Addressing quality constraints to agricultural technology adoption in the Ugandan market for maize seed

Caroline Miehe[*], Bjorn Van Campenhout[†], Robert Sparrow[‡], David Spielman[§]

April 6, 2023

Abstract

We test two hypothesis on how (perceived) quality of agricultural inputs affect adoption. First, poor quality is caused by agro-input dealers' lack of knowledge on proper handling and storage; a training is expected to improve input quality and subsequent adoption. Second, information asymmetry crowds out the market for quality inputs—a classic lemons problem. Here, we implement an information clearinghouse based on crowd-sourced reviews similar to yelp.com. Both hypotheses are tested in a randomized control trial for the case of improved maize seed varieties in Uganda. We find positive effects for the information clearing house, but not for the training.

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

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

Acknowledgments: We would like to thank Charles Marc Wanume, Leocardia Nabwire, Richard Ariong and Wilberforce Walukano for their support in the field. This project received funding

[*]LICOS, KU Leuven - corresponding author: caroline.miehe@kuleuven.be
[†]Development Strategy and Governance Division, IFPRI
[‡]Development Economics Group, Wageningen University and Research
[§]Development Strategy and Governance Division, IFPRI

from The Netherlands - Consultative Group for International Agricultural Research research programme on Seed Systems Development, grant number W08.240.105, funded by the Netherlands Organisation for Scientific Research. The research was also supported by the Fonds Wetenschappelijk Onderzoek - Vlaanderen and the Fonds de la Recherche Scientifique under EOS project G0G4318N.

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

1 Introduction

Over the next few decades, farmers in sub-Saharan Africa will need to produce more food on less land and under increasingly difficult climatic conditions (Tilman et al., 2011). The use of climate-smart agricultural practices and improved inputs such as higher-yielding and drought-tolerant crop varieties are thought to be at least part of the solution (Evenson and Gollin, 2003). Unfortunately, there is concern that the use of improved inputs and technologies across the region seems to be stagnating—or at least advancing at a slower pace than required (Suri and Udry, 2022). As a result, differences in agricultural yields between sub-Saharan Africa and countries in Latin America and Asia have almost doubled since 1961 (Magruder, 2018).

Several key constraints to agricultural technology adoption have been rigorously tested in the last decade. These include poor access to information (Ashraf, Giné, and Karlan, 2009), procrastination and time-inconsistent preferences of farmers (Duflo, Kremer, and Robinson, 2011), heterogeneity in the net benefits to the technology due to infrastructure and transaction costs (Suri, 2011), missing markets for risk and credit (Karlan et al., 2014), and opportunities and challenges related to learning about a new technology (Conley and Udry, 2010; Hanna, Mullainathan, and Schwartzstein, 2014).

More recently, quality related issues of the technology (often inputs such as improved seed varieties, inorganic fertilizers, or pesticides) have emerged as a potential constraint. In a widely cited article, Bold et al. (2017) argue that because quality is often difficult to assess by the farmers from simple visual inspection, information asymmetries between sellers and buyers characterize the markets for seed and fertilizer, crowding out the market for quality inputs. However, 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 clear if these quality issues are real: While some studies argue that input quality is indeed lacking (Bold et al., 2017; Ashour et al., 2019), others argue that farmers' perceptions may be to blame (Michelson et al., 2021; Wossen, Abay, and Abdoulaye, 2022). Gharib et al. (2021) find that concerns about seed quality reduce farmers' willingness to invest in seeds, as farmers are willing to pay 15% more for bags directly from the seed company than for bags from local retailers.

We attempt to answer some of these questions by means of a field experiment in the Ugandan market for improved maize seed varieties (high-yielding cultivars like open-pollinated and hybrid varieties). To test if low seed quality is primarily due to poor handling and storage, we organize trainings for a random sub-sample of agro-input dealers and look at the impact of at both agro-input dealer level and farmers living in their catchment areas. Furthermore, we implement an information clearinghouse which is based on crowd-sourced ratings and works through reputational mechanisms like yelp.com or tripadvisor.com. By aggregating the experiences of many users under similar conditions, farmers can learn more about an agro-input dealer and the quality of the products they sell than if they have to rely on own experience only. This allows farmers to switch to higher rated input dealers. However, as the ratings are also available to the agro-input dealers, it also provides dealers with an incentive to increase the quality of products and services. If the quality of seed in the market is already sufficient, the clearinghouse may also rectify misperceptions of non-adopters. Both interventions are tested in a randomized control trial (RCT) among 350 agro-input dealers and an associated 3,500 smallholder maize farmers in their catchment areas in eastern Uganda over the course of two agricultural seasons.

Results show that the training does not have a clear impact on dealers or their customers. The information clearinghouse affects both actors positively. Treated farmers start switching to different shops; treated dealers increase their efforts to outperform their competitors. Treated agro-input dealers have higher knowledge about seed handling and improve their services, suggesting that if they are incentivized, they additional information does seem to have a positive effect. Treated shops are also more likely to be registered with the Uganda National Agro-Input and Dealers' Association (UNADA), perhaps to signal quality, and are inspected more often. Dealers in the clearinghouse treatment group are more successful: we measure a higher revenue at midline and more customers at endline. Farmers in the treatment group perceive the quality of maize seed at agro-input shops to be better and are more likely to adopt improved maize seed at both midline and endline. As a result, their yield at endline significantly exceeds yields of control farmers.

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

The remainder of this paper is structured as follows: Section 2 provides information on the background of the study, section 3 introduces the model and section 4 the experimental design. The interventions, empirical strategy and data are described in sections 5, 6 and 7. After presenting the results in section 8, we outline potential threats to validity in section 9. Then we discuss our findings and conclude in sections 10 and 11.

2 Problem statement and hypotheses

There are different reasons why quality of inputs may be lacking. For instance, it could be that inputs are stored in sub-optimal conditions (eg. in direct sunlight, in moist environments,...) or handled in harmful ways (eg. stored beyond expiry date, repackaging,...). At least for some agro-input dealers, this will be due to the fact that they lack knowledge about proper storage and handling. If these agro-input dealers would acquire this knowledge, they would act accordingly.

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 the quality of this input. For example, dealers often repack seed from larger bags packed by seed companies into smaller packages in order to offer quantities which are convenient and affordable for 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 (Buveera) which affect aeration and seed viability. The 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 baseline data collected as part of this study, we find a positive correlation between a seed bag's shelf-life and its moisture.

The fact that seed quality can not easily be observed by farmers may also result in a lack of incentives for the agro-input dealers to invest in quality preservation. In a context similar to ours, Hoffmann et al. (2021) look at maize grain as an output in rural Kenya and find that there is no incentive for sellers to address food safety issues because they are not observable for buyers. Worse, dealers may also sacrifice quality to cut costs and increase profits, for instance mixing improved and fresh seed with local seed or old seed. There is empirical evidence of this kind of adulteration at some points 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. A National Seed Policy report written by the Ugandan Ministry of Agriculture, Animal Industry and Fisheries states that 30-40% of seed traded in the market is counterfeit (2018). Note that both, buyers and sellers, suffer from the resulting poor average quality in this lemon market.

Farmers may still fail to adopt if the quality of maize seed is sufficient but farmers misperceive it. Michelson et al. (2021) establish that the nutrient content of fertilizer in Tanzania is good and meets industry standards but that farmers believe that it is adulterated. One would simply need to correct farmers' beliefs which are inconsistent with the reality to increase adoption. Also Wossen, Abay, and Abdoulaye (2022) show that farmers in developing countries routinely misperceive input quality and that rectifying this misperception may improve farmers' investment choices and productivity outcomes. Note that also here, a vicious cycle emerges, where farmers that were confronted with poor seed quality because of any of the reasons above may continue to perceive quality to be poor even though the quality may have been improved, and this asymmetric information in turn reduced incentives for agro-input dealers to maintain quality.

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

Figure 1 illustrates the theory of change of an agro-input dealer training is expected to increase adoption of improved seed varieties. Dealers handle and store maize seed in better ways after learning how to do so during the training. Better handling and storage leads to better maize seed quality. If

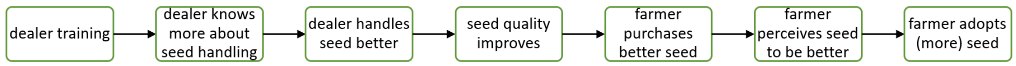

Figure 1: Theory of change - Agro-input dealer training

farmers start purchasing better seed, their perceptions could improve, and ultimately, they could start adopting (more) improved seed.

In a second hypothesis, we assume that asymmetric information reduces dealers' incentives to provide quality seed; addressing these asymmetries may lead to better quality, in turn increasing adoption. In Kenya, seed companies have started marketing their seed using novel packaging features to signal product quality and authenticity (Gharib et al., 2021). Uganda regulates seed quality by means of certifications and standards, but they provide farmers with a relatively weak and unreliable indication of quality. We bought seed bags from agro-input dealers in our sample, and only 8% of them have a certification sticker from an inspection agency. Alternatives such as electronic verification systems have also been experimented with, but the cost of implementation has proven challenging, and they depend on the reliability of the underlying seed certification system.

