain as seed for the next season. We collect these variables into an overall production index. The index shows no effect of the agro-input dealer training, and a positive effect of the clearinghouse on farmer level production related outcomes (but only after two seasons of implementation).

Looking into individual production related outcomes, we see that the average farmer in our sample produces about 460 kilograms of maize. As the average area used for cultivation is about 1.1 acre, productivity is similar. We do not find an impact of the clearinghouse intervention on production or productivity at midline. However, at endline, we see that farmers that live in areas where the clearinghouse was implemented report higher production and productivity. Yield differences are significant at the 1 percent level and amount to 10 percent of baseline means.

Under the heading of market participation, we see that the average farmer sells almost 2 bags of 100 kilograms at about UGX 50,000 per bag, the total which would correspond to less than USD 30. The clearinghouse intervention seems to have a positive impact on the sales price, but the higher prices do not translate into increased revenue. Finally, we also look at the amount of maize grain that farmers keep for seed in the next season. We find that the average farmer at baseline keeps about 15 kilograms. At midline, we see that clearinghouse treatment farmers save less grain for seed, which is in line with expectations.

As a second important family of outcomes at the farmer level, we look at adoption of improved seed varieties. For the agro-input dealer training, we can again be very brief: We do not find any effect on farmers at midline, nor at endline. The effect for the clearinghouse treatment on overall adoption as measured by the index is positive and significant at the 5 percent level both at midline and at endline. We describe individual outcomes in detail next.

A first key outcome in this family simply asks if farmers used quality maize seed in

Table 7: Effects on bag of maize seed bought at dealer

	baseline	*midline*			*endline*		
	mean	training	CH	obs.	training	CH	obs.
Moisture in percent†	13.564	0.017	-0.122	175	-0.041	-0.220	261
	(1.482)	(0.142)	(0.144)		(0.198)	(0.197)	
Bag shows packaging date†	0.689	0.053	0.050	179	-0.091	0.035	265
	(0.464)	(0.069)	(0.072)		(0.063)	(0.064)	
Shelflife in days[1]†	60.951	-18.930	-8.272	164	13.091	6.352	240
	(40.960)	(22.091)	(20.869)		(8.243)	(8.289)	
Seed is in original undamaged bag†	0.940	0.025	0.002	179	0.006	0.051	265
	(0.238)	(0.044)	(0.046)		(0.053)	(0.055)	
Bag shows lot number†	0.508	0.025	-0.001	179	-0.138*	0.027	265
	(0.501)	(0.106)	(0.107)		(0.062)	(0.064)	
Overall index	0.065	0.083	0.108	160	-0.067	0.108	236
	(0.364)	(0.103)	(0.103)		(0.094)	(0.090)	
Max. number of obs.[2]				179			265

Note: 1st column reports baseline means and standard deviations below; 2nd, 3rd, 5th and 6th column reports differences between treatment and control groups and standard errors below; they are clustered at the level of randomization; 4th and 7th 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; larger indices indicate more desirable outcomes.

[1]Days since the packaging date or, if the bag does not show the packaging date, days since the expiry date minus 6 months.

[2]The comparisons were only made for shops in which the enumerator was able to buy a bag of maize seed at mid- or endline. Also, we do not control for the baseline values of the outcome variables in the entire table because only 144 of the 179 dealers who had seed at midline also had seed at baseline and only 183 of the 265 dealers who had seed at endline also had seed at baseline, so that controlling for baseline values would reduce the sample sizes drastically.

Table 8: Effects on farmer outcomes: Harvest on specific plot

	baseline	*midline*			*endline*		
	mean	training	CH	obs.	training	CH	obs.
Production in kg†	463.203	-0.806	-20.372	2884	16.959	38.570*	2898
	(399.595)	(14.050)	(14.529)		(17.957)	(17.833)	
Area in acres	1.094	-0.013	-0.003	3004	0.000	0.010	3066
	(0.655)	(0.029)	(0.029)		(0.032)	(0.031)	
Yield in kg/acre†	443.222	-12.216	-23.006	2878	5.118	44.372**	2889
	(304.964)	(16.234)	(16.964)		(15.596)	(15.603)	
Amount sold in kg§†	195.295	-0.046	-0.201	3063	-0.147	0.139	3137
	(297.545)	(0.126)	(0.124)		(0.159)	(0.157)	
Sales price in UGX/kg	506.954	-7.787	33.027*	610	-47.215	43.506	639
	(139.389)	(14.395)	(14.244)		(30.547)	(30.380)	
Revenue in UGX§†	97.783	-0.141	-0.393	3058	-0.354	0.263	3109
	(156.538)	(0.260)	(0.257)		(0.341)	(0.336)	
Amount kept as seed in kg§	14.506	-0.098	-0.188*	2931	-0.043	0.036	2861
	(18.530)	(0.092)	(0.092)		(0.108)	(0.104)	
Overall index	-0.020	-0.015	-0.061	2932	0.018	0.097*	2900
	(0.784)	(0.039)	(0.039)		(0.041)	(0.041)	
Max. number of obs.				3407			3441

Note: 1st column reports baseline means and standard deviations below; 2nd, 3rd, 5th and 6th column reports differences between treatment and control groups and standard errors below; they are clustered at the level of randomization; 4th and 7th 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; larger indices indicate more desirable outcomes.
§Due to the skewness of this variable, the regression was run after an Inverse Hyperbolic Sine transformation. Coefficient estimates can therefore be interpreted as percentage changes. The baseline mean column shows the untransformed variable.

the previous season on any of their maize plots. We find that at baseline roughly half of the sample used quality seed. We see that by midline, farmers residing in catchment areas of agro-input dealers that were subjected to the clearinghouse treatment were 3.5 percentage points more likely to be using quality seed than control farmers. After two full agricultural seasons, the difference between treatment and control farmers increased to 4.2 percentage points. Related, we ask if farmers bought maize seed at an agro-input shop for any plot during the previous season. Here, we see that on average about one in three farmers uses fresh seed from an agro-input dealer. At midline, we find a difference between the clearinghouse treatment group and control group of about 6 percentage points (which amounts to an almost 20 percent increase relative to baseline mean). At endline, the difference is about 3 percentage point, but it is not significant anymore. For farmers that did buy from agro-input dealers, we also asked how much seed they bought. Farmers buy on average 10 kilograms of seed at baseline. We do not see any impact of the clearinghouse treatment. However, it should be kept noted that sample size is very small.

