Miracle Seed: Biased Expectations, Complementary Input Use, and the Dynamics of Smallholder Technology Adoption

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Abstract

Farmers that try out agricultural technologies, such as improved seed varieties obtained from agro-input dealers, may hold unrealistic expectations about this technology. The fact that they paid a significant price for certain traits of the technology, such as higher yield or pest resistance, may lead them to invest less in complementary inputs such as fertilizer or pesticides and reduce management practices such weeding. Subsequent disappointment about the performance of the technology may then be erroneously attributed to the technology itself, resulting in dis-adoption. We provide a simple model of technology adoption and derive a cluster of predictions and test these predictions using a field experiment among 3,500 smallholder maize farmers in Uganda. In the experiment, a treatment group gets explicit information on the importance of combining improved technologies and recommended farming practices. We find some evidence that in the short run, our message scares farmers away from commercial seed, back to local land-races. There is further suggestive evidence that least some farmers adjust expectations and move back into adoption. We conclude that policy makers and industry should focus on technology adoption as a package of complementary inputs and efforts, instead of marketing a single technology.

JEL codes: O33, D84, Q16

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1 Introduction

To feed a growing population in a sustainable way, farmers throughout the developing world will have to grow more food on less land (Garnett et al., 2013; Tilman et al., 2011). To achieve this objective, much is expected from new technologies, especially higher yielding cultivars (Evenson and Gollin, 2003). At the same time, due to the climate crisis, agricultural production will become, more challenging. Also in this context, seed varieties that are selected to be more resilient are thought to be at least part of the solution (Lybbert and Sumner, 2012).

Unfortunately, the adoption of such technologies is lagging in areas where it has the largest potential. Recent trends in agricultural productivity in Africa reflect how technological progress has stagnated on the continent (Suri and Udry, 2022). Underlying this general stagnation is significant heterogeneity. For instance, at the micro level, we often observe disadoption, where farmers choose to switch back to technologies they have been using for ages after trying out a new technology once or twice (Chen, Hu, and Myers; Moser and Barrett, 2006).

There are many reasons why farmers do not move into a state of consistent adoption. One obvious reason why farmers stop using an input is because the inputs that were previously used were simply not available anymore (Shiferaw et al., 2015). Farmers may also have learned over time that a particular technology is not suitable for them or does not meet their expectations (Custodio et al., 2016). Heterogeneity in the quality of the input, coupled with the fact that it is often hard to judge the quality of the input ex-ante, may also result in disadoption (Bold et al., 2017). Farmers that are faced with credit constraints or face additional risk may also reconsider past adoption behavior (Karlan et al., 2014). In the longer run, general equilibrium effects due to the fact that more farmers use the new technology will also increase supply and reduce prices, leading farmers with higher marginal cost to exit (Cochrane, 1958).

In this paper, we consider the possibility that farmers hold inflated expectations of inputs as an explanation for disadoption adoption. These inflated expectations have their origin in the fact that monetary outlays are necessary for improved technologies, and farmers may consider this a signal that modern inputs are substitutes for other investments they would typically make. In reality, however, for improved technologies to reach full potential, equal or even additional complementary investments are necessary. For instance, Chen, Hu, and Myers show that farming with hybrid seed is far more costly than farming with traditional seeds. The extra production costs include seed costs, but also fertilizer costs as hybrid farming requires more chemical fertilizers to achieve significant yield improvement, and (hired) labor and land preparation costs as hybrid farming again requires more specific and complex cultivation techniques. [1]

[1] Over the years, we uncovered many anecdotes in a variety of context that point to this explanation. For instance, many farmers use (inorganic) fertilizer once and assume this will lead to lasting improves of their soil fertility; however, these fertilizer need to be applied for

Inflated expectations about the performance of improved technologies can have lasting impacts on adoption if farmers attribute poor outcomes to the technology, instead of to the reduced use of complementary inputs. This learning failure is understandable: as many factors simultaneously affect yields, learning about the causal impact of a new technology from a single use instance is hard, and cognitive constrained farmers may pay attention to the wrong attributes (Hanna, Mullainathan, and Schwartzstein, 2014).

In this paper, we present a simple model of technology adoption that incorporates the above ideas. In this model, budget constrained farmers compare expected returns of an improved technology to business-as-usual. The new technology comes at a cost, while the traditional technology does not. Both technologies, though, require complementary inputs and effort that directly affect productivity, yet for farmers that experiment with the new technology, the new technology is considered a substitute for (some of the) other inputs.

We test model predictions using a field experiment among maize farmers in eastern Uganda. At the heart of the field experiment is a light-touch information intervention that attempts to correct the perception that the improved technology is a substitute for other inputs and effort. In particular, we show farmers a short, engaging video on the use of improved agro-inputs and recommended management practices for maize growing. In a treatment group we essentially show the same video, except that in certain parts—for instance when the use of inorganic fertilizers is demonstrated or when weeding is explained—we highlight that when using improved seed varies it is still important to also use these additional inputs or perform these management practices.

We start by testing if farmers are able to extract the relevant information from the treatment video by testing knowledge after two full seasons post intervention. We find some indications that more farmers in the treatment group are aware of the importance of combining inputs than in the control group. Turning to adoption behavior, we see that farmers in the treatment group are more likely to use seed saved from the previous season. If we confine attention to only farmers that adopted at baseline, we see that farmers that were exposed to the treatment video were also less likely to obtain seed from agro-input dealers, more likely to use landraces, and less likely to use improved seed varieties such as hybrids or Open Pollinated Varieties (OPVs). However, in the subsequent season, these differences between treatment and control groups have disappeared.