We test an alternative, decentralized clearinghouse that is based on crowd-sourced information and works through reputational mechanisms, much like yelp.com or tripadvisor.com. We ask smallholder farmers to rate dealers in their proximity on a number of seed quality attributes. We use this information to score and rank agro-input dealers, and we disseminate these scores back to farmers and dealers. Studies in other contexts have shown that new crowd-based sources of pre-purchase information can be particularly useful. For instance, Reimers and Waldfogel (2021) compare the impacts of professional critics and Amazon star ratings of books on consumer welfare. The aggregate effect of star ratings on consumer surplus is more than ten times the effect of traditional review outlets.

Information clearinghouse mechanisms in developing countries have been studied to some extent, but mostly to address market price information asymmetries between smallholder farmers and middlemen. Assuming that middlemen are better informed about prevailing prices in the market than farmers, theory suggests that providing farmers with price information improves the bargaining power of farmers and the prices they can ask. However, evidence is mixed: while Goyal (2010) finds that internet kiosks that provide wholesale

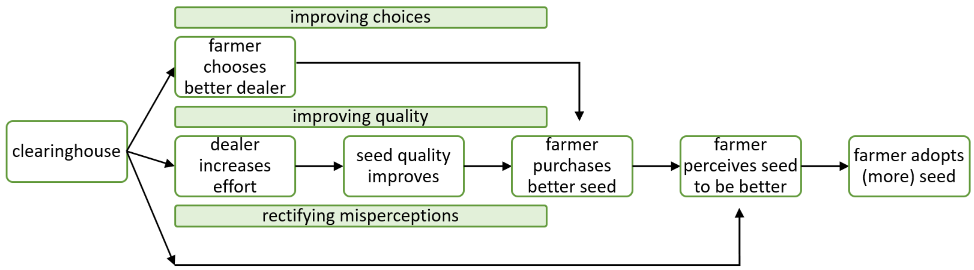

Figure 2: Theory of change - Information clearinghouse

price information significantly increase soy prices farmers received in India, Fafchamps and Minten (2012) do not find a statistically significant effect of market information delivered to farmers' mobile phones in a neighboring state. A clearinghouse that relies on crowd-sourced ratings may be more effective in increasing seed quality in the market. While prices can generally be observed quite easily, assessing an experience good such as seed is much more difficult. Aggregating the experiences of many users may thus be a particularly powerful way to reveal the quality.

An information clearinghouse could work through different impact pathways which are illustrated in Figure 2. Firstly, farmers who already adopt at baseline could switch from low rated shops to higher rated shops after learning that their dealer received a poor rating. Secondly, dealers could anticipate this and increase their efforts to outperform their competitors. Farmers could also pressure their usual dealers to improve. If dealers do not know how to increase their efforts, they may actively seek information. All these scenarios lead to seed of better quality, farmers purchasing better seed which improves their experiences by reducing risk and increasing profitability and later their perception of seed. Thirdly, farmers who did not buy seed before could start adopting improved seed when they learn that an agro-input dealer in their vicinity has a good rating. As mentioned above, the literature indicates that this pathway of improving the perception of quality without actually improving quality could be relevant (Michelson et al., 2021; Wossen, Abay, and Abdoulaye, 2022). Ultimately, all this is expected to lead to increased adoption of improved maize seed varieties.

3 Robert's model which differentiates between temporal and cross-sectional learning (more T vs. more N)

While the potential benefit of a training seems straightforward, one could argue that a clearinghouse is redundant as Ugandan farmers plant maize twice a year, and can infer relatively fast which agro-input dealers in their neighborhood provide good quality. However, these farmers might not trust their own judgment of quality even after using and experiencing the seed material. If farmers observe impressive yield and correctly infer that the quality of the seed they used is good, they perceive this as only one source, as only one observation. On the other hand, the aggregation of the experiences of many users may be a powerful way to reveal the quality of the product in a trustworthy manner. The extension literature shows that smallholders are more likely to trust information if it comes from more than one source, e.g. from a clearinghouse rating that is computed based on multiple opinions.

It is crucial that the "more N" who provide the ratings are *peers* operating under similar conditions in terms of location, soil, weather and so forth, because the identity of the one providing the information matters for technology adoption: For example, Arslan et al. (2022) conducted a randomized experiment to assess the effects of information communicated by either a peer farmer or a market actor, and show that farmers who received information from the peer outperformed others.

4 Experimental design

To test the two hypotheses outline in Section 2, we developed two interventions (described in detail in the next section), and evaluate the impact using a randomized control trial (RCT). For the randomization of the interventions, we define catchment areas. Catchment areas are defined relative to clusters of agro-input shops, and capture its potential customers. Generally, dealers are clustered in towns, villages, markets, trading centers and other key market sheds and so a catchment area may be served by several agro-input shops. If the catchment areas of two or more shops overlap because these dealers operate in the same town, street or right next to each other, they are assigned to the same catchment area and receive the same treatment.

Grouping of agro-input dealers into catchment areas is done on the basis of geographical location.[1]

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

We used simulations to determine the sample sizes for this experiment. Simulating provides a flexible and intuitive way to analyze power. Furthermore, instead of relying on theoretical distributions for the outcome variables that make assumptions and return analytic solutions, simulations can sample from real data. Power simulations based on previously collected data show that if the number of catchment areas is larger than 112, our experiments will return statistically significant results 80% of the time.[2] 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.[3]

The two interventions are combined in a field experiment which takes the form of a 2^2 factorial design. The resulting layout is illustrated in Figure 3. Impact is measured at both agro-input dealers and on farmers.

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

[2] 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.

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

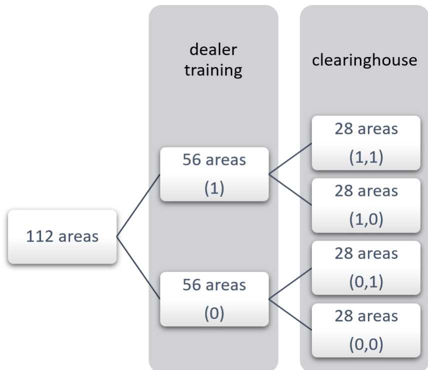

Figure 3: Factorial design

5 Interventions

This section provides a detailed description of the two interventions that will be used to test the hypotheses outline in Section 2. We start with the agro-input dealer training and then explain the information clearinghouse we implemented.

5.1 Agro-input dealer training

Content and training material

To determine the content of the training and to make sure it is locally anchored, we consulted experts from different Ugandan institutions and organizations like the ministry of agriculture, the seed sector and agro-input dealer associations. A series of semi-structured interviews and a workshop were organized. The experts identified common problems and malpractices by dealers, and then determined effective and realistic solutions and best seed storage and handling practices. 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 treatment catchment area, all shops were selected to receive a training. Of each treated shop, both the owner and the shop manager who is in charge of day to day activities and decides upon labor-intensive practices were invited. The owner was invited because some of the recommended techniques and practices required investments. The shop manager was invited because many of the recommendations were hands-on practices. We handed out one free portable seed moisture meter per shop as an incentive and tried to increase attendance by all means.[4] Trainings were organized in small groups, with on average agro-input dealers present. The trainings took place in locations that were easily reachable for agro-input dealers.

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

The trainings took one day and were organized in May 2021, late enough so that dealers were not busy with selling for the first agricultural season but early enough so that they could use the newly learned practices on the seed of the second agricultural season. A timeline is illustrated in Figure 4. The trainings were organized together with the Uganda National Agro-input Dealer Association (UNADA), the national organization for agro-inputs in Uganda.

5.2 Information clearinghouse

Collection and computation of ratings

At the time of baseline data collection from smallholder farmers, we asked them to rate agro-input dealers in their proximity on a number of characteristics. Enumerators were guided by an application that iterated through all the agro-input dealers in the catchment area. For each dealer, we provided the common names that are used to refer to the shop, a description of where the store was located, and a picture of the store front (obtained during the agro-input dealer census—see Section 7.1). We further asked if farmers knew

[4] 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.

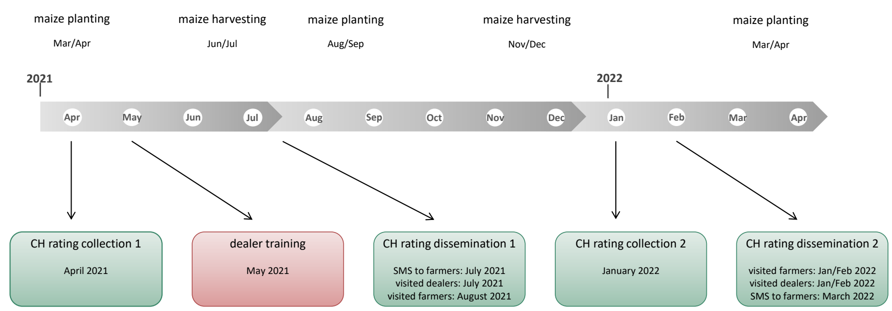

Figure 4: Timeline

the dealer. We then asked farmers to rate them using the questions which are outlined in Table 1. For example, we asked farmers to rate the maize seed that an agro-input shop sells on a scale of one to five stars on germination. Ratings were always collected after harvest, when smallholders were able 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 4 for a timeline of the interventions.

