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

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May 4, 2021

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 clearinghouse, 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 the 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 than 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 the 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 clearinghouse 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 clearinghouse 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 clearinghouse 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 clearinghouse 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. In addition, the clearinghouse 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, 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 villages. 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,...).

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 clearinghouse, 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 village[1].

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

[1]The main motivation to randomize at the village level is to eliminate potential spillover effects for the third treatment. However, as we will discuss later, we make sure there is correspondence between villages and input dealers, which would allow us to also look at the impact of the farmer training treatment on outcomes at the input dealer level. However, at that level, spillovers may affect results.

with overlapping catchment areas. Randomization at the level of the input dealer prompted ethical concerns. For instance, it may be that one dealer gets assigned to the treatment group for the information clearinghouse and receive a good rating, while his/her neighbor gets assigned to the control group of that particular treatment (and does not get rated). Farmers in the vicinity of the two input dealers farmers may be more inclined to switch to the dealer with that received the rating, 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 dealer that got the rating, the reverse may be true if the dealer gets a poor rating. 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 sizes indicated in each treatment cell (obtained through power calculations that can be found in Section 4) is illustrated in Figure 1. The first two interventions are implemented at the catchment area level. 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 clearinghouse 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 and 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 village, it is also important to preserve balance in the orthogonal factors. In other words, we need to make sure that an equal number of villages 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, 40 villages (347 villages in 130 catchment areas, ie. 2,67 villages per catchment area, so that 14 areas correspond to 37,37 villages) will be randomly assigned to the third treatment while another 40 villages 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 were 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

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

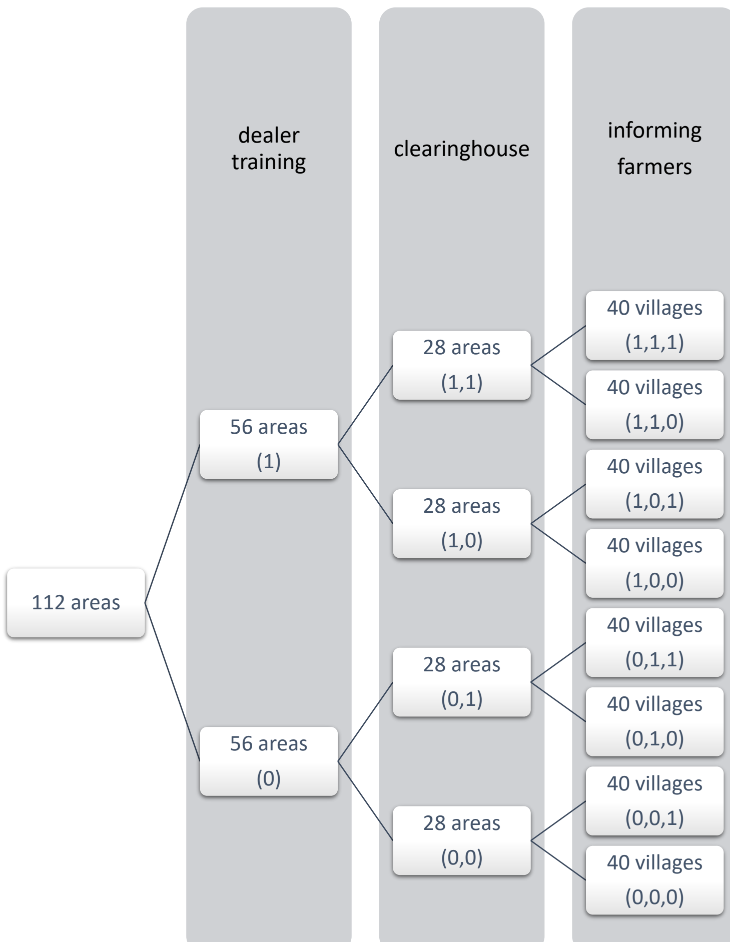

Figure 1: Design

two outcome variables: (i) the quantity of seed sold by the input dealer in 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, farmers rate 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 ratings 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 of the map, the size of an average village and reported distance between farmers and input dealers. This procedure resulted in 68 input dealers being distributed over 24 catchment areas. In the data we used for power simulations, a catchment area has thus on average 2.8 input dealers, 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 level. 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 outcomes 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 coeffi-