We then turn to seed use on a randomly selected plot and ask if farmers used improved seed varieties (defined as non farmer-saved OPV or hybrid seed) on this plot during the previous season. Also here, we estimate positive treatment effects for the clearinghouse treatment, but the coefficients are not significantly different from zero. As for the more general questions above, we also ask if the seed that was used on the random plot was obtained from an agro-input dealer. We find an almost 5 percentage point treatment effect for the clearinghouse treatment at mideline and a 3.6 percentage point effect at endline. A related question asks if farmers used farmer-saved seed on the randomly selected plot. At baseline almost 60 percent of sampled farmers used farmer saved seed. Again in line with expectations, we find that farmers that were exposed to the clearinghouse treatment reduced the use farmer-saved seed, albeit only significantly so during midline.

Finally, we look at the amount of maize seed that was used on the randomly selected plot, what the price per kg was for the maize seed that was used on the selected plot, and the product of the two to get the total cost of maize seed used on that plot. The fact that at baseline the price of seed used on the plot is lower than the one for the OPV in Table 6 suggests many farmers use farmer-saved seed (perhaps obtained from neighbors). We also see that among farmers in areas where the clearinghouse was implemented, the price of the seed that farmers used is higher (particularly at midline) and this also translates into higher investment in seed on the randomly selected plot.

7 Causal Chain and Mechanisms

The clearinghouse is a unique intervention because it solves a variety of potentially interlinked problems simultaneously. If the quality of maize seed at agro-input shops is reasonable but some farmers think agro-input dealers provide sub-standard quality, a clearinghouse may correct perceptions of at least some farmers. If quality of seed differs

Table 9: Effects on farmer outcomes at end of causal chain: Adoption

	baseline	*midline*			*endline*		
	mean	training	CH	obs.	training	CH	obs.
Farmer used quality maize seed on any plot†	0.492	-0.021	0.035^{+}	3206	-0.009	0.042^{*}	3282
	(0.500)	(0.020)	(0.020)		(0.020)	(0.020)	
Farmer bought maize seed at agro-input shop for any plot†	0.325	-0.014	0.059^{**}	3145	0.004	0.031	3225
	(0.468)	(0.021)	(0.021)		(0.019)	(0.020)	
Amount of this maize seed farmer bought at agro-input shop in kg	9.519	0.512	-0.105	599	0.457	0.378	621
	(6.920)	(0.348)	(0.358)		(0.419)	(0.431)	
Farmer used hybrid/open-pollinated maize seed on specific plot[1]†	0.432	-0.019	0.035	2954	0.009	0.030	3047
	(0.495)	(0.023)	(0.023)		(0.023)	(0.023)	
Farmer bought maize seed at agro-input shop for specific plot†	0.330	-0.010	0.047^{*}	3153	0.012	0.036^{+}	3240
	(0.470)	(0.022)	(0.022)		(0.019)	(0.019)	
Farmer used farmer-saved maize seed on specific plot	0.579	0.020	-0.042^{+}	3153	-0.009	-0.016	3240
	(0.494)	(0.022)	(0.022)		(0.020)	(0.020)	
Cost of maize seed used on specific plot in UGX§†	14078.272	-0.181	0.499^{*}	2848	0.283	0.350^{+}	2942
	(24654.685)	(0.235)	(0.235)		(0.208)	(0.209)	
Overall index	-0.013	-0.030	0.087^{*}	2854	0.015	0.086^{*}	2978
	(0.899)	(0.043)	(0.042)		(0.039)	(0.039)	
Max. number of obs.				3407			3441

Note: 1st column reports baseline means and standard deviations below; 2nd, 3rd, 5th and 6th column reports differences between treatment and control groups and standard errors below; they are clustered at the level of randomization; 4th and 7th 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; larger indices indicate more desirable outcomes.

[1]For this variable, only non-recycled (newly purchased, not farmer-saved) seed counted hybrid/open-pollinated seed.

§Due to the skewness of this variable, the regression was run after an Inverse Hyperbolic Sine transformation. Coefficient estimates can therefore be interpreted as percentage changes. The baseline mean column shows the untransformed variable.

between agro-input dealers, it provides farmers with information that can help them to switch to agro-input dealers that provide better quality. Furthermore, the rating system is expected to provide a direct incentive to agro-input dealers to stay ahead of immediate competitors. The mechanism underlying the dealer training is increased knowledge. In this section, we provide some additional evidence on the relative importance of these different impact pathways, starting with the latter.

7.1 Learning

The primary mechanism underlying the agro-input dealer training is learning, which in turns is expected to increase knowledge of treated agro-input dealers. To test if our interventions affect knowledge at the agro-input dealer level, we construct two indices that summarize different underlying measures of knowledge. The first summary index aims to measure knowledge about seed storage and handling and directly tests if the information that was provided to agro-input dealers during the training was retained. This was done using a short multiple choice quiz of five questions. The questions tested knowledge related to seed carryover between agricultural seasons, how seed should be stored after repackaging, what the minimal distance between floor and seed should be when storing, how seed should be stored in the storeroom, and whether seed should be repackaged. The exact questions, the options presented to the farmers and the correct answer are explained in Appendix A.4.