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

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

Table 1: Questions for farmers to rate dealers

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

computations can be found in appendix A.1.

Dissemination of ratings to farmers

For the success of the clearinghouse it is crucial to disseminate the agro-input dealer ratings before farmers start buying seed for the next agricultural season, such that they can use this information when choosing whether and where to purchase inputs; see Figure 4. Ratings were disseminated to farmers in person and by means of text messages.

Text messages We sent farmers one text message (Short Message Service - SMS) per dealer in their proximity. This message was translated into three local languages - Lusoga, Lugwere, Samia - chosen at the sub-county level to increase specificity. Table 17 in the appendix provides more details about these messages. Also in control catchment areas, farmers received text messages with the names of dealers in their proximity, so that they were aware of the presence of these dealers. Dillon, Aker, and Blumenstock (2020) demonstrate the importance of these control messages. They introduced a "Yellow Pages" phone directory with contact information for local enterprises in central Tanzania. They find that enterprises randomly assigned to be listed in the directory receive more business calls, make greater use of mobile money, and are more likely to employ workers. To separate this knowledge effect from the effect emanating from the information clearing house, we also disseminate control dealer information. An additional advantage is that it is harder for farmers to identify if they are being treated or not, reducing the likelihood of experimenter demand effects (Bulte et al., 2014).

In person The enumerators also re-visited the farmers in our sample. For this purpose, we designed a visually appealing dissemination app which cycles through all dealers in the proximity 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. Then the enumerator showed the stars associated with the score. Again, we also cycled through dealers in control areas without providing the rating, but just indicating to farmers that these agro-dealers are operating in their area. As was the case for the collection of ratings at baseline, the application provides different names under which the shop is known, a description of where the store was located, and a picture of the store front to make sure farmers have the right shop in mind.

Dissemination of ratings to dealers

Agro-input dealers received their ratings by means of a report on laminated paper which was delivered to their shops. The front shows a visually appealing certificate with a logo and the own general rating; see Figure 5. 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 4. We expect dealers to be more likely to change their behavior if they know that

Figure 5: SeedAdvisor certificate

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.

6 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 our estimated average treatment effect. For farmer level outcomes a similar equation is estimated, where Y_{ij} is now the outcome variable for farmer i in catchment area j at mid- or endline, ε_{ij} is an error term that is potentially correlates within catchment areas, and all other terms are defined as above.

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

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

7 Data

7.1 Sample

Our sample consists of agro-input dealers, and smallholder maize farmers who live in the catchment areas of these dealers. The dealer sample was obtained by listing all input shops in 11 districts in southeastern Uganda, which roughly corresponds to the Busoga kingdom. We found 348 dealers,

[5] Each index is computed as a weighted mean of the standardized values of the outcome variables. The weights of this efficient generalized least squares estimator are calculated to maximize the amount of information captured in the index by giving less weight to outcomes that are highly correlated with each other.

sufficient to detect treatment effects according to our power simulations; see section 4.

After the census, these agro-input shops were assigned to 130 catchment areas (for details, see Section 4, Footnote 1 in particular). We find that 1 to 18 dealers operate in an area, with a mean of 2.7. To connect shops to customers, we asked dealers the name of the villages where most of their customers come from. Then enumerators were instructed to randomly sample ten households that grow maize in these villages. Consequently, about 3500 smallholder maize farmers were sampled, sufficient to detect treatment effects according to our power simulations (see Section 4).

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.

7.2 Descriptive statistics

This subsection describes the baseline sample. Information about the average *agro-input shop* can be found in Table 2. When enumerators approached a shop, they tried to interview the person who is most knowledgeable about the day to day operations, which was usually the shop manager. The average respondent is 32 years old. 60% are male and more than 90% finished primary education. In 55% of the cases, the respondent is also the owner of the shop.

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

We also collected 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 last season.

We also purchased a bag of maize seed. However, only 232 of the 348 shops in our sample had seed in stock at the time of the baseline interview. We measured the moisture in the bag and found that it was 13.6% on average, with a minimum of 10.3 and a maximum of 17.4. Note that seed moisture content determines whether molds and storage pests thrive. It is recommended to keep moisture below 13%. While 68% of seed bags show a packaging date, only 18% show an expiry date, and 8% show a certification sticker.

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

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

Half of the farmers in our sample adopted improved maize seed on at least one of their fields last season. Of these adopting farmers, 2 out of 3 bought seed at an agro-input shop. Only 25% applied chemical fertilizers like Di-Ammonium Phosphate (DAP) or Nitrogen, Phosphorus, and Potassium (NPK) on a randomly selected maize field. Productivity is low with 500 kilograms per acre.

7.3 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 preregistered variables for both dealers and farmers (Tables 2 and 3 respectively). Some of these characteristics are unlikely to be affected by the intervention, while others are picked from the primary and secondary outcomes we will use to measure the impact of our interventions in the next section.

For outcomes at the agro-input dealer level reported in Table 2, we find that from a total of 16 comparisons, only one is significant at the 5 percent level for the agro-input dealer training. For the clearing house treatment, we find two significant differences, both at the 10 percent level. This is consistent with a balanced sample. For outcomes at the farmer level, out of

32 comparisons, none is statistically significant.

8 Results

This section presents results on the impact of the agro-input dealer training and the information clearinghouse. We investigate a set of primary outcomes and various secondary outcomes to explore the effects in detail, to identify steps along the causal chain and understand the mechanisms at work. As agro-input dealers and farmers could benefit from the interventions, we will assess changes in outcomes at both levels in separate subsections. We account for multiple hypothesis testing by aggregating different outcomes within each domain into overall summary indices, following Anderson (2008).[6] The information on what variables are included in which indices can be found in the notes below the tables.

Note that 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. Additionally, we completed the entire econometric analysis on simulated data in a mock report and added it to the AEA registry before midline data was collected.[7] All documents, codes, and data are under revision control and publicly accessible via GitHub which provides time-stamped records of all changes made over the course of the project.

8.1 Impact on agro-input dealers

Primary outcome variables

The average treatment effects on primary outcomes at agro-input dealer level are reported in Table 4. At midline, the overall index is significantly larger among information clearinghouse treated dealers. Looking at individual outcomes, we see that dealers in the treatment group sold more maize seed at

[6] 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, leading to less observations and reduced statistical power.

[7] Mock reports serve to 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.

Table 2: Descriptive statistics and orthogonality tests at dealer level

	mean	training	CH
Respondent's age in years	32.43	0.56	-2.24^{+}
	(11.49)	(1.19)	(1.21)
Respondent is male	0.59	0.02	-0.01
	(0.49)	(0.06)	(0.06)
Respondent finished primary education	0.92	0.01	-0.01
	(0.27)	(0.03)	(0.03)
Respondent owns shop	0.55	0.03	0.02
	(0.50)	(0.06)	(0.06)
Respondent received training on maize seed handling	0.53	0.05	0.12^{+}
	(0.50)	(0.07)	(0.07)
Respondent knows how to store seed after repackaging	0.27	0.07	0.08
	(0.44)	(0.06)	(0.06)
Shop's distance to nearest tarmac road in km	6.56	-0.92	-1.58
	(10.39)	(2.21)	(2.24)
Shop only sells farm inputs	0.74	-0.09	0.03
	(0.44)	(0.07)	(0.06)
Years since shop establishment	5.34	-0.09	0.21
	(6.30)	(0.77)	(0.78)
Number of customers per day	41.49	11.35	6.43
	(46.49)	(7.16)	(6.72)
Amount of maize seed sold last season in kg	910.88	275.42	258.56
	(2683.24)	(408.65)	(386.41)
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 randomly selected seed bag in percent	13.58	0.12	-0.11
	(1.52)	(0.26)	(0.27)

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

Table 3: Descriptive statistics and orthogonality tests at farmer level

	mean	training	CH
Household head's age in years	48.62	-0.08	-0.24
	(13.38)	(0.56)	(0.56)
Household head is male	0.78	-0.02	0.03
	(0.42)	(0.03)	(0.03)
Household head finished primary education	0.51	0.00	0.04
	(0.50)	(0.03)	(0.03)
Homestead's distance to nearest tarmac road in km	9.39	0.33	-1.23
	(10.81)	(1.69)	(1.71)
Homestead's distance to nearest agro-input shop in km	3.78	-0.11	0.11
	(4.79)	(0.37)	(0.37)
Number of people in household (incl. respondent)	8.70	-0.16	-0.09
	(3.98)	(0.18)	(0.18)
Number of rooms in house	3.49	-0.01	0.02
	(1.45)	(0.09)	(0.09)
Farmer's land for crop production in acres	3.35	0.07	0.00
	(4.32)	(0.21)	(0.22)
Years since farmer started growing maize	23.09	0.61	-0.55
	(13.14)	(0.55)	(0.58)
Yield in kg/acre	499.52	43.75	8.61
	(771.17)	(28.99)	(27.66)
Farmer planted improved maize seed on any field last season	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 maize seed bought at agro-input shop in kg	3.53	0.04	-0.19
	(9.20)	(0.43)	(0.44)
Farmers thinks seed at agro-inputs shop is counterfeit	0.68	0.01	0.00
	(0.46)	(0.03)	(0.03)
Farmer used DAP/NPK	0.25	0.04	0.02
	(0.43)	(0.03)	(0.04)
Farmer used organic manure	0.07	-0.01	0.01
	(0.26)	(0.01)	(0.01)

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

a higher price, albeit not significantly so. However, the combination of this does lead to significantly higher revenues. On the other hand, the dealer training does not affect the index significantly. In fact, we find a negative impact of the training on the average sales price of improved maize varieties.