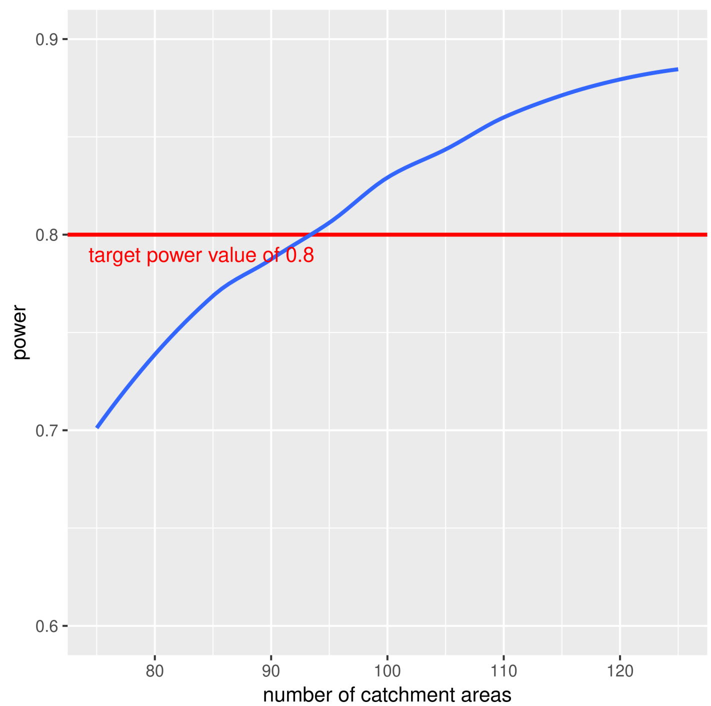

Figure 2: Power analysis simulations for quantity sold

cient on the treatment indicator is significant at the 5 percent level. Finally, we determine how often, out of 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 with that particular candidate sample size. Power can then be plotted against sample size to obtain power curves.

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.

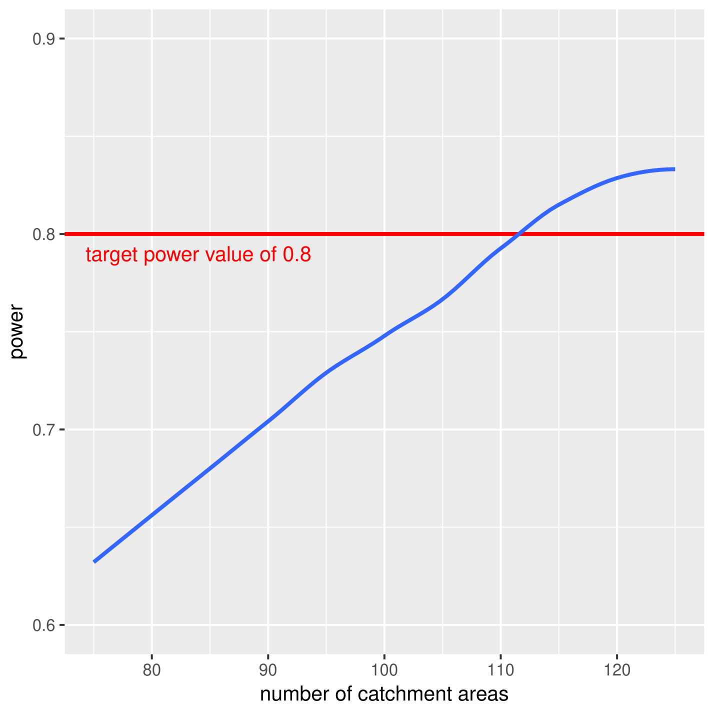

Figure 3: Power analysis simulations for reputation

Once we have decided 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 rate each input dealer, we will allocate a 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 dealer. 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 to the control condition. To the farmer level outcomes of interest 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 of 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 rating 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, ie. the adoption of improved maize seed, a binary variable. In our data, 63 percent of farmers