The second index that we use to measure knowledge is broader. It does not only focus on the seed storage and handling recommendations that we highlighted in the agro-input dealer training, but aims to capture knowledge about seed more broadly. We again use multiple choice questions to test if dealer knows which seed variety to recommend if farmer complains about poor soil, if farmer complains about lack of rain, if farmer is late for planting, and whether they know what to tell clients when they inquire about yield benefits of hybrid seed. The exact questions, the options presented to the farmers and the correct answer are again explained in Appendix A.4.

Table 10 suggests a positive impact of the agro-input dealer training on knowledge at midline, but the coefficient is just not significant at the 10 percent level. The (in-significant) effect of the training is strongest at midline, which seems reasonable as the training was organized only once at the start of the study. Interestingly, we also find knowledge effects from the clearinghouse treatment, particularly knowledge related to seed storage and handling. This effect also becomes stronger over time, which again seems reasonable given that this treatment is repeated over time. As agro-input dealers become aware of the recurrent nature of the ratings, they will try to improve the quality of their seed by searching for information on better ways to store and handle seed.

The above suggests that simply providing knowledge through trainings is unlikely to improve outcomes if agro-input dealers lack motivation to improve quality. At the same time, when agro-input dealers experience bottom-up pressure to increase quality, they may respond by actively seeking out information. Taken together, this suggest that knowledge may be more useful if agro-input dealers are also motivated to put it into practice. To further look into this, we can exploit our factorial design, where a random subset of agro-input dealers received both a training and were also in the clearinghouse treatment group. We indeed find that there is a significant positive interaction effect between the training and clearinghouse treatment on key outcomes at the agro-input dealer level (most notably the overall operations index). The positive interaction effect for the index seems to be driven by a significant increase in (both capital intensive and labor intensive) seed handling practices. This confirms that if agro-input dealers are encouraged to excel through a clearinghouse, they are more likely to put into practice the seed handling practices that they were taught during the training. However, care should be taken when interpreting this finding as we are likely to be under-powered to estimate interaction effects.

7.2 Dealer Effort and Services Rendered

The rating system provides agro-input dealers with an incentive to become better than their direct competitors. To do so, agro-input dealers may increase effort and may also start providing more services to their customers in an effort to get better scores and retain or even increase the number of customers.

In Table 11 we provide evidence that agro–input dealers that are exposed to the clearinghouse indeed provide more effort and services than agro-input dealers in the control group. The table shows results for one overall index, and four separate indices that each try to capture different dimensions of effort and service provision. A first index focuses on effort and service provision as reported by the agro-input dealer him or herself. It is composed of 7 different variables: whether shop offers explanations on how to use improved seed, whether agro-input dealers recommend complementary inputs to get optimal results from improved seed varieties, whether agro-input dealers provide extension or training, whether they offer discounts for larger quantities, whether they offer credit, whether they received seed related customer complaints since last season, and whether the agro-input dealer accepts mobile money. A second index summarizes the perceptions of farmers that are customers at the agro-input dealer. This index is also constructed from 7 variables: whether shop offers refund/insurance, whether the agro-input dealer provides credit, if the agro-input dealer offers training/advice to customers, if the shop delivers at the farm-gate, whether the shop provides after-sales services, accepts different payment methods, and sells small quantities. The answers of the farmers are aggregated at dealer level before the index is computed.

Improving quality of seed requires a mix of labor intensive practices and investments. Also during the agro-input dealer training, we made sure that we had a good mix of recommended practices and investments that were in reach of the different types of agro-input dealers, some of which may have excess labour while others have access to money to invest. A third index groups a set of labour intensive practices. The index of labor-intensive seed handling practices contains 6 variables: whether seed is stored in dedicated area, whether the shop has no pest problem, whether seed is stored in correct lighting, whether seed is stored on correct surface, whether seed is

Table 10: Effects on dealer knowledge

	baseline	*midline*			*endline*		
	mean	training	CH	obs.	training	CH	obs.
Index of dealer's knowledge about seed storage[1]†	0.000	0.091	0.115	306	0.030	0.124^{*}	297
	(0.482)	(0.076)	(0.075)		(0.053)	(0.055)	
Index of dealer's knowledge about seed[2]†	0.000	0.102	0.065	306	-0.009	-0.007	297
	(0.533)	(0.072)	(0.070)		(0.080)	(0.078)	
Overall index	0.000	0.208	0.211^{+}	306	0.038	0.142	297
	(0.729)	(0.125)	(0.119)		(0.107)	(0.102)	
Max. number of obs.				306			297

Note: 1st column reports baseline means and standard deviations below; 2nd, 3rd, 5th and 6th column reports differences between treatment and control groups and standard errors below; they are clustered at the level of randomization; 4th and 7th 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; larger indices indicate more desirable outcomes.

[1]The index of dealer's knowledge about seed storage contains 5 variables: whether dealer knows how long seed can be carried over, how seed should be stored after repackaging, what the min. distance between floor and seed is, how seed should be stored in storeroom, whether seed should be repackaged.

[2]The index of dealer's knowledge about seed contains 4 variables: whether dealer knows which seed variety to recommend if farmer complains about poor soil, if farmer complains about little rain, if farmer is late for planting, what to tell clients about yield benefits of hybrid seed.