We then look at some of the secondary outcomes to explore mechanisms at work behind the intervention. First, we test if the intervention has an effect on the use of complementary inputs such as fertilizer and pesticides, as well as on cultivation practices such as row planting and weeding. We would have expected a positive impact here, at least in the longer run when farmers are given sufficient time realign their production to this new knowledge, but statistical

each cropping cycle to be effective. In the context of seed, extension officers often complain that farmers consider the trial seed packs they provide as some kind of "miracle seed" that they think they can just broadcast on their least fertile plots without further management and still get exceptional harvests.

power may be an issue. Second, without adjustments in complementary input use and practices, the intervention may still have lasting impacts if farmers' expectations become more realistic, as we do see that a larger share of farmers in the treatment group report that yields are what they expected than in the control group.

Our work has important implications for both public and private sector stakeholders. The main conclusion is that a more holistic or systems approach is necessary when encouraging varietal turnover and adoption of improved seed varieties by smallholder farmers. Governments should provide (free or subsidized) innovation packages that include complementary inputs as well, instead of focusing on a single technology such as for example seed trial packs. Agricultural advisory services should manage expectations of farmers with respect to modern agricultural inputs. Agro-input dealers should be careful when marketing individual products for a particular trait.

The remainder of the article is organized as follows. In the next section, we provide a brief overview of the related literature. Section three provides a simple theoretical framework and derives testable hypotheses. In the fourth section, we discuss the context of the experiment and the treatment. The next section provides some descriptive statistics and illustrates the dynamics of seed adoption. Section six looks at treatment impact, with subsections for knowledge, adoption, and impact pathways. A final section concludes.

2 Related literature

The role of technology adoption in agricultural development and structural transformation is at the heart of food security, poverty reduction and economic development. The history of thinking about agricultural technology adoption goes back to (Griliches, 1957) and is covered in widely cited review articles such as Feder, Just, and Zilberman (1985) and Sunding and Zilberman (2001). More recently, as field experiments proliferated in development economics, theories related to technology adoption have been subjected to the scrutiny of Randomized Control Trials (RCT), often under the auspices of the Agricultural Technology Adoption Initiative (ATAI), a collaboration between J-PAL and Berkeley's Center for Effective Global Action (CEGA) (Jack, 2013).

Studies on technology adoption often (implicitly) assume some kind of graduation model, where farmers switch to a high level equilibrium of sustained adoption once initial conditions, in terms of for instance access to information or access to finance, are satisfied (Shiferaw et al., 2015; Abate et al., 2016; Karlan et al., 2014). Especially in applied microeconomic field experiments, researchers focus on a limited number of agricultural seasons, and are unable to fully appreciate the dynamics of technology adoption. However, a number of studies document significant levels of disadoption (eg. Ainembabazi and Mugisha, 2014). Studies that take a longer run perspective find significant levels of transient technology use among smallholder farmers in Africa (Chen, Hu, and Myers; Moser and Barrett, 2006). Our study takes a similar dynamic approach and differentiates "always adopter" and "never adopters" from "adopters" and "disadopters".

At the core of our theoretical framework presented in the next sections is some kind of learning failure that leads to disadoption. Indeed, heterogeneity in farmer characteristics means that farmers need to learn if a technology is suitable for their specific case (Suri, 2011). However, learning about a new technology is hard. It is often difficult to determine on beforehand what the quality of an input is based on observable characteristics, and some may even argue that many technologies are credence goods (Ashour et al., 2019). Ex-post, evaluation of a technology is also hard, as many factors, including some that are out of the control of the farmer such as weather conditions and pests, affect outcomes (Bold et al., 2017). Generally, it is thought that farmers learn through a combination of own experience and learning from observing others (Foster and Rosenzweig, 1995).

One strand of the literature argues that experiential learning by farmers is through sequential adoption. In cases where technologies are bundled in packages, it is often observed that farmers sequentially adopt components of the package, rather than the entire package (eg. Byerlee and De Polanco, 1986). Leathers and Smale (1991) argue that this is due to farmers employing a bayesian approach to learning, where farmers try to isolate the impact of a component of the package.

However, there may be circumstances under which such a strategy is not optimal. Such a strategy does not allow the farmer to identify potential interaction effects between the inputs. Indeed, the reason why interventions are presented as a package probably means that interaction effects are not trivial. For instance, Kabunga, Dubois, and Qaim (2012) find that banana tissue culture, a technology to ensure banana plantlets are free from pests and diseases, leads to a 7% yield gain in Kenya. However, they also find that improving access to irrigation could lift yield gains above 20%. It seems unlikely that farmers follow a sequential learning path that allows for all possible interactions for the different technologies. Furthermore, behavioural constrains may also prevent farmers from effective learning. For instance, it may be that farmers are paying attention to the wrong attributes (Hanna, Mullainathan, and Schwartzstein, 2014).

When learning about a new technology, farmers will ex-post compare realized yields that what they expected. The effect of expectation about future returns on a decision has been studied in the context of education. Both Jensen (2010) and Nguyen (2008) find that providing information about the correct returns significantly increased investment in schooling (in the Dominican Republic and Madagascar respectively). Van Campenhout (2021) found that a video intervention that informs farmers about the returns on intensification investments in rice growing increased adoption in Uganda. In all these studies, it is assumed that expected returns are underestimated; in the present study, we expect the reverse.

Finally, our treatment comes in the form of short and engaging videos. There is a large literature that shows video can be in important vehicle for changing behavior in a variety of settings. Ferrara, Chong, and Duryea (2012) show how in Brazil, telenovela's have an impact on fertility. Riley (2019) finds that in Uganda, students that watched the Disney feel good movie Queen of Katwe about a chess prodigy did better on their exams, particularly on maths. In the context of agricultural technology adoption, Van Campenhout, Spielman, and Lecoutere (2021) show that farmers that were exposed to engaging videos similar to the one we use in the present study were performing significantly better on a knowledge test, were more likely to apply recommended practices, and were more likely to use fertilizer than households that did not view the video. These same households also reported maize yields about 10.5% higher than those that did not view the video. Our study also contributes to this literature in testing if video mediated information dissemination can also be used to transmitting subtle information.

