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 that tests two hypotheses on how the (perceived) quality of agricultural inputs affects adoption among smallholder farmers in Uganda. First, poor quality could be caused by agro-input dealers' lack of knowledge about proper handling and storage. A training is expected to improve input quality and subsequent adoption. Second, information asymmetries could crowd 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 agro-input dealers and farmers benefit from the clearinghouse, but not from the training.

Note: Author order is alphabetical.

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

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

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1 Introduction

Over the next decades, farmers in sub-Saharan Africa will need to produce more food on less land 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 is thought to be at least part of the solution (Evenson and Gollin, 2003). Unfortunately, the adoption of improved agricultural 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 recent years. 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 new technologies (Hanna, Mullainathan, and Schwartzstein, 2014).

More recently, issues related to the quality of inputs such as improved seed varieties, inorganic fertilizers, and pesticides have emerged as a potential constraint to their adoption by smallholder farmers. Bold et al. (2017) argue that farmers can hardly assess quality from simple visual inspection at the time of purchase, so information asymmetries between sellers and buyers characterize the markets for seed and fertilizer, in turn crowding out the market for quality inputs in Uganda, similar to what happens in Akerlof's seminal "Market for Lemons" study (1970). However, subsequent research argues 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 input quality is sufficient but farmers' perceptions are 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 varieties (high-yielding cultivars like open-pollinated and hybrid varieties) in eastern Uganda. Agro-input dealers are essential for agricultural technology adoption in countries with large farmer populations living in remote areas with poor infrastructure. A reasonably dense network of semi-formal agro-input shops provides access to technologies to rural farmers. Often, these dealers also provide services like agricultural advice or even credit to smallholders.

At the same time, the informal nature of many agro-input shops may imply that they are a weak link in the supply chain for quality inputs, a risk that is likely to be smaller upstream where larger producers and importers face more scrutiny from the government. Agricultural inputs such as seeds and fertilizers are sometimes stored in sub-optimal conditions (e.g., in direct sunlight or in moist environments) or handled in harmful ways (e.g., stored beyond the expiry date or repackaged). There is some evidence of this kind of quality reduction. In a comprehensive study of the Ugandan seed supply chain, Barriga and Fiala (2020) document various issues related to handling and storage that may reduce input quality. For example, dealers often repack seed from larger bags packed by seed companies into smaller bags 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 expect that a lack of dealer knowledge leads to deterioration in maize seed quality. Training agro-input dealers and providing them with information on proper seed handling and storage could 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 small piece of information can make a large difference (Duflo and Banerjee, 2011). Also in the context of smallholder technology adoption, 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, and we are unaware of studies that tackle knowledge gaps among (small) agro-input dealers.

The fact that seed quality cannot easily be observed by farmers may also result in a lack of incentives for 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 intentionally sacrifice quality to cut costs and increase profits, e.g., by mixing improved or fresh seed with local or old seed. There is some evidence of this kind of adulteration and counterfeiting 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.

That is why, in a second hypothesis, we expect that asymmetric information reduces dealers' incentives to provide quality seed. Addressing these asymmetries may lead to better quality, in turn increasing adoption. Uganda regulates seed quality by means of certifications and standards, but they provide farmers with a relatively weak and unreliable indication of quality. 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 these problems caused by the lack of incentives for agro-input dealers, asymmetric information may 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 continue to perceive quality to be poor even though it may have improved, which in turn reduces incentives for agro-input dealers to maintain quality.

To address issues caused by asymmetric information, we implement a novel intervention: 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 disseminate these ratings back to both, farmers and agro-input dealers. Ratings were collected and disseminated twice to increase the likelihood that dealers change their behavior and that farmers know and trust the scores.

The objective of the clearinghouse is thus to make maize seed quality observable. However, some may argue that farmers can assess seed quality well after one agricultural season: shortly after planting, farmers can observe germination rates, i.e., the proportion of seeds that germinate, and later how fast the seed matures. Some seed may also be more susceptible to pests and diseases, while other seed may be particularly tolerant in terms of drought. After harvest, the farmer can observe the yield. In the limit, farmers can perfectly observe seed quality, and there is no need for a clearinghouse. However, others may argue that farmers cannot assess seed quality 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. This would imply that the clearinghouse will not work, as farmers cannot assess seed quality at all. 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. While there is considerable evidence that farmers cannot perfectly assess seed quality (e.g., Bold et al., 2017) and authors like Tjernström et al. (2021) argue that sub-Saharan Africa's soil heterogeneity further hampers farmer learning about the returns to inputs, we argue that it seems unlikely that farmers cannot learn anything from their 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 therefore likely to provide a good signal about the quality of seed.[1]

Seeing that farmers cannot perfectly assess seed quality ex ante or ex post, one could argue that a better remedy against information asymmetries would be to objectively measure seed quality (e.g., by sending mystery shoppers, followed by DNA fingerprinting) or agro-input dealer practices (e.g., by sending objective inspectors incognito). However, these strategies are often not practical, not cost effective, or introduce other challenges (e.g., they may be prone to corruption or may not reach the most remote areas). Furthermore, peer ratings measure the dimensions of seed quality that matter most to smallholders. It is for example plausible that farmers do not mind about varietal purity (indicating whether seed is a particular variety, only detectable by DNA fingerprinting) but care a lot about seed performance (e.g., germination rate, vigor, and yield). Their preferences may be reflected in their ratings, whereas DNA fingerprinting may measure a dimension that matters less to farmers. The opinion of peers, who are familiar with the heterogeneous conditions farmers face, may be more useful and trustworthy for smallholders than the judgment of an inspector or DNA test. That is why we believe that our crowd-sourced clearinghouse strategy is an alternative worth exploring.

A training is expected to work mainly through increasing agro-input dealer knowledge, which when applied will lead to improved seed quality. An information clearinghouse is expected to work through various impact pathways. Firstly, farmers may switch from lower 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 improve quality and agro-input dealers may want to signal this to farmers. To achieve good ratings, dealers could also start offering credit, advice, or

[1]To support our claim, we show that the ratings are correlated with objective indications of seed quality in Appendix A.1.

other services that may increase customer satisfaction but will not directly affect seed quality. Finally, farmers who did not buy improved maize seed before (because they believed agro-input dealer sell poor quality seed) could start adopting 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. Note that both interventions can only work if the perceived quality issues arise at the agro-input dealer level, they will fail if poor seed quality is caused further up the seed supply chain, e.g., by breeding results that are not in line with farmers' expectations.

We test the training and the clearinghouse 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 improves outcomes for both, dealers and farmers. Shops in areas exposed to the clearinghouse intervention receive more customers, sell more, and have higher revenues from maize seed than shops in control areas, and these effects become stronger with time. Clearinghouse treated farmers are significantly more likely to use improved maize varieties from agro-input dealers, and consequently have higher yields than control farmers after two seasons. We find indications that farmers move from lower rated agro-input dealers to higher rated ones. Impact also seems to come from treated agro-input dealers who increase their efforts and expand the services that they provide to farmers. Treated shops are also more likely to be registered with the Uganda National Agro-input Dealers Association (UNADA), perhaps to signal quality. Finally, we find that farmers in the treatment group rate maize seed of shops in their neighborhood better, suggesting that the clearinghouse treatment is also effective in changing perceptions.

