Demand and supply factors constraining the emergence and sustainability of an efficient seed system: A proposal and pre-analysis plan

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Abstract

Agricultural technology remains under-adopted among smallholder farmers in Sub-Saharan Africa. We investigate how the quality of an agricultural technology – improved maize seed – affects its adoption. The research entails three hypotheses that will be tested in a series of randomized controlled trials among agro-input dealers and smallholder farmers in Uganda. In a first hypothesis, quality concerns that constrain uptake are caused by information inefficiencies at the level of the agro-input dealer, who is assumed to lack knowledge about proper storage and handling. An intensive training program is expected to increase improved maize seed quality and subsequent adoption by farmers. A second hypothesis conjectures that information asymmetry between seller and buyer with respect to the quality of seed

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– a classic lemons technology – leads to under-adoption. We implement a crowd-sourced information clearinghouse similar to yelp.com to test this hypothesis. This hypothesis targets the interaction between farmers and input dealers. A third hypothesis targets farmers directly, as sub-optimal adoption is assumed to be caused by learning failures: Farmers might attribute disappointing outcomes to poor input quality, while in reality many input dimensions like the time of planting, weeding and fertilizer application co-determine outcomes. An ICT-mediated information campaign that stresses the importance of paying attention to all input dimensions is implemented to test this hypothesis.

keywords: seed systems, information clearing house, learning failures, information, input quality, agricultural technology adoption

JEL codes: O13; Q12; Q16; D82; D83

1 Background

One of the most effective ways to increase agricultural productivity is through the adoption of improved agricultural technologies and practices. These include mechanization, but the Green Revolution has demonstrated that large gains can also be expected from improved inputs such as inorganic fertilizers and high yielding cultivars. Technology adoption remains lower than projected, particularly among the poor in sub-Saharan Africa (Gollin, Morris, and Byerlee, 2005). As a result, differences in yields between sub-Saharan Africa and areas that experienced a green revolution have nearly doubled since 1961 (Magruder, 2018). To reduce this yield gap, it is important to identify the drivers of, and constraints to, technology adoption.

In line with the general trend in economics, the drivers and constraints of agricultural technology have increasingly been studied using field experiments (de Janvry et al., 2016; De Janvry, Sadoulet, and Suri, 2017). For instance, the Agricultural Technology Adoption Initiative (ATAI), a collaboration between MIT's Abdul Latif Jameel Poverty Action Lab (J-PAL) and UC Berkeley's Center for Effective Global Action (CEGA) has funded a series of field experiments to illuminate what helps and hinders technology adoption among smallholder farmers. Key constraints identified include poor access to information (Ashraf, Giné, and Karlan, 2009), procrastination and time-inconsistent preferences (Duflo, Kremer, and Robinson, 2011), heterogeneity in the net benefits to the technology due to high transaction costs (Suri, 2011), the lack of access to insurance (Karlan et al., 2014), and learning failures (Hanna, Mullainathan, and Schwartzstein, 2014).

This study addresses quality considerations about the technology as a particular constraint to adoption, a topic that has received considerable attention recently (Bold et al., 2017; Michelson et al., 2018a). We specifically explore (perceived) quality of improved maize seed as a constraint to its adoption among a sample of smallholder maize farmers in Uganda. Maize is an important crop there, both for home consumption and as a source of income. While improved maize seeds are adopted to some extent, various factors constrain the further development and sustainability of an efficient Ugandan seed system. Recent studies argue that smallholder adoption of improved inputs in Uganda, and of improved maize seed in particular, is limited by farmers' beliefs that the inputs are of poor quality - counterfeited, adulterated, or otherwise non-performant (Bold et al., 2017; Ashour et al., 2019; Barriga and Fiala, 2020)). Our study will test interventions aimed at identifying the relative importance of potential sources of these (perceived) quality issues at different levels for agricultural technology adoption. It will bring to light the cognitive, economic and behavioral aspects that underlie under-adoption of these technologies.

2 Hypotheses

Seed quality, or the perception thereof, may arise at different stages in the seed supply chain. Poor seed quality may occur as a result of input dealer practices. This may be unintentional, for example poor handling and storage practices, or intentional, for instance by mixing poor quality seed with good quality seed to cut costs. The problem may also be situated at the level of the smallholder farmer. For instance, a farmer may lack confidence in the input dealer or his/her products, and the nature of the input may make it impossible for the farmer to assess the quality. It may also be that the farmer wrongly attributes poor outcomes caused by factors other than seed quality to seed quality. We test interventions at different stages in the seed supply chain to assess the relative importance of each potential cause for low demand for improved seed. The first intervention targets the input dealer, the second targets the interaction between the input dealer and the farmer, while last targets the farmer. Regardless of who is targeted by the intervention, we will assess changes in outcomes at both the input dealer level and at the level of the farmer.

H1: Seed is of poor quality due to poor handling and storage at the input dealer level.

Lack of information is pervasive in developing countries and often leads to sub-optimal outcomes for the rural poor. As a result, a simple piece of information can make a big difference (Duflo and Banerjee, 2011). Also in the context of agricultural technology adoption among smallholders, informational inefficiencies have been documented, and governments around the world invest in public agricultural advisory services to increase productivity in the sector (Anderson and Feder, 2004). Various studies look at knowledge gaps at the farmer level and the consequences on outcomes like technology adoption and production. For example, Van Campenhout, Spielman, and Lecoutere (2020) show that maize farmers in Uganda appear to benefit from information on available technologies and recommended agronomic practices. While the need for policies and interventions that strengthen input marketing capacity and infrastructure has been acknowledged decades ago (Tripp and Rohrbach, 2001), we find few examples of studies that look at knowledge gaps at the input dealer level.

The first hypothesis asserts that poor handling and storage at the level of the input dealer may lead to poor seed quality, in turn reducing the profitability of seeds at the farmer level, resulting in low adoption. There is indeed some evidence of input quality reduction at this level. In a comprehensive study of the seed supply chain in Uganda, Barriga and Fiala (2020) document various issues related to handling and storage that may reduce the quality of the input. For example, farmers often need smaller quantities that what is in the standard bags, and input dealers thus often repackage in smaller bags in sub-optimal environments. Poor rotation of seed stock and storage in open bags in moist conditions or in direct sunlight also reduce seed quality.

To test this hypothesis, an information treatment that consists of an intensive input dealer training to increase input dealer skills regarding seed handling and storage will be implemented. This is expected to improve seed quality, in turn reducing risk and increasing profitability at the level of the farmers. This will lead to more farmers adopting improved seed. It is important to note that this hypothesis implicitly assumes that the dealer is not aware of the fact that he or she sells poor quality seed. In other words, sales of poor quality seed is not intentional.

H2: Seed is of poor quality due to intentional adulteration at the input dealer level.

The second hypothesis focuses on information asymmetry between seed sellers and seed buyers. As argued in Bold et al. (2017), the market for seed in Uganda appears similar to the market for used cars as described in Akerlof's classic study (1970). In such a market, the quality of goods can degrade in cases where the quality is known by the seller, but not (yet) by the buyer. This problem can be solved by reducing information asymmetries between the two parties. While Uganda does regulate seed quality through seed certification processes and standards, this mechanism provides farmers with a relatively weak and unreliable indication of quality. Alternative mechanisms such as electronic verification systems have also been experimented with, but the cost of implementation has proven challenging, and they depend on the reliability of the underlying seed certification system. In our study, we will test an alternative, decentralized information clearing house that is based on crowd-sourced information and works through reputational mechanisms, much like yelp.com or tripadvisor.com.

While the previous intervention aims to reduce unintentional seed quality deterioration that is caused by lack of knowledge, the clearinghouse may also reduce instances where quality is reduce intentionally to increase profit. In Uganda, there are some indications that adulteration happens at some point in the seed value chain. Bold et al. (2017) find that hybrid maize seed contains less than 50% authentic seed, while Ashour et al. (2019) find that nearly one in three bottles of herbicide contains less than 75% of the labeled concentration of the active ingredient.