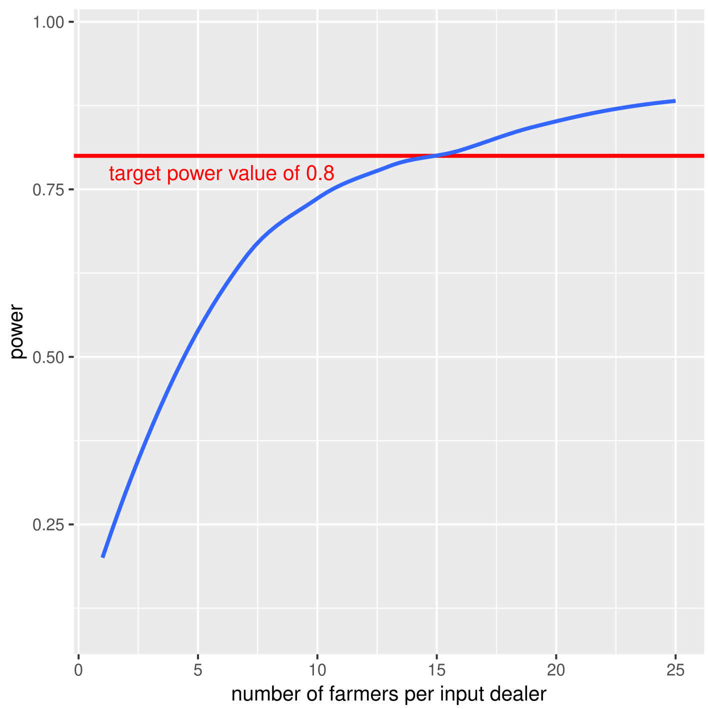

Figure 4: Power analysis simulations for yield

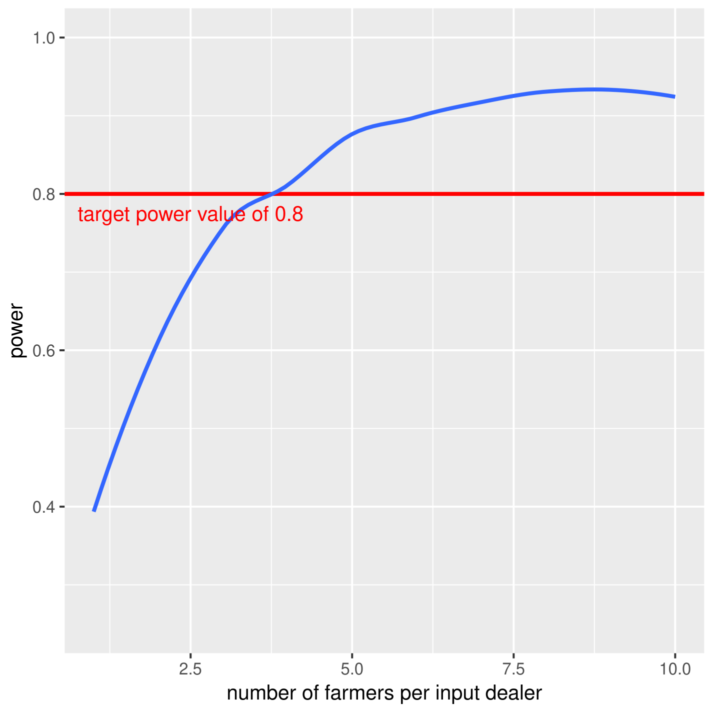

Figure 5: Power analysis simulations for input use

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 of 1,272 farmers.

The last outcome we consider in our power analysis is the quality of seed assessed by farmers. The initial quality rating 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

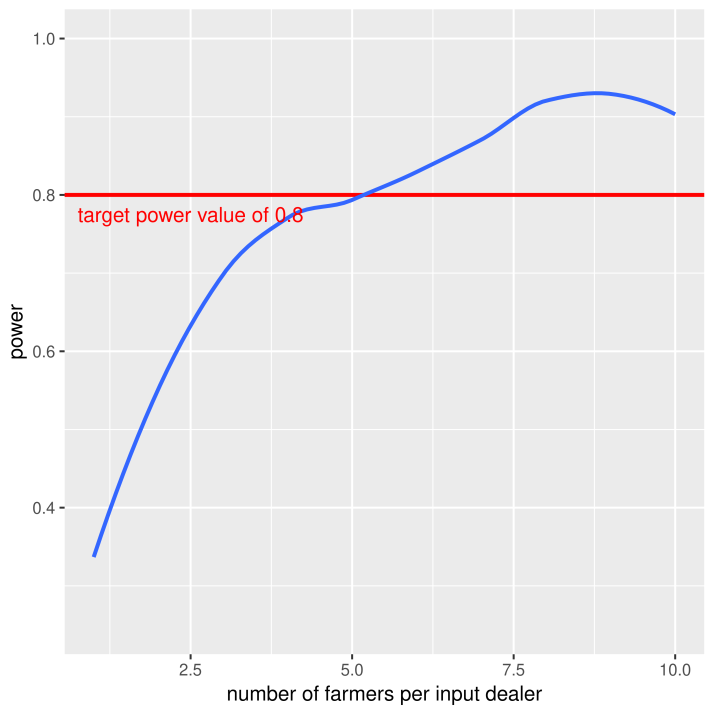

Figure 6: Power analysis simulations for seed quality

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 a 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 life further reduce quality.

During qualitative data collection, we learn that input dealers repackage seed to sizes/quantities convenient and affordable to smallholder farmers who may not afford buying seed in sizes/quantities packed by seed companies. This is very common with OPVs whose packaging come in sizes of at least 5kg. During repackaging however, input dealers pack seed in bad material which affect seed quality. For example, they repack seed in air tight polyethylene bags (Buveera) which affect aeration yet seed is a living material that requires fresh air to breath. This practice consequently results into seed losing viability in a very short time. A lot of information which can help track seed quality is also lost during repackaging. Such information include seed expiry date, variety name, and lot number.

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. A consultation workshop will be organized in Bugiri and a series of semi structured interviews will be organized with experts of different institutions and organizations. This information will then be process and function as our knowledge base for designing training materials.

During the workshop or the semi-structured interviews, the facilitator will keep the focus on “seed storage and handling”. First, the problems are identified by determining input dealers typically do wrong in terms of seed storage and handling, leading to farmers ending up with sub-optimal seed quality. These problems will also be ranked (Which of these problems are most common? What do almost all input dealers do wrong? Which problems are less common?). In a next step, solutions are associated to each of the problems (What should input dealers do to rectify the problem? What are the recommended storage and handling practices?). The solutions are also ranked in terms of effectiveness.