3 Theoretical model

The farmers are solving an intertemporal problem, allocating resources at t in order to get maximal profit in *t+1*. In line with Suri (2011), we assume that farmers are risk-neutral and chooses a seed type (Hybrid or local landrace) to maximize profits per area of land. In particular, they compare the expected profit functions of hyrids ${\pi_{it}^{*}}^{H}$ and landraces ${\pi_{it}^{*}}^{L}$, which in turn are defined as:

$$E\left(\pi_{it+1}^{H}\right) = E\left(p_t Y_{it+1}^{H}\right) - b_t s_{it} - \sum w_t X_{it} \tag{1}$$

$$E\left(\pi_{it}^{L}\right) = E\left(p_t Y_{it}^{L}\right) - \sum w_t X_{it} \tag{2}$$

wiht E the expectations operator and we assume that consumers do not differentiate between maize obtained from hybrid or local seed and so the expected price at which output is valued is the same for both seed types $(E\left(p_t\right))$. Landraces are assumed to be free, while hybrid seeds are procured at a cost b_t. In both profit functions, a range of complementary inputs and cultivation practices are used, which are summarized in the vector X_{it} with corresponding factor prices w_t.

Farmers adopt hybrid seed if it is more profitable than using landraces, or $E\left(\pi_{it+1}^{H}\right) > E\left(\pi_{it}^{L}\right)$ or:

$$\left(E\left(Y_{it+1}^{H}\right) - \sum \frac{w_t}{p_t} X_{it}^{*}\right) - \left(E\left(Y_{it+1}^{H}\right) - \sum \frac{w_t}{p_t} X_{it}^{*}\right) > \frac{b_t}{p_t} s_{it}^{*} \tag{3}$$

where we normalize by output price.

Equation 3 shows that adoption decisions based on profits depend fundamentally on yield comparisons. In in both cases, yield is a function of inputs used:

$$Y_{it}^{H} = Y_{it}^{H}\left(X_{it}^{H}\right) \tag{4}$$

$$Y_{it}^{L} = Y_{it}^{L}\left(X_{it}^{L}\right) \tag{5}$$

and this relationship is assumed to be positive with increasing returns to scale. We assume $\frac{dY_{it}^{H}}{dX_{it}} > 0$, $\frac{dY_{it}^{L}}{dX_{it}} > 0$ and $\frac{dY_{it}^{H}}{dX_{it}} \gtreqless \frac{dY_{it}^{L}}{dX_{it}}$.

3.1 Input complementary

We assume that $Y_{it}^{H} > Y_{it}^{L}$, but only if $X_{it}^{H} = X_{it}^{L} = X_{it}$. However, there may be reasons why farmers reduce input use when they use hybrid seed. For instance, if farmers face a budget constrained, then inputs will be reduced, resulting in lower yields:

$$Y_{it}^{H} = Y_{it}^{H}\left(X_{it} - \frac{b_t s_{it}}{w_t}\right) \tag{6}$$

The decision to adopt will depend on the difference in yield between hybrid and local seed, relative prices of the inputs, and yield response of inputs.

3.2 Farmer expectations

We introduce farmer heterogeneity into the model by assuming that at least some farmer are not aware of the relationship between Y_{it}^{H} and X_{it}, with results in disappointing outcomes when $Y_{it+1}^{H} < E\left(Y_{it}^{H}\right)$. This will lead to farmers not adopting in the future.

3.3 Model predictions

The model leads to different farmer types based on their dynamic profile and knowledge. First, there will be a group of farmers that are knowledgeable about the interaction effect between improved seed and complementary inputs, and as a result have expectations that match production outcomes. For at least part of these farmers, the marginal cost of adoption is lower than the marginal return, and as a result they adopt and always adoption strategy. For subset of these farmers, the marginal cost of adoption is higher than the marginal return, and so they will never adopt. Providing information about the complementary between improved seed and inputs will have no effect on these farmers.

A next subset of farmers does not have knowledgeable about the interaction effect. A subset of these farmers does not adopt because their marginal cost of adoption exceeds the marginal return. For some of these farmers, provision of this information will change expectations and so this may change marginal cost and marginal benefit comparisons, so some may start adopting in the future (while others will not).

A second subgroup are farmers that is not knowledgeable about the interaction effect between improved seed and complementary inputs and in addition their expected return to

The model leads to the following predictions:

1. Farmers that acquire new information related to the interaction effects between improved seed varieties and complementary inputs disadopt in the next season. This effect will especially be important for farmers that just started adoption (as opposed to the always adopter)

2. Farmer that acquire new information related to the interaction effects between improved seed varieties and complementary inputs use more complementary inputs and provide more effort. This effect will be especially important for farmers that adopted but

3. Farmers that acquire new information related to the interaction effects between improved seed varieties and complementary inputs adapt their expectations. This effect will especially be important for farmers that adopted baseline

4 The experiment

4.1 Study population

The field experiment was implemented in eastern Uganda, an area know for its maize production. Maize is considered both a food and cash crop in that area. As a matter of fact, much of the maize that is used as food aid in Sudan is sourced from here. As this study was part of a larger study that involved seed supply chains, smallholder farmers were drawn from the catchment areas of agro input dealers. As such, farmers should have reasonable access to improved seed varieties.

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

4.2 The treatment

This treatment was implemented using short, engaging 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 (Van Campenhout, Spielman, and Lecoutere, 2021; Riley, 2022; Bernard et al., 2015).

Based on extensive interviews with experts, we developed a script that served as a basis for a video about best practices in maize cultivation. The video starts off with a couple (man and woman) in a healthy maize field inspecting their crops. The man narrates that they have been farmers for over ten years but that their maize fields have not always been this productive. He recounts how they used to struggle to feed their children, but that over time, they learned how to grow more maize. The secret of their success, they continue, lies in the adoption of improved technologies and best practices, such as the use of organic fertilizer, and optimal plant spacing and seed rates. Furthermore, they argue that the use of improved seed and fertilizer also contributed significantly to increased production. They conclude this introduction by stating that they are proud to be successful farmers that can feed their families and even has some marketable surplus that they can sell on the market. The viewer is then invited to become a successful farmer as well by paying close attention as the role model farmers explain in detail the most important inputs and practices that changed their lives.