Information clearing house mechanisms have been studied to some extent, but mostly to address market price information asymmetry between smallholder farmers and middlemen. Assuming that middlemen are better informed about prevailing prices in the market than farmers, theory suggests that providing farmers with price information increases their bargaining power. However, evidence is mixed: while Goyal (2010) finds that internet kiosks that provided wholesale price information significantly increased soy prices in India, Fafchamps and Minten (2012) do not find a statistically significant effect of market information delivered to farmers' mobile phones by a commercial service called Reuters Market Light (RML) in a neighboring state.

A clearing house that relies on crowd-sourced ratings may be more effective to increase seed quality in the market. While prices can generally be observed reasonably easy, assessing an experience good such as seed is much harder. At the time of purchase, visual seed inspection is limited to seed purity and the presence of mold. Germination can only be assessed after planting. Some seed may also be more susceptible to pests and diseases, so the overall quality of seed can only be judged after harvest. Aggregation of the experience of many users may thus be a particular powerful way to reveal the quality of the product.

The study by Hasanain, Khan, and Rezaee (2019), who set up a rating system for public veterinary services in Pakistan, is probably the closest to ours. They find that farmers who use the clearinghouse enjoy a 25 percent higher success rate of artificial insemination. Their research suggests that this is mostly due to increased veterinarian effort, as few farmers seem to be switching from veterinaries that receive poor ratings to veterinaries that receive good ratings.

An information clearing house intervention may work through different impact pathways. First, farmers that do not buy improved seed may start buying when they see that the quality of the input dealer in their vicinity is better than expected (eg. above average). Furthermore, farmers may switch from low rated input dealers to higher rated input dealers. Furthermore, the clearing house could raise the input dealer's effort as he/she wants to improve his/her 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 such as regulating quality due to its likely lower cost, self-sustaining nature and scaleability, and helps to overcome problems such as insufficient public investment in regulatory systems, regulatory enforcement, and market surveillance.

H3: Seed is of good quality but farmers are unable to adequately learn about this quality.

In the context of new agricultural technology, production functions are not known. Farmers learn from own experience (Foster and Rosenzweig, 1995) as well as from observing the experience of others (Conley and Udry, 2010).

Learning involves an iterative process of forming and updating beliefs about yield or profit distributions. Many researchers have addressed how individuals process information and update beliefs when making repeated decisions (e.g. Camerer and Hua Ho, 1999). Barham et al. (2015) analyze how learning heuristics vary across farmers and how they affect technology adoption decisions. Gars and Ward (2019) test whether farmers' learning heterogeneity is a barrier to adoption. They find that even though Bayesian learning is well suited to learn about hybrid rice, it is also more cognitively demanding, such that only 25 percent of farmers can be characterized as pure Bayesian learners while 40 percent rely on first impressions. Present-biased learning and relying on first impressions is likely to hinder technology adoption.

Erroneous perceptions and false beliefs at the farmer level may complicate learning and affect technology uptake. For instance, high yielding varieties may be less resistant to particular pests and diseases or to droughts than local maize varieties that farmers in a particular area selected themselves over the course of centuries. Therefore, additional inputs such as pesticides, insecticides and irrigation may be needed to bring the seed to its full potential. Worse, farmers they may think that improved seed is a guarantee for higher yield and reduce management and use of other inputs. This may lead to disappointing yields, and farmers may erroneously attribute these low returns to poor input quality, which may lead to dis-adoption. The problem may thus be rooted in negative experiences which conflate low product quality with incorrect management practices and can be characterized as a learning failure. Consistent with this, Michelson et al. (2018b) find that fertilizers in Tanzania meet the requisite quality standards even though Tanzanian farmers persistently believe that the fertilizer they purchase from the market is adulterated.

In the present context, we hypothesize that there exists a particular learning constraint of interest. Because farmers must make decisions on a variety of input dimensions that interact in the production function - the time of planting, the amount and timing of water, the choice of technology, additional inputs such as fertilizer or pesticides and insecticides - they cannot easily learn about the quality of seed from their own or others' experience. A key remedy to this learning problem is information, but the availability of such information alone does not automatically guarantee learning. Limited attention to particular input dimension may necessitate interventions that highlight previously unattended-to relationships in the data (Allen et al., 2011; Hanna, Mullainathan, and Schwartzstein, 2014; Beaman, Magruder, and Robinson, 2014).

3 Experimental design

To test the three hypotheses, we will implement three interventions that are combined in a field experiment where various treatment and control groups are randomly assigned to either a treatment or control condition. The randomized control trial (RCT) will take the form of a 2^3 factorial design, with each intervention corresponding to one hypothesis. To test the first hypothesis, a random sub-sample of input dealers will receive training on proper seed handling and storage. To test the second hypothesis, a rating system will be set up among a random sub-sample catchment areas of input dealers catchment areas, and farmer and input dealers will receive feedback on the ratings before the start of the planting season. To test the third hypothesis, a video that points out the importance of combining improved seed with other inputs and careful crop management will be shown to a random subset of farmers. The treatments are further elaborated in Section 5. Impact will be judged by looking at outcomes both at the input dealer level (eg. investments in seed storage infrastructure, quantity of seed sold,...) as well as at the farmer level (eg. likelihood that farmer adopted improved seed, maize yields,...)[1].

Factorial designs allow recycling of treated units in the orthogonal factor to be used as controls. As such, to estimate main effects, less observations are needed than would be the case in parallel designs. The factorial design we will use deviates from commonly used factorial designs in that the experimental unit will differ depending on the factor. For the first two factors, corresponding to the input-dealer training and the information clearing house, randomization will happen at the level of the catchment area. For the third factor that address learning failures of farmers, randomization will happen at the level of the farmer.

The decision to randomize the first two interventions at the level of the catchment area instead of at the level of the input dealer has two main reasons. Often, input dealers are clustered in markets or trading centers with overlapping catchment areas. Randomization at the level of the input dealer prompted ethical concerns. For instance, it may be that one farmer gets assigned to the treatment group for the information clearing house and

[1]Except for the third intervention where we only look at effects at the level of the farmer

receive a good score, while his neighbor gets assigned to the control group of that particular treatment (and does not get scored). Farmers in the vicinity of the two input dealers farmers may be more inclined to switch to the dealer with that received the score, even though the services of the input dealer in the control group may be the same. While, in this case, the rating would lead to a competitive advantage for the farmer that got the score, the reverse may be true if the farmer gets a poor score. Delineating a catchment area based on overlapping areas that are served by the input dealers and randomizing at this level reduces this concern. While this is less of a concern for the first treatment, we were still worried that providing an intense training treatment to one input dealer but not to his or her immediate neighbor may be difficult in practice. So also for this treatment, catchment areas will be targeted.

The second reason why we decided to randomize at the catchment area level is because we also want to measure the effect of the first two treatments at the level of the farmer. For example, if we would randomize the input dealer training at dealer level, one dealer might be trained but his or her neighbor not. If we want to know if the dealer training leads to increased adoption of improved seed among farmers in the vicinity of an input dealer, we need to be able to connect each farmer unambiguously to each input dealer. We avoid this problem by randomizing at the catchment area level because then all dealers within that catchment area received the training (or not) and all farmers within that area are potential customers of only dealers who received the training (or not). A similar argument applies to the second treatment.