Training material and trainings

Based on the information collected, we will develop detailed training manuals that the trainers are expected to adhere to. We will also create visually appealing posters showing the most important best practices that will be given to input dealers to mount in their shop. 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.

The training will be implemented by three trainers, one from ISSD, one from UNADA, and one consultant . It will take place in a location that is easily reachable for all sampled attendants within the catchment area. For each treated shop, we will invite the shop owner (who is able to invest and eg. buy manual air conditioning systems which are important for the ventilation of the shop) and the shop attendant (who is in charge of day to day activities like storing the seed correctly). They will be invited one week beforehand via telephone. To ensure that all invited attendants come, they will be compensated for transport (both, owner and attendant will be compensated) and lunch and drinks will be provided. As an additional incentive, we will hand out one free seed moisture meter per shop. Futhermore, the training will take place at a time when dealers are not busy with their daily business because farmers have already bought their inputs for the first agricultural season but did not start buying inputs for the second agricultural season, yet (May 2021).

Our trainers will explain the correct handling and storage practices for improved maize seed and the main advantages and challenges. 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 dealer baseline data in September/October 2020 and farmer baseline data in April 2021. The input dealer training will take place in May 2021, late enough so that dealers are not busy with selling for the first agricultural season but early enough so that dealers can use the newly trained handling and storage practices on the seeds they buy in June/July 2021, which are going to be purchased by farmers for the second agricultural season that begins in August 2021. At midline in January 2022, 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 second agricultural season 2021 to lead to higher seed adoption and volume/value of input dealers' seed sales in the first agricultural season of 2022. We expect the increased adoption to result in even higher maize yields/revenues/profits for farmers after the first season. Those outcomes will be measured at end line in August 2021. The timeline is illustrated in Figure 7.

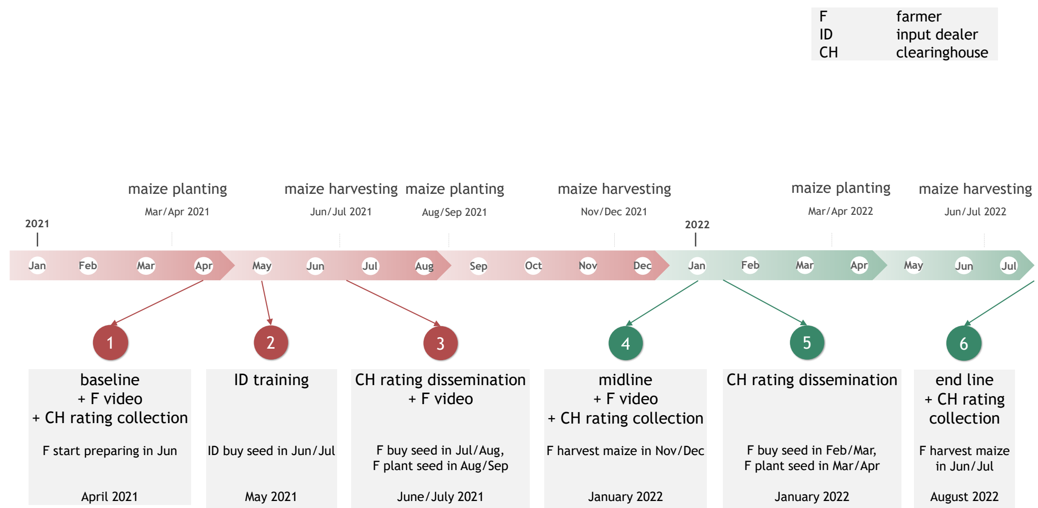

Figure 7: Timeline

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 farmers in randomly selected 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 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.

Farmer baseline data including farmers' ratings of dealers will be collected in April 2021. At this point, farmers will be able to assess attributes such as price, input dealer services, seed quality itself based on germination and observing yields, the resistance of the seeds against pests etc. Based on the responses of all farmers in the catchment area, we will compute the ratings for each dealer.

Disseminating clearinghouse information

The first rating dissemination, ie. the first distribution of input dealer ratings to farmers and input dealers, will happen in June/July 2021 because farmers buy seed in July/August. In the treated catchment areas, farmers will be provided with information on all input dealers within that area. These farmers will be presented a list with all dealers in their proximity containing the ranking of these dealers. This way is also understandable for farmers that are not experienced with interpreting numbers. Input dealers will receive their own general and specific ratings. They will not receive the ratings of their competitors. Input dealers will also get a certificate to display the ratings on their store front, similar to a "certificate of excellence" of trip-advisor.

Second rating, second dissemination and third rating

A second round of input dealer ratings will be collected during midline data collection in January 2022, after farmers harvested in November/December and the second season of 2021 is over. Enumerators will revisit farmers for the midline survey and collect the second dealer ratings in person. The second clearinghouse rating will be disseminated to farmers and input dealers later in January 2022 because farmers buy seed in Feburary/March and plant seed in March/April. Finally, after the first agricultural season of 2022, the third dealer ratings will be collected as part of the end line data collection in August 2022, because farmers harvest maize in June/July. The third rating is a post-treatment outcome variable. Knowing that the clearinghouse will remain in place for some time will motivate dealers to change their behaviour. The timeline is illustrated in Figure 7.