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

Our study contributes to the literature on effective ways to reduce information asymmetries. For instance, Lane, Schonholzer, and Kelley (2022) show how providing information about bus safety to passengers affects the demand and supply of safer public transport, but only if there is a public signal (i.e., when bus drivers know that they are tracked and that this information is revealed to passengers). The article further fits into an emerging literature that tests how crowd-sourced information and reputational mechanisms can reduce information asymmetries and effectively change behavior. Even though advances in Information and Communications Technology and the rise of e-commerce has led to numerous platforms that allow for consumer feedback and a variety of websites that aggregate crowd-sourced reviews, there is surprisingly little evidence on the effects of these developments. The few rigorous studies that are available report impressive impact. Reimers and Waldfogel (2021) compare the effects 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.

More specifically, we advance the literature on information clearinghouse mechanisms in developing countries, which have been studied to some extent, but mostly address market price information asymmetries between smallholders 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 the functioning of rural agricultural markets. However, evidence is mixed: while Goyal (2010) finds that internet kiosks that provide wholesale price information significantly increase soy prices farmers receive 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. However, a clearinghouse that relies on crowd-sourced ratings may be more effective in increasing the (perceived) 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 their quality. For example, Hasanain, Khan, and Rezaee (2023) implement a crowd-sourced information clearinghouse in the market for artificial insemination of livestock in Punjab, Pakistan, where individual signals of quality are noisy. Using an RCT, they find that farmers who receive information enjoy 25% higher insemination success and no higher prices. The existing veterinarians seem to increase effort, while farmers are not likely to switch to better providers. This result illustrates how information clearinghouses can successfully aggregate information in low-capacity markets.

Our study also contributes to a large literature on the effectiveness of providing training to small businesses in developing countries. Helping entrepreneurs to grow small firms by teaching them business skills has yielded mixed results when subjected to rigorous impact evaluation methods (e.g., Karlan and Valdivia, 2011; Drexler, Fischer, and Schoar, 2014; Giné and Mansuri, 2021). While these studies often suffer from methodological issues such as lacking 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 trainings to trainings designed to instill personal initiative (Campos et al., 2017).[2] Our study similarly shows the importance of (external) motivation in making trainings reach their objective.

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

2 Experimental design

We designed an experiment with two interventions (described in detail in the next section), and evaluate their impact using an RCT. The interventions are randomized at the catchment area level. Generally, agro-input shops are clustered in towns, villages, markets, trading centers, and other key market sheds, so that a single catchment area may be served by several dealers. 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 treatment. Clustering agro-input dealers into catchment areas is done on the basis of geographical location.[3]

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 or more agro-input dealers operate very close to each other, treating only one of them may lead to a competitive (dis-)advantage. Randomizing at catchment area level substantially reduces the risk of (dis-)advantaging shops. Secondly, it reduces the likelihood of spillovers 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 that was collected in previous surveys.[4] Power simulations show that if the number of catchment areas is larger than 112, our experiments will return statistically significant results 80% of the time on a selection of primary outcomes. 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.[5]

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 Table 1. We measure impact on both, agro-input dealers and farmers.

[3]We use the haversine function to construct an adjacency matrix based on GPS coordinates, and shops 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 survey data from a previous study of the maize value chain that can be found here.

[4]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.

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

Table 1: Factorial design

		dealer training	
		1	0
clearinghouse	1	28 areas	28 areas
	0	28 areas	28 areas

3 Interventions

3.1 Agro-input dealer training

Training content and 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, and then determined effective and realistic solutions and best practices in seed storage and handling. We then developed a training manual to ensure standardization and a simple but visually appealing poster illustrating the most important best practices.

Training

In each treated 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 require investments. The shop manager was invited because many of the recommendations are 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 the participants.

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.

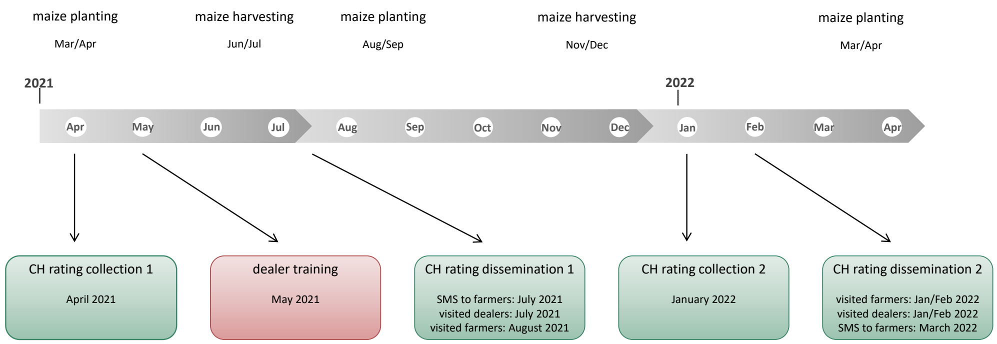

Figure 1: Timeline

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 1. The trainings were organized together with UNADA, the national association for agro-input dealers in Uganda.

3.2 Information clearinghouse

Rating collection and computation

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 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 is located, and a picture of the store front (obtained during the agro-input dealer census—see Subsection 5.1). If farmers knew the dealer, we asked them to provide ratings using the questions which are outlined in Table 2. 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 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 1 for a timeline of the interventions.

Some may argue that by asking farmers to rate dealers, one also makes farmers

Table 2: 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

aware of the existence of all dealers in the area, and that this awareness effect potentially confounds 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 aspect of 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. As illustrated in Figure 1, there were two rounds of rating collections. However, these ratings were not pooled, meaning that the second score is independent of the first score. More details about the rating computations can be found in Appendix A.2.

Rating dissemination 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 1. Ratings were disseminated to farmers by means of text messages and in person.

Text messages We sent farmers one text message per dealer in their proximity by Short Message Service (SMS). This message was translated into three local languages - Lusoga, Lugwere, Samia - chosen at the sub-county level to increase specificity. Table 19 in Appendix A.3 provides more details about the 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 clearinghouse, we also disseminate control dealer information including their names but excluding the ratings. 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.

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 to inform farmers that these agro-dealers are operating in their neighborhood.

As it was the case for the collection of ratings, the application provides different names under which the shop is known, a description of where the store is located, and a picture of the store front to make sure farmers associate the rating with the correct shop.

Rating dissemination 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 2. 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 1. 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. Again, the second rating does not depend on the first rating.

Figure 2: SeedAdvisor certificate

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, 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 jackknife variance estimator (Bell and McCaffrey, 2002).

In terms of variable construction, we follow some pre-registered 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 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% of observations have the same value within the relevant sample will be omitted from the analysis.

We account for multiple hypothesis testing by aggregating different outcomes within each domain into summary indices, following Anderson (2008).[6] 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 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. 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 3 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 for the names 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.

[6] 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.

5.2 Descriptive statistics

This subsection describes the baseline sample. Information about the average agro-input shop can be found in Table 3. When enumerators approached a shop, 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 4 reports means in the farmer sample. When approaching a household, enumerators were instructed to interview the person who is most knowledgeable about maize farming. However, a set of questions deals with the household head, who could be or could not be the respondent. 78% of household heads in our sample are male, 51% have finished primary education. The average household head is 49 years old.

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

Half of the farmers in our sample adopted improved maize seed on at least one of their plots last season. 1 out of 3 bought this 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 plot. Productivity is low at about 440 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 3 and 4 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 3, we find that from a total of 16 comparisons, only one is significant at the 5% level for the agro-input dealer training. For the clearinghouse treatment, we find two significant differences, both at the 10% level. This is consistent with a balanced sample. For outcomes at the farmer level, out of 32 comparisons, one is significant at the 10% level.