After this introduction, a poorly managed maize field is shown. Maize growth is stunted because of striga, a parasitic weed that feeds on the roots of maize plants. It is explained that this was how their garden looked in the past, when they thought weeding was a waste of time, improved seed was too expensive, and soil does not need fertilizer. But after a particularly bad season, they suffered and decided things needed to change. It is then shown how crop residues and animal dung is used to make organic manure, and how this is applied to the field. It is advised to start field preparations early, as timely planting (immediately after the first rains) is very important to get good yields. The focus then shifts to row planting, where the recommended spacing of one foot between plants and 2.5 feet between rows is shown. The role model farmers also mention the expected increase in yield from row planting. At this stage, it is also recommended to add inorganic fertilizer (Di-ammonium Phosphate). It is then shown that one seed of a common hybrid seed is place in each hill.

The video then proceeds by recommending resowing of hills where seed did not germinate after ten to 12 days to keep optimal plant density. The actor in the video then notes that weeding is especially important in the first 40 days as maize does not compete well for light and nutrients. It is recommended to start a first round of weeding 18 to 20 days after planting. It is also mentioned that at this stage, removal of striga is very important as the weed has reached the roots of the maize plant yet and damage can still be avoided. A second round of weeding is recommended 2 to 3 weeks later. Four weeks after planting, when maize is knee high, it is demonstrated how another type of inorganic fertilizer (Urea) is applied as top dressing. Around the tasseling stage, a final round of weeding is recommended.

The treatment was implemented in the form of two different versions of the video. The control video is essentially the video as described above. In the treatment video, we added subtle messages that recommended practices and inputs that feature in the video are particularly important when the farmer uses improved seed varieties. The treatment video is about 12 minutes long and can be found here. The control video is about 8 minutes long and can be found here.

5 Data

Our sample consists smallholder maize farmers who live in the catchment areas of at least one or more agro-input dealers. We started by listing all agro-input shops in 11 districts in southeastern Uganda, which roughly corresponds to the Busoga kingdom, an exercise that let to about 350 agro-input dealers.

We then asked these agro-input dealers about the locations of their customers. Enumerators were then instructed to randomly sample ten households that grow maize in these locations. Consequently, about 3500 smallholder maize farmers were sampled. Confining attention to farmers that were interviewed at all survey rounds, we remain with a balanced panel of 3,400 farmers.

We define smallholder technology adoption as follows: For each farmer in the sample, we asked on how many plots the farmer cultivated maize in the preceding season. From these plots, we than randomly select one plot on which detailed questions are asked on input use and cultivation practices. A farmer is assumed to be an adopter if they use fresh hybrid seed or an OPV that was recycled less than four times.

Figure 1 provides us with a visual representation improved seed adoption among farmers in our survey. We see that the share of adopters slowly increases over time. A baseline, we find that about 45 percent of farmers report to have adopted improved maize seed varies on the randomly selected plot. At midline, this figure has already increased to about 50 percent. At endline, the share of adopters is 54 percent of farmers.

The figure also shows interesting dynamics. At the top of the figure, we see a substantial share of households (22 percent) that adopted in all three surveys. These could be considered "always adopters". At the bottom of the chart, we find and equally substantial share (23 percent of households) that can similarly be categorized as "never adopting". However, we also see that a large group of farmers that adopt at baseline revert to local seed at midline (16 percent) or still adopt at midline but eventually also disadopt (7 percent). Fortunately, large groups of households also enter into adoption. We see that 19 percent of non-adopting households are adopting at midline and 12 percent of households that are not adopting at both base and mildine become adopters at endline. Finally, there are also some households that seem to be moving in and out of adoption (8 percent) or moving out and back into adoption (9 percent).

Furthermore, at baseline, we find that a significant share of farmer that adopted according to the above definition seem to be disappointed. Almost 30 percent of farmers indicate that were not satisfied with quality of the planting material (seed) that you used; One in four indicates that they will not use the seed in the future.

6 Results

6.1 Impact on knowledge

We first test if farmers were able to pick up the subtle messages hidden in the treatment video. This was done through as small quiz where farmers need to select the response that they feel is most appropriate from a set of alternative answers that were read to them by the enumerators. The quiz was only implemented at endline because we were wary of priming.

We start with a general question, asking if farmers think recommended cul-

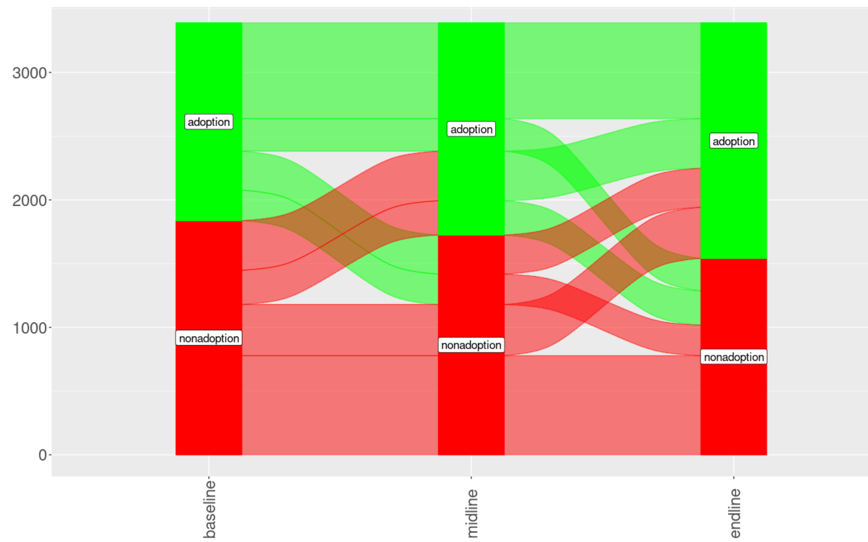

Figure 1: Dynamics of seed adoption

tivation practices like weeding and application of fertilizer is less, equally, or more important when using quality maize seed like OPV or hybrid seed.