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 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, a consultative workshop and semi structured interviews will be organized with experts of different institutions and organizations.

The aim here is to gather information to help develop a video to be shown to farmers that shows what complementary inputs and practices are important to create an enabling environment for improved seed to flourish. The facilitator should now keep focus on the use of improved varieties and try to avoid capturing general practices and inputs, but particularly inputs and practices that are important in combination with improved seed. In particular, experts are asked to identify what may result in farmers getting lower than expected yields from improved seed varieties. Problems may often be formulated as an absence of management (eg. when using improved seed, more weeding needs to be done and farmers do not do that). The problems also need to be ranked. Experts are also asked to reflect on specific seed varieties that are common in the area as each seed is different, and so recommended complementary inputs and practices may differ by seed. In a next step, solutions are identified (also for each seed specific). This information will then be used to produce a script for the video.

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. A treatment and a control video will be produced, both show best seed management practices. The only difference is one piece of information, namely that this seed management is especially important when using improved seed.

Timing

Prior to the intervention, we will collect dealer and farmer baseline data. Right after the farmer baseline data collection in April 2021, we will show the treatment and control videos because farmers start preparing the second season in June. It is cost effective that the videos are shown right after the surveys, as we have to visit the 3200 farmers in our sample anyway. We will however show the videos to farmers a second time in June/July 2021, so that they are reminded of the best practices and can use the newly learned information in the second agricultural season that begins in August 2021.

Mind that farmers plant seed in August/September. At midline in January 2022, we will show the videos to farmers again as a reminder but we already 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 second agricultural season 2021 to lead to higher seed adoption in the first agricultural season of 2022. We expect the increased adoption to result in even higher maize yields for farmers after this season. Those outcomes will be measured at end line in August 2022. The timeline is illustrated in Figure 7.

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 village 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 village 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 outcome 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 adjust 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 that we will do ourselves so that we will have a list. 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 a village connected to each input dealer. This will be done by asking every dealer from which village most his/her customers from. If this village was already named by another dealer, the village with the second most customers will be chosen. Enumerators will be sent to these villages and are instructed to randomly sample a fixed number of households that meet 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 farmers use to refer to these 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 dealer baseline survey will be conducted in September and October 2020, the farmer baseline survey in April 2021, both before the second agricultural season of 2021. The interventions will be carried out before the second agricultural season of 2021. To assess their impact, midline data will be collected after the second agricultural season of 2021, and end line data will be collected after the first agricultural season of 2022. The baseline, midline 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 can be found in the next section.

8 Variables

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

8.1 Baseline variables for balance

Standard orthogonality tables will be included in the report. At each outcome level (farmer and input dealer), we pre-register 10 variables. Half of these are characteristics that are less likely to be affected by the intervention, while the other 5 are picked from the primary and secondary outcomes listed in the next subsection. To test balance at the level of the *farmer*, the following variables will be compared at baseline:

1. age of household head - years (q14)
2. household head has finished primary education - 1 is yes (q17)
3. gender of household head - 1 is male (q15)
4. household size - number of people in household/that eats in house on a regular basis (including interviewee) (q18)
5. distance of homestead to nearest agro-input shop selling maize seed - km (q10)
6. has used quality maize seed on any plot in last season - 1 is yes (q25a)
7. thinks that maize seed that you can buy at agro-input dealer is counterfeit/adulterated - 1 is yes (q25h)
8. has bought quality maize seed from agro-input shop for any plot in last season - 1 is yes (q25a, q25b aggregated at household level)
9. quantity of quality maize seed bought from an input dealer in last season - kg (q25d)
10. maize yields on a randomly chosen plot in last season - production/size of plot (q29, q50, q51) (intercropping was not taken into account because if maize is intercropped, it is almost always the main crop, so that there are equal numbers of maize crops on intercropped and not intercropped plots)

To test balance at the level of the *input dealer*, the following variables will be compared at baseline:

1. age of person interviewed (most knowledgeable person) - years (age)

2. gender of person interviewed (most knowledgeable person) - 1 is male (gender)

3. person interviewed (most knowledgeable person) has finished primary education - 1 is yes (educ)

4. number of years business has been in operation (today - year business was founded) (q8)

5. distance of shop to nearest tarmac road - km (q3)

6. number of customers buying something related to agriculture on average day during week (q6)

7. quantity of quality maize seed sold during last season - kg (q25, q37, q50, q62)

8. quantity of seed that was lost/wasted during last season - kg (q27, q39, q52, q64)

9. someone who works in this store received a training on handling and storage of maize seed - 1 is yes (q10)

10. person interviewed knows how to repackage seed in a proper way (in paper bags/perforated polyethylene bags) - 1 is yes (q105)