Table 11: Effects on dealer efforts

	baseline	*midline*			*endline*		
	mean	training	CH	obs.	training	CH	obs.
Index of dealer's self-reported efforts and services[1]†	0.000	-0.063	0.066	243	-0.031	0.086^{+}	297
	(0.454)	(0.062)	(0.060)		(0.051)	(0.048)	
Index of dealer's efforts and services according to farmers[2]†	-0.027	-0.151*	0.301**	259	0.006	0.086	271
	(0.583)	(0.074)	(0.069)		(0.092)	(0.084)	
Index of labor-intensive seed handling practices[3]†	0.010	0.058	0.099	285	0.083	0.074	274
	(0.484)	(0.070)	(0.065)		(0.067)	(0.068)	
Index of capital-intensive seed handling practices[4]†	0.000	-0.019	0.000	270	-0.087	0.070	265
	(0.508)	(0.063)	(0.072)		(0.092)	(0.081)	
Overall index	0.032	-0.029	0.359**	189	0.006	0.165^{+}	234
	(0.540)	(0.121)	(0.113)		(0.099)	(0.091)	
Max. number of obs.				306			297

Note: 1st column reports baseline means and standard deviations below; 2nd, 3rd, 5th and 6th column reports differences between treatment and control groups and standard errors below; they are clustered at the level of randomization; 4th and 7th 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; larger indices indicate more desirable outcomes.
[1]The index of dealer's self-reported efforts and services contains 7 variables: whether shop offers explanations, complementary input recommendations, extension/training, discounts for larger quantities, credit, did not receive seed related customer complaint, accepts mobile money.
[2]The index of dealer's efforts and services according to farmers contains 7 variables: whether shop offers refund/insurance, credit, training/advice, delivery, after-sales service, accepts different payment methods, sells small quantities. The answers are aggregated at dealer level, then the index is computed.
[3]The index of labor-intensive seed handling practices contains 6 variables: whether seed is stored in dedicated area, whether shop has no pest problem, whether seed is stored in correct lighting, whether seed is stored on correct surface, whether seed is not stored in open containers, cleanness and professionality rating by enumerator.
[4]The index of capital-intensive seed handling practices contains 6 variables: whether roof is leak-proof, whether roof is insulated, whether walls are insulated, whether shop is ventilated, whether any official certificate is displayed, whether expired seed is handled correctly.

not stored in open containers, and a cleanness and professionality rating provided by the enumerator. A fourth index groups a set of capital intensive practices. This index groups 6 variables: whether roof is leak-proof, whether roof is insulated, whether walls are insulated, whether shop is ventilated, whether any official certificate is displayed, and whether expired seed is handled correctly. Many of these variables were collected or at least confirmed through visual inspection by enumerators.

We find that the clearinghouse intervention increased dealer effort and services, especially at midline. The effect at midline is driven by a significant difference in efforts and services provided by treated agro-input dealers according to farmers. We also see an increase in labor intensive seed handling practices. We do not find that the agro-input dealer training increased efforts and services.

As it is hard to assess quality via visual inspection, agro-input dealers may use various strategies to signal to customers that their seed is of good quality. One way to do this is through membership of professional organizations. Agro-input dealers that try to signal quality will also not shy away from inspections; on the contrary, they may actively seek out inspection such that they can then advertise this in their shops. Alternatively, it could also be that inspectors use the ratings in guiding their inspections.

Table 12 collects a set of variables that agro-input dealers can use to signal quality, including membership of the Uganda National Agro-Input and Dealers' Association (UNADA), number of inspections that took place in the last season, and warnings or confiscation of seed. We find that at endline, judged by the overall index, the clearinghouse treatment led to a significant increase in quality assurance measures. Looking at the individual outcomes, the effect seems due to an increase registration with UNADA. We also find that the number of inspections increased significantly.

7.3 Switching

An important potential mechanism underlying the clearinghouse treatment is farmers' propensity to switch from lower rated agro-input dealers to shops that get better scores. We provide some evidence here on this impact pathway.

At the farmer level, we asked farmers if they switched agro-input dealers from the previous season (reported in Table 13). We see that few farmers reported switching at baseline. However, at midline we see that in the clearinghouse treatment group a significantly higher share of farmers reported switching agro-input dealer. Also at endline, we find a higher propensity to switch dealers among clearinghouse treated farmers.

The above reveals increased mobility in the treatment group, but it does not establish that farmers move from poorly rated shops to better rated agro-input dealers. To further investigate if farmers switch from lower ranked to higher ranked dealers, we simply calculate the difference between the rating from shop where the farmer is switching to and the rating of the shop that the farmer is switching from. If farmers indeed move to better rated shops, we expect this difference to be positive. We do find

Table 12: Effects on dealer memberships, licenses, inspections

	baseline	*midline*			*endline*		
	mean	training	CH	obs.	training	CH	obs.
Shop is registered with UNADA†	0.442	0.040	0.066	252	-0.050	0.118^{+}	258
	(0.497)	(0.072)	(0.068)		(0.072)	(0.070)	
Shop is member of other professional association†	0.345	-0.035	0.058	268	0.001	0.069	267
	(0.476)	(0.051)	(0.052)		(0.073)	(0.066)	
Shop has trading license issued by local government†	0.749	-0.042	0.021	288	-0.033	0.008	285
	(0.435)	(0.053)	(0.054)		(0.056)	(0.057)	
Number of shop inspections§†	1.532	0.037	-0.097	293	0.038	0.292^{*}	273
	(1.859)	(0.247)	(0.259)		(0.109)	(0.111)	
Shop received warning after inspection†	0.317	0.045	0.005	291	0.013	-0.009	284
	(0.466)	(0.072)	(0.073)		(0.062)	(0.063)	
Shop's products were confiscated after inspection†	0.145	0.021	-0.027	293	0.014	-0.025	285
	(0.353)	(0.046)	(0.046)		(0.033)	(0.036)	
Overall index	-0.004	-0.005	0.047	266	-0.006	0.203^{**}	253
	(0.433)	(0.056)	(0.055)		(0.078)	(0.074)	
Max. number of obs.				306			297

Note: 1st column reports baseline means and standard deviations below; 2nd, 3rd, 5th and 6th column reports differences between treatment and control groups and standard errors below; they are clustered at the level of randomization; 4th and 7th 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; larger indices indicate more desirable outcomes.
§Due to the skewness of this variable, the regression was run after an Inverse Hyperbolic Sine transformation. Coefficient estimates can therefore be interpreted as percentage changes. The baseline mean column shows the untransformed variable.