6 Results

This section presents results on the impact of the agro-input dealer training and the information clearinghouse. We report effects at the agro-input dealer level as well as at the level of the farmers that reside in catchment areas of the dealers. Furthermore, we separately present impact one agricultural season after the intervention (referred to as impact at midline) and two seasons after the intervention (referred to as impact at endline).

We take transparency and replicability seriously. 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's registry before midline data was collected.[7] Mock reports are dynamic documents that integrate all code.[8] As such, when midline and endline data became available, we simply replaced the simulated data with the real data. All documents, code, and data are under revision control and publicly accessible via GitHub which

[7]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.

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

Table 3: Descriptive statistics and orthogonality tests - Agro-input dealer

	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 %	13.56	0.25	-0.18
	(1.44)	(0.25)	(0.26)

Note: Column (1) reports sample means at baseline and standard deviations below; columns (2)-(3) report 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% levels.

Table 4: Descriptive statistics and orthogonality tests - Farmer

	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: Column (1) reports sample means at baseline and standard deviations below; columns (2)-(3) report 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% levels.

provides time-stamped records of all changes made over the course of the project.[9]

The results Tables 5 to 15 have a common layout. Column (1) provides baseline sample means with standard deviations in parentheses below, mainly to get an idea of effect sizes. That is why we always provide these averages in levels, even though we may report the difference between treatment and control group after using inverse hyperbolic sine transforms. In column (2), we provide the average treatment effect of the agro-input dealer training at midline, while column (3) reports the average treatment effect of the information clearinghouse treatment at midline. We also report the standard errors below in parentheses and the number of observations that were used for the regressions at midline in column (4). Column (5) and (6) report average treatment effects of the 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 in column (7). As mentioned in Section 4, we account for multiple hypothesis testing by aggregating different outcomes within families into overall summary indices, following Anderson (2008). Results for these indices are reported at the bottom of the tables.[10]

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 in Table 5. Sales volume and price, revenue, and number of customers and maize varieties in stock are included as outcomes under this heading. A measure of sales volume was constructed by asking how much of a specific maize seed variety dealers sold in the previous season. We restrict attention to the four most popular improved varieties, two of which are hybrid varieties (Longe 7H and Longe 10H) and two of which are Open Pollinated Varieties (OPVs) (Longe 4 and Longe 5). Total quantity sold is the sum of quantities sold of these four varieties. We also

[9] The presentation of results in this paper differs somewhat from the way it was pre-registered and presented in the mock report (and midline report, endline report, and previous versions of this manuscript). The pre-registered reports mainly serve to tie our hands, commit to decisions, and reduce our freedom in choosing which specifications and variables to select when testing hypotheses, to avoid fishing and make this study more reliable (Humphreys, De la Sierra, and Van der Windt, 2013). Hence the presentation of results in the pre-registered reports mainly determines if the interventions worked or not. As such, we included tables of key outcomes along the entire causal chain (and combined them in an index) to assess overall treatment impact, see Appendix A.4. Other tables then went into detail (e.g., focusing on a particular seed type sold by an agro-input dealer or on a particular plot cultivated by a farmer). In this paper however, we reorganize the reporting to match a structure where we first look at impact on outcomes at the end of the causal chain and then look at impact on intermediate outcomes to explore potential mechanisms. While this change does affect the construction of some of the indices, overall conclusions remain the same. Some of the pre-registered tables can be found in Appendix A.4. The entire analysis that follows the pre-registered structure can be found through the project history in GitHub, for instance here.

[10] 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.

asked dealers about the sales price of the four seed types at the start of the season and then calculated the simple average at the dealer level. We then calculate the revenue (expressed in million UGX) by first multiplying prices with quantities sold and then summing over the four seed types. We also include the number of customers that buy maize seed on an average day at the start of the season, as well as the number of maize varieties that the agro-input dealer has in stock.

Table 5 shows that we do not find an impact of training agro-input dealers on their business operations. Both at midline and at endline, 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 training on the average sales price. At endline, the training seems to have reduced amounts sold, which is also reflected in a lower revenue.

However, we do find a positive impact of the information clearinghouse intervention on agro-input dealer operations. At midline, the overall index is significantly higher among dealers in the clearinghouse treatment group. Looking at individual outcomes, we see that treated dealers sold more maize seed at a higher price, albeit not significantly so. However, in combination, this leads to revenues that are almost 20% higher (and this difference is significant at the 10% level).[11] At endline, the positive effect of the clearinghouse intervention seems to become stronger, with the overall index now being significant at the 1% level. The effect is driven by a 31% increase in the number of customers that a treated shop attracts, which translates into 6 additional customers.

While Table 5 looks at the impact on overall business operations, Tables 6 and 7 focus on the effect of the interventions on operations related to one particular seed type. We look at the most recently released hybrid variety (Longe 10H) in Table 6 and the most recent OPV (Longe 5) in Table 7.

In line with Table 5, we start by looking at sales volumes, prices, and revenues. We also focus on outcomes related to stock management, as seed quality decreases with shelf-life. We asked agro-input dealers how much of the particular seed was carried over from the previous season. Many dealers reported that they did not carry over any seed, leading to low baseline means. Furthermore, we asked them to estimate how much they bought from any provider during the same season. For both varieties, this is slightly more than what dealers reported to have sold. We expect our treatments to decrease the amount of seed carried forward and increase the amount of fresh seed procured from providers. We also asked agro-input dealers to provide an estimate of how much of the seed stock they lost or wasted during the season, and how often they ran out of stock. We expect the interventions to reduce both, losses and stock-outs.

For the variety Longe 10H, we do not find significant effects of the training nor the clearinghouse treatment at midline. At endline however, all individual coefficient estimates go in the expected direction for the information clearinghouse, and when outcomes are combined in an index, the effect is positive and significant at the 1%

[11] For reasonably large values, coefficients of regressions that involve a dependent variable that has been transformed using the inverse hyperbolic sine can be interpreted as elasticities (Bellemare and Wichman, 2020).

Table 5: Effects on agro-input dealer outcomes: 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	-0.499^{+}	0.239	286
	(1497.183)	(0.220)	(0.227)		(0.250)	(0.253)	
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	-0.131	0.238**	270
	(0.610)	(0.095)	(0.092)		(0.086)	(0.082)	
Max. number of obs.				306			297

Note: Column (1) reports baseline means and standard deviations below; columns (2), (3), (5), and (6) report differences between treatment and control groups and standard errors below; they are clustered at the level of randomization; columns (4) and (7) report number of observations; **, *, and + denote significance at the 1, 5 and 10% 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.

level. Results are similar for Longe 5.

One step further up the impact chain, increased numbers of customers, sales, and revenues are likely to be driven by an increase in the (perceived) quality of improved maize seed that these agro-input dealers sell. 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 attributes. First, we measured the moisture content of the seed. In Table 8, we see that the clearinghouse treatment reduced moisture as expected, but the parameter is estimated imprecisely, perhaps due to the smaller data set as we were not able to source seed from all dealers and the comparisons were only made for shops in which the enumerator was able to buy a bag of maize seed at mid- or endline. We further look at the integrity of the package and whether it shows important information such as the packaging date and the lot number, but also at the shelf-life and whether seed is in the original bag without any signs of damage. 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. However, because our proxies of seed quality are far from perfect[12] and we rely on a smaller sample, we cannot safely conclude that the treatments did not affect seed quality.

