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

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March 24, 2023

JEL Codes: O33, D84, Q16

Abstract

To fully capitalize on new agricultural technologies like improved seed varieties, significant complementary investments in the form of inputs (such as fertilizers or pesticides) and greater attention to management practices like row planting are required. Farmers frequently fail to recognize the importance of this fact, and occasionally invest less than they would if they were utilizing farmer-saved seed, which can result in unsatisfactory outcomes and eventual abandonment of the technology. We provide a simple model of biased expectations, complementary input use and technology adoption and test its predictions using a field experiment among a sample of smallholder maize farmers in eastern Uganda. We find that pointing out the importance of complementary investments using a short engaging video scares some farmers away from commercial improved seed varieties, back to farmer-saved seed, in turn reducing complementary input use. Consistent with the theoretical model and theory of change, we find some evidence that this behavior change emanates from increased knowledge and expectations that are more in line with realized outcomes. Our findings have important implications for the dynamics of technology adoption, as disappointment about the performance of a technology that is erroneously attributed to the technology itself lead may lead to disadoption. 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.

Keywords: agricultural technology adoption, expectations, complementary inputs, seed systems, Uganda

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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 (Tilman et al., 2011; Garnett et al., 2013). To achieve this objective, much is expected from new technologies, especially from higher yielding cultivars (Evenson and Gollin, 2003). At the same time, agricultural production will become more challenging due to the climate crisis. Also in this context, varieties that are selected to be more resilient against droughts and pests 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 they has the largest potential. Recent trends in agricultural productivity in Africa reflect how technological progress has stagnated on the continent (Suri and Udry, 2022). Significant heterogeneity underlies this general stagnation. For instance, at the micro level, we often observe dis-adoption, where farmers choose to switch back to technologies they have been using for decades after trying out a new technology once or twice (Moser and Barrett, 2006; Chen, Hu, and Myers, 2022).

There are many reasons why farmers do not move into a state of consistent adoption. One obvious reason is that the inputs that some farmers previously used simply become unavailable (Shiferaw et al., 2015). Farmers may also learn 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 even ex-ante, may also result in dis-adoption (Miehe et al., 2023; Bold et al., 2017). Farmers that are faced with credit constraints or face additional uninsured risk may also reconsider past adoption behavior (Karlan et al., 2014). In the longer run, general equilibrium effects due to more farmers using the new technology—which will increase supply and reduce output prices—may lead farmers with higher marginal cost to exit (Cochrane, 1958).

In this paper, we consider the possibility that farmers hold inflated expectations of new technologies as an explanation for their dis-adoption. These inflated expectations are a result of the fact that farmers often seem unaware (or fail to recognize) that these inputs generally need substantial complementary investment. For instance, Chen, Hu, and Myers (2022) show that farming with seed of a hybrid variety is far more costly than farming with seed of a traditional variety. The extra production costs include the cost of seed, but also fertilizer costs as hybrid farming requires more chemical fertilizers to achieve significant yield improvements, and (hired) labor and land preparation costs as hybrid farming again requires more specific and complex cultivation techniques.

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 insufficient complementary inputs and effort. This learning failure is understandable: as many factors simultaneously affect yields, learning about the causal impact of a new technology from a single experience is difficult, and cognitive constrained farmers may pay attention to the wrong attributes

(Hanna, Mullainathan, and Schwartzstein, 2014; Foster and Rosenzweig, 1995).

Over the years, we uncovered many anecdotes in a variety of contexts that illustrate the importance of biased expectations, sub-optimal complementary investments, and subsequent disadoption when disappointing outcomes are attributed to the technology itself. For instance, many farmers use inorganic fertilizer once and assume this will lead to lasting improvements of their soil fertility. However, fertilizer need to be applied in each cropping cycle to be effective, and it is recommended to combine them with organic fertilizer or lime to maintain physical soil characteristics such as acidity. In the context of seed, extension officers often complain that farmers consider seed of improved varieties as some kind of "miracle seed" that they think they can just broadcast on their plots without further management and still get exceptional harvests. However, seed of improved maize varieties needs a lot of nutrients, often leaving soil more depleted than when farmer-saved seed is used. In the areas where our research is situated, Striga (*striga hermonthica*), a parasitic weed that feeds on the roots of maize plants and cause stunted growth, is a serious problem. Unfortunately, Striga proliferates in poor soils and as a result some farmers now believe that improved seed varieties are responsible for increased Striga infestations on their fields.