The resulting layout, with sample size indicated in each treatment cell (obtained through power calculations that are in Section 4) is illustrated in Figure 1. The first two interventions are implemented at the catchment area. A total of 112 catchment areas are included in the study. Half of these are randomly allocated to the first treatment: all input dealers in 56 catchment areas receive the input dealer training, while input dealers in the remaining 56 catchment areas function as the control for this treatment. Data that was collected in three of the study districts indicates that this corresponds to about 160 input dealers in each treatment arm. Orthogonal to the first factor, the second factor is placed, corresponding to the second treatment that is also implemented at the catchment area level. Also here, in half of the 112 catchment areas an information clearing house will be implemented, and half of the catchment areas will function as a control for this treatment. However, this will be done in such a way that balance with respect to the first treatment exists in both treatment and control groups for the second treatment. This means that the treatment group of the second treatment will consist of 28 catchment areas that received the first treatment an 28 catchment areas that function as the control for the first treatment. Similarly, for the control catchment areas for the second treatment, half will consist of catchment areas where input dealers received the input dealer training and half of catchment areas where input dealers did not get trained.

While the third treatment is implemented at the level of the farmer, it is also important to preserve balance in the orthogonal factors. In other words, we need to make sure that an equal number of farmers that are assigned to receive a treatment against learning failures are drawn from catchment areas where input dealers received training as from catchment areas where the input dealer training did not take place. Similarly, orthogonality should also be maintained for the second treatment. Therefore, in each of the four treatment cells formed by interacting the first two treatments, 400 farmers (10 farmers per input dealer or about 28 farmers per catchment area) will be randomly assigned to the third treatment while another 400 farmers will be assigned to the control.

4 Power Analysis Simulations

We used simulations to determine sample size for the experimental layout in Section 3. Simulation, where the experiment is run thousands of times and one simply counts how frequently the treatment comes up significant, provides a flexible and intuitive way to analyze power. Furthermore, instead of relying on a theoretical distribution for the outcome variables that takes assumptions and returns an analytic solution, simulations can sample from real data. In our case, we use survey data from about 80 input dealers that was collected in three districts in eastern Uganda in July 2019. Furthermore, we surveyed 1,500 farmers in the catchment areas of these 80 input dealers[2].

We will investigate both outcomes at the input dealer level and at the farmer level. We analyze power at the input dealer level first and consider two outcome variables: (i) the quantity of seed sold by the input dealer of the last season, and (ii) the reputation of the input dealer. The quantity of seed that the input dealer sold is a continuous variable (kilogram) with mean 325 and standard deviation 454. For the reputation outcome variable,

[2] The data was part of a survey of the maize value chain, and can be found here

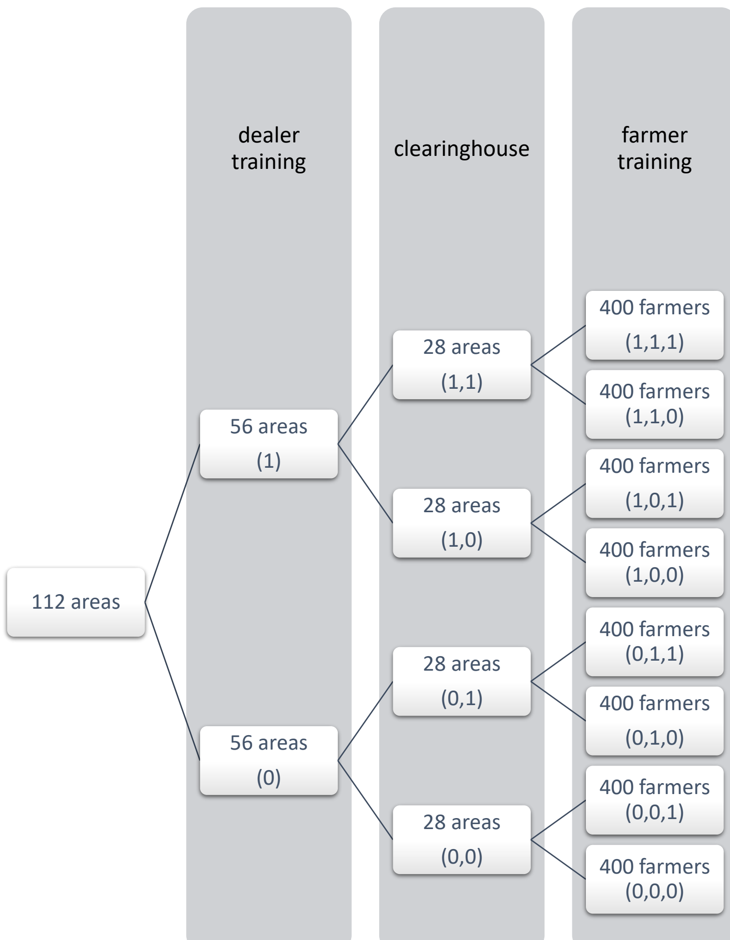

Figure 1: Design

farmers score the input dealers in their catchment areas on a scale from 1 to 5. A dealer's reputation is then calculated as the average of those scores and treated as a continuous variable. The mean reputation of an input dealer in the sample is 3.68 and the standard deviation is 0.61.

Assignment of the input dealers to catchment areas is done on the basis of geographical location. Using GPS coordinates of the input dealers, the halversine function is used to construct an adjacency matrix, and input dealers that are less than 5 kilometer apart are grouped into a single catchment area. The 5 kilometer threshold was selected based on visual inspection on the map, the size of an average village and reported distance between farmer and input dealers. This procedure resulted into 68 input dealers being distributed over 24 catchment areas. A catchment area has thus on average 2.8 input dealer, with a minimum of 1 and a maximum of 6.

We also need to assume a treatment effect size for the interventions that will be implemented at the catchment area. As we did not immediately find credible studies that evaluated the impact of catchment area level interventions on quantity sold nor reputation, we decided to define expected treatment effect size in terms of cohen's d, settling for a size that is between small and medium, of 0.35 times the standard deviation. For quantity sold, this means 159 kilogram, while for reputation the minimal detectable effect size becomes 0.21.

To determine sample size (defined in terms of the number of catchment areas for the first two treatments), the algorithm iterates over different candidate sample sizes (eg from 75 catchment areas up to 125 catchment areas with increments of 5 catchment areas). For each candidate sample size, a random sample with replacement is drawn from the survey data. This sample is then used to run a number (eg 1000) of simulations of the experiment. In particular, for each simulation, all input dealers that are in half of the catchment areas are assigned to the treatment condition and the other half to the control condition. To the outcome of interest that are assigned to the treatment condition, the assumed effect is added and the analysis is conducted. In our case, we are interested in the average treatment effect, so we simply regress the outcome on a treatment indicator and record if the coefficient on the treatment indicator is significant at the 5 percent level. Finally, we determine how often, out the total number of simulations, we were able to detect the effect at the 5 percent significance level. This will give us the power associated to that particular candidate sample size. Power can then be plotted against sample size to obtain power curves.

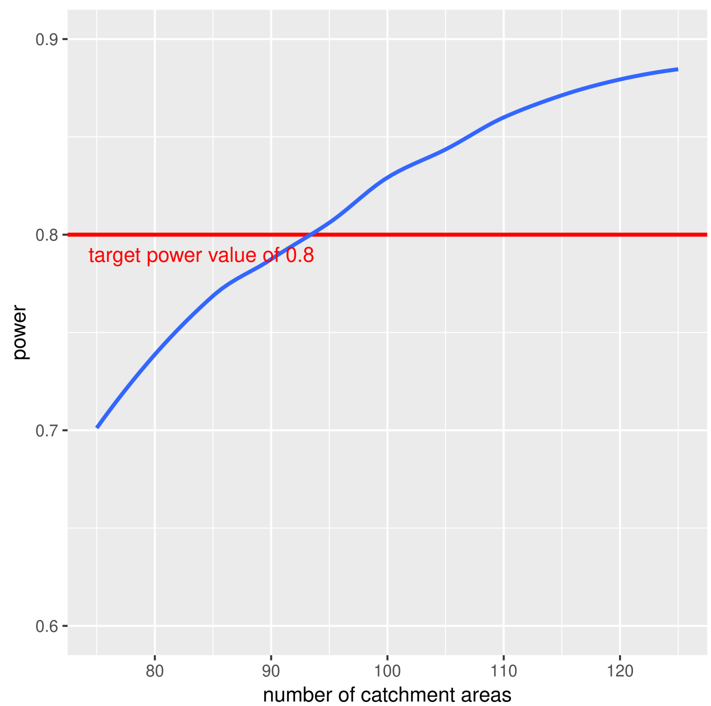

Figure 2: Power analysis simulations for quantity sold

Figure 2 looks at power levels for different sample sizes (in terms of number of catchment areas included in the study) to detect an increase of 159 kilogram of improved seed sold by the input dealer at the 5 percent significance level. If the number of catchment areas is larger than 93, we hit the 80 percent power threshold. These 93 catchment areas correspond to about 263 input dealers.