6.2 Impact on smallholder farmers

We first look at harvest related outcomes for farmers that live in the catchment areas of agro-input dealers involved in our study and report the results in Table 9. We start by looking at overall production, the area of a specific maize plot, and the production scaled by plot size, i.e., yield. We also look at market participation (amount sold, sales price, and revenue from maize sales) and how much grain farmers save to use as seed in the next season. All these outcome variables deal with one randomly selected plot. While we expect positive effects on harvest and sales, the amount kept as seed enters the index negatively.

The coefficient estimates for the overall index show no effect of the agro-input dealer training, and a positive effect of the information clearinghouse, but only after two seasons of implementation. Farmers that live in areas where the clearinghouse was implemented report higher production and productivity at endline. Yield differences

[12] As elaborated in a recent World Bank Blog, assessing seed quality is not only challenging for farmers, but also for researchers (Beegle et al., 2021). The most important seed quality dimensions are analytical purity (indicating whether seed is the correct species), germination rate (indicating whether seed germinates) and varietal purity (indicating whether seed is the correct variety, e.g., a particular variety with specific traits, only detectable by DNA fingerprinting). For example, Barriga and Fiala (2020) use laboratory tests to investigate the DNA variation (indicating how genetically similar a sample of seed is to itself), analytical purity, and performance of seeds (germination rate, moisture, and vigor) as their measure of seed quality. Even though investigating moisture is an attempt to test the quality of seeds in a quantitative and objective way, this variable is one-dimensional and only a weak indication of seed quality.

Table 6: Effects on agro-input dealer outcomes: 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 over 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: Column (1) reports baseline means and standard deviations below; columns (2), (3), (5), and (6) report differences between treatment and control groups and standard errors below; they are clustered at the level of randomization; columns (4) and (7) report number of observations; **, *, and + denote significance at the 1, 5 and 10% 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 7: Effects on agro-input dealer outcomes: 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 over 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: Column (1) reports baseline means and standard deviations below; columns (2), (3), (5), and (6) report differences between treatment and control groups and standard errors below; they are clustered at the level of randomization; columns (4) and (7) report number of observations; **, *, and + denote significance at the 1, 5 and 10% 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.

Table 8: Effects on agro-input dealer outcomes: Bag of maize seed

	baseline	*midline*			*endline*		
	mean	training	CH	obs.	training	CH	obs.
Moisture in %†	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)	
Shelf-life 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: Column (1) reports baseline means and standard deviations below; columns (2), (3), (5), and (6) report differences between treatment and control groups and standard errors below; they are clustered at the level of randomization; columns (4) and (7) report number of observations; **, *, and + denote significance at the 1, 5 and 10% 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.

are significant at the 1% level and amount to 10% compared to the baseline means. Finally, we look at the amount of maize that farmers keep to use as seed in the next season. At midline, we see that, in line with expectations, clearinghouse treated farmers save less grain for seed.

To explore the large effect of the clearinghouse on yields, we investigate which subgroup of farmers enjoyed most yield gains. Rerunning the regression only for farmers who did not adopt at baseline led to a coefficient of 56.44 with a standard error of 17.38 (hence, significance at the 1% level). For farmers that did adopt at baseline, we find a coefficient of 30.79 with a standard error of 20.38 (hence, no significance). This indicates that the effect is driven by farmers who did not adopt at baseline, started adopting due to the clearinghouse, and in turn enjoy higher yields. Assuming that non-adopting farmers are the less advantaged ones, the impact on their adoption and yield is particularly desirable.

To further test this, we look at the adoption of improved maize seed varieties as a second important family of outcomes at the smallholder level. For the agro-input dealer training, we do not find any effect at midline, nor at endline. The effect of the information clearinghouse treatment on overall adoption as measured by the index is positive and significant at the 5% level at mid- and endline.

Zooming in on individual outcomes, a first key question simply asks farmers if they used quality maize seed for any plot in the previous season. Here, the definition of "quality maize seed" is up to the farmer. We see that at midline, farmers that were subjected to the clearinghouse treatment were 3.5 percentage points more likely to answer this question with "yes" than control farmers. After two agricultural seasons, the difference between treatment and control farmers increases to 4.2 percentage points. Related, we ask if farmers bought maize seed at an agro-input shop for any plot. At midline, we find a difference between the clearinghouse treatment and control groups of about 6 percentage points, and this amounts to an almost 20% increase relative to the baseline mean. At endline, the difference is about 3 percentage points, but not significant anymore. We do not find an impact of the clearinghouse on the amount that farmers bought at agro-input shops. However, one should note that the sample size is smaller because we only ask this question to farmers who bought from agro-input dealers.

We then ask questions about adoption on a randomly selected plot. For the adoption of hybrid or open-pollinated maize varieties, we estimate positive treatment effects of the clearinghouse, but the coefficients are not significantly different from zero.[13] 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 at midline and a 3.6 percentage point effect at endline. A related question asks if farmers used farmer-saved seed on the

[13] Here, we asked farmers which variety they planted in the previous season. If a farmer used Longe 10H, Longe 7H, Longe 7R/Kayongo-go, Bazooka, Longe 6H, Longe 5/Nalongo, Longe 4, Panner, Wema, KH series, or other hybrid/OPV, and this seed was not recycled or farmer-saved but newly purchased, it counted as hybrid/open-pollinated maize seed.

Table 9: Effects on farmer outcomes: Harvest on specific maize plot

	baseline	*midline*			*endline*		
	mean	training	CH	obs.	training	CH	obs.
Production in kg†	463.203	-0.806	-20.372	2884	16.959	43.937*	2898
	(399.595)	(14.050)	(14.529)		(17.957)	(17.922)	
Area in acres	1.094	-0.013	-0.003	3004	0.000	0.006	3066
	(0.655)	(0.029)	(0.029)		(0.032)	(0.038)	
Yield in kg/acre†	443.222	-12.216	-23.006	2878	5.118	56.436**	2889
	(304.964)	(16.234)	(16.964)		(15.596)	(17.382)	
Amount sold in kg§†	195.295	-0.046	-0.201	3063	-0.147	0.173	3137
	(297.545)	(0.126)	(0.124)		(0.159)	(0.173)	
Sales price in UGX/kg	506.954	-7.787	33.027*	610	-47.215	12.614	639
	(139.389)	(14.395)	(14.244)		(30.547)	(41.238)	
Revenue in UGX§†	97.783	-0.141	-0.393	3058	-0.354	0.355	3109
	(156.538)	(0.260)	(0.257)		(0.341)	(0.363)	
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: Column (1) reports baseline means and standard deviations below; columns (2), (3), (5), and (6) report differences between treatment and control groups and standard errors below; they are clustered at the level of randomization; columns (4) and (7) report number of observations; **, *, and + denote significance at the 1, 5 and 10% 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.

randomly selected plot. Again in line with expectations, we find that farmers that were exposed to the clearinghouse treatment reduced the use of farmer-saved seed, albeit only significantly so at midline. Finally, we look at the product of the amount and the price of maize seed, i.e., the total cost of seed on that plot. We see that in areas where the clearinghouse was implemented, farmers invest significantly more in seed.

7 Causal chain and mechanisms

The information 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 sufficient but some farmers think that dealers provide sub-standard quality, a clearinghouse may correct their perceptions. If the quality of seed differs between agro-input dealers, it provides farmers with information that may help them to switch to dealers that provide better products. Furthermore, the rating system is expected to provide a direct incentive to agro-input dealers to stay ahead of immediate competitors. For the agro-input dealer training, the underlying mechanism is increased knowledge. In this section, we investigate the relative importance of these different impact pathways.