At endline, the positive effects of the clearinghouse intervention seems to become stronger. The overall index is now significant at the 5 percent level. Interestingly, this effect seems to be driven by different variables than at midline. Now, we see a substantial increase in the number of customers that shops attract and an increase in the index which measures dealer efforts and services. Furthermore, all other effects go in the expected direction and some are close to the significance threshold. For instance, we see that shops in the clearinghouse treatment group apply better seed storage and handling practices,[8] have lower moisture levels in randomly sampled seed bags, sell more maize seed, and are rated better by farmers.[9] Results are more puzzling for the dealer training. Here, we find that exposed dealers sell and earn less. We also do not find that dealers that received the training use more of the proper seed storage and handling practices that they were taught. The index of primary outcomes confirms that the dealer training had no statistically significant impact.

Secondary outcome variables

As a first set of secondary outcomes at dealer level, we construct a set of indices which aggregate several related variables, again following Anderson (2008). The results are reported in Table 5. A first index attempts to measure dealer's motivation and satisfaction, which remains constant among treatment groups. A second index reflects self-ratings of agro-input dealers and is similarly unaffected by the two treatments. While the index of dealer efforts and services among the primary outcomes in Table 4 was based on what dealers reported, we also asked farmers which services the dealers offer. We find strong evidence that the information clearinghouse increases farmers'

[8]These agro-input shop features were noted by our enumerators who inspected the area where seed was stored.

[9]Note that the rating indices are pre-registered outcomes but treatment and control groups can be compared only at endline. At base- and midline, only clearinghouse treated farmers rated dealers in their proximity because we consider the act of rating itself an important 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.

Table 4: Effects on primary dealer outcomes

	baseline	*midline*			*endline*		
	mean	training	CH	obs.	training	CH	obs.
Transf. quantity of maize seed sold in kg (IHS)†	5.898	-0.092	0.284	292	-0.499^{+}	0.239	286
	(1.965)	(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)	
Transf. revenue from maize seed in mln UGX (IHS)†	1.108	-0.069	0.185^{+}	292	-0.227^{+}	0.143	286
	(1.023)	(0.104)	(0.108)		(0.118)	(0.118)	
Transf. number of maize seed customers per day (IHS)†	3.248	-0.056	0.127	294	-0.190	0.310**	288
	(0.941)	(0.098)	(0.101)		(0.116)	(0.112)	
Moisture in randomly selected seed bag in percent	13.563	0.017	-0.122	175	-0.041	-0.220	261
	(1.442)	(0.142)	(0.144)		(0.198)	(0.197)	
Index of capital-intensive seed handling practices^{1†}	0.000	-0.019	0.000	270	-0.087	0.070	265
	(0.508)	(0.063)	(0.072)		(0.092)	(0.081)	
Index of labor-intensive seed handling practices^{2†}	0.010	0.058	0.099	285	0.083	0.074	274
	(0.484)	(0.070)	(0.065)		(0.067)	(0.068)	
Index of all seed handling practices^{3}	0.009	0.042	0.052	251	0.021	0.083	248
	(0.382)	(0.051)	(0.053)		(0.063)	(0.059)	
Index of dealer's efforts and services^{4†}	0.000	-0.063	0.066	243	-0.031	0.086^{+}	297
	(0.454)	(0.062)	(0.060)		(0.051)	(0.048)	
Index of shop's maize seed ratings by farmers^{5}	-0.018				0.020	0.122	327
	(0.595)				(0.102)	(0.101)	
Overall index	0.007	-0.004	0.214^{+}	215	-0.058	0.239*	258
	(0.591)	(0.130)	(0.121)		(0.128)	(0.117)	
Max. number of obs. for dealer survey outcomes				306			297

Note: 1st column reports baseline means and standard deviations below; 2nd, 3rd, 5th and 6th column reports differences between treatment and control groups and standard errors below; they are clustered at the level of randomization; 4th and 7th column reports number of observations; **, * and + denote significance at the 1, 5 and 10 percent levels; † indicates that the variable is included in the overall index; larger indices indicate more desirable outcomes; IHS stands for Inverse Hyperbolic Sine.

[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.

perceptions about dealers' efforts and services at midline. Surprisingly, we find that the dealer training seems to have the opposite effect. To investigate changes in skill and knowledge, we construct two more indices. For the index of dealer's knowledge about seed storage and handling and a similar index for knowledge related to seed, the difference between treatment and control groups is not significantly different from zero at midline. At endline however, we find a positive impact on dealer's knowledge about seed handling. Somewhat surprisingly, we do not find that knowledge is significantly affected by the training that we provided, but does increase due the clearinghouse. This seems to suggest that if dealers are provided with the right incentive, they actively seek out information. However, merely providing the information to dealers does not increase their knowledge.

We also consider outcomes associated with particular seed varieties. Because dealers often do not stock all varieties, sample sizes are smaller here. The next set of variables deals with *Longe 10H*, a popular hybrid maize variety. At midline, Table 6 reveals that the only significant result is found for the agro-input dealer training, which seems to have reduced the cost at which seed was obtained and stock-outs, measured as the number of times per month a shop ran out of Longe 10H. For the clearinghouse treatment, many coefficients go in the expected direction but none of the comparisons is significant. At endline however, the results regarding Longe 10H are generally consistent with the findings for primary dealer outcomes. Most importantly, we find a significant and positive overall effect of the clearinghouse treatment as judged by the overall index. This is driven by increased sales and decreased stock-outs, for which both coefficient estimates are just above the significance threshold. For the agro-input dealer training, we do not find an overall effect at endline.

The same questions were asked for *Longe 5*, a commonly traded open-pollinated maize variety. Table 7 shows that again, the clearinghouse treatment affected this family of outcomes significantly, as measured by the overall index at endline.

We also collected information about memberships, licenses, and inspections. Table 8 reports that there is no impact of the interventions at midline. At endline, we measure a positive impact of the information clearinghouse on the overall index. This result is driven by an almost 12 percentage point increase in the likelihood that the agro-input shop is registered with UNADA. The clearinghouse also crowds-in shop inspections, perhaps due to increased registrations, licenses, and memberships of shops in the treatment group. Al-

Table 5: Effects on secondary dealer outcomes: Indices

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

Note: 1st column reports baseline means and standard deviations below; 2nd, 3rd, 5th and 6th column reports differences between treatment and control groups and standard errors below; they are clustered at the level of randomization; 4th and 7th column reports number of observations; **, * and + denote significance at the 1, 5 and 10 percent levels; † indicates that the variable is included in the overall index; larger indices indicate more desirable outcomes; IHS stands for Inverse Hyperbolic Sine.
[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 6: Effects on secondary dealer outcomes: Longe 10H

	baseline	*midline*			*endline*		
	mean	training	CH	obs.	training	CH	obs.
Transf. amount carried forward in kg (IHS)†	0.318	-0.186	0.090	262	-0.012	-0.034	250
	(1.083)	(0.212)	(0.215)		(0.138)	(0.134)	
Transf. amount shop bought from provider in kg (IHS)†	4.212	0.118	0.206	257	-0.022	0.283	243
	(2.723)	(0.218)	(0.213)		(0.250)	(0.253)	
Transf. cost in UGX/kg (IHS)	9.209	-0.056*	-0.035	180	-0.026	0.008	179
	(0.130)	(0.024)	(0.022)		(0.029)	(0.030)	
Transf. quantity sold in kg (IHS)†	4.132	0.050	0.236	256	-0.205	0.352	242
	(2.749)	(0.206)	(0.204)		(0.231)	(0.239)	
Transf. sales price in UGX/kg (IHS)	9.417	-0.025	-0.013	194	-0.019	0.010	187
	(0.145)	(0.026)	(0.026)		(0.030)	(0.029)	
Transf. amount lost/wasted in kg (IHS)†	0.018	-0.001	0.019	257	-0.058	-0.038	243
	(0.197)	(0.093)	(0.097)		(0.037)	(0.041)	
Transf. number of times per month shop ran out (IHS)†	0.632	-0.236+	-0.045	192	-0.180	-0.205	185
	(0.788)	(0.129)	(0.133)		(0.128)	(0.136)	
Overall index	0.116	0.119	0.034	249	0.014	0.206**	233
	(0.470)	(0.074)	(0.075)		(0.063)	(0.067)	
Max. number of obs.[1]				268			254

Note: 1st column reports baseline means and standard deviations below; 2nd, 3rd, 5th and 6th column reports differences between treatment and control groups and standard errors below; they are clustered at the level of randomization; 4th and 7th column reports number of observations; **, * and + denote significance at the 1, 5 and 10 percent levels; † indicates that the variable is included in the overall index; larger indices indicate more desirable outcomes; IHS stands for Inverse Hyperbolic Sine.
[1]The comparisons were only made for shops which had Longe 10H in stock at mid- or endline.