Table 13: Effects on farmer switching behavior

	midline	*midline*			*endline*		
	mean	training	CH	obs.	training	CH	obs.
Farmer switched to different agro-input shop[1]	0.168	-0.013	0.042^{**}	3407	-0.024	0.026^{+}	3441
	(0.374)	(0.014)	(0.014)		(0.015)	(0.015)	
Max. number of obs.				3407			3441

Note: 1st column reports baseline means and standard deviations below; 2nd, 3rd, 5th and 6th column reports differences between treatment and control groups and standard errors below; they are clustered at the level of randomization; 4th and 7th 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; larger indices indicate more desirable outcomes.

[1]We report the mean and standard deviation at midline because this variable was not collected at baseline.

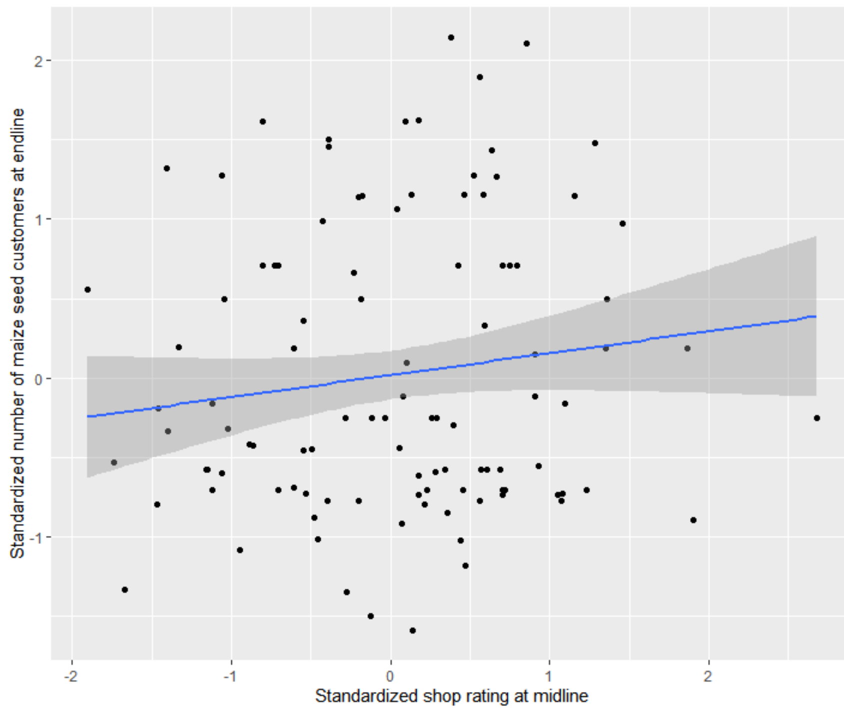

Figure 4: Switching

that this is indeed the case, and more so during the second season, but the difference is not significantly different from zero at conventional levels (p=0.166).

We also explore switching at the agro-input dealer level. Here we explore the relationship between ratings that agro-input shops receive and the number of customers (standardized within catchment area). If farmers switch from poorly rated input dealers to higher rated agro-input dealers, we would expect to see a positive correlation in areas where the information clearinghouse treatment was implemented. Figure 4 shows that shops that are rated higher at midline also receive more customers at endline. However, also here, the evidence is not very robust.

7.4 Perceptions

Finally, the rating system is assumed to change perceptions held by farmers about the quality of seed sold by agro-input dealers. Table 14 provides a more detailed analysis of this impact pathway.

A first variable we use to measure perceptions is at the farmer level. We simply asked farmers if they think that maize seed that they can buy at agro-input dealers is counterfeit or adulterated. Recall that at baseline, more than 2 in 3 farmers responded affirmative on this question (Table 3). The first four columns show impact of the clearinghouse intervention at midline and endline for the full sample. We do not find that the treatment significantly affects farmer perceptions as measured by this variable.

However, we expect that the effect on perceptions will be largest for farmers in treatment areas that are not adopting improved seed at baseline. Therefore, in columns 5 to 8, we repeat the analysis but only for the subset of farmers that do not adopt improved maize seed varieties at baseline. We see that at midline, farmers that do not adopt at baseline and live in areas exposed to the clearinghouse are now 12.5 percentage points less likely to think that agro-input dealers sell adulterated seed than similar farmers that live in areas not affected by the treatment. The effect disappears at endline.

Two other important outcomes are related to the perception of product quality, shop and seller. To be able to calculate these indices at the smallholder level, the farmer needs to have rated at least one dealer in the catchment area on all the components of the indices, which leads to a reduction of the sample size, which in turn may have affected power. Nonetheless, we see that the index of farmer's maize seed ratings of shops within the catchment area is significantly and positively affected by the clearing house treatment, albeit only at the 10 percent significance level. Furthermore, if we restrict the sample to farmers that did not adopt improved maize seed varieties at baseline, the increase in ratings becomes significant at the 5 percent significance level.

Finally, we also test if average ratings at the dealer level differ between treatment and control groups for the clearing house. While we do see that agro-input dealers are higher rated in treatment areas, the difference is not significant, probably due to the small sample.

8 Attrition

Table 15 reports attrition levels in the treatment and comparison groups. We failed to collect data from 12% of dealers and 2% of farmers at midline, and from 14% of dealers and 1% of farmers at endline. To test if non-response is related to one of the treatments, we regress the likelihood of leaving the sample on the treatment indicators. We find that clearinghouse treated dealers are significantly less likely to leave the sample.

Whether our estimates are biased or not depends on whether this attrition is random or not. It is for instance plausible that the worst performing shops in the clearinghouse control group went out of business. 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.