7.1 Dealer knowledge

The primary mechanism underlying the agro-input dealer training is learning, which is in turn expected to increase knowledge of treated dealers. To test if the interventions affect knowledge at the agro-input dealer level, we construct two indices that summarize different measures of knowledge. The first index aims to measure knowledge about seed storage and handling and tests if dealers retain the information that was provided during the training, using a short multiple choice quiz of five questions. The questions test knowledge related to seed carryover between agricultural seasons, how seed should be stored after repackaging, how seed should be stored in the storeroom, and whether seed should be repackaged. The questions, the options presented to farmers, and the correct answers are outlined in Appendix A.5 and all variables constituting this index are self-reported.

The second knowledge index does not focus on seed handling recommendations, but aims to capture knowledge about seed more broadly. We again use multiple choice questions to test if dealers know which seed variety to recommend if a farmer complains about poor soil or lack of rain, if a farmer is late for planting, and whether they know what to tell clients who inquire about the yield benefits of hybrid seed. Again, the questions and (correct) answer options are explained in Appendix A.5 and all variables in this index are self-reported.

Table 11 suggests a positive impact of the agro-input dealer training on knowledge at midline, but the coefficient is just not significant at the 10% level. The (insignificant) effect of the training is strongest at midline, which seems reasonable as the training was organized only once at the start of the study, see Figure 1. Interestingly, we

Table 10: Effects on farmer outcomes: 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: Column (1) reports baseline means and standard deviations below; columns (2), (3), (5), and (6) report differences between treatment and control groups and standard errors below; they are clustered at the level of randomization; columns (4) and (7) report number of observations; **, *, and + denote significance at the 1, 5 and 10% 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.

find knowledge effects from the clearinghouse treatment, particularly when it comes to dealer knowledge related to seed storage seed and handling. This effect becomes stronger over time, which again seems reasonable as this treatment is repeated over several agricultural seasons. As agro-input dealers become aware of the recurrent nature of the ratings, they may try to improve the quality of their products by searching for information on better ways to store and handle seed.

The above suggests that providing only knowledge through trainings is unlikely to improve outcomes. However, if dealers have incentives to improve quality, they may respond by actively seeking out information. Together, this suggests that extra knowledge is only useful if agro-input dealers are also motivated to put it into practice. To further look into this, we exploit the factorial design, where a random subset of agro-input dealers was assigned to both, the training and the clearinghouse treatment group. We indeed find a significant positive interaction effect on key outcomes at the agro-input dealer level at endline (most notably on the overall operations index, as in Table 5, and the overall index of primary dealer outcomes, as in Table 20). The positive interaction effect seems to be driven by significant improvements in efforts and practices (as in Table 12). This confirms that if a clearinghouse encourages dealers to excel, they are more likely to put the seed handling practices that they were taught during the training into practice. If we look at knowledge in particular, we also find an interesting interaction effect on the index of dealer knowledge about seed at midline, but when we correctly cluster at catchment area level, the effect is just not significant (p-value = 0.14). However, these findings should be interpreted with care as we are likely to be under-powered to estimate interaction effects.

In addition to the hypothesis that trainings are less effective if dealers do not have incentives to learn, social desirability bias could be another explanation why we do not find stronger effects of the training on knowledge, as all variables which constitute the knowledge indices are self-reported. If dealers strategically do something incorrectly, they might report that they do not know how to do it, as being uninformed is more socially desirable than making mistakes intentionally. For example, if dealers often repack seed even though they know that they should not, and the enumerator is aware of that because repacked seed is laying on the counter for sale, they may report that they agree most with the statement "You should repackage all your seed to visually verify that you are selling good quality seed" instead of "You should avoid repackaging your seed as much as possible." However, we do not expect this to be a problem for the second Index of dealer knowledge about seed, as it mainly includes questions related to which maize varieties dealers would recommend under specific circumstances and what they tell clients about the yield benefits of hybrid seeds. We do not see why dealers would answer these questions incorrectly if they know the correct answer, as neither enumerators nor anyone else would notice if there is a difference between the answer they provide to us and the information they give clients, e.g., about the yield benefits of hybrid seeds. As we do not have any measures of knowledge that are not self-reported, we cannot provide an analysis that is robust to social desirability bias.

Table 11: Effects on agro-input dealer outcomes: Knowledge

	baseline	*midline*			*endline*		
	mean	training	CH	obs.	training	CH	obs.
Index of dealer 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 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: Column (1) reports baseline means and standard deviations below; columns (2), (3), (5), and (6) report differences between treatment and control groups and standard errors below; they are clustered at the level of randomization; columns (4) and (7) report number of observations; **, *, and + denote significance at the 1, 5 and 10% levels; † indicates that the variable is included in the overall index; larger indices indicate more desirable outcomes.

[1]The index of dealer 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 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.

7.2 Dealer efforts, services, and practices

The information clearinghouse provides agro-input dealers with an incentive to become better than their direct competitors. To do so, they may increase effort and start providing more or better services to get higher ratings, hoping that they will retain or even increase their number of customers.

In Table 12, we provide evidence that agro-input dealers that are exposed to the clearinghouse indeed invest more effort than dealers in the control group. The table shows results for one overall index and four individual indices that each capture different dimensions of efforts, services, and practices. A first index focuses on effort and service provision as reported by agro-input dealers themselves. It is composed of seven different variables: whether dealers offer explanations on how to use improved seed, recommend complementary inputs to get optimal results from improved varieties, provide extension or training, offer discounts for larger quantities, offer credit, received a seed related customer complaint since last season, and accept mobile money. A second index summarizes the perceptions of farmers that are customers at these agro-input dealers. This index is also constructed from seven variables: whether a shop offers refunds or insurance, provides credit, offers training or advice to customers, delivers to the farm-gate, provides after-sales service, accepts different payment methods, and sells small quantities. The answers of farmers are aggregated at the dealer level before the index is computed.

To handle and store seed correctly, a combination of investments and labor-intensive practices is necessary. Also during the agro-input dealer training, we recommended a mix of practices that are in reach of different types of dealers, some of which may have excess labor while others may have access to money to invest. A third index groups a set of labor-intensive seed handling and storage practices. It contains six variables: whether seed is stored in a dedicated area, in correct lighting, on appropriate surface, and not in open containers, whether the shop has no pest problem, and a cleanness and professionality rating provided by the enumerator. All of these variables were collected or at least confirmed by enumerators through visual inspection, none of them is self-reported. A fourth index summarizes some capital-intensive practices, including these six variables: whether the roof is leak-proof, and insulated, whether the walls are insulated, whether the shop is ventilated, displays any official certificate, and whether expired seed is handled correctly. Most of these variables were collected or at least confirmed by enumerators through visual inspection, only one of them (whether expired seed is handled correctly) is self-reported.[14]

We find that the clearinghouse intervention increases dealer efforts and services, especially at midline, where the coefficient of the overall index is significant at the 1% level. This effect is driven by treated agro-input dealers who significantly raised their

[14]To check whether social desirability affects this result, we exclude the variable from the index and rerun the analysis, as dealers might report that they handle expired seed correctly but strategically not do so, e.g., to cut costs. Doing this does not change the coefficients for the Index of capital-intensive seed handling practices in any notable way.

efforts and services, according to farmers. We see that impact persists until endline, where the significant effect on the overall index seems to be driven by the self-reported measure of effort. We do not find that the agro-input dealer training improved services or practices.