Table 7: Effects on secondary dealer outcomes: Longe 5

	baseline	*midline*			*endline*		
	mean	training	CH	obs.	training	CH	obs.
Transf. amount carried forward in kg (IHS)†	0.414	0.247	-0.092	270	-0.095	-0.004	263
	(1.243)	(0.324)	(0.306)		(0.148)	(0.155)	
Transf. amount shop bought from provider in kg (IHS)†	5.350	-0.005	0.253	262	-0.179	0.289	260
	(2.228)	(0.221)	(0.215)		(0.232)	(0.235)	
Transf. cost in UGX/kg (IHS)	8.507	-0.019	-0.030^{+}	231	-0.010	0.001	231
	(0.082)	(0.015)	(0.016)		(0.021)	(0.020)	
Transf. quantity sold in kg (IHS)†	5.258	-0.040	0.304	261	-0.215	0.316	259
	(2.190)	(0.222)	(0.216)		(0.234)	(0.230)	
Transf. sales price in UGX/kg (IHS)	8.730	0.017	-0.015	249	-0.002	0.013	241
	(0.110)	(0.016)	(0.016)		(0.022)	(0.022)	
Transf. amount lost/wasted in kg (IHS)†	0.245	-0.150	0.031	266	-0.055	-0.033	261
	(0.894)	(0.128)	(0.128)		(0.055)	(0.058)	
Transf. number of times per month shop ran out (IHS)†	0.498	0.053	0.086	248	0.094	-0.054	237
	(0.767)	(0.100)	(0.101)		(0.120)	(0.126)	
Overall index	0.054	0.024	0.031	259	-0.020	0.148*	253
	(0.506)	(0.095)	(0.094)		(0.069)	(0.069)	
Max. number of obs.[1]				275			269

Note: 1st column reports baseline means and standard deviations below; 2nd, 3rd, 5th and 6th column reports differences between treatment and control groups and standard errors below; they are clustered at the level of randomization; 4th and 7th column reports number of observations; **, * and + denote significance at the 1, 5 and 10 percent levels; † indicates that the variable is included in the overall index; larger indices indicate more desirable outcomes; IHS stands for Inverse Hyperbolic Sine.

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

ternatively, dealers could voluntarily expose themselves to increased scrutiny and actively seek inspections to signal costumers that they offer products of good quality. The dealer training did not affect this set of outcome variables at endline.

8.2 Impact on smallholder farmers

Primary outcome variables

Table 9 reports the effects of the interventions on a set of key outcomes at the smallholder level. We do not find an impact on the overall primary outcome index at midline. Looking at the variables individually, we see a substantial increase in the share of farmers who switched to a different agro-input shop: In areas where the clearinghouse was implemented, we record a 4 percentage point higher likelihood to switch, which corresponds to a 25 percent increase relative to the baseline mean. Furthermore, the clearinghouse increased adoption: Treated farmers are 3.5 percentage points more likely to have used improved maize seed on at least one plot. We also see a 6 percentage point increase in the share of farmers who used quality maize seed bought from an agro-input dealer. Finally, for our measure of effort perception, farmers indicate that dealers in areas exposed to the clearinghouse provide more services such as training, credit, etc. than dealers in control areas. We do not find an effect of the dealer level training on farmer outcomes at midline, except for the index of shop services. Somewhat surprisingly, the training seemed to have reduced services.

At endline, we see that the information clearinghouse has a positive impact on farmers when looking at the overall index. Considering individual primary outcomes, we find that the adoption effect we found at midline persists: farmers who were exposed to the clearinghouse treatment are now 4 percentage points more likely to have used improved seed on at least one of their maize plots. Two other important outcomes are related to the perception of product quality, shop and seller. To be able to calculate these indices at the smallholder level, the farmer needs to have rated at least one dealer in the catchment area on all the components of the indices, which leads to a reduction of the sample size, which in turn may have affected power. Nonetheless, we see that the index of farmer's maize seed ratings of shops within the catchment area is significantly and positively affected by the clearing house treatment. Other variables that are significantly impacted

Table 8: Effects on secondary 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 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)	
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)	
Transf. number of shop inspections (IHS)†	0.956	0.037	-0.097	293	0.038	0.292*	273
	(0.772)	(0.247)	(0.259)		(0.109)	(0.111)	
Shop received warning after inspection†	0.317	0.045	0.005	291	0.013	-0.009	284
	(0.466)	(0.072)	(0.073)		(0.062)	(0.063)	
Shop's products were confiscated after inspection†	0.145	0.021	-0.027	293	0.014	-0.025	285
	(0.353)	(0.046)	(0.046)		(0.033)	(0.036)	
Overall index	-0.004	-0.005	0.047	266	-0.006	0.203**	253
	(0.433)	(0.056)	(0.055)		(0.078)	(0.074)	
Max. number of obs.				306			297

Note: 1st column reports baseline means and standard deviations below; 2nd, 3rd, 5th and 6th column reports differences between treatment and control groups and standard errors below; they are clustered at the level of randomization; 4th and 7th column reports number of observations; **, * and + denote significance at the 1, 5 and 10 percent levels; † indicates that the variable is included in the overall index; larger indices indicate more desirable outcomes; IHS stands for Inverse Hyperbolic Sine.

include the likelihood that farmers switch shops, or the efforts and services that farmers receive from dealers. In general, results at the farmer level are consistent with outcomes at the dealer level. For instance, in Table 4 we also see that dealers report more customers and provide more effort and services. We again do not find an impact of the dealer training on farmers at endline.

Secondary outcome variables

To explore impact pathways at the level of the smallholder, we often consider outcomes associated with a randomly selected maize plot.[10] In Table 10 we look at the adoption of improved maize seed on that a randomly selected plot. While we do not find any significant impact of the agro-input dealer training at midline, we do find some interesting results for the information clearinghouse treatment even though the overall index is not impacted. It improves the adoption of improved seed varieties by increasing the likelihood that treated farmers plant seed bought at agro-input shops and decreasing the likelihood that they plant farmer-saved seed. At endline we again find that farmers that were exposed to the clearinghouse are more likely to have planted seed that was bought at an agro-input shop. Most of the other variables also go into the expected direction, but estimates are not significantly different from zero. According to the index, we also do not find an impact of the clearinghouse. We find no effect of the dealer training on the adoption of improved maize seed.

In Table 11, we zoom in on the maize seed that farmers planted on the randomly selected plot, and investigate their quality perceptions. On fields exposed to the clearinghouse treatment, farmers use more expensive seed leading to higher seed costs. This is consistent with the explanation that the clearinghouse increases the adoption of commercial seed. At midline, the overall index is also affected by the clearinghouse. We see no effect of the training.

We further look at harvest related outcomes, like maize yield and revenue,

[10] Farmers often have more than one plot. As outcomes on different plots from the same farmer are likely to be strongly correlated, it is not cost effective to ask questions about all fields. An unbiased estimate of the outcome at the household level can be obtained by randomly selecting one plot.