On the other hand, 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 not found are not different from the ones that were found. The sub-sample of dealers that remained in

Table 14: Effects of clearinghouse on farmer perceptions

	baseline	*midline*		*endline*		*midline*		*endline*	
	mean	CH	obs.	CH	obs.	CH	obs.	CH	obs.
Farmer thinks maize seed at agro-input shops is adulterated†	0.685	-0.041	2113	0.020	2167	-0.125**	903	0.010	944
	(0.465)	(0.027)		(0.028)		(0.036)		(0.035)	
Index of farmer's maize seed ratings of shops within catchment area[1]†	0.000			0.092+	1664			0.141*	693
	(0.637)			(0.054)				(0.063)	
Index of farmer's general ratings of shops within catchment area[2]†	0.000			-0.005	1706			0.006	717
	(0.657)			(0.042)				(0.056)	
Overall index	0.023			0.068	1462				
	(0.697)			(0.052)					

Note: 1st column reports sample means and standard deviations below; 2nd column reports differences between treatment and control groups and standard errors below; 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; larger indices indicate more desirable outcomes.
[1]The index of farmer's maize seed ratings contains 6 ratings: general quality, yield, drought tolerance, pest/disease tolerance, time of maturity, germination. The ratings are aggregated at farmer level (one farmer rates multiple shops), then this index is computed.
[2]The index of farmer's general ratings contains 6 ratings: general quality, location, price, product quality, stock, reputation. The ratings are aggregated at farmer level (one farmer rates multiple shops), then this index is computed.
[3]The index of shop's maize seed ratings by farmers contains 6 ratings: general quality, yield, drought tolerance, pest/disease tolerance, time of maturity, germination. Ratings are aggregated at shop level (one shop is rated by multiple farmers), then the index is computed.

Table 15: Attrition

	mean	training	CH
		midline	
Agro-input dealer left the sample	0.121	-0.007	-0.108**
	(0.326)	(0.034)	(0.035)
Farmer left the sample	0.018	-0.005	0.001
	(0.134)	(0.005)	(0.005)
		endline	
Agro-input dealer left the sample	0.144	0.017	-0.079+
	(0.351)	(0.040)	(0.042)
Farmer left the sample	0.008	-0.003	-0.001
	(0.091)	(0.003)	(0.003)

Note: 1st column reports sample means at mid- or endline and standard deviations below; 2nd-3rd column reports differences between treatment and control groups and standard errors below; they are clustered at the level of randomization; **, * and + denote significance at the 1, 5 and 10 percent levels.

the control group would then be representative for the entire control group, hence our estimates would be unbiased. Attrition would only reduce power.

We noticed the attrition problem after midline data collection and instructed our enumerators to be more thorough at endline. Consequently, 7 of 28 clearinghouse control dealers who were not found for the midline interview, were found for the endline interview later that year. This supports our claim that at least a share control dealer attrition can be explained by a lack of enumerator effort instead of bankruptcy. Furthermore, even if attrition is non-random, the bias is likely to be negative and treatment effects are expected to be positive. As such, the unadjusted selection-contaminated estimates provide lower bounds for the true treatment effect (Angrist, Bettinger, and Kremer, 2006; Duflo, Glennerster, and Kremer, 2007).

9 Conclusion

Even though agricultural technologies like high yielding seed varieties and inorganic fertilizers are considered to be key in increasing agricultural productivity and accelerate rural transformation, the adoption by smallholders remains persistently low in sub-Saharan Africa. We studied a particular constraint to technology adoption: the perceived quality of agricultural inputs. We hypothesized that seed quality deteriorates because agro-input dealers lack knowledge and/or because asymmetric information results in excessive search costs for farmers and reduced incentives for dealers.

To assess the importance of these potential constraints to agricultural technology adoption, we tested two interventions in the market for improved maize seed varieties in eastern Uganda using a randomized control trial. A training informed agro-input dealers about correct seed handling and storage practices. An information clearinghouse based on crowd-sourced ratings of the quality of seed that agro-input dealers sell similar to yelp.com reduced the information asymmetry between seller and buyer by making the quality of maize seed sold by agro-input dealers observable.

The results of our analyses showed that training dealers did not change agro-input dealer practices and did not increase observable quality attributes of the seed. We also did not find any impact among farmers that are living in catchment areas of agro-input dealers that were trained: they did not rate quality differently nor had higher adoption rates than farmers that were not exposed to trained dealers.

The clearinghouse had clear impacts on the Ugandan market for maize seed as sellers and buyers started behaving in a way that is consistent with theory of change. Agro-input dealers reported more business and farmers reported higher yields and increased use of improved seed varieties. A large share of this effect seems to stem from increased competition that motivates agro-input dealers to increase effort and expand service provision. There is also evidence that the negative opinions that farmers hold about agro-input dealers is reduced by the information clearinghouse intervention. While we also find indications that farmers switch more between agro-input dealers in areas where the clearinghouse was implemented, it remains unclear if farmers switch from lower rated to higher rated input dealers.

We conclude that quality consideration are an important constraint to the adoption of agricultural inputs. Strategies to reduce information asymmetry between seller and buyer by making input quality more observable, through for instance certification, electronic verification, inspection etc., is likely to benefit the development of a market for quality inputs and increase adoption. A crowd-sourced information clearinghouse can be an important institutional innovation to solve the problem of asymmetric information in the market for agricultural inputs. It may be preferable to alternative strategies due to its likely lower cost and self-sustaining nature, and helps to overcome problems such as insufficient public investment in regulatory systems, regulatory enforcement, and market surveillance.

Finally, the null results for the agro-input dealer training experiment shows that simply investing in training may not be an effective strategy as long as agro-input dealers are not incentivized. In fact, our results suggest that if agro-input dealers are exposed to the incentives created by competition and full information, farmers may actively seek out knowledge necessary to further improve and keep ahead of competitors.