In Figure 3, we show how power increases when more catchment areas are included in the study if we want to detect a 0.21 increase in the reputation of the input dealers. If the number of catchment areas is larger than 112, our experiments will return statistically significant results 80 percent of the time. This corresponds to about 318 input dealers.

Once we have decided on how many catchment areas (and associated input dealers) are necessary to detect effects at the level of the input dealer, we need to determine how many farmers we need to sample from these catchment areas to identify impact of the interventions on that level. To make sure we have sufficient farmers to score each input dealer, we will allocate a

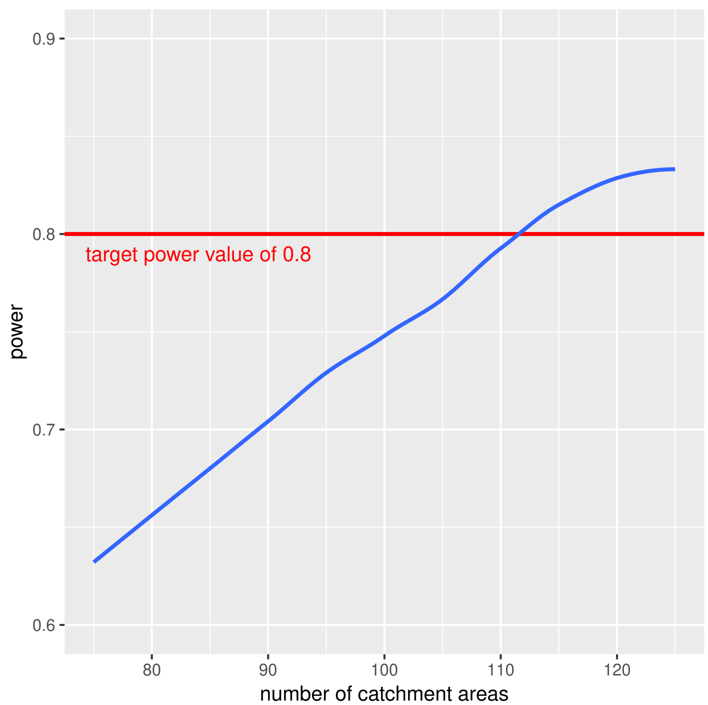

Figure 3: Power analysis simulations for reputation

fixed number of farmers to each input dealer. This may mean that we have slightly differing numbers of farmers in the different treatment groups, as the randomization happened at the catchment area. While this may reduce power somewhat, this does not bias impact estimates.

We again use simulation to determine the number of farmers per input dealers. As we already determined the minimum number of catchment areas (and corresponding input dealers), we fix the number of catchment areas at this number (we will take the most conservative estimate obtained above, namely 112 catchment areas or 318 input dealers). We then iterate over different candidate sample sizes of farmers per input dealer (ranging from only one farmer per input dealer, which would lead to a total sample size of 318 farmers, to 25 farmers per input dealer, which would lead to a sample size of almost 8,000 farmers). The resulting sample in each iterations is used to run a number (eg 1000) of simulations of the experiment. For each simulation, all farmers that are in the catchment area of input dealers that are in half of the catchment areas are assigned to the treatment condition and all other farmers are assigned the control condition. To the farmer level outcome of interest of farmers that are assigned to the treatment condition in this way, the assumed effect is added and the analysis is conducted. We again determine how often, out the total number of simulations, we were able to detect the effect at the 5 percent significance level, which will give us the power associated to that iteration.

We consider three variables at the level of the farmer: yield, input use and seed quality (based on the score that farmers give to the seed). Maize yield per acre is a continuous variable with a mean of 541 kilogram per acre and a standard deviation of 412 kilogram per acre. Van Campenhout, Spielman, and Lecoutere (2020) find a treatment effect of 10.5 percent when they investigated the effectiveness of videos as means of delivering information on input use and improved maize management practices to farmers. Using a similar effect size, Figure 4 shows that we need at least 15 farmers per input dealer, which would result in a total sample size of 4,770 farmers.

Another outcome variable of interest is input use, i.e. the adoption of improved maize seed, a binary variable. In our data, 63 percent of farmers adopt improved seed and the standard deviation is 0.48. Van Campenhout, Spielman, and Lecoutere (2020) find an effect of 0.065 percentage points of videos to deliver information on fertilizer use. If we assume a similar effect size, Figure 5 suggests we need at least 4 farmers per input dealer. This would result in a sample 1,272 farmers.