This is followed up by a more specific question, asking the farmer to indicate what applies for weeding when they are using hybrid seed. The options from wihc the farmer can choose are: 1) You do not need to weed and remove striga because all hybrid seed varieties are treated to resist weed infestation; 2) You do not need to weed and remove striga in the first four weeks because hybrid seed is better at competing for sun, nutrients and water than normal seed; 3) You need to weed and remove striga just as you would with normal seed because maize seed does not compete well for sunlight, water and nutrients.

We have a similar question for fertilizer application when hybrid seeds are used. The options here are that 1) You do not need to use inorganic fertilizer because you already bought seed. 2) You can use less fertilizer than you normally would since improved maize seed grows faster 3) You need to use the amount of fertilizer that you would with normal seed because also improved seed varieties need nutrition; 4) You should use more fertilizer than you would normally use.

We then have a question that checks if farmers use sub-optimal plots by asking which plots are best suited to plant improved seed on. The options here are 1) that it is best to save improved seed for poor plots, as these need less nutrients; 2) that is best to use your improved seed for plots that are furthest away from the home, as improved seed need less care than normal seed; and 3) that the decision on what plot to plant improved seed should not be affected by the seed.

Another question tests if farmers think it is better to combine or put all eggs in one basket. The question simply asks how to best invest money in agriculture.

The options are that 1) It is best to invest all your money in seed, because poor seed quality is the main cause of low yields; 2) It is best to invest all your money in fertilizer, because poor soil is the main cause of low yields; and 3) It is best to buy both fertilizer and seed, because good seed without fertilizer does not give good results.

Finally, we include a control questions, where we do not expect a difference between treatment and control because the answer featured in both treatment and control videos. In particular, we ask about the optimal spacing and seed rate for maize. The options are 1) One foot between plants and 2 and $\frac{1}{2}$ foot between rows with one seed per hill; 2) One foot between plants and 2 and $\frac{1}{2}$ foot between rows with two seeds per hill; and 3) Two foot between plants and 2 and $\frac{1}{2}$ foot between rows with two seeds per hill.

Results are in Table 1. The first column in the table (1) provides the mean in the control group (and standard deviations in brackets below), mainly to get an idea of the effect size of the intervention. We see that knowledge is already high: 88 percent of farmers in the control farmers know that recommended cultivation practices like weeding and application of fertilizer is also important when using improved seed. The only outcome where there is still significant scope for improvement appears to be the control question.

The second column (2) shows the estimated difference between treatment and control at endline, while the third column (3) shows the estimated difference between treatment and control at endline, but only for the subset of farmers that report to be adopting improved seed varieties at baseline. We look at treatment heterogeneity at this level because the treatment is likely not relevant to all farmers: some farmers may not adopt because of other reasons than the ones we conjecture. For instance, they may simply not have access to seed, or access to credit may be the primary constraint.

We see that for all outcomes, knowledge, as measure by the quiz, has increased for most of the relevant questions, except for the control question. For instance, the share of farmers that knows complementary inputs and practices are at least as important when using improved seed increased from 88 percent to 90.2 percent. Furthermore, the share of farmers that recommends investing in different inputs (as opposed to investing all their money in only one input), increases from 75 percent to to 77.2 percent. If we only consider farmers that adopted at baseline, the increase over the control amounts to almost 5 percentage points. Unfortunately, after adjusting standard errors for clustering at the village level, none of the differences is statistically significant at conventional levels. This may be due to the fact that ex-post it turned out that many of the farmers are able to indicate the correct response, and hence there is little scope for further improvement. At the same time, we note that all coefficient estimates are going in the same direction. Furthermore, even though farmers may possess the knowledge, there is still a difference between knowing and actually doing. We suspect that our intervention does not only increase knowledge but also nudges farmer to practice what they know. Such aspirations effects are common when engaging videos featuring role models are used (Riley, 2019; Bernard et al., 2015).

Table 1: Treatment effects: knowledge

	(1)	(2)	(3)
Knows inputs and practices are important	0.88	0.022	0.021
when using improved seed	(0.32)	(0.015)	(0.018)
Knows weeding is still important	0.80	0.025	0.034
when using improved seed	(0.40)	(0.022)	(0.026)
Knows fertilizer application is still important	0.84	0.009	0.005
when using improved seed	(0.37)	(0.016)	(0.020)
Knows that selection of plot should be independent	0.80	0.007	0.007
of the use of improved seed	(0.40)	(0.025)	(0.030)
Knows it is best to spend money on different inputs	0.75	0.022	0.044
instead of putting all eggs in one basket	(0.44)	(0.023)	(0.027)
Knows recommended plant spacing and seed rate	0.14	-0.002	-0.031
	(0.35)	(0.017)	(0.022)
Knowldge index	0.04	0.046	0.064
	(0.57)	(0.036)	(0.042)
nobs	3441	3441	1570

Note: First column (1) reports control group means (and standard deviations below); second column (2) reports difference between treatment and control for outcomes at endline; third column (3) reports difference between treatment and control for outcomes at endline for farmers that adopt at baseline. Standard errors are clustered at the village level.