Table 9: Effects on primary farmer outcomes

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

Note: 1st column reports baseline means and standard deviations below; 2nd, 3rd, 5th and 6th column reports differences between treatment and control groups and standard errors below; they are clustered at the level of randomization; 4th and 7th column reports number of observations; **, * and + denote significance at the 1, 5 and 10 percent levels; † indicates that the variable is included in the overall index; larger indices indicate more desirable outcomes; IHS stands for Inverse Hyperbolic Sine.
[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 10: Effects on secondary farmer outcomes: Adoption on randomly selected maize field

	baseline	*midline*			*endline*		
	mean	training	CH	obs.	training	CH	obs.
Farmer planted hybrid seed†	0.264	0.002	0.009	2654	-0.023	0.032	2700
	(0.441)	(0.022)	(0.022)		(0.023)	(0.023)	
Farmer planted open-pollinated seed†	0.260	-0.017	0.002	2654	0.010	-0.007	2700
	(0.439)	(0.022)	(0.022)		(0.020)	(0.021)	
Farmer planted farmer-saved seed†	0.579	0.020	-0.042^{+}	3153	-0.009	-0.016	3240
	(0.494)	(0.022)	(0.022)		(0.020)	(0.020)	
Farmer planted seed bought at agro-input shop†	0.330	-0.010	0.047*	3153	0.012	0.036^{+}	3240
	(0.470)	(0.022)	(0.022)		(0.019)	(0.019)	
Farmer planted hybrid or open-pollinated seed[1]	0.477	-0.024	0.033	2954	-0.004	0.021	3047
	(0.500)	(0.022)	(0.021)		(0.020)	(0.021)	
Overall index	-0.003	0.000	0.002	2867	-0.010	0.026	2963
	(0.553)	(0.024)	(0.024)		(0.025)	(0.025)	
Max. number of obs.				3407			3441

Note: 1st column reports baseline means and standard deviations below; 2nd, 3rd, 5th and 6th column reports differences between treatment and control groups and standard errors below; they are clustered at the level of randomization; 4th and 7th column reports number of observations; **, * and + denote significance at the 1, 5 and 10 percent levels; † indicates that the variable is included in the overall index; larger indices indicate more desirable outcomes; IHS stands for Inverse Hyperbolic Sine.

[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.

Table 11: Effects on secondary farmer outcomes: Seed planted on randomly selected maize field

	baseline	*midline*			*endline*		
	mean	training	CH	obs.	training	CH	obs.
Index of farmer's seed ratings[1]†	-0.004	-0.055	0.052	3012	0.038	0.060	3123
	(0.606)	(0.037)	(0.038)		(0.038)	(0.039)	
Farmer was satisfied with seed quality†	0.678	-0.011	0.010	3217	0.012	0.002	3299
	(0.467)	(0.020)	(0.021)		(0.022)	(0.023)	
Farmer would use seed again†	0.764	0.007	0.018	3217	0.011	0.020	3299
	(0.425)	(0.019)	(0.019)		(0.020)	(0.020)	
Amount of seed farmer used in kg†	8.859	0.055	-0.160	2909	0.018	-0.039	2991
	(6.332)	(0.222)	(0.229)		(0.244)	(0.247)	
Price of seed in UGX/kg†	1922.330	-73.500	220.627^{+}	2982	124.242	163.688	3047
	(2947.034)	(122.416)	(123.758)		(136.416)	(139.864)	
Transf. cost of seed in UGX (IHS)	4.237	-0.181	0.499*	2848	0.283	0.350^{+}	2942
	(5.320)	(0.235)	(0.235)		(0.208)	(0.209)	
Overall index	-0.005	-0.023	0.057^{+}	2859	0.025	0.042	2953
	(0.568)	(0.032)	(0.032)		(0.031)	(0.032)	
Max. number of obs.				3407			3441

Note: 1st column reports baseline means and standard deviations below; 2nd, 3rd, 5th and 6th column reports differences between treatment and control groups and standard errors below; they are clustered at the level of randomization; 4th and 7th column reports number of observations; **, * and + denote significance at the 1, 5 and 10 percent levels; † indicates that the variable is included in the overall index; larger indices indicate more desirable outcomes; IHS stands for Inverse Hyperbolic Sine.

[1]The index of farmer's seed ratings contains 6 ratings: general quality, yield, drought tolerance, pest/disease tolerance, time of maturity, germination.

associated with the randomly selected plot.[11] Table 12 shows that there is no impact of the agro-input dealer intervention at mid- or endline. For the information clearinghouse treatment, the impact is ambiguous at midline. There are some indications of reduced productivity, but farmers also seem to save less seed to sow in the upcoming season, signaling that they plan to buy improved seed. At endline, judged by the index, the clearinghouse treatment had a significant and positive impact on this family of outcomes. This is driven by a significant increase in production and an equally large increase in productivity, suggesting the increase in production is due to an increase in the intensive margin. Note that picking up a yield effect of this size is particularly convincing because this outcome is relatively far down the causal impact chain and shows high variability. The increase in production and yield at endline is consistent with the increased adoption at midline.

8.3 Heterogeneity analysis for competitive areas

One could argue that the information clearinghouse will not work in areas with only one agro-input dealer, as farmers have less opportunities to switch to better dealers and dealers would have less incentives to improve their services and increase their efforts if there is no threat of competition nearby. In our sample, 46 of 130 catchment areas are served by only one dealer. We exclude these smallest clusters which leaves us with 302 shops and 3020 farmers in 84 areas. Tables 13 and 14 report that the effects are not stronger here. We conclude that the clearinghouse does not work better in more competitive areas and that our results for the entire sample are not driven by these dealers. One potential explanation for this is that some dealers provide great seed but farmers are not aware of it, so that the clearinghouse corrects a misperception. This way the intervention can also work in areas without dealer competition and the results of the heterogeneity analysis stand to reason.

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

Table 12: Effects on secondary farmer outcomes: Harvest on randomly selected maize field

	baseline	*midline*			*endline*		
	mean	training	CH	obs.	training	CH	obs.
Production in kg	463.203	-0.806	-20.372	2884	16.959	38.570*	2898
	(399.595)	(14.050)	(14.529)		(17.957)	(17.833)	
Yield in kg/acre†	443.222	-12.216	-23.006	2878	5.118	44.372**	2889
	(304.964)	(16.234)	(16.964)		(15.596)	(15.603)	
Transf. amount sold in kg (IHS)†	3.168	-0.046	-0.201	3063	-0.147	0.139	3137
	(3.220)	(0.126)	(0.124)		(0.159)	(0.157)	
Transf. revenue in UGX (IHS)†	2.764	-0.141	-0.393	3058	-0.354	0.263	3109
	(2.873)	(0.260)	(0.257)		(0.341)	(0.336)	
Transf. amount kept as seed in kg (IHS)	2.254	-0.098	-0.188*	2931	-0.043	0.036	2861
	(1.803)	(0.092)	(0.092)		(0.108)	(0.104)	
Overall index	-0.018	-0.018	-0.073+	2945	0.008	0.097*	2926
	(0.819)	(0.043)	(0.043)		(0.043)	(0.043)	
Max. number of obs.				3407			3441

Note: 1st column reports baseline means and standard deviations below; 2nd, 3rd, 5th and 6th column reports differences between treatment and control groups and standard errors below; they are clustered at the level of randomization; 4th and 7th column reports number of observations; **, * and + denote significance at the 1, 5 and 10 percent levels; † indicates that the variable is included in the overall index; larger indices indicate more desirable outcomes; IHS stands for Inverse Hyperbolic Sine.

Table 13: Effects on primary dealer outcomes: Heterogeneity analysis

	baseline	*midline*			*endline*		
	mean	training	CH	obs.	training	CH	obs.
Transf. quantity of maize seed sold in kg (IHS)†	0.136	-0.013	0.305	249	-0.315	0.073	245
	(1.942)	(0.239)	(0.253)		(0.271)	(0.272)	
Sales price of maize seed in UGX/kg	28.105	-276.253*	56.030	237	-36.637	121.043	228
	(963.152)	(129.655)	(127.407)		(157.902)	(152.272)	
Transf. revenue from maize seed in mln UGX (IHS)†	0.072	-0.043	0.177	249	-0.113	0.079	245
	(1.054)	(0.113)	(0.119)		(0.132)	(0.133)	
Transf. number of maize seed customers per day (IHS)†	0.033	-0.051	0.089	255	-0.128	0.229+	249
	(0.969)	(0.105)	(0.111)		(0.126)	(0.118)	
Moisture in randomly selected seed bag in percent	13.559	-0.009	0.011	154	-0.108	-0.055	226
	(1.465)	(0.150)	(0.148)		(0.221)	(0.217)	
Index of capital-intensive seed handling practices[1]†	-0.001	0.009	0.011	232	-0.053	0.044	233
	(0.510)	(0.063)	(0.081)		(0.093)	(0.083)	
Index of labor-intensive seed handling practices[2]†	0.004	0.092	0.119+	247	0.066	0.088	240
	(0.489)	(0.073)	(0.068)		(0.072)	(0.072)	
Index of all seed handling practices[3]	0.004	0.067	0.066	218	-0.003	0.073	220
	(0.388)	(0.051)	(0.056)		(0.064)	(0.060)	
Index of dealer's efforts and services[4]†	0.000	-0.057	0.030	206	-0.012	0.041	256
	(0.454)	(0.071)	(0.066)		(0.052)	(0.051)	
Index of shop's maize seed ratings by farmers[5]	-0.020				0.053	0.165	288
	(0.600)				(0.112)	(0.112)	
Overall index	-0.004	0.038	0.196	182	-0.038	0.181	225
	(0.599)	(0.132)	(0.128)		(0.140)	(0.128)	
Max. number of obs. for dealer survey outcomes				263			257

Note: 1st column reports baseline means and standard deviations below; 2nd, 3rd, 5th and 6th column reports differences between treatment and control groups and standard errors below; they are clustered at the level of randomization; 4th and 7th column reports number of observations; **, * and + denote significance at the 1, 5 and 10 percent levels; † indicates that the variable is included in the overall index; larger indices indicate more desirable outcomes; IHS stands for Inverse Hyperbolic Sine.