8.2 Primary outcome variables

The ultimate objective of this study is to see how the interventions increase technology adoption and ultimately well-being of the actors involved. At the level of the input dealer, we pre-register 7 primary outcomes, aimed at measuring increased seed sales both at the extensive (total sales) and intensive (sales per customer) margins:

1. quantity of quality maize seed sold in last agricultural season (derived from quantities of different varieties of maize sold) - kilograms (q25, q37, q50, q62)

2. price of quality maize seed sold in last agricultural season (derived from prices of different varieties of maize sold) - Ugandan shilling per kilogram (q26, q38, q51, q63)

3. seed related revenue: price of quality maize seed sold*quantity of quality maize seed sold - Ugandan shilling (q25*q26, q37*q38, q50*q51, q62*q63)

4. number of customers that bought seed from shop in last season (q7)

5. moisture content of one bag of seed (q2-reading)

6. index of seed handling and storage practices (based on q69 - q80, q82, q83, q90, q92, q121, q122)

7. index of dealer service/effort (based on q85 - q98)

At the farmer level, we also pre-register 7 primary outcomes, again evaluating the interventions at the extensive and intensive margins. We will also look at production and yield, but we do not pre-register these as key outcomes as we did not power the experiment to pick up the kind of effects that are identified in other studies (see section 4).

1. *purchased* quality maize seed in last season for any plot - 1 is yes (q25a, q25b aggregated at household level)

2. bought quality maize seed from agro-input shop for any plot in last season - 1 is yes (q25a, q25b aggregated at household level)

3. quantity of quality maize seed bought from an input dealer in last season - kg (q25d)

4. index of seed quality perception: average ratings of maize seed of all input dealers in catchment area (q68, q69 aggregated at household level)

5. index of dealer (effort) perception (q68b-q68f, q70-q76)

6. share of farmers switching to different dealers (q67)

7. index of farmers practices: interaction between adoption on that plot (q31, (q32)) and farmers' practices on that plot (q40-q49)

Indices are constructed following (Anderson, 2008) as also indicated in Section 6.

8.3 Secondary outcome variables

To identify the steps along the causal chain, we pre-register a range of secondary outcomes. At the level of the input dealer, we start by investigating changes in skills and knowledge, particularly related to seed handling and storage. This will be done through 10 multiple choice questions. Each multiple choice question will have 3 possible answers from which the input dealer can choose (there will also be a "don't know" option).

- How long can seed be carried over before losing viability? (q104)
- How should seed best be stored after repackaging? (q105)
- What is the minimum recommended distance between the floor and where seed is stored? (q106)
- How should seed ideally be stored in your store room? (q107)
- What statement do you agree most with? (q108)
  - You should repackage all your seed to visually verify that you are selling good quality seed.
  - You should repackages all your seed so you can sell more to small farmers.
  - You should avoid repackaging your seed as much as possible.
- If a farmer complains about poor soil, which of the following 3 seed varieties do you recommend? (q109)
- How often can OPVs be recycled without significant yield loss? (q110)
- What do you tell clients who inquire about the yield benefits of hybrid seed? (q111)
- If a farmer misses the rains or lives in areas that receive little rain, what variety of maize do your recommend? (q112)
- When a farmer is late for planting in the short season and needs fast maturing variety, which maize do you recommend? (q113)
- What is the most important determinant in deciding which seed to buy and how much? (q84)

Another set of key outcomes is related to seed variety stock and turn over. We start with establishing how many improved seed varieties were stocked during the second season of 2020 (nr_var, q19, q44). We then iterate over the two most important hybrid seeds that are generally sold in the area (Longe 10H, Longe 7H). We will ask for each seed variety:

- How much was carried forward from the previous season (first season 2020) into the second season of 2020 (kg) (q21)
- How much was bought by you from any provider during the second season of 2020 (in kg) (q22)
- From whom did you as a agro-input dealer directly buy in the second season of 2020? (q23)
- What was the cost from where you obtained it during the second season of 2020? (per kg) (q24)
- Total quantity sold over the second season of 2020 (kg) (q25)
- Sales price per kilogram at the beginning of the second season of 2020 (q26)
- How much was lost/wasted the second season of 2020 (kg) (q27)
- Did you ever run out of this during the second season of 2020 (ie. did you have to disappoint clients) (q29)
  - Estimate how often you ran out of stock during the second season of 2020 (q30)
  - How long (days) did it on average take to get restocked during the second season of 2020 (days) (q31)

The same questions will be repeated for the two most commonly traded Open Pollinated Varieties (Longe 4 and Longe 5).