6.2 Impact of treatment on adoption dynamics

We start by testing the main hypothesis of this paper—that farmers that were made aware of the fact that improved seed also need complementary inputs—behave differently in terms of seed use in the subsequent season. In particular, we look at use of fresh improved seed varieties (our key adoption indicator that was also used in Figure 1 to illustrate the dynamics of technology adoption). However, we also look at other outcomes that are often partly overlapping or related. For instance, we also look at the use of landraces, which is in a sense the reverse of technology adoption. We also test whether there are differences in the use of recycled seed between the treatment and control group. Also here we consider the opposite: the share of farmers that buy from agro-input dealers. The four outcomes are also combined in an index following Anderson (2008).

Results are in table 2. The first column of the table shows sample means at baseline for the five outcomes (and standard deviations in brackets below). For instance, we see that 46 percent of farmers use improved seed varieties and that one third of farmers report that the seed that they planted on the randomly selected plot was obtained from an agro-input dealer.[2] The second column serves as the typical orthogonality test and compares treatment and control outcomes at baseline. We see that the randomization was successful, as there is no difference between outcomes of farmers that will be exposed to the treatment and those that will not in seed adoption behavior. The third column shows the difference between treatment and control at midline, after households received treatment. Our theory suggests that in response to being sensitized about the importance of using complementary inputs and cultivation practices, less farmers would use improved seed varieties from agro-input dealers, and revert to farmer saved landraces. We find that the coefficients go in the right direction, however, we only find a significant difference for the share of farmers that planted recycled seed at midline.

The differences in the fourth column are for all farmers, while the fifth column restricts the sample to only farmers that adopted at baseline. We do indeed see effects become stronger if we restrict attention to this subgroup. We now see that farmers that were exposed to the treatment are almost 6 percentage points less likely to adopt improved seed, and 5 percentage points more likely to adopt landraces. We see a particularly strong increase in the share of farmers that use seed recycled from the previous harvest in the treatment group and a somewhat lower but still significant reduction in farmer that bought seed from an agro-input dealer. For the subgroup of farmers that adopted in at baseline, the adoption index is now also significantly negative for the treated farmers

The fifth column shows the difference between treatment and control at endline, after households received treatment a second time, while the sixth column repeats this analysis but only for farmers who report adopting at baseline. At endline, differences between treatment and control seemed to have disappeared, suggesting that the disadoption effect is only temporary. This may because farmers have moved to a new equilibrium where they are now more likely to

[2] As the index involves standardization, the average is zero.

Table 2: Treatment effects

	(1)	(2)	(3)	(4)	(5)	(6)
adoption	0.46	0.006	-0.027	-0.056*	-0.011	-0.020
	(0.50)	(0.022)	(0.021)	(0.026)	(0.021)	(0.026)
landraces	0.43	-0.026	0.027	0.051*	-0.002	-0.001
	(0.49)	(0.024)	(0.022)	(0.023)	(0.021)	(0.020)
recycled	0.57	0.020	0.041+	0.088**	0.018	0.023
	(0.50)	(0.022)	(0.022)	(0.026)	(0.022)	(0.027)
agro-input	0.33	-0.004	-0.015	-0.052+	-0.009	-0.019
	(0.47)	(0.020)	(0.020)	(0.027)	(0.021)	(0.028)
index	0.00	0.013	-0.051	-0.117**	-0.012	-0.024
	(0.88)	(0.040)	(0.039)	(0.044)	(0.039)	(0.043)
nobs	3389	3389	3389	1552	3389	1552

Note: First column (1) reports control group means (and standard deviations below); second column (2) reports difference between treatment and control farmers for outcome measured at baseline; third column (3) reports difference between treatment and control for outcomes at midline; fourth column (4) reports difference between treatment and control for outcomes at midline for farmers that adopt at baseline; fifth column (5) reports difference between treatment and control for outcomes at endline; sixth column (6) reports difference between treatment and control for outcomes at endline for farmers that adopt at baseline; **, * and + denote significance at the 1, 5 and 10 percent levels. Standard errors are clustered at the village level.

become always adopters.

6.3 Causal mechanisms

6.3.1 complementary inputs use and cultivation practices

The effect of making farmers aware that improved seed needs the same complementary inputs and effort than normal seed on the actual use of complementary inputs and practices is not clear a-priori. On the one hand, the intervention advocates for the use of complementary inputs and practices, and so one may expect that adopters increase use in the future as they adjust their practices to this new knowledge. However, we see that the first order response of the average farmer is to reduce the use of improved seed, which may offset the increased use of complementary inputs, at least in the short run. However, in subsequent seasons, when farmers adopt again, one would expect that at least some treatment farmers now also use more complementary inputs and put in more effort.

We look at a range of practices and inputs in line with what is features in both treatment and control video. A first outcome is an indicator for single-stand row-planting. Row planing is an important management practice that can lead to significant yield gains. Under row planting, space is used optimally and plants have sufficient nutrients and sunlight. However, row planting increases workload, hence farmers often engage in broadcasting.

A second outcome is the recommendation to reduce seed rate. Farmers often plant more seed than necessary because they fear that seed may not germinate. However, using more than 2 seeds per hill leads to stunted maize growth due to competition for light and nutrients. At the same time, just as for row-planting, a lower seed rate may increase the workload, as farmers may need to engage in gap filling after one week if seed fails to germinate.

The next three outcomes look at fertilizer use. Organic fertilizer application is important for soil structure, while DAP and Urea are used to provide maize essential nutrients at particular points in time. The cost of organic fertilizer is mainly in terms of labour, while both DAP and Urea needs to be bought from an agro-input shop and applied during planting (DAP) and at early stage of growth (Urea).

Weeding should be done within one week of planting and as often as possible. Official recommendations are to weed at least three times. Furthermore, invasive insects such as fall armyworm (Spodoptera frugiperda) or maize stalk borer (Busseola fusca) can severely reduce yields. Pesticides, including insecticides, are widely available in agro-input shops under commercial names such as Rocket,, Lalafos and Dudu acelamectin, and used buy many farmers. Again, while weeding requires labour that can potentially be supplied by household members, pesticides comes at a pecuniary cost.