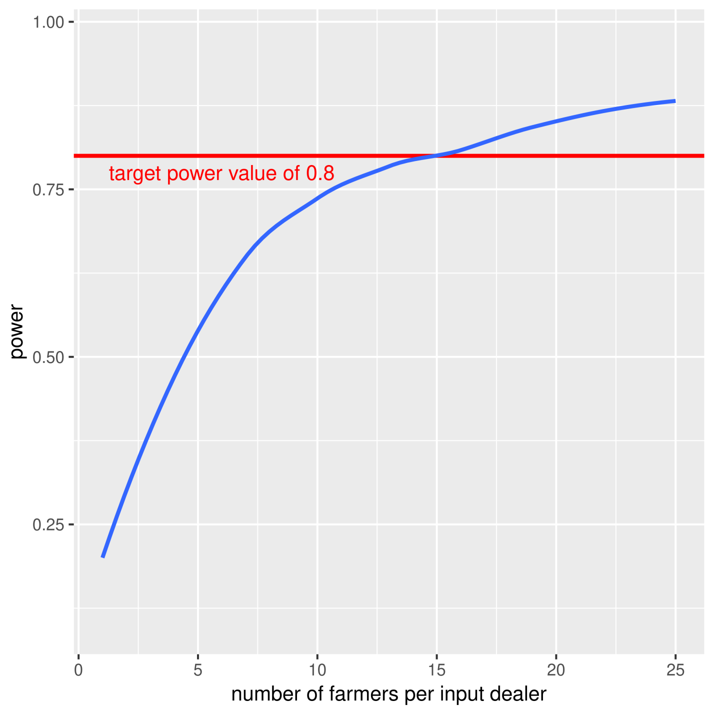

Figure 4: Power analysis simulations for yield

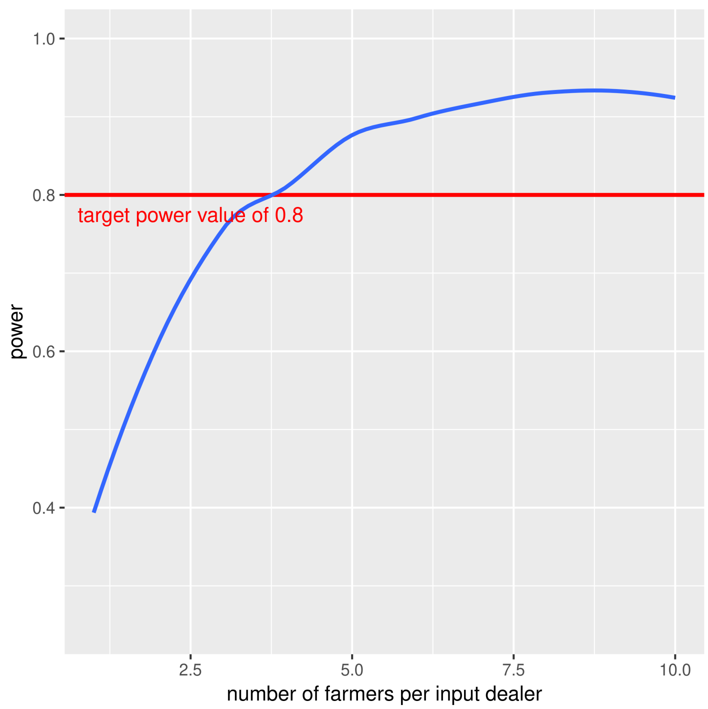

Figure 5: Power analysis simulations for input use

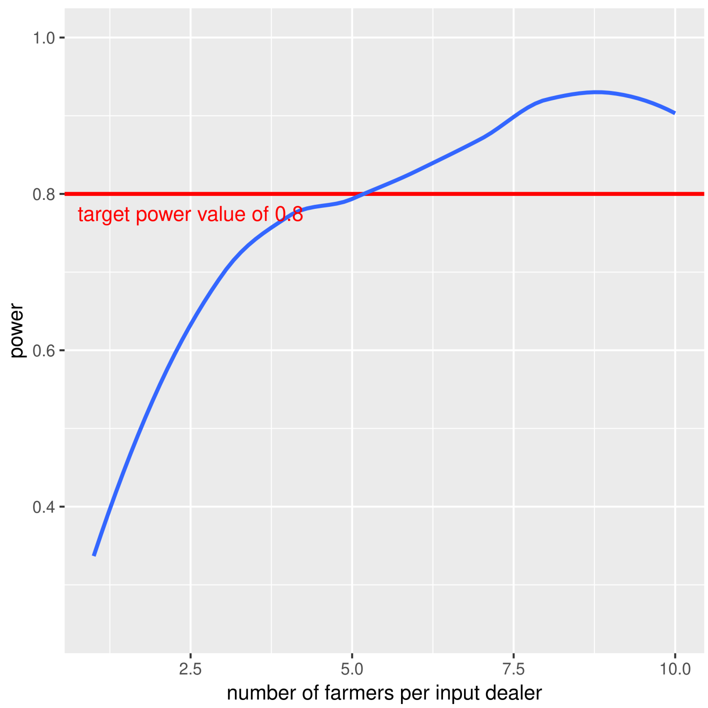

Figure 6: Power analysis simulations for seed quality

The last outcome we consider in our power analysis is the quality of seed assessed by farmers. The initial quality score from 1 to 5 is transformed into a binary variable with a mean of 0.26 and a standard deviation of 0.44. We assume a small effect in terms of Cohen's d (0.2 times the standard deviation or 0.088 percentage points). Given this assumption, Figure 6 shows we need at least 5 farmers per input dealer, corresponding to a total sample size of almost 1,600 farmers.

We conclude that we need at least 15 farmers per input dealer to detect effect sizes similar to the ones Van Campenhout, Spielman, and Lecoutere (2020) found. Ideally, the total number of farmers that need to be included in the study is thus 4,770. However, finding impact on yields is hard, as this is an outcome that is pretty far down the causal impact chain. Yields also show high variability. Finally, our project is mainly concerned with increasing seed quality as an intermediary to increase yield. As such, more direct outcomes such as input use and quality are of primary interest. Further considering financial constraints and logistics, we decided to collect information on 10 farmers per input dealer, leading to a sample size of 3,200 households.

5 Interventions

This section provides a detailed description of the three interventions that will be implemented.

I1: Input dealer training on seed handling and storage

Poor seed storage may lead to poor seed quality. Bold et al. (2017) suggest repacking and open air storage of bags is an reason for low quality of hybrid seed. Storage practices also affect moisture levels that in turn affect the occurrence of storage fungi, which become active in seeds when moisture is above 14 percent (Govender, Aveling, and Kritzinger, 2008). Barriga and Fiala (2020) believe that temperature control after the seed leaves the breeders is crucial, too. Inventory carryover and long shelf live further reduce quality.

Content

To determine the content of the seed storage and handling training packages and make sure it is locally anchored, we will consult experts from the Ugandan ministry of agriculture, from the seed sector and from input dealer associations in Uganda prior to the experiment. In particular, semi structured interviews will be organized with experts of these different institutions (a list can be found in the Appendix). We will ask them about their opinion on the importance of properly handling and storing seed. We then ask them to go into detail on the different dimensions that input dealers need to pay attention to. Interviewers can probe (repackaging, open air storage, moisture levels and temperature control, direct light (UV),...) if the interviewee is hesitant. We will also ask what they think input dealers are doing wrong. We then ask them to rank the different dimensions that they feel input dealers need to pay more attention to. This information will then be process and function as our knowledge base for designing training materials.

Training material

Based on the information collected, we will develop detailed training manuals that he trainers are expected to adhere to. We will also create visually appealing posters to mount in the shop, and handouts with pictograms showing the most important best practices that can be given to input dealers. Information will be kept as simple as possible, as Bertrand et al. (2010) find a strong positive effect of displaying fewer example loans on outcomes, indicating that presenting recipients with larger menus can trigger choice avoidance and/or deliberation such that the information transfer becomes less effective.

Training the trainers

Updating handling and storage practices can be bothersome and related investments can be risky. That is why we have to safeguard that the treated dealers experience the training as a reliable, credible, and trustworthy source of information, and understand its relevance. The social proximity of the trainer may matter. We will therefore train "lead input dealers" which are educated and hence regarded as experts but also close to the target population, a person dealers can relate to.

We will coach about 10 trainers. This coaching will take place in one of the IFPRI office spaces in Kampala and take one week. It will be held in Lusoga/English. An expert will teach the previously defined content as well as the methods to pass on this information. The lead input dealers will also practice the training, discuss and comment, ask questions and receive feedback from their peers. This way we hope to create trainers with competence and a good approach to teaching. At the end of this train-the-trainer week, we will ask all participants for feedback, so that we can further improve the subsequent dealer training. Trainers will also receive a fee.

Training the input dealers

The district's input dealer training will take place in a location that is easily reachable for all sampled dealers within the district. Dealers will be invited a month beforehand via telephone. To ensure that all input dealers come, they will be reminded via SMS a week and a day beforehand, lunch and a monetary compensation for their time will be provided. They will also be compensated for transport and their accommodation will be provided for.

The trainers will explain the correct handling and storage practices for improved maize seed and the main advantages and challenges to a group of 15 input dealers. This presentation will take half a day. The trainers will use the previously mentioned poster that illustrates the best practices in a easily understandable and appealing way. Afterwards they will supervise the dealers rehearsing the more challenging practices in small groups, ensuring that every dealer practices at least once. The presentation and exercises are followed by a discussion where questions can be asked and concerns can be raised. Trainers will react to the comments and requests. At the end of the training, all dealers will be asked to answer a couple of multiple choice questions. They will be informed about this quiz at the beginning of the training, which might motivate them to pay closer attention. They will also receive a handout which shows the most important best practices and can be taken to and eventually hung in their store.

Timing

Prior to the intervention, we will collect baseline data in September 2020. The input dealer training will take place in towards the end of 2020 such that the dealers can use the newly trained handling and storage practices on the seeds that are going to be purchased by farmers for the first agricultural season that begins in March 2021. At midline in July 2021, we expect input dealers to be more skilled and knowledgeable regarding seed handling and storage. Due to the better handling and storage, we expect seed quality to improve and hence, we expect farmers to have higher maize yields/revenues/profits and to perceive seed quality as higher and input dealers as better. We expect these positive experiences from the first agricultural season to lead to higher seed adoption and volume/value of input dealers' seed sales in the second agricultural season of 2021. We expect the increased adoption to result in even higher maize yields/revenues/profits for farmers after the second season. Those outcomes will be measured at end line in December 2021. The timeline is illustrated in Figure 7.