We present a simple model of technology adoption that incorporates the above ideas. In this model, 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 efforts that directly affect productivity, but for the new technology, productivity gains only materialize when complementary input use exceeds levels that would be used for the traditional technology. Based on the model, we define several farmer types and derive predictions about how they would behave if they would would know the true shape of the production function of the new technology.

We test the predictions of the model using a field experiment among 3,500 maize farmers in eastern Uganda. At the heart of the field experiment is a light-touch information intervention that highlights the importance of complementary investments when using improved seed varieties. In particular, we show all farmers in our sample a short engaging video about the use of improved agro-inputs and recommended management practices for maize growing. In the 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 it is particularly important to use additional inputs and to perform management practices when using seed of an improved variety.

We start by testing if farmers are able to extract the relevant information from the treatment video using a simple quiz to test knowledge post-intervention. While we do not find treatment effects that differ significantly from zero, we see that all coefficients go in the expected direction. Turning to adoption behavior, we see that farmers in the treatment group are less likely to use seed of an improved variety such as a hybrid or Open Pollinated Variety

(OPV). 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 and more likely to use farmer-saved seed, in addition to reducing adoption of hybrid or Open Pollinated Variety (OPV). We also test if the intervention has an effect on the use of complementary inputs such as fertilizer and pesticides, as well as on best practices in crop management such as row-planting and weeding. We find little evidence that the intervention increased the use of inputs or recommended practices; on the contrary, we see reductions in costly inputs such as inorganic fertilizer use and row planting. We also see that in the treatment group, farmer's expectations become more in line with realized output.

Our findings have important implications for the dynamics of technology adoption. Disappointment about the performance of a technology that is erroneously attributed to the technology itself lead may lead to dis-adoption. Furthermore, from a public welfare point of view, overestimating the benefits of new technologies leads to less than optimal adoption. Even though in the short run, many farmers seem to disadopt in response to our intervention, the fact that farmers' expectations become more realistic suggests that farmers that do adopt are now also in for the longer run. Furthermore, if disappointing outcomes stick more and spread more easily than good outcomes, correcting misperceptions may substantial positive spillover effects (Ledgerwood and Boydstun, 2014; Hornik et al., 2015).

Our work also has important implications for both public and private sector stakeholders. The main conclusion is that a more holistic approach is necessary when encouraging varietal turnover and adoption of improved 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 seed or fertilizer 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 if their aim is to build a loyal customer base.

The remainder of the article is organized as follows. In the next Section 2, we provide a brief overview of the related literature. Section 3 provides a simple theoretical framework and derives testable hypotheses. In Section 4, we discuss the intervention we will use to test model predictions. The next Section 5 provides some descriptive statistics and illustrates the dynamics of varietal adoption in our sample. It also presents the empirical strategy. Section 6 looks at results, with subsections for knowledge, adoption, expectations, and complementary inputs. A final Section 7 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 reviewed in widely cited articles such as Feder, Just, and Zilberman (1985) and Sunding and Zilberman (2001). More recently, as field experiments started to proliferate in development economics, theories related to technology adoption have been subject to the scrutiny of randomized controlled trials, often under the auspices of the Agricultural Technology Adoption Initiative, a collaboration between the Abdul Latif Jameel Poverty Action Lab (J-PAL) and Berkeley's Center for Effective Global Action (CEGA) (Jack, 2013).

Studies about 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 (Karlan et al., 2014; Shiferaw et al., 2015; Abate et al., 2016). Especially in applied micro-economic 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 dis-adoption (e.g. Ainembabazi and Mugisha, 2014), and studies that take a longer run perspective find significant levels of transient technology use among smallholder farmers in Africa (Chen, Hu, and Myers, 2022; Moser and Barrett, 2006).