Furthermore, we asked enumerators if they saw the SeedAdvisor certificate in the shop at endline. The answer to this question does not contribute to any of the outcome indices because it only showed up in interviews with clearinghouse treated dealers. For this subgroup, 55% of enumerators reported that they saw it.

As it is difficult to assess seed quality via visual inspection, agro-input dealers may use various strategies to signal to customers that their products are of good quality. Becoming a member of professional organizations is one way to do so, as these memberships signal professionalism. Dealers who try to signal quality will also not shy away from inspections. On the contrary, they may actively seek inspection so that they can advertise the result in their shops. Alternatively, the SeedAdvisor certificates could attract inspectors if they increase the visibility of the shop.

Table 13 collects a set of variables related to signaling quality, including memberships in UNADA and other professional associations, trading licenses, the number of inspections in the last season, and warnings or confiscations of seed after inspection. 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 overall effect seems to be driven by an increase in registrations with UNADA. We also see that shops were inspected significantly more often.

7.3 Switching

An important potential mechanism underlying the effect of the information clearinghouse is the possibility that farmers switch from lower rated agro-input dealers to shops that have better ratings. To explore this impact pathway, we asked farmers if they switched agro-input dealers since the previous season and report the results in Table 14. We see that only 17% of farmers reported switching at baseline. However, at midline, a significantly higher share of farmers in the clearinghouse treatment group reported switching dealers. 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 lower rated agro-input dealers to higher rated ones. To further investigate this, we calculate the difference between the rating of shop the farmer is switching to and the rating of the shop the farmer is switching from. If farmers move to better rated shops, this difference would be positive. We find 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-value = 0.166).

We also explore switching from the agro-input dealer perspective. Here we look at the relationship between the rating a shop received and its number of customers (standardized within the catchment area). If farmers switch from poorly rated dealers

Table 12: Effects on agro-input dealer outcomes: Efforts and practices

	baseline	*midline*			*endline*		
	mean	training	CH	obs.	training	CH	obs.
Index of dealer efforts and services, self-reported[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 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: Column (1) reports baseline means and standard deviations below; columns (2), (3), (5), and (6) report differences between treatment and control groups and standard errors below; they are clustered at the level of randomization; columns (4) and (7) report number of observations; **, *, and + denote significance at the 1, 5 and 10% levels; † indicates that the variable is included in the overall index; larger indices indicate more desirable outcomes.

[1]The index of dealer efforts and services, self-reported 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 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, in correct lighting, on correct surface, not in open containers, whether shop has no pest problem, cleanness and professionality rating by enumerator.

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

Table 13: Effects on agro-input dealer outcomes: 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: Column (1) reports baseline means and standard deviations below; columns (2), (3), (5), and (6) report differences between treatment and control groups and standard errors below; they are clustered at the level of randomization; columns (4) and (7) report number of observations; **, *, and + denote significance at the 1, 5 and 10% 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 14: Effects on farmer outcomes: 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: Column (1) reports baseline means and standard deviations below; columns (2), (3), (5), and (6) report differences between treatment and control groups and standard errors below; they are clustered at the level of randomization; columns (4) and (7) report number of observations; **, *, and + denote significance at the 1, 5 and 10% 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.

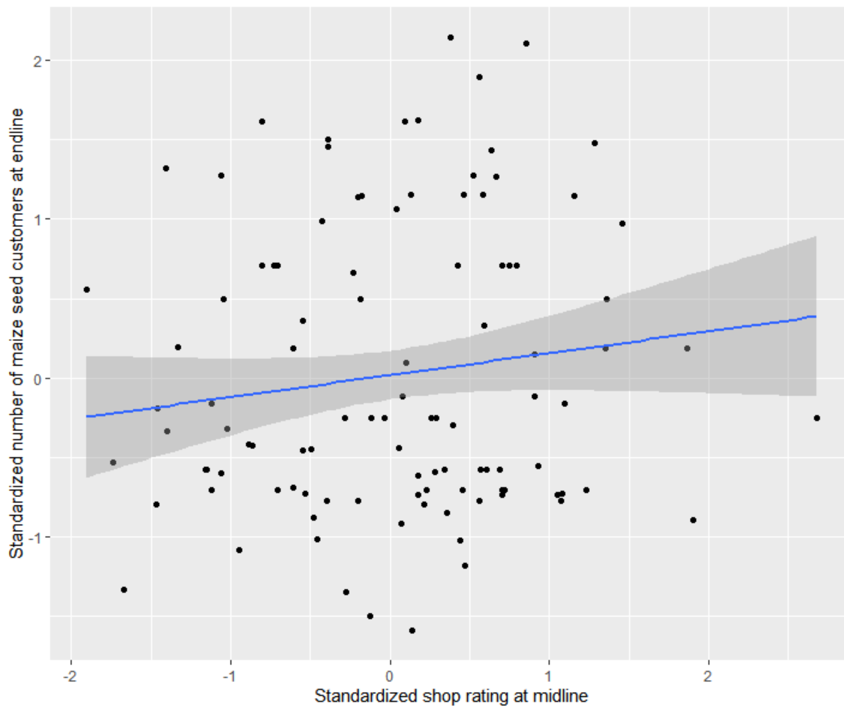

Figure 3: Relationship between midline rating and endline number of customers

to better rated ones, we would expect to see a positive correlation in areas where the clearinghouse treatment was implemented. Figure 3 shows that shops with higher ratings at midline receive more customers at endline. However, this evidence is not very strong and at most suggestive.

7.4 Perceptions

Finally, the information clearinghouse may change farmer perceptions of the quality of seed sold by agro-input dealers. Table 15 provides an analysis of this impact pathway. As a first measure of their perceptions, we asked farmers if they think that maize seed that they can buy at agro-input shops is counterfeit or adulterated. At baseline, two in three farmers responded affirmative to this question. Columns (2) to (5) show the impact of the clearinghouse for the full sample. The treatment does not significantly affect farmer perceptions as measured by this variable at mid- or endline. However, we expect the effect of the clearinghouse on perceptions to be strongest for farmers who did not adopt improved maize varieties at baseline. Therefore, we repeat the analysis for this subgroup of farmers in columns (6) to (9). At midline, farmers that did not adopt at baseline and live in areas exposed to the clearinghouse are 12.5 percentage points less likely to think that agro-input dealers sell adulterated seed than similar farmers in areas not assigned to the treatment. The effect disappears at endline.

Another important outcome is related to farmer perceptions of product quality: the index of maize seed ratings contains the general quality, yield, drought tolerance, pest and disease tolerance, time of maturity, and germination rating. These ratings are aggregated at the farmer level (as one farmer rates multiple shops), then the index is calculated. To compute this index at smallholder level, a farmer needs to have rated at least one dealer in the catchment area on all components of the index, which leads to a sample size reduction, which in turn may affect statistical power. Nonetheless, we see that the index is positively and significantly affected by the clearinghouse treatment, even though the effect is only significant at the 10% level. If we restrict the sample to farmers that did not adopt improved maize varieties at baseline, the treatment effect on the ratings is significant at the 5% level. Also the impact on the overall combining index is significant for this sub-sample.