I2: Information clearinghouse

Input dealer ratings

To measure seed quality and dealer effort/service and to subsequently disseminate this information to farmers, we will set up an information clearinghouse. Prior to the intervention, we will collect baseline data of randomly selected farmers in catchment areas of the input dealers that are enrolled in the study. During this baseline interview, we will ask farmers to rate input dealers in their catchment area on a number of characteristics (see Appendix 2). To

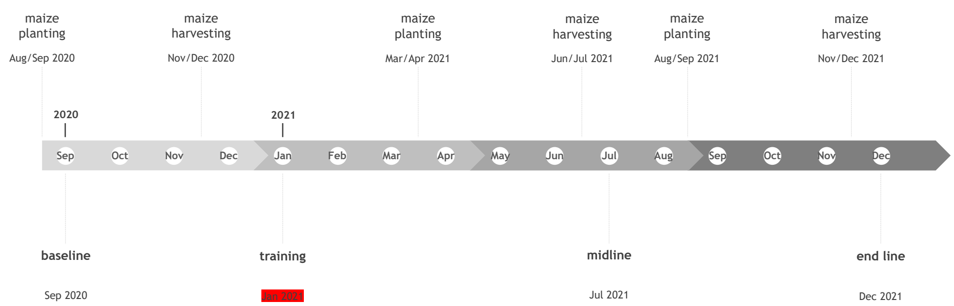

Figure 7: Input dealer training timeline

make sure we are talking about the same input dealer, we can use detailed location data, names under which they may be known in the community, and also pictures of the shop which were collected during a census (See Section 7 below). This information will be pre-loaded onto the tablet computers and the relevant input dealers will show up during the interview.

Baseline data will be collected in September or October 2020. At this point, farmers may be better able to assess attributes such as price and input dealer services, but they will only able to judge seed quality itself based on germination. Therefore, we collect ratings from farmers a second time in December 2020 or January 2021 when harvesting was done. After observing yields, farmers may have updated their beliefs with respect to eg. the resistance of the seeds against pests. This data for the second rating will be collected via mobile phone. This will also increase the number of data points that can be used per input dealer to base his or her score on. Based on the farmers' responses of all farmers in the catchment area, we will compute a score for each dealer, as well as an overall score.

Disseminating clearinghouse information

The first distribution of input dealer ratings to farmers and input dealers will happen in February 2021. In the treated catchment areas, farmers will be provided with information on all input dealers within that area. These farmers will receive a list with all dealers in their proximity containing their overall and specific ratings. The overall and specific ratings will be illustrated in a way that is also understandable for farmers that are not experienced with interpreting numbers: we will use symbols like smileys/emoticons/stars/thumbsup/down signs. A score that is better than 75% is colored in green, a score worse than 25% in red and everything else in yellow to further improve understanding. Input dealers will receive their own general and specific ratings, and the overall average rating. They will not receive the ratings of their competitors.

Second rating, second distribution and third rating

A third round of input dealer scores will be collected via mobile phone in April 2021, immediately after maize for the first season of 2021 was planted. In July 2021, enumerators will revisit farmers for the midline survey and collect the fourth dealer scores in person. The third and fourth scores form the second rating which will be distributed in August 2021 to farmers and input dealers. Finally, in the second agricultural season of 2021, the fifth dealer scores will be collected by phone and the sixth dealer scores as part of the end line data collection, in September and in December, respectively. The fifth and the sixth scores result in the third rating, which is a post-treatment outcome variable. Knowing that the clearinghouse will remain in place for some time will motivate dealers to change their behaviour.

I3: Addressing learning failures at the farmer level

While sowing improved seed should lead to higher yields than sowing traditional seed, it also often requires more inputs and management. Farmers may be unaware of these requirements, or may even believe that they have purchased “miracle” seed, and as a result actually reduce complementary inputs and provide less effort. Foster and Rosenzweig (1995) find for example that imperfect knowledge about the management of improved seed is a significant barrier to adoption. This may lead to disappointing yields, and farmers may erroneously attribute these disappointing yields to the poor quality of

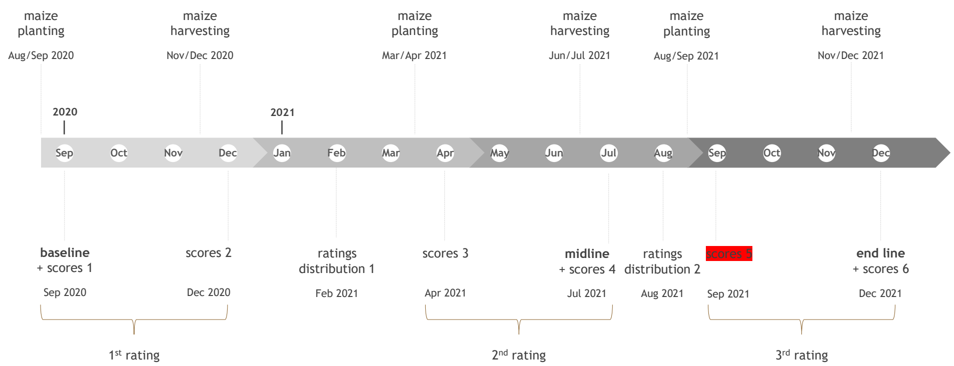

Figure 8: Information clearinghouse timeline

inputs, which may reduce subsequent technology adoption. Farmers conflating low product quality with incorrect practices can be characterized as a learning failure. Learning is important in this context because production functions, yield and profit distributions are not known but learned from one's own experience, as well as from observing the experience of others (Foster and Rosenzweig, 1995; Conley and Udry, 2010).

Our intervention addresses a particular learning constraint: Farmers need to decide on a variety of factors that might affect yield - the time of planting, the amount and timing of water, the choice of technology - and observe only the end result, making it hard for them to learn about a particular input or practice from their own or others' experience. Our intervention promotes a holistic approach, focusing on creating conditions for optimal performance of improved seed. By trying to keep complimentary inputs and management practices fixed, farmers may be able to distinguish disappointing yields due to poor input quality from disappointing yields due to wrong handling and storage. They will not conflate low product quality with incorrect practices anymore and be able to learn about the quality of seed from their own experience.

Although the access to information is important for learning, providing information on the existence and use of the new technology alone does not guarantee learning (Allen et al., 2011; Hanna, Mullainathan, and Schwartzstein, 2014). This may partly explain the mixed track record of conventional agricultural extension (Waddington et al., 2014). According to Hanna, Mullainathan, and Schwartzstein (2014), extension may not lead to (long term) adoption because farmers may fail to notice important features of the data. A recent article by Liang and Mu (2019) shows that sufficient complementary information needs to be available, as otherwise it is impossible to learn about confounding variables.

Content

Similar to how the content for the input dealer seed storage and handling training was determined, we will consult experts from the Ugandan ministry of agriculture, from the seed sector and from input dealer associations in Uganda prior to the experiment. Also here, semi structured interviews will be organized with experts of these different institutions (a list can be found in the Appendix). We will ask them about their opinion on the importance of creating a conducive environment for seed. We then ask them to go into detail on the different dimensions that farmers that use improved seed need to pay attention to. Interviewers can probe (irrigation, seed spacing and seed rates, weeding, fertilizer application,...) if the interviewee is hesitant. We will also ask what they think input dealers are doing wrong and ask them to rank the different dimensions that they feel are most effective. We will combine this information with agronomic studies that test different input combinations in field trials. This information will then be used to produce.