[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 14: Effects on primary farmer outcomes: Heterogeneity analysis

	baseline	*midline*			*endline*		
	mean	training	CH	obs.	training	CH	obs.
Farmer planted improved maize seed on any field†	0.002	-0.024	0.028	2774	-0.005	0.045*	2848
	(0.500)	(0.022)	(0.022)		(0.021)	(0.021)	
Farmer bought maize seed at agro-input shop for any field†	0.003	-0.019	0.055*	2717	0.002	0.033	2794
	(0.470)	(0.022)	(0.022)		(0.021)	(0.021)	
Amount of this seed farmer bought at agro-input shop in kg	-0.039	0.473	-0.390	521	0.673	-0.072	538
	(6.887)	(0.379)	(0.390)		(0.450)	(0.464)	
Index of farmer's maize seed ratings of shops within catchment area[1]	0.000				0.037	0.116*	1483
	(0.637)				(0.057)	(0.057)	
Index of farmer's general ratings of shops within catchment area[2]	0.000				-0.011	-0.024	1521
	(0.657)				(0.044)	(0.043)	
Index of services of shops within catchment area according to farmers[3]	-0.035	-0.133+	0.126+	291	0.033	0.134+	299
	(0.598)	(0.075)	(0.069)		(0.083)	(0.078)	
Farmer switched to different agro-input shop[4]†	0.168	-0.018	0.040*	2959	-0.024	0.030+	2996
	(0.374)	(0.016)	(0.016)		(0.016)	(0.016)	
Index of farmer's practices on randomly selected field[5]†	0.009	-0.013	-0.032	2519	-0.009	0.017	2637
	(0.402)	(0.020)	(0.020)		(0.022)	(0.023)	
Farmer thinks maize seed at agro-input shops is adulterated	0.004	-0.029	-0.036	1818	-0.039	0.013	1870
	(0.463)	(0.029)	(0.028)		(0.031)	(0.031)	
Farmer planted land race maize seed on randomly selected field†	-0.001	0.017	0.000	2541	0.008	-0.022	2637
	(0.497)	(0.023)	(0.022)		(0.024)	(0.024)	
Overall index[6]	0.010	-0.026	-0.006	2519	-0.036	0.068+	2667
	(0.696)	(0.035)	(0.036)		(0.036)	(0.036)	
Max. number of obs.				2959			2996

Note: 1st column reports baseline means and standard deviations below; 2nd, 3rd, 5th and 6th column reports differences between treatment and control groups and standard errors below; they are clustered at the level of randomization; 4th and 7th column reports number of observations; **, * and + denote significance at the 1, 5 and 10 percent levels; † indicates that the variable is included in the overall index; larger indices indicate more desirable outcomes; IHS stands for Inverse Hyperbolic Sine.

[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 299 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.

9 Attrition

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

Whether our estimates are biased or not depends on whether this attrition is random or not. For instance, a non-random subset of agro-input dealers might have left the sample, meaning that attritors and non-attritors differ significantly, which could bias our results. It is for instance plausible that the worst performing shops in the clearinghouse control group went bankrupt. Our clearinghouse treatment might have prevented bankruptcy and helped dealers to stay in the market because it served as some kind of advertisement if the rating was good.

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,

Table 15: Attrition

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

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

and Kremer, 2006; Duflo, Glennerster, and Kremer, 2007).

10 Discussion

Why does the agro-input dealer training not work?

The training has to increase agro-input dealer's knowledge about seed storage to improve their behavior and subsequently seed quality, see Figure 1. Dealers cannot handle seed correctly if they do not know how to do so. However, the dealer knowledge indices in Table 5 do not seem to be significantly affected by the training treatment. That is why we zoom into their knowledge at midline in January and February 2022 after being trained in May 2021. Table 16 shows that the training has no measurable effect on the individual knowledge questions even though it addressed these topics specifically and knowledge was not surprisingly high at baseline. Dealers do not learn or do not remember what they have learned during the training, despite receiving a poster which illustrates the most important practices to hang in their store. We conclude that providing dealers with information about seed handling and storage does not work as long as dealers do not have an incentive to learn.

Table 16: Effects of training on dealer's knowledge about seed storage

	baseline	*midline*	
	mean	training	obs.
Dealer knows...			
...how long seed can be carried over	0.336	0.085	306
	(0.473)	(0.078)	
...how seed should be stored after repackaging	0.270	0.067	306
	(0.445)	(0.065)	
...min. distance between seed and floor	0.526	0.079	306
	(0.500)	(0.060)	
...how seed should be stored in storeroom	0.552	0.007	306
	(0.498)	(0.058)	
...whether seed should be repackaged	0.638	0.008	306
	(0.481)	(0.064)	
Index of dealer's knowledge about seed storage	0.000	0.091	306
	(0.482)	(0.076)	

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

Why does the information clearinghouse work?

The clearinghouse is a unique intervention because it solves a variety of potentially interlinked problems simultaneously. If the quality of maize seed at agro-input shops is good, it corrects the misperception of farmers. If the quality of maize seed is poor, it provides farmers with information about where to find better seed and dealers with an incentive to change their behavior. Our results in Section 8 show that all 3 impact pathways play a role. We find evidence of farmers switching to different shops, the behavior of dealers is also affected as we see significant effects on several measures of their efforts and services, and the clearinghouse improves smallholder perceptions of the maize seed at shops nearby. Clearly, both actors take the ratings serious. Hereafter we attempt to disentangle the different impact pathways and investigate what exactly is going on.

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. Furthermore, the heterogeneity analysis in Subsection 8.3 shows that the clearinghouse also works in areas with only one agro-input shop and no competition where farmers are less likely to switch and dealers have less incentives to increase their efforts. 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. 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.

In addition, the clearinghouse works through the other impact channels simultaneously. At endline, when all farmers rated all dealers, we find that smallholders perceive seed at clearinghouse treated dealers to be better. The rectifying incorrect perceptions argument made above does not explain why seed at treated shops received higher ratings. Clearly something else has changed due to the clearinghouse. It would be straightforward to assume that farmers perceive seed at treated shops to be better because the clearinghouse has improved seed quality. Unfortunately, we cannot verify this because are not able to objectively measure seed quality as DNA fingerprinting is the only reliable way to detect varietal purity. 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 for example 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.

Potential threats to the functioning of the information clearinghouse

Farmers cannot 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 for example 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. After all, scholars infer the quality of maize seed in a similar way, by focusing on yield responses (Bold et al., 2017) or using germination rates (Tjernström, Lybbert, and Carter, 2016).

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. Dealers with better labor-intensive seed handling practices have higher ratings, so do dealers with better capital-intensive 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.

Some dealers will cheat 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. However, if the clearinghouse intervention would be scaled up, these kind of challenges would need to be addressed. However, the objective of this paper is to test whether a prediction of the theory occurs in practice, namely whether making quality observable improves the market for maize seed, and not to provide a policy intervention, sophisticated enough to be applied without further considerations.

11 Conclusion

Even though agricultural technologies like high yielding seed varieties and inorganic fertilizers are considered to be key in increasing agricultural productivity and accelerate rural transformation, the adoption by smallholders remains persistently low in sub-Saharan Africa. We studied a particular constraint to technology adoption: the perceived quality of agricultural inputs.

We hypothesized that seed quality deteriorates because agro-input dealers lack knowledge and/or because asymmetric information results in excessive search costs for farmers and reduced incentives for dealers.

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

The results of our analyses showed that training dealers did not lead to increased knowledge, did not change agro-input dealer practices and did not increase observable quality attributes of the seed. We also did not find any impact among farmers that are living in catchment areas of agro-input dealers that were trained: they did not rate quality differently nor had higher adoption rates than farmers that were not exposed to the dealer level training. However, the clearinghouse had clear impacts on the Ugandan market for maize seed as sellers and buyers started behaving in a way that is consistent with theory of change. Effects at farmer level included an increased likelihood of switching to different dealers (especially after one season), increased adoption of improved seed varieties, and increased productivity (especially after the second season). Effects at the dealer level included increased number of customers and more services provided to farmers.

We conclude that quality consideration are an important constraint to the adoption of agricultural inputs. Implications for policy are that any strategy which reduces the information asymmetry between seller and buyer by making input quality more observable, through for instance certification, electronic verification, inspection etc., is likely to improve the market and increase adoption. However, it has been well established that differences in seemingly small attributes in information campaigns can have important consequences for behavior change (Duflo and Banerjee, 2011). For instance, BenYishay and Mobarak (2019) find that information farmers appear most convinced if information comes from sources they share a group identity with. Furthermore, the heterogeneous settings farmers face (in terms of soil fertility and (micro-)climatic conditions) means that uniform information messages or blanket recommendations are often less effective than site-specific or (hyper) local information (Ayalew, Chamberlin, and Newman, 2022). An information clearinghouse based on crowd-sourced information combines many of the attributes that are found to be important as peers who are familiar with the heterogeneous conditions farmers face provide the ratings.