It would be straightforward to assume that treated farmers perceive seed to be better because the clearinghouse improved seed quality. Unfortunately, we cannot verify this because objectively measuring seed quality is challenging (see Footnote 12). That is why we cannot confidently conclude that farmers' perceptions of seed improve because treated dealers improve seed quality by handling seed better. Instead, there could be other variables at play, farmers could e.g., rate seed at treated dealers better because these dealers decide to provide advice and recommendations in response to the clearinghouse, which is surely useful but has no impact on the actual quality of maize seed. Even though we cannot conclude that the clearinghouse improved objective maize seed quality, it did so in the eyes of smallholder farmers, which is what counts after all.

Alternatively, the clearinghouse may have mainly improved perceptions, and there are also arguments in favor of this hypothesis. We demonstrate that the intervention affects several measures of adoption already at midline. If we assume that changing dealer behavior and farmers noticing this change takes some time, rectifying incorrect perceptions of smallholders must have played an important role in increasing their adoption.

Also note that the average agro-input shop was rated 3.4 out of 5 at baseline which indicates that seed quality was not so poor to begin with. One could argue that this statement contradicts the one above stating that two in three farmers thought that maize seed at agro-input shops is counterfeit or adulterated at baseline. However, we do not necessarily agree: when farmers are asked about seed quality at agro-input shops *in general*, their perceptions are negative, but when they rate seed *at a particular shop*, they are not. This indicates that smallholders' general opinions about the market are pessimistic but when they focus on their own or someone else's individual experiences, they realize that they are not too dissatisfied after all. Hence the two statements do not necessarily contradict each other, they are answers to differently asked questions. This illustrates that farmers' perceptions of the quality of the inputs in the market are not robust and that misperceptions are quite likely. Furthermore, note that the entire farmer sample provided answers to the counterfeiting/adulteration question, whereas only farmers who bought seed at a particular shop or know someone who did were able to provide ratings, so that the share of adopters is likely to be larger among farmers who rated at baseline then in the full sample. This could indicate that farmers who do

Table 15: Effects of the clearinghouse on farmer outcomes: Perceptions

		full sample				*sub-sample*			
	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 area[1]†	0.000			0.092+	1664			0.141*	693
	(0.637)			(0.054)				(0.063)	
Overall index	0.019			0.104	1462			0.160*	596
	(0.770)			(0.071)				(0.074)	
Max. number of obs.			3407		3441		1719		1741

Note: Column (1) reports baseline means and standard deviations below; columns (2) and (4) report differences between treatment and control groups and standard errors below; they are clustered at the level of randomization; columns (3) and (5) report number of observations; columns (6) to (9) mirror this structure for the sub-sample of farmers that did not adopt at baseline, **, *, and + denote significance at the 1, 5 and 10% 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 the index is computed. Note that treatment and control groups can only be compared at endline. At base- and midline, only clearinghouse treated farmers rated dealers in their proximity because being confronted with these questions is part of the treatment. Hence control dealers were not rated and this line is left blank at midline. At endline, all farmers rated all shops, so that this variable can be investigated.

not adopt have worse perceptions of seed quality than farmers who do.

We interpret this as support for the hypothesis that the quality of maize seed at some shops in our sample is sufficient but non-adopting farmers misperceive it. This is in line with Michelson et al. (2021) and Wossen, Abay, and Abdoulaye (2022) who establish that input quality is good but that farmers' beliefs are often incorrect, so that one simply needs to rectify this misperception to increase adoption. The information clearinghouse provides an innovative way to do so.

8 Attrition

Table 16 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 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).

Table 16: 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: Column (1) reports sample means at mid- or endline and standard deviations below; columns (2)-(3) report 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% levels.

9 Conclusion

Even though agricultural technologies like high yielding seed varieties and inorganic fertilizers are considered to be key in increasing agricultural productivity and accelerating rural transformation, the adoption by smallholders remains persistently low in sub-Saharan Africa. We study one particular constraint to technology adoption: the perceived quality of agricultural inputs. We hypothesize 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 an RCT. A training informed agro-input dealers about correct seed handling and storage practices. An information clearinghouse based on crowd-sourced ratings of the seed that agro-input dealers sell was expected to reduce the information asymmetry between seller and buyer by making the quality of maize seed observable.

The results of our analyses show that training agro-input dealers does not change their practices, and consequently, their operations remain unaffected. We also do not find any impact on farmers that live in the catchment areas of dealers that were trained: they do not perceive seed quality differently nor have higher adoption rates than farmers that were not exposed to trained dealers. These null results show that investing in trainings only may not be an effective strategy as long as dealers are not incentivized. In fact, our results suggest that if agro-input dealers have the right incentives, they actively seek out knowledge necessary to improve and keep ahead of competitors. If dealers are exposed to both, incentives and information, they handle and store seed better and attract more business.

The information clearinghouse clearly affected the Ugandan market for maize seed as sellers and buyers started behaving in line with our theory of change. Agro-input dealers report more business and smallholders report increased use of improved maize varieties. This effect seems to partly originate from dealers who increase effort and expand service provision to outperform their competition. There is also evidence that the clearinghouse improves the opinions that farmers hold about agro-input shops and their products. In areas where the clearinghouse was implemented, farmers are also more likely to switch between agro-input dealers, but our evidence that they move from lower rated dealers to higher rated ones is at most suggestive. However, as clearinghouse treated farmers report higher yields than control farmers, we can safely conclude that this intervention affected smallholders positively, which is important in terms of welfare implications.

We conclude that quality considerations are important constraints to the adoption of agricultural inputs. This has notable implications for the public sector. Ideally, it needs to safeguard seed supply chains to prevent mishandling and secure the delivery of high quality inputs to farmers. One way to do so would be controls and checks along the supply chain, including inspections of agro-input shops. A complementary strategy would be to inform farmers how to examine bags of seed and identify characteristics that indicate mishandling, such as expired dates, or even tampering or fraud, such as torn seals and seams, and scratched e-verification labels.

We also see important implications for the private sector. If seed companies want to successfully market their products, they need to acknowledge that many of their potential customers have concerns about quality. Their current efforts to make products identifiable and traceable have not been very effective: we bought seed bags from dealers in our sample, and only 8% of them have a certification sticker, and only 3% show an electronic verification label. To assure farmers that they are buying authentic, high-quality seed, companies need stronger signals of product quality. Some of them started labeling their bags with information about germination testing, and in Kenya, some companies started marketing their seed using novel packaging features to signal product authenticity (Gharib et al., 2021). Any strategy to reduce information asymmetries between sellers and buyers by making input quality more observable is likely to benefit the market for quality inputs. These are clear opportunities for innovations in the private sector that could build consumer confidence in the quality of the improved maize seed available at agro-input dealers.

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. Furthermore, peers, who are familiar with the heterogeneous conditions farmers face, provide the clearinghouse ratings, and their opinion may be more useful and trustworthy for smallholders than the judgment of an inspector or a seed certification or verification system.

The objective of this paper is to prove a concept and to test whether a prediction of the theory occurs in practice, namely whether making quality observable improves the market for maize seed. If the clearinghouse would be scaled up, several challenges would need to be addressed. For example, one should decide how long SeedAdvisor certificates remain valid and whether they have to be removed at some point, as old certificates could provide incorrect signals, and dealers who received a good certificate at some point in time would not have any incentive to keep up the good work if the outdated certificate remains displayed in their store. Furthermore, farmers may favor dealers they personally know well or discriminate against minorities, and these preferences, instead of quality differences, may be reflected in the ratings. In this case, the ratings would need to be monitored and potentially adjusted, to avoid that the clearinghouse amplifies bias or discrimination. Another danger to the functioning of the clearinghouse could be agro-input dealers who start to influence ratings in a dishonest manner, e.g., by faking ratings or by bribing farmers. Note that during this trial, rating and rated participants were connected by asking dealers where their customers come from, and collecting ratings from ten randomly selected farmers in that village. Dealers would need to understand our experimental design in order to know which farmer they would need to influence, so that it is almost impossible that they cheat during this trial, but details like this need to be considered before scaling up the experiment.