Finally, we also look at differences in resowing or gap-filling. This involves revisiting the field after about one week and inspecting hills for seed germination. When a seed did not germinate, new seeds are planted in that location. Gap-filling, seed rate and row planting are thus likely correlated. We also combine all outcomes into an overall index of practices.

Results are in Table 3. As in previous tables, the first two columns show control group means and orthogonality tests for outcomes before the treatment. Interestingly, we find some imbalance on the number of times that farmers report to have been weeding the randomly selected plot and the likelihood that farmers resow after one week. Note that the imbalance is in different directions, which makes it less likely that the imbalance is due to structural difference between treatment and control group, but should be attributed to chance.

At midline, column (3) shows that farmers do not use more inputs or put in more effort; on the contrary (and especially if we only consider a subset of farmers that adopted at baseline in column (4)) farmers appear to be less likely to engage in row planting and less likely to use DAP. However, according to the index, there is no overall effect of the intervention on input use and recommended cultivation practices at midline. After a second season (when the negative effect on improved seed use for treated farmers has disappears — see Table 2) we also do not find that a consistent increase in input use.

The above results may indicate that farmers' response to the treatment is limited to decisions related to seed. However, it may also be that we lack power as a result to heterogeneous treatment effects. For instance, our theoretical model predicts a positive effect at endline only for farmers that adopt at baseline, disadopt at midline and are responsive to the treatment (that is, they are not already aware of the importance of using improved seed, which is likely the case for always adopters). If compare treatment and control farmers for the subset of farmers that adopts at baseline, does not adopt at midline, and adopts again at endline, we do indeed find that treated farmers use more fertilizer and pesticides and the index is significant at the 10 percent level. However, such comparisons are likely to suffer from endogeneity bias, as the treatment affects adoption decisions are both mid- and endline.

6.3.2 expectations and outcomes

Another key mechanism in the model is related to expectations. In this section, we see if the treatment had an impact on farmers expectations. Furthermore, we look at actual outcomes in terms of production and yield.

To measure expectations, we simply asked farmers if they harvested as much maize from the plot as what they expected expected. We also measure production on the randomly selected plot. We look at total production, but also at productivity by dividing production of the plot by the size of the plot.

Results are reported in Table 4. We again report control group means and baseline balance in the first 2 columns. At baseline, we did not ask if expectations were met on the randomly selected plot. Therefore we report the average in the control group at midline and we do not test for baseline balance. Note that a large majority of farmers indicated that they harvested less than expected.

Column (3) shows that in the treatment group, a significantly higher share of farmers than in the control group say that what they produced was also what they expected. This is even more so for the subset of farmers that adopted at

Table 3: Treatment effects on input use

	(1)	(2)	(3)	(4)	(5)	(6)
Row planting	0.24	0.025	-0.066*	-0.091**	-0.029	-0.044
	(0.43)	(0.022)	(0.028)	(0.033)	(0.028)	(0.034)
Reduced seed rate	0.24	0.010	0.013	-0.016	0.037+	0.018
	(0.43)	(0.021)	(0.021)	(0.030)	(0.022)	(0.030)
Organic fertilizer	0.08	-0.009	-0.011	-0.017	0.008	0.017
	(0.26)	(0.011)	(0.017)	(0.022)	(0.019)	(0.025)
DAP use	0.25	-0.020	-0.038+	-0.064*	-0.003	0.018
	(0.43)	(0.024)	(0.023)	(0.030)	(0.024)	(0.032)
Urea application	0.08	0.001	0.004	0.017	0.009	0.002
	(0.26)	(0.013)	(0.015)	(0.022)	(0.015)	(0.023)
Nr of times weeding	2.56	0.084**	0.007	0.026	-0.044	-0.065+
	(0.65)	(0.026)	(0.029)	(0.038)	(1.209)	(0.039)
Pesticide use	0.41	0.031	0.020	0.016	0.012	0.011
	(0.49)	(0.024)	(0.025)	(0.033)	(0.024)	(0.031)
Resowing	0.48	-0.046*	0.013	0.029	0.013	0.028
	(0.50)	(0.023)	(0.021)	(0.028)	(0.020)	(0.027)
Inputs and Practices Index	0.01	0.015	-0.020	-0.022	0.006	0.016
	(0.45)	(0.022)	(0.023)	(0.028)	(0.020)	(0.025)
nobs	3389	3389	3202	1470	3256	1495

Note: First column (1) reports control group means (and standard deviations below); second column (2) reports difference between treatment and control farmers for outcome measured at baseline; third column (3) reports difference between treatment and control for outcomes at midline; fourth column (4) reports difference between treatment and control for outcomes at midline for farmers that adopt at baseline; fifth column (5) reports difference between treatment and control for outcomes at endline; sixth column (6) reports difference between treatment and control for outcomes at endline for farmers that adopt at baseline; **, * and + denote significance at the 1, 5 and 10 percent levels. Standard errors are clustered at the village level.

Table 4: Treatment effects on input use

	(1)	(2)	(3)	(4)	(5)	(6)
yield as expected	0.15		0.029^{+}	0.053^{*}	-0.004	-0.004
	(0.36)		(0.017)	(0.023)	(0.017)	(0.023)
production	469.64	20.904	7.566	-10.195	-8.690	2.457
	(412.71)	(18.279)	(14.445)	(21.924)	(16.787)	(25.418)
yield	437.89	10.108	13.654	18.345	-4.666	7.118
	(282.26)	(12.188)	(13.071)	(16.630)	(13.218)	(17.453)
index	0.00	0.014	0.049	0.058	-0.016	0.007
	(0.76)	(0.038)	(0.036)	(0.049)	(0.037)	(0.049)
nobs	2496	2496	3202	1470	3256	1495

Note: First column (1) reports control group means (and standard deviations below); second column (2) reports difference between treatment and control farmers for outcome measured at baseline; third column (3) reports difference between treatment and control for outcomes at midline; fourth column (4) reports difference between treatment and control for outcomes at midline for farmers that adopt at baseline; fifth column (5) reports difference between treatment and control for outcomes at endline; sixth column (6) reports difference between treatment and control for outcomes at endline for farmers that adopt at baseline; **, * and + denote significance at the 1, 5 and 10 percent levels. Standard errors are clustered at the village level.

baseline (column (4)). At endline, there is no difference between treatment and control anymore (columns (5) and (6)). This pattern suggests that a subset of farmers indeed started out with inflated expectations, and this was corrected after they learned that improved seed is not miracle seed.