A crowd-sourced information clearinghouse can be an important institutional innovation to solve the problem of asymmetric information in the market for agricultural inputs. It may be preferable to alternative strategies due to its likely lower cost and self-sustaining nature, and helps to overcome problems such as insufficient public investment in regulatory systems, regulatory enforcement, and market surveillance.

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

References

Anderson, J. R. and G. Feder. 2004. "Agricultural Extension: Good Intentions and Hard Realities." *The World Bank Research Observer* 19 (1): 41–60.

Anderson, M. L. 2008. "Multiple inference and gender differences in the effects of early intervention: A reevaluation of the Abecedarian, Perry Preschool, and Early Training Projects." *Journal of the American statistical Association* 103 (484): 1481–1495.

Angrist, J., E. Bettinger, and M. Kremer. 2006. "Long-Term Educational Consequences of Secondary School Vouchers: Evidence from Administrative Records in Colombia." *American Economic Review* 96 (3): 847–862.

Arslan, C., M. Wollni, J. Oduol, and K. Hughes. 2022. "Who communicates the information matters for technology adoption." *World Development* 158.

Ashour, M., D. O. Gilligan, J. B. Hoel, and N. I. Karachiwalla. 2019. "Do Beliefs About Herbicide Quality Correspond with Actual Quality in Local Markets? Evidence from Uganda." *The Journal of Development Studies* 55 (6): 1285–1306.

Ashraf, N., X. Giné, and D. Karlan. 2009. "Finding missing markets (and a disturbing epilogue): Evidence from an export crop adoption and marketing intervention in Kenya." *American Journal of Agricultural Economics* 91 (4): 973–990.

Ayalew, H., J. Chamberlin, and C. Newman. 2022. "Site-specific agronomic information and technology adoption: A field experiment from Ethiopia." *Journal of Development Economics* 156: 102788.

Barriga, A. and N. Fiala. 2020. "The supply chain for seed in Uganda: Where does it go wrong?" *World Development* 130: 104928.

Bell, R. M. and D. F. McCaffrey. 2002. "Bias reduction in standard errors for linear regression with multi-stage samples." *Survey Methodology* 28 (2): 169–181.

BenYishay, A. and A. M. Mobarak. 2019. "Social learning and incentives for experimentation and communication." *The Review of Economic Studies* 86 (3): 976–1009.

Bold, T., K. C. Kaizzi, J. Svensson, and D. Yanagizawa-Drott. 2017. "Lemon technologies and adoption: measurement, theory and evidence from agricultural markets in Uganda." *The Quarterly Journal of Economics* 132 (3): 1055–1100.

Bulte, E., G. Beekman, S. Di Falco, J. Hella, and P. Lei. 2014. "Behavioral responses and the impact of new agricultural technologies: Evidence from a double-blind field experiment in Tanzania." *American Journal of Agricultural Economics* 96 (3): 813–830.

Conley, T. G. and C. R. Udry. 2010. "Learning about a New Technology: Pineapple in Ghana." *American Economic Review* 100 (1): 35–69.

Curzi, D., P. Nota, and S. Di Falco. 2022. "Post-Harvest Losses and Climate Conditions in Sub-Saharan Africa." *Contributed Paper prepared for presentation at the 96th Annual Conference of the Agricultural Economics Society* .

De, A., C. Miehe, and B. Van Campenhout. 2022. "Gender bias in consumer perceptions: The case of agro-input dealers in Uganda." *IFPRI Discussion Paper* .

Dillon, B., J. C. Aker, and J. E. Blumenstock. 2020. "How Important is the Yellow Pages? Experimental Evidence from Tanzania." *CEPR Discussion Paper* .

Duflo, E. and A. Banerjee. 2011. *Poor economics.* PublicAffairs.

Duflo, E., R. Glennerster, and M. Kremer. 2007. "Using randomization in development economics research: A toolkit." *Handbook of development economics* 4: 3895–3962.

Duflo, E., M. Kremer, and J. Robinson. 2011. "Nudging farmers to use fertilizer: Theory and experimental evidence from Kenya." *American economic review* 101 (6): 2350–90.

Evenson, R. E. and D. Gollin. 2003. "Assessing the impact of the Green Revolution, 1960 to 2000." *science* 300 (5620): 758–762.

Fafchamps, M. and B. Minten. 2012. "Impact of SMS-based agricultural information on Indian farmers." *The World Bank Economic Review* 26 (3): 383–414.

Gharib, M. H., L. H. Palm-Forster, T. J. Lybbert, and K. D. Messer. 2021. "Fear of fraud and willingness to pay for hybrid maize seed in Kenya." *Food Policy* 102: 102040.

Govender, V., T. Aveling, and Q. Kritzinger. 2008. "The effect of traditional storage methods on germination and vigour of maize (Zea mays L.) from northern KwaZulu-Natal and southern Mozambique." *South African Journal of Botany* 74 (2): 190–196.

Goyal, A. 2010. "Information, Direct Access to Farmers, and Rural Market Performance in Central India." *American Economic Journal: Applied Economics* 2 (3): 22–45.

Hanna, R., S. Mullainathan, and J. Schwartzstein. 2014. "Learning through noticing: Theory and evidence from a field experiment." *The Quarterly Journal of Economics* 129 (3): 1311–1353.

Hasanain, S. A., M. Y. Khan, and A. Rezaee. 2023. "No bulls: Experimental evidence on the impact of veterinarian ratings in Pakistan." *Journal of Development Economics* 161: 102999.

Hoffmann, V., S. K. Mutiga, J. W. Harvey, R. J. Nelson, and M. G. Milgroom. 2021. "Observability of food safety losses in maize: evidence from Kenya." *Food Policy* 98: 101895.

Humphreys, M., R. S. De la Sierra, and P. Van der Windt. 2013. "Fishing, commitment, and communication: A proposal for comprehensive nonbinding research registration." *Political Analysis* 1–20.

Karlan, D., R. Osei, I. Osei-Akoto, and C. Udry. 2014. "Agricultural decisions after relaxing credit and risk constraints." *The Quarterly Journal of Economics* 129 (2): 597–652.

Lane, G., D. Schonholzer, and E. Kelley. 2022. "Information and Strategy in Lemon Markets: Improving Safety in Informal Transit."

Liang, K.-Y. and S. L. Zeger. 1986. "Longitudinal data analysis using generalized linear models." *Biometrika* 73 (1): 13–22.

Lin, W. 2013. "Agnostic notes on regression adjustments to experimental data: Reexamining Freedman's critique." .

Magruder, J. R. 2018. "An Assessment of Experimental Evidence on Agricultural Technology Adoption in Developing Countries." *Annual Review of Resource Economics* 10 (1): 299–316.

Michelson, H., A. Fairbairn, B. Ellison, A. Maertens, and V. Manyong. 2021. "Misperceived quality: Fertilizer in Tanzania." *Journal of Development Economics* 148: 102579.

Ministry of Agriculture, A. I. and Fisheries. 2018. *National Seed Policy*. Tech. rep.

Muralidharan, K., M. Romero, and K. Wüthrich. 2019. *Factorial designs, model selection, and (incorrect) inference in randomized experiments*. Tech. rep., National Bureau of Economic Research.

Reimers, I. and J. Waldfogel. 2021. "Digitization and pre-purchase information: the causal and welfare impacts of reviews and crowd ratings." *American Economic Review* 111 (6): 1944–71.

Suri, T. 2011. "Selection and comparative advantage in technology adoption." *Econometrica* 79 (1): 159–209.

Suri, T. and C. Udry. 2022. “Agricultural Technology in Africa.” *Journal of Economic Perspectives* 36 (1): 33–56.

Tilman, D., C. Balzer, J. Hill, and B. L. Befort. 2011. “Global food demand and the sustainable intensification of agriculture.” *Proceedings of the national academy of sciences* 108 (50): 20260–20264.

Tjernström, E., T. J. Lybbert, and M. Carter. 2016. “Counterfeit seed: Comparing genetic tests and germination rates to identify the prevalence and source of counterfeit maize seed in western Kenya.” *Working Paper* .

Tjernström, E., T. J. Lybbert, R. F. Hernández, and J. S. Correa. 2021. “Learning by (virtually) doing: experimentation and belief updating in smallholder agriculture.” *Journal of Economic Behavior & Organization* 189: 28–50.

Tripp, R. and D. Rohrbach. 2001. “Policies for African seed enterprise development.” *Food Policy* 26 (2): 147–161.

Wossen, T., K. A. Abay, and T. Abdoulaye. 2022. “Misperceiving and misreporting input quality: Implications for input use and productivity.” *Journal of Development Economics* 157: 102869.

A Appendix

A.1 Details about rating computations

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

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

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

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

A.2 Details about rating dissemination

Table 17: 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*?