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A Appendix

A.1 Can farmers assess maize seed quality?

The objective of the clearinghouse is to make maize seed quality observable, so that its functioning would be endangered if farmers' ratings do not actually measure quality but e.g., the personal relationship between a farmer and a dealer. Some could even argue that farmers cannot assess the quality of maize seed at all, even not 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. Learning about the true quality becomes more difficult when this misattribution is present (Hoel et al., 2021). Tjernström et al. (2021) agree that sub-Saharan Africa's soil heterogeneity hampers farmer learning about the returns to inputs. Maize seed would then be a credence good instead of an experience good and clearinghouse ratings of farmers would be useless. 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 unreliable.

We argue that farmers' ability to infer maize seed quality is indeed not perfect but they can assess it to some extent. Shortly after planting, farmers can observe germination rates, i.e. the proportion of seeds that germinate, and later how fast the seed matures. Some seed may also be more susceptible to pests and diseases, while other seed may be particularly tolerant in terms of drought. After harvest, the farmer can observe the yield. All these attributes of seed quality can be judged to some extent after one agricultural season.

To support our claim, we test if the ratings are correlated with objective indications of seed quality. We find that specialized agro-input shops which only sell farm inputs have higher ratings, so do dealers with better seed handling practices. Furthermore, farmers did not only rate the seed of agro-input shops but also the seed they used on a randomly selected maize field, using the same questions. We find that these seed ratings are positively correlated with farmers' yield. All this shows that the clearinghouse ratings do measure maize seed quality to some extent.

Table 17: Correlating ratings & quality indicators - dealer level

	dependent variable: rating index$_{\text{endline}}$
independent variables:	
Shop only sells farm inputs$_{\text{endline}}$	0.205^{**}
Index of labor-intensive seed handling practices$_{\text{endline}}$	0.164^{+}
Index of capital-intensive seed handling practices$_{\text{endline}}$	0.204^{*}
Index of all seed handling practices$_{\text{endline}}$	0.225^{+}
Shop received seed related complaint from customer$_{\text{endline}}$	-0.108
Shop received a warning after inspection$_{\text{endline}}$	-0.034
Randomly selected seed bag shows packaging date$_{\text{endline}}$	0.052
Days since packaging date/expiry date minus 6 months$_{\text{endline}}$	0.000
Seed is in the original bag without any signs of damage$_{\text{endline}}$	0.101
Randomly selected seed bag shows lot number$_{\text{endline}}$	0.111
Moisture in randomly selected seed bag in percent$_{\text{endline}}$	0.027

Table 18: Correlating ratings & quality indicators - farmer level

	dependent variable:
	Yield in kg/acre on randomly selected field$_{\text{endline}}$
independent variables:	
Index of farmer's ratings of seed used on randomly selected field$_{\text{midline}}$	144.971**
Index of farmer's ratings of seed used on randomly selected field$_{\text{endline}}$	35.225**

A.2 Rating computation: details

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

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

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

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

A.3 Rating dissemination: details

Table 19: 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 Outcome variables and results as they were pre-registered

Table 20: 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	-0.499^{+}	0.239	286
	(1497.183)	(0.220)	(0.227)		(0.250)	(0.253)	
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 %	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	-0.058	0.239*	258
	(0.591)	(0.130)	(0.121)		(0.128)	(0.117)	
Max. number of obs. for dealer survey outcomes				306			297

Note: Column (1) reports baseline means and standard deviations below; columns (2), (3), (5), and (6) report differences between treatment and control groups and standard errors below; they are clustered at the level of randomization; columns (4) and (7) report number of observations; **, *, and + denote significance at the 1, 5 and 10% 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 21: 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: Column (1) reports baseline means and standard deviations below; columns (2), (3), (5), and (6) report differences between treatment and control groups and standard errors below; they are clustered at the level of randomization; columns (4) and (7) report number of observations; **, *, and + denote significance at the 1, 5 and 10% 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 22: Effects on primary farmer outcomes

	baseline	*midline*			*endline*		
	mean	training	CH	obs.	training	CH	obs.
Farmer planted improved 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 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 plot^{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 plot†	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: Column (1) reports baseline means and standard deviations below; columns (2), (3), (5), and (6) report differences between treatment and control groups and standard errors below; they are clustered at the level of randomization; columns (4) and (7) report number of observations; **, *, and + denote significance at the 1, 5 and 10% 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 23: Effects on secondary farmer outcomes: Adoption on randomly selected maize plot

	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: Column (1) reports baseline means and standard deviations below; columns (2), (3), (5), and (6) report differences between treatment and control groups and standard errors below; they are clustered at the level of randomization; columns (4) and (7) report number of observations; **, *, and + denote significance at the 1, 5 and 10% 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.

A.5 Multiple choice questions to measure dealer knowledge

Dealer knowledge about seed storage

1. How long can seed be carried over before losing viability?
   (a) <u>Seed can be carried over into the next seasons as you can store seed for 12 months.</u>
   (b) Seed cannot be carried over into the next seasons as 6 months is the longest seed can be stored.
   (c) This depends on the seed: hybrids cannot be carried over, OPVs can be carried over for 5 seasons.
   (d) I don't know.

2. How should seed best be stored after repackaging?
   (a) Airtight in polyethylene bags.
   (b) <u>In paper bags or perforated polyethylene bags.</u>
   (c) In a sealed tin/plastic container.
   (d) I don't know.

3. What is the minimum recommended distance between the floor and where seed is stored?
   (a) 0 inches, seed should be stored directly on the floor for maximum stability.
   (b) Minimum 2 inches from the floor.
   (c) <u>Minimum 6 inches from the floor.</u>
   (d) I don't know.

4. How should seed ideally be stored in your store room?
   (a) In sealed cardboard boxes.
   (b) <u>Stacked on pallets.</u>
   (c) Arranged on shelves with sufficient space between packets.
   (d) I don't know.

5. Which statement do you agree most with?
   (a) You should repackage all your seed to visually verify that you are selling good quality seed.
   (b) You should repackages all your seed so you can sell more to small farmers.
   (c) <u>You should avoid repackaging your seed as much as possible.</u>
   (d) I don't know.

Dealer knowledge about seed

1. If a farmer complains about poor soil, which maize variety do you recommend?
   (a) Longe 5.
   (b) Bazooka.
   (c) Longe 10H.
   (d) I don't know.

2. What do you tell clients who inquire about the yield benefits of hybrid seeds?
   (a) Hybrid seeds double maize yields (increasing yield from about 4 to 8 bags/acre).
   (b) Hybrid seeds triple maize yields (increasing yield from about 4 to 12 bags/acre).
   (c) Hybrid seeds increase yields tenfold (increasing yield from about 4 to 40 bags/acre).
   (d) I don't know.

3. If a farmer misses the rains or lives in an area that receives little rain, which maize variety do you recommend?
   (a) Longe 10H.
   (b) Longe 7H.
   (c) Wema.
   (d) I don't know.

4. If a farmer is late for planting in the short season and needs a fast maturing variety, which maize variety do you recommend?
   (a) Bazooka.
   (b) Longe 10H.
   (c) Myezi mitatu (mm3).
   (d) I don't know.