Finally, the table shows that the average control group farmer cultivates about 470 kg on the random plot. The random plot seems to be on average slightly larger than one acre, such that productivity is about 440 kg per acre. The intervention does not seem to have any impact on production of productivity.

7 Conclusion

This paper is motivated by qualitative evidence that some farmers appear to overestimate the potential benefits of certain improved agricultural technologies. The cost of a particular modern commercial input that a farmer wants to start using, such as improved seed varieties or inorganic fertilizers, is often substantial and competes with other (complementary) agricultural inputs. Furthermore, modern inputs are generally marketed with a focus on a few dimensions (eg seed that is treated against certain types of weed), and so farmers may reduce inputs (like herbicides) and efforts (like manual weeding) related to this dimension. However, to get the most out of improved technologies, it is important to also use complementary inputs and proper agronomic practices, otherwise outcomes may not be as expected. If farmers incorrectly attribute disappointing outcomes to the technology itself rather than improper use, this could lead to a pattern where farmers who try out a new technology switch back to local seed in the next season. In a sample of maize smallholder farmers in Uganda, we indeed see substantial disadoption over time. Furthermore, a large majority of farmers indicate that they expected higher yields from their plots.

To credibly test the hypothesis that farmers think of improved seed varieties are "miracle seed", we set up a field experiment around an engaging video on recommended cultivation practices for maize growing that was shown to farmers before the planting season at the time when farmer select the seed that they will use. Two versions of the video were produced: one control video and one treatment video. The treatment video was essentially the same video as the control video, expect that in the treatment video, after each practice or input that was shown, it was explicitly mentioned that this is "also important when you are using improved seed varieties such as hybrid seed or OPVs". We then randomly allocate treatment and control status to villages, where a set of farmers are then shown the corresponding video. We revisited farmers in treatment and control villages a first time after one season and a second time after a second agricultural season to test if there were differences farmer knowledge, seed use, complementary input use and agronomic practices, and expectations.

We first test if farmers pick up the subtle messages that lie at the heart of our light touch information treatment. To do so, we subject farmers to a multiple choice quiz. While we do not find average treatment effects that differ significantly from zero, we do see that all coefficients are going into the expected direction. We suspect that the lack of statistical significance may be due to the already high knowledge at baseline. However, even when most farmers already possess the knowledge, the treatment may still serve to make this knowledge more salient.

Turning to the main outcome—behavior related to seed use—we find that in the season immediately following the treatment, treated farmers are less likely to use improved seed obtained from agro-input dealers and revert back to farmer saved landraces. In line with our expectations, this switching back to landraces is only short lived: in the next season, there is no difference between treatment and control groups anymore.

To see if the main impact pathway is through the budget constraint, we look at complementary input use. We find little evidence that the intervention increased input use or the use of recommended practices. If anything, we actually see that at midline, the use of inputs in the treatment group is lower than in the control. However, if we restrict the sample to farmers that disadopt at midline and adopt again at endline, we do see an increase in input use at endline. Another intermediate outcome is related to expectations. We find that farmers that received the treatment are more likely to report at midline that what they harvested in in line with what they expected.

Our results differ from various other studies that find that improved technology enhances agricultural productivity by crowding in modern inputs and cultivation practices (Emerick et al., 2016; Bulte et al., 2023). The reason for these opposite effects may be due to the fact that Bulte et al. (2023) and Emerick et al. (2016) provide free seed as part of there experiment, potentially resulting in an income effect in the sense that money that is not used to buy seed can now be used to buy other inputs.[3] In our experiment, no free seed is provided, so when the adoption decision is made, farmers have take into account the additional cost of seed and the fact that expensive complementary inputs will need to be purchased, leading to disadoption.

Our study casts doubt on the suggestion that bayesian learning via sequential adoption can be a successful strategy for smallholder farmers in the long run (Leathers and Smale, 1991; Ma and Shi, 2015). If important interaction effects between different inputs are present, it is unlikely that farmers can try out all possible combinations of inputs to learn about these interactions. Furthermore, if farmers can not learn about the interactions, expectations may be incorrect, leading to sub-optimal adoption patterns, further complicating learning.

Our study also has important implications for both policy markers and the private sector. When designing agricultural extension and advisory services, policy makers should highlight the complementary of modern inputs. If not, their efforts risk to be short lived. Worse, false perceptions of poor seed quality

[3]Emerick et al. (2016) do discuss the possibility that their effects are driven by an income effect. However, under income effect, they understand the effect of the additional income resulting from the adoption of the technology (a flood tolerant seed variety). The income effect we are concerned about is the one that is due to the fact that farmers receive seed for free, potentially freeing up money for other investments.

may crowd out the market for quality seed (Bold et al., 2017). These days, policy makers often focus on subsidizing While this may work for some stand-alone technologies (eg. Omotilewa, Ricker-Gilbert, and Ainembabazi, 2019), promoting other technologies that require complementary inputs (such as the use of subsidized or even free seed trial packs) may be counterproductive.

There is also a role for industry. As part of their marketing strategy, seed producers and agro-input dealers tend to highlight particular traits of the technology they use, such as high yields. Furthermore, they may not be tempted to actively promote the use of complementary inputs if they are produced by companies that target the same customers as they do. In both cases, short term benefits may lead to long run losses.

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