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A Appendix

A.1 Outcome variables and results as they were pre-registered

A.2 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

Table 16: Effects on primary dealer outcomes

	baseline	*midline*			*endline*		
	mean	training	CH	obs.	training	CH	obs.
Quantity of maize seed sold in kg§†	695.503	-0.092	0.284	292	-0.597*	0.747*	334
	(1497.183)	(0.220)	(0.227)		(0.289)	(0.307)	
Sales price of maize seed in UGX/kg	4273.897	-192.784+	99.272	275	-33.867	145.861	264
	(955.073)	(114.934)	(113.292)		(143.152)	(138.816)	
Revenue from maize seed in mln UGX§†	2.890	-0.069	0.185+	292	-0.227+	0.143	286
	(6.286)	(0.104)	(0.108)		(0.118)	(0.118)	
Number of maize seed customers per day§†	19.764	-0.056	0.127	294	-0.190	0.310**	288
	(20.689)	(0.098)	(0.101)		(0.116)	(0.112)	
Moisture in randomly selected seed bag in percent	13.563	0.017	-0.122	175	-0.041	-0.220	261
	(1.442)	(0.142)	(0.144)		(0.198)	(0.197)	
Index of capital-intensive seed handling practices[1]†	0.000	-0.019	0.000	270	-0.087	0.070	265
	(0.508)	(0.063)	(0.072)		(0.092)	(0.081)	
Index of labor-intensive seed handling practices[2]†	0.010	0.058	0.099	285	0.083	0.074	274
	(0.484)	(0.070)	(0.065)		(0.067)	(0.068)	
Index of all seed handling practices[3]	0.009	0.042	0.052	251	0.021	0.083	248
	(0.382)	(0.051)	(0.053)		(0.063)	(0.059)	
Index of dealer's efforts and services[4]†	0.000	-0.063	0.066	243	-0.031	0.086+	297
	(0.454)	(0.062)	(0.060)		(0.051)	(0.048)	
Index of shop's maize seed ratings by farmers[5]	-0.018				0.020	0.122	327
	(0.595)				(0.102)	(0.101)	
Overall index	0.007	-0.004	0.214+	215	-0.054	0.220*	257
	(0.591)	(0.130)	(0.121)		(0.118)	(0.109)	
Max. number of obs. for dealer survey outcomes				306			297

Note: 1st column reports baseline means and standard deviations below; 2nd, 3rd, 5th and 6th column reports differences between treatment and control groups and standard errors below; they are clustered at the level of randomization; 4th and 7th 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; larger indices indicate more desirable outcomes.

§Due to the skewness of this variable, the regression was run after an Inverse Hyperbolic Sine transformation. Coefficient estimates can therefore be interpreted as percentage changes. The baseline mean column shows the untransformed variable.

[1]The index of capital-intensive seed handling and storage practices contains 6 variables: whether roof is leak-proof, whether roof is insulated, whether walls are insulated, whether shop is ventilated, whether any official certificate is displayed, whether expired seed is handled correctly.

[2]The index of labor-intensive seed handling and storage practices contains 6 variables: whether seed is stored in dedicated area, whether shop has no pest problem, whether seed is stored in correct lighting, whether seed is stored on correct surface, whether seed is not stored in open containers, cleanness and professionality rating by enumerator.

[3]The index of all seed handling and storage practices contains 12 variables: the ones included in the index of capital-intensive practices and the ones included in the index of labor-intensive practices.

[4]The index of dealer's efforts and services contains 7 variables: whether shop offers explanations, complementary input recommendations, extension/training, discounts for larger quantities, credit, did not receive seed related customer complaint, accepts mobile money.

[5]The index of shop's maize seed ratings by farmers contains 6 ratings: general quality, yield, drought tolerance, pest/disease tolerance, time of maturity, germination. Ratings are aggregated at shop level (one shop is rated by multiple farmers), then the index is computed.

Table 17: Effects on secondary dealer outcomes: Indices

	baseline	*midline*			*endline*		
	mean	training	CH	obs.	training	CH	obs.
Index of dealer's motivation and satisfaction[1]	0.000	0.033	0.000	306	-0.109	-0.076	286
	(0.674)	(0.082)	(0.085)		(0.082)	(0.086)	
Index of dealer's self-ratings[2]	0.000	-0.068	-0.002	306	-0.132	0.080	297
	(0.651)	(0.084)	(0.079)		(0.086)	(0.079)	
Index of dealer's efforts and services according to farmers[3]	-0.027	-0.151*	0.301**	259	0.006	0.086	271
	(0.583)	(0.074)	(0.069)		(0.092)	(0.084)	
Index of dealer's knowledge about seed storage[4]	0.000	0.091	0.115	306	0.030	0.124*	297
	(0.482)	(0.076)	(0.075)		(0.053)	(0.055)	
Index of dealer's knowledge about seed[5]	0.000	0.102	0.065	306	-0.009	-0.007	297
	(0.533)	(0.072)	(0.070)		(0.080)	(0.078)	
Max. number of obs.				306			297

Note: 1st column reports baseline means and standard deviations below; 2nd, 3rd, 5th and 6th column reports differences between treatment and control groups and standard errors below; they are clustered at the level of randomization; 4th and 7th 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; larger indices indicate more desirable outcomes.

[1]The index of dealer's motivation and satisfaction contains 3 variables: whether dealers see themselves working as agro-input dealers in future, would recommend working as dealers, how happy dealers feel when they come to work. We report the mean and standard deviation at midline because these variables were not collected at baseline.

[2]The index of dealer's self-ratings contains 5 ratings: location, price, product quality, stock, reputation.

[3]The index of dealer's efforts and services according to farmers contains 7 variables: whether shop offers refund/insurance, credit, training/advice, delivery, after-sales service, accepts different payment methods, sells small quantities. The answers are aggregated at dealer level, then the index is computed.

[4]The index of dealer's knowledge about seed storage contains 5 variables: whether dealer knows how long seed can be carried over, how seed should be stored after repackaging, what the min. distance between floor and seed is, how seed should be stored in storeroom, whether seed should be repackaged.