We will also buy one bag of Longe 10H (the most common hybrid). On the basis of this, we will:

- test moisture content (see primary outcomes) (q2-reading)
- record production date indicated on package (q3b-date_pack)

- Is the bag airtight without any signs of damage? (q4-origin)
- Does it have a certification sticker from inspection agency? (q5-cert)
- Does packaging have a Lot number? (q6-lot)
- Does packaging have e-verification? (q7-verif)

Enumerators are also asked to inspect the area where seed is stored. Here, we will check:

- Temperature (q70)
- Is seed stored in a dedicated area, away from other merchandize? (q69)
- Are there any noticeable pests (insects, rats)? (q71)
- Is the roof leak proof? (q72)
- Is the roof insulated to keep heat out? (q73)
- Are the walls insulated to keep heat out? (q74)
- Is the area ventilated? (q75)
- Are the walls plastered? (q76)
- Material of floor (q77)
- Lighting conditions (q78)
- On what surface is seed stored? (q79)
- Do you see maize seed that is stored in open bags? (q80)
- Do you see any official certificates displayed (eg. that the shop was inspected, that the owner attended trainings or that the business is registered with some association) (q81)
- On a scale of 1 to 5, rate this shop in terms of cleanness and professionalism (q82)

The interventions may also lead input dealers to voluntarily expose themselves to increased scrutiny to signal to farmers that they deliver quality products. We thus also ask about membership of business associations:

- Is this business registered as a seed dealer with UNADA (Uganda National Agro-input Dealers Association)? (q114)
- Does this business have a trading license issued by local government? (q115)
- Is this business a member of any other professional association? (q116)
- How often were you inspected by DAO/MAAIF last year (q117)
- Have you ever received a warning as a result of inspection if something was not up to standard? (q118)
- Has some of your produce ever been confiscated after inspection? (q119)
- Has this business ever been closed down due to quality issues after inspection? (q120)
- Do you have equipment to monitor moisture in the seed? (q121)
- Do you monitor temperature in your seed store? (q122)

We will look a range of outcomes related to services offered by the dealer/the effort of the dealer:

- What do you do with seed that has exceeded shelf live (expired)? (q83)
- What is the most important determinant in deciding which seed to buy and how much? (q84)
- When farmers buy seed, do you explain how the seed should be used? (q85)
- When farmers buy seed, do you usually recommend complementary inputs? (q86)
- Do you offer extension/training to your clients on how to use improved seed varieties? (q87)
- Did you offer discounts to clients that buy large quantities of maize seed during the second season of 2020? (q88)

- What is that smallest package of improved seed that you stocked during this season (without repackaging)? (q89)
- Do you repackage seed yourself when clients want smaller packages than what the seed comes in? (q90)
- Do you charge more per kg if customers only want to buy 1 kg? (q91)
- When repackaging seed, do you keep track of expiry date (eg. include it in the bag/write it on the bag)? (q92)
- Do you provide seed on credit (pay after harvest)? (q93)
  - Give an estimate of how many people you gave credit since last season. (q94)
  - How many of these were women? (q95).
- Since last season, did you receive any complaint from a customer that seed you sold was not good? What did you do? (q96, q96b)
- What payment modalities do you accept? (q97)
- Do you deliver seeds to the premises of farmers? (q98)

Finally, we ask input dealers to rate themselves on the following attributes:

- Location – are you located close to clients, in a convenient location? (q99)
- Price – are you competitively priced? (q100)
- Quality of produce, seed in particular – do you sell good products, no fake seed? (q101)
- Stock – is seed available at all time and in the quantities that customers want? (q102)
- Reputation – are others recommending you? (q103)

At the level of the *farmer*, we will also look at knowledge. However, as the intervention aimed at farmers is less about creating new knowledge and more about changing false beliefs, we ask fewer questions, and questions that are more open ended and are only asked in the endline questionnaire to avoid priming effects.

- Is good seed handling/management less, equally, or more important when using quality maize seed like OPV or hybrid seed?
- Please indicate what applies for weeding including removing striga when you are using hybrid seeds.
- Please indicate what applies for fertilizer application when you are using hybrid seeds.
- Where to best plant your improved seed?
- How to invest your money?
- If you want to be a successful farmer, what is the best spacing and number of seeds per hill you should use for your maize?

Additional questions are asked to learn about possible impact pathways:

- What is the most important reason you didn't buy improved maize seed at the agro-input shop during the last season? (q25f)
- What is the most important reason you bought improved maize seed at that particular agro-input shop during the last season? (q25f_2)
- Why was the seed at agro-input shops not of good quality during the last season? (q25g)
- Do you think that maize seed that you can buy at agro-input dealer is counterfeit/adulterated? (q25h)
- enumerator: Ask the farmer to mention as many improved maize varieties that they are aware of. (q26)

The farmer level questionnaire has a set of questions about all the input dealers that are in the catchment area of the farmer. As this is part of the information clearinghouse treatment, this module is only administered to households in catchment areas that are assigned to the clearinghouse treatment. We start by asking:

- Do you know this input dealer? (q64)
- Have you ever bought seed from this input dealer? (q65)

- For how long have you been a customer of this input dealer? (q65b)
- Do you know anyone who ever bought seed from this input dealer? (q66)

We then ask farmers to provide ratings similar to the self-rating of input dealers:

- General quality (q68a)
- Location – close to clients, in a convenient location? (q68b)
- Price – competitive pricing, discounts? (q68c)
- Quality of seed – good products, no fake seed? (q68d)
- Stock – availability of seeds at all time? (q68e)
- Reputation – others are recommending him? (q68f)

We then ask farmers to provide ratings of input dealers' maize seed:

- Does the seed that the agro input dealer sell is generally considered of good quality? (q69a)
- Does the seed that this input dealer sells normally leads to yields as advertised? (q69b)
- Is the seed that this input dealer sells as drought tolerant as advertised? (q69c)
- Is the seed that this input dealer sells as pest/disease tolerant as advertised? (q69d)
- Is the seed that this input dealer sells as early maturing seed also early maturing in reality? (q69e)
- In general, does the seed that this input dealer sells germinate well? (q69f)

In addition, we check if the treatments affect the services provided by the agro-input dealer:

- If there is a problem with the seed of this input dealer, can you carry the seed back to this input dealer and get a refund (insurance)? (q70)
- Does this input dealer give credit, ie. gives you seed (or inputs more in general) that you can pay for later (after harvest) (q71)
- Does this input dealer train/advise you on how to use improved seed varieties while buying seed? (q72)
- Does this input dealer deliver seeds to clients at home? (q73)
- Does this input dealer offer after-sales service? (q74)
- Does this input dealer accept different payment methods? (q75)
- Does this input dealer sell small quantities if necessary (1kg)? (q76)

We also cycle through maize plots and ask, for a randomly selected plot, the following questions:

- farmers' seed adoption
  - percentage of farmers reporting that they planted a quality maize seed variety on randomly selected plot in last season (q31)
  - percentage of farmers reporting that they planted a quality maize seed variety bought from agro-input shop on randomly selected plot in last season (q31, q32)
  - percentage of farmers reporting that they planted farmer saved seed on randomly selected plot in last season (q32)
- quality perceptions of seed used: Please rate the particular seed you used on the randomly selected plot in the last season, on these dimensions: (q35a - q35j)
  - General quality (1 to 5)
  - High yield (1 to 5)
  - Drought tolerant (1 to 5)
  - Pest/disease tolerant (1 to 5)
  - Early maturing (1 to 5)

  - Higher market price/easy to market/in high demand (1 to 5)
  - Good taste of variety or high nutritional content (1 to 5)
  - Low Price (including obtained for free) (1 to 5)
  - Availability (1 to 5)
  - Germination rate (1 to 5)

- Were you satisfied with quality of the planting material (seed) that you used on the randomly selected plot in the last season? (q36)

- If not satisfied, did you tell the supplier of the seed that you were not satisfied? (q36b)

- Would you use this seed that was used on the randomly selected plot again in the future? (q37)

- 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 (q65), combined with data on ratings of the two dealers in case the farmers has changed input dealers (q69a-q69f)

- practices adopted by farmers on the randomly selected plot:

  - How much seed did you use in the last season? (kg) (q38)
  - How much was the cost of 1 kg of this seed? (UGX) (q39)
  - What seed/plant spacing was used in the last season? (q40)
  - Number of seeds per hill used in the last season? (q41)
  - Did you apply organic manure to the soil before planting in the last season? (q42)
  - Did you apply DAP (black in color) or NPK (brown in color) in the last season? How much DAP in the last season? (kg) (q43, q43a)
  - Did you apply Urea (white in color) in the last season? How much Urea in the last season? (kg) (q44, q44a)
  - How many times did you weed in the last season? (q45)

  - How many days after planting did you do first weeding in the last season (q46)
  - Did you use any pesticides, herbicides or fungicides? (q47)
  - When did you plant the seed in the last season? (q48)
  - Did you re-sow where seeds did not germinate in the last season? (q49)

- maize yield/revenue/profit

  - How many bags of maize did you harvest from this randomly selected plot in the last season (including maize that was consumed)? (q50)
  - How many kgs is in one bag? (q51)
  - What was the market value of one such bag during the time of the harvest in the last season? (q52)
  - Did you sell any maize that you harvested on this randomly selected plot in the last season? (q53)
  - How many bags of maize did you sell from this randomly selected plot in the last season? (q54)
  - How much did you charge for one bag? (q55)
  - How much did you keep for seed (record in kg)? (q56)
  - How many bags of maize do you expect to harvest from this randomly selected plot (including maize that will be consumed) in the next season? (q57)

8.4 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.

8.5 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.

9 Ethical clearance

This research received clearance form Makerere's School of Social Sciences Research Ethics Committee (MAKSS REC 08.20.436/PR1) as well as from IFPRI IRB (DSGD-20-0829). The research was also registered at the Ugandan National Commission for Science and Technology (UNCST SS603ES).

10 Transparency and replicability

Throughout this project, we will go the extra mile in tying our hands to avoid issues related to specification search, variable selection, etc. Here we outline the various strategies.

- pre-analysis plan
- revision control
- mock report: After baseline data is collected and the randomization on the computer has happened, a pre-registered report will be produced and added to the AEA RCT registry and GitHub.

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