Training material

This intervention will rely on short, visually appealing videos, shown to the farmers on tablet computers. Video's featuring role models have been found effective in changing people's behaviour in a range of applications (Riley et al., 2017; Van Campenhout, Spielman, and Lecoutere, 2020; Vandevelde, Van Campenhout, and Walukano, 2018; Bernard et al., 2015). A script will be written and a professional video producer will be engaged.

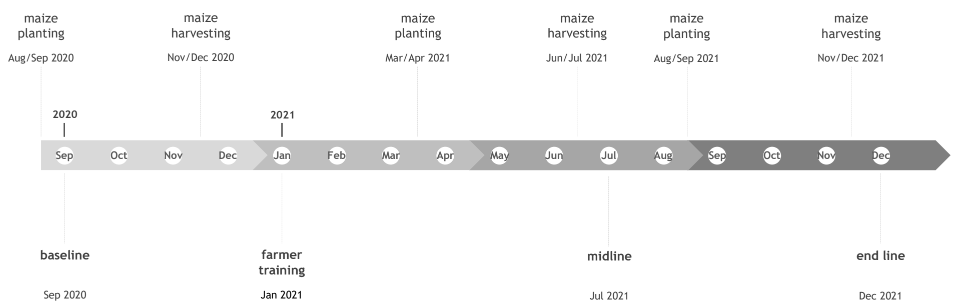

Figure 9: Farmer training timeline

Timing

Prior to the intervention, we will collect baseline data in September 2020. The farmer training will take place in January 2021 so that the farmers can use the newly trained handling and storage practices in the first agricultural season that begins in March 2021. At midline in July 2021, we expect farmers to be better able to judge the importance of seed quality and of combining inputs and proper management. As a result, we expect farmers to have higher maize yields and to perceive seed quality as higher and input dealers as better (conditional on input dealers providing good quality seed). We expect these positive experiences from the first agricultural season to lead to higher seed adoption in the second agricultural season of 2021. We expect the increased adoption to result in even higher maize yields for farmers after the second season. Those outcomes will be measured at end line in December 2021.

6 Methodology

Due to the randomized assignment to treatment and control groups, simply comparing outcome variable means of treatment and control farmers and input dealers provides unbiased estimates of the effect of the interventions on the outcomes of interest. To increase power, we condition the estimates on baseline values of the outcome variables.

For the first two interventions that happen at the catchment area level, we look at impact both at the input dealer level and at the farmer level. We estimate the following specification using ordinary least-squares (OLS) to get the average treatment effects (ATE) of our interventions:

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

where Y_{1ij} is the outcome variable for input dealer/farmer i in catchment area j at end line, 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 all the interactions between the different orthogonal catchment area level treatments in the factorial design (Muralidharan, Romero, and Wüthrich, 2019), and ε_{ij} is an input dealer/farmer-specific error term. The coefficient β is our estimated ATE for the treatment under consideration.

At the last intervention, where randomization happened at the farmer level, we estimate a similar equation:

$$Y_{1ij} = \alpha + \beta T_i + \gamma' X_{ij} + \delta Y_{0ij} + \varepsilon_{ij} \tag{2}$$

The only difference with Equation 1 is that the T_i is now a dummy for the treatment status of farmer i.

Throughout the study, we will use randomization inference for consistently estimating standard errors in our finite sample. In general, we will use two-tailed tests and traditional confidence thresholds of 10, 5 and 1 percent.

Because we will test for treatment effects on a range of outcomes measures, we will deal with multiple outcomes and multiple hypotheses testing by means of two approaches. Firstly, we follow a method proposed by Anderson (2008) and aggregate different outcome measures within each domain into single summary indices. Each index is computed as a weighted mean of the standardized values of the outcome variables. The weights of this efficient generalized least squares estimator are calculated to maximize the amount of information captured in the index by giving less weight to outcomes that are highly correlated with each other. Combining outcomes in indices is a common strategy to guard against over-rejection of the null hypothesis due to multiple inference. However, it may also be interesting to see the effect of the intervention on individual outcomes. An alternative strategy to deal with the multiple comparisons problem is to adjustment the significance levels to control the Family Wise Error Rates (FWER). We used re-randomization to construct the joint null distribution for the family of outcomes we are testing. From this family-wise sharp null, we obtained the corresponding FWER-consistent significance thresholds by determining which cutoffs yield 10 percent, five percent and one percent significant hypothesis tests across all tests and simulations (Ottoboni et al., 2021; Caughey, Dafoe, and Seawright, 2017).

7 Sample and data

This section describes the samples to be used in the study. Our samples will include input dealers located in trading centers and villages (key market sheds) as well as maize farmers that are located in the catchment areas of these market sheds. The input dealer sample is obtained by including all input dealers of 11 districts in Busoga. These input dealers will be listed during a census. After the census, dealers will be assigned to a particular catchment area. Dealers that are less than 5 km apart are assigned to the same catchment area. This final list of catchment areas will then be used for the allocation of the first treatments according to the design in Figure 1. The assignment will be done using a computer algorithm.

We will also randomly sample a fixed number of farmers in the catchment area of each input dealer, again defined as 5 kilometer circumference. As farmers need to be able to submit and receive ratings over mobile phone, we will restrict our sample to maize growing households that have access to a phone. Sampling will be done by drawing concentric circles around the input dealer 500 meters apart and dropping pins at a random location of the circle. Enumerators will be sent to these GPS coordinates and are instructed to interview the closest household that meets the inclusion criteria.

For some outcomes, details at plot level will be needed (for instance, seed spacing and seed rate). However, farmers often have more than one plot. As outcomes on different plots within the same household are likely to be strongly correlated and the interventions are assigned at a higher level, it may not be cost effective to survey all plots. An unbiased estimate of the outcome at the household level can be obtained by randomly selecting one plot. To do so, we ask enumerators to first list all plots, with names to which farmers refer to the plots (eg. home plot, irrigated plot, plot near the sugar cane factory,...). The ODK program then randomly selects one plot for which detailed questions are asked.

We will measure the key outcomes of interest before and after the treatments, so that we can assess the treatment effects of the three interventions. The baseline survey will be conducted before the first agricultural season of 2021. The interventions will be carried out before the first agricultural season of 2021. To assess their impact, end line data will be collected after the second agricultural season of 2021. The baseline and endline surveys will constitute the key sources of data for the study. We will collect information on a range of outcome indicators at the level of the input dealer. The key outcomes of interest include information on input dealer skill/knowledge, farmers' seed quality perception, farmers' input dealer perception, farmers' seed adoption, input dealers' volume/value/price of seed sales, number/share of farmers switching input dealers, input dealer's effort, farmer skill/knowledge, maize yield/revenue.

8 Variables

In this section, we register the variables that will be used in the study.

8.1 Baseline variables for balance

To test balance, the following variables will be compared at baseline:

- age of the household head (years)
- head as finished primary education? (1 is yes)
- gender of the household head (1 is male)
- household size
- has used improved seed on any plot in the last season (1 is yes)
- has used fertilizer (inorganic or organic) on any plot in the last season (1 is yes)
- has purchased improved seed from input dealer in the last year (1 is yes)

- maize yields in the last season (total estimated production/estimated area allocated to maize production)
- distance to closest input dealer
- input dealer rating score

8.2 Outcomes variables

To identify the steps along the causal chain, we specify the following key outcomes of interest and how we will measure them as specific as possible:

- input dealer skill/knowledge
  - input dealer skill/knowledge, as measured by a question on the input dealer baseline/end line questionnaire which asks whether the input dealer feels skilled/knowlegable/confident regarding the handling and storage of seed e.g. Do you feel skilled regarding the handling and storage of seed?
  - input dealer skill/knowledge, as measured by questions on the input dealer baseline/end line questionnaire which ask about the input dealers' seed handling and storage e.g. Do you store seed in the open air?
  - input dealer skill/knowledge, as measured by questions on the input dealer baseline/end line questionnaire which ask about the input dealers' knowledge regarding seed handling and storage e.g. Do you think it is ok to store seed in the open air?
  - input dealer skill/knowledge, as measured by questions on the enumerator baseline/end line questionnaire which ask to decribe the input dealers' seed handling and storage as observed during a visit e.g. Is seed stored in the open air?
- farmers' seed quality perception
  - farmers' seed quality perception, as measured by a question on the farmer baseline/end line questionnaire which asks to give the seed which the farmer uses (improved maize seed/farmer-saved maize seed/maize seed exchanged between farmers) a ranking from 1 (low quality) to 5 (high quality)