[5]The index of dealer's knowledge about seed contains 4 variables: whether dealer knows which seed variety to recommend if farmer complains about poor soil, if farmer complains about little rain, if farmer is late for planting, what to tell clients about yield benefits of hybrid seed.

Table 18: Effects on primary farmer outcomes

	baseline	*midline*			*endline*		
	mean	training	CH	obs.	training	CH	obs.
Farmer planted improved maize seed on any field†	0.492	-0.021	0.035^{+}	3206	-0.009	0.042^{*}	3282
	(0.500)	(0.020)	(0.020)		(0.020)	(0.020)	
Farmer bought maize seed at agro-input shop for any field†	0.325	-0.014	0.059^{**}	3145	0.004	0.031	3225
	(0.468)	(0.021)	(0.021)		(0.019)	(0.020)	
Amount of this seed farmer bought at agro-input shop in kg	9.519	0.512	-0.105	599	0.457	0.378	621
	(6.920)	(0.348)	(0.358)		(0.419)	(0.431)	
Index of farmer's maize seed ratings of shops within catchment area[1]	0.000				0.021	0.092^{+}	1664
	(0.637)				(0.054)	(0.054)	
Index of farmer's general ratings of shops within catchment area[2]	0.000				-0.026	-0.005	1706
	(0.657)				(0.043)	(0.042)	
Index of services of shops within catchment area according to farmers[3]	-0.037	-0.138^{+}	0.161^{*}	312	0.034	0.131^{+}	320
	(0.609)	(0.073)	(0.067)		(0.081)	(0.077)	
Farmer switched to different agro-input shop[4]†	0.168	-0.013	0.042^{**}	3407	-0.024	0.026^{+}	3441
	(0.374)	(0.014)	(0.014)		(0.015)	(0.015)	
Index of farmer's practices on randomly selected field[5]†	0.008	0.011	-0.026	2929	0.001	0.016	3053
	(0.400)	(0.019)	(0.019)		(0.021)	(0.021)	
Farmer thinks maize seed at agro-input shops is adulterated	0.685	-0.033	-0.041	2113	-0.041	0.020	2167
	(0.465)	(0.027)	(0.027)		(0.028)	(0.028)	
Farmer planted land race maize seed on randomly selected field†	0.448	0.015	-0.013	2954	0.009	-0.024	3047
	(0.497)	(0.021)	(0.020)		(0.022)	(0.022)	
Overall index[6]	0.009	0.008	0.017	2933	-0.023	0.063^{+}	3083
	(0.698)	(0.033)	(0.034)		(0.034)	(0.034)	
Max. number of obs.				3407			3441

Note: 1st column reports baseline means and standard deviations below; 2nd, 3rd, 5th and 6th column reports differences between treatment and control groups and standard errors below; they are clustered at the level of randomization; 4th and 7th 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; larger indices indicate more desirable outcomes.

[1] The index of farmer's maize seed ratings contains 6 ratings: general quality, yield, drought tolerance, pest/disease tolerance, time of maturity, germination. The ratings are aggregated at farmer level (one farmer rates multiple shops), then this index is computed.

[2] The index of farmer's general ratings contains 6 ratings: general quality, location, price, product quality, stock, reputation. The ratings are aggregated at farmer level (one farmer rates multiple shops), then this index is computed.

[3] The index of services of shops within catchment area contains 7 variables: whether shop offers refund/insurance, credit, training/advice, delivery, after-sales service, accepts different payment methods, sells small quantities. The answers are aggregated at shop level, then the index is computed at farmer level. Only 320 farmers answered all 7 questions for at least one shop within the catchment area at baseline and at endline.

[4] We report the mean and standard deviation at midline because this variable was not collected at baseline.

[5] The index of farmer's practices contains 10 variables: whether farmer spaced seed correctly, sowed correct number of seeds/hill, applied organic manure, DAP/NPK, Urea, pesticides/herbicides/fungicides, weeded sufficiently, weeded at correct time, planted at correct time, re-sowed.

[6] We report the mean and standard deviation at midline because not all variables in this index were collected at baseline.

Table 19: Effects on secondary farmer outcomes: Adoption on randomly selected maize field

	baseline	*midline*			*endline*		
	mean	training	CH	obs.	training	CH	obs.
Farmer planted hybrid seed†	0.264	0.002	0.009	2654	-0.023	0.032	2700
	(0.441)	(0.022)	(0.022)		(0.023)	(0.023)	
Farmer planted open-pollinated seed†	0.260	-0.017	0.002	2654	0.010	-0.007	2700
	(0.439)	(0.022)	(0.022)		(0.020)	(0.021)	
Farmer planted farmer-saved seed†	0.579	0.020	-0.042^{+}	3153	-0.009	-0.016	3240
	(0.494)	(0.022)	(0.022)		(0.020)	(0.020)	
Farmer planted seed bought at agro-input shop†	0.330	-0.010	0.047*	3153	0.012	0.036^{+}	3240
	(0.470)	(0.022)	(0.022)		(0.019)	(0.019)	
Farmer planted hybrid or open-pollinated seed[1]	0.432	-0.019	0.035	2954	0.009	0.030	3047
	(0.495)	(0.023)	(0.023)		(0.023)	(0.023)	
Overall index	-0.003	0.000	0.002	2867	-0.010	0.026	2963
	(0.553)	(0.024)	(0.024)		(0.025)	(0.025)	
Max. number of obs.				3407			3441

Note: 1st column reports baseline means and standard deviations below; 2nd, 3rd, 5th and 6th column reports differences between treatment and control groups and standard errors below; they are clustered at the level of randomization; 4th and 7th 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; larger indices indicate more desirable outcomes.
[1]For this variable, only seed which was not farmer-saved counted as hybrid seed and only seed which was not recycled too often counted as open-pollinated seed.

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.3 Details about rating dissemination

Table 20: 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*?

A.4 Multiple choice questions to measure dealer knowledge