  - farmers' satisfaction with the seed, as measured by a question on the farmer baseline/end line questionnaire which asks how satisfied the farmer is with the seed he/she uses (improved maize seed/farmer-saved maize seed/maize seed exchanged between farmers) by ranking from 1 (not satisfied) to 5 (very satisfied)

- farmers' input dealer perception
  - input dealer quality perception, as measured by a question on the farmer baseline/end line questionnaire which asks to give the input dealer a ranking from 1 (low quality) to 5 (high quality)
  - satisfaction with the input dealer, as measured by a question on the farmer baseline/end line questionnaire which asks how satisfied the farmer is with the input dealer by means of a ranking from 1 (not satisfied) to 5 (very satisfied)

- farmers' seed adoption
  - percentage of farmers reporting to be using quality maize seed on at least one plot during the last maize growing season
  - percentage of farmers reporting to be using improved varieties (hybrid or OPV) on at least one plot during the last maize growing season
  - percentage of farmers reporting to be using hybrid or OPV maize seed bought at an input dealers shop on at least one plot during the last maize growing season
  - percentage of farmers reporting to be using farmer-saved (recycled) maize seed, on at least one plot during the last maize growing season
  - number/share of farmers using maize seed exchanged between farmers, as measured by a question on the farmer baseline/end line questionnaire which asks whether the farmer currently uses maize seed exchanged between farmers or not
  - volume/value/price of seed sales, as measured by a question on the input dealer baseline/end line questionnaire which asks how much seed they sold in this agricultural season and for which price

- input dealers' volume/value of different varieties of maize seed sales, as measured by a question on the input dealer baseline/end line questionnaire which asks how much seed they sold in this agricultural season and for which price
- number/share of farmers switching to an input dealer with a higher ranking, as measured by a question on the farmer baseline/end line questionnaire which ask the farmer for the input dealer of his/her latest seed purchase, combined with data on ratings of the two dealers in case the farmers has changed input dealers
- input dealer's effort, as measured by the difference between farmers' input dealer perception (see above) before and after the treatment
- farmer skill/knowledge
  - farmer skill/knowledge, as measured by a question on the farmer baseline/end line questionnaire which asks whether the farmer feels skilled/knowlegable/confident regarding the handling of improved maize seed e.g. Do you feel skilled regarding the handling of improved maize seed?
  - farmer skill/knowledge, as measured by questions on the farmer baseline/end line questionnaire which ask about the farmers' seed handling e.g. When and how much do you irrigate?
  - farmer skill/knowledge, as measured by questions on the farmer baseline/end line questionnaire which ask about the farmers' knowledge regarding seed handling e.g. What is the ideal amount and timing of irrigation?
  - farmer skill/knowledge, as measured by questions on the enumerator baseline/end line questionnaire which ask to decribe the farmers' seed handling and storage as observed during a visit e.g. When and how much does the farmer irrigate?
- maize yield/revenue/profit
  - maize yield, as measured by a question on the baseline/end line questionnaire which asks how much maize yield the farmer had in this agricultural season

- revenue, as measured by a question on the baseline/end line questionnaire which asks how much renenue from maize the farmer had in this agricultural season
- profit , as measured by a question on the baseline/end line questionnaire which asks how much profit from maize the farmer had in this agricultural season

8.3 Variable construction

For continuous variables, 5 percent trimmed values will be used to reduce influence of outliers (2.5 percent trimming at each side of the distribution). Inverse hyperbolic sine transforms will be used if skewness exceeds 1.96. Trimming will always be done on end results. For instance, if the outcome is yield at the plot level, then production will first be divided by plot area, after which inverse hyperbolic sine is taken and the end result is trimmed. Outcomes for which 95 percent of observations have the same value within the relevant sample will be omitted from the analysis and will not be included in any indicators or hypothesis tests.

8.4 Missing variables

When we field our surveys, some respondents will not answer one or more questions that measure an outcome. We will handle missing variables from survey questions by checking whether item non-response is correlated with treatment status, and if it is, construct bounds for our treatment estimates that are robust to this. To be more precise, we will assess the relationship between missing outcomes and treatment assignment using a hypothesis test and report these results. If $p<.05$ for the assessment of the relationship between treatment and missing outcomes, we will report an extreme value bounds analysis in which we set all of the missing outcomes for treatment to the (block) maximum and all missing outcomes for control to the (block) minimum. If $p \geq 0.5$ for the assessment of the relationship between treatment and missing outcomes, we will impute the missing outcomes using the mean of the assignment-by-block subcategory.

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Appendix: List of actors that will be interviewed to determine seed handling and storage trainings

1. National Crop Resources Research Institute (NaCRRI): Names of persons interviewed ____

2. seed companies: multiply seed (using foundation seed farms/contract growers), not licensed as breeders but can hire breeders to supervise & oversee, obtain breeder/foundation seed from research station/National Agricultural Research Organization/Center for Crop Resource Genetic, can have several seed company outlets

3. distribution network (company outlets, wholesalers, retailers): pack and sell company-produced/labeled seed to farmers

4. breeder: authorized with variety development, release, variety maintenance, producing foundation seeds (usually from National Agricultural Research Organization/universities/research institutes)

5. wholesaler: licensed to bulk & sell commercial seed classes from seed growers, categorized as seed grower/vendor, consist of seed companies, usually registered under Uganda National Agro-Input Dealers Association

6. retailers: licensed to distribute/sell seeds of different classes, categorized as seed merchants, usually agro dealers, consist of seed companies, licensed under the Uganda National Agro-Input Dealers Association

7. company retail outlet: seed company shops, categorized as seed vendors/growers, authorized to sell seed classes from the branded company/other seed companies but without rebranding, company factory gate/company warehouse sells seeds at production site

8. foundation seed farms

9. contract growers/seed growers

10. research station/research institutes

11. National Agricultural Research Organization

12. Center for Crop Resource Genetic
13. universities
14. Uganda National Agro-Input Dealers Association
15. seed vendor
16. seed merchants (agro dealers)

Appendix 2: questions used to rate input dealers

based on the following questions :

"Please rate your/an input dealer on a scale from one to five on the following attributes:

1. Location – close to clients, in a convenient location? (1 extremely inaccessible – 5 very good location and access)
2. !!! Price – competitive pricing, discounts? (1 way too expensive, 5 extremely cheap)
3. !!! Quality of seed – good products, no fake seed (1 very poor quality-often fake, 5 excellent quality)
4. !!! Stock – availability of seeds at all time (1 always out of stock and sells in only large quantities, 5 always has stock and accepts to sell in smaller quantities)
5. Reputation – others are recommending him (1. they think is a lousy agro-dealer, 5. they think it is an excellent agro-dealer)
6. (If there is a problem with the seed, can you carry the seed back and get a refund (insurance)?)
7. (Does this agro-input dealer give you credit, i.e. gives you seed (or inputs more in general) that you can pay for later (after harvest))
8. (Does this agro-input dealer train you on how to use improved seed varieties)

9. (Does this agro-input dealer deliver seeds? If yes, how long does it take?)
10. (Does this agro-input dealer offer after-sales service?)
11. (Does this agro-input dealer offer different payment methods?)
12. (Does this agro-input dealer pack seeds well?)
13. (For how long have you been a customer of this input dealer?)
14. (Does the price of this agro-input dealer fluctuate a lot?)