At the core of our theoretical framework presented in the next Section (Section 3) is a learning failure where farmers have inflated expectations about the return of a new technology but fail to uncover the true form of the production function through experience, leading to disappointment and subsequent dis-adoption. Indeed, heterogeneity in farmer characteristics implies that farmers need to learn if using a new technology is optimal for their specific case given costs and benefits (Suri, 2011). Farmers learn through a combination of own experiences and observing others (Foster and Rosenzweig, 1995). However, learning about a new technology is hard. Based on observable characteristics, it is often difficult to determine what the quality of an input is before using it. Some even argue that many technologies are credence goods (Ashour et al., 2019) because their evaluation is also hard ex-post, 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).

One strand of the literature argues that sequential adoption leads to experiential learning by farmers. 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 (e.g. Byerlee and De Polanco, 1986). Leathers and Smale (1991) argue that this is due to farmers employing a Bayesian approach to learning, where they try to isolate the impact of one component of the package. However, there are circumstances under which this strategy is not optimal because it does not allow farmers to identify potential interaction effects between the inputs. Indeed, the reason why many interventions are presented as a package means that these interaction effects are not trivial. For instance, Kabunga, Dubois, and Qaim (2012) find that banana tissue culture, a technology to ensure that banana plantlets are free from pests and diseases, leads to a seven percent yield gain in Kenya. However, they also find that improving access to irrigation could lift yield gains above 20 percent. It seems unlikely that farmers follow a sequential learning path that allows for all possible interactions between the different technologies. Furthermore, behavioral constrains may prevent farmers from effective learning. It is for instance possible that farmers pay attention to the wrong attributes (Hanna, Mullainathan, and Schwartzstein, 2014).

When learning about a new technology, farmers will ex-post compare realized yields to the yields they expected at the time they made the decision to adopt. This information will then be used to decide on subsequent adoption. The effect of incorrect expectations about future returns on decision making has been studied most 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) tests if a video intervention that informs farmers about the returns on intensification investments in rice growing affects adoption in Uganda. In all these studies, it is assumed that expected returns are underestimated. In the present study, we expect different reactions of different groups of farmers: one group of farmers overestimates returns, leading to too much investment; another group underestimates returns (perhaps due to a previous disappointment), leading to too little investment.

Finally, our treatment comes in the form of short and engaging videos. There is a large literature that shows videos featuring role models can be an important vehicle for changing behavior in a variety of settings. Ferrara, Chong, and Duryea (2012) show how telenovelas have an impact on fertility in Brazil. Riley (2022) finds that in Uganda, students that watched a Disney feel-good movie called "Queen of Katwe" about a chess prodigy growing up in the slums of Kampala did better on their exams, particularly in math. In the context of agricultural technology adoption, Van Campenhout, Spielman, and Lecoutere (2021) show that farmers that were exposed to videos similar to the ones we use in the present study were performing significantly better on a knowledge test, were more likely to apply recommended practices and fertilizer than households that did not view the video. These same households also reported maize yields 10.5 percent higher than the ones of the control group. In Ethiopia, Abate et al. (2023) assess the impacts of video-mediated agricultural extension service provision on farmers' adoption of improved agricultural technologies and practices in Ethiopia using data from a two-year randomized experiment. Our study also contributes to this literature as it tests if a video is effective in transmitting subtle information.

3 Theoretical framework

Farmers are solving an intertemporal problem, allocating resources at t in order to get maximum profit at $t+1$.[1] In line with Suri (2011), we assume that farmers

[1] For simplicity, we assume a discount factor of 1, but another discount factor will not alter the results.

(indexed i in the model below) are risk-neutral and choose a seed type, which is either of an improved variety (a high-yielding cultivar, i.e. an OPV or a hybrid variety) or farmer-saved seed, to maximize their profits per area of land. In particular, they compare the expected profit functions of seed of an improved variety ${\pi_{it}^{*}}^{H}$ and farmer-saved seed ${\pi_{it}^{*}}^{L}$ which are defined as:

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

$$E\left(\pi_{it+1}^{L}\right) = E\left(p_{t+1}Y_{it+1}^{L}\right) - \sum w_t X_{it}^{L} \tag{2}$$

where E is an expectations operator and $E\left(p_{t+1}\right)$ is the expected price at which output is valued, assuming that consumers do not differentiate between maize obtained from seed of improved varieties and maize obtained from farmer-saved seed. $E\left(Y_{it+1}^{H}\right)$ and $E\left(Y_{it+1}^{L}\right)$ is the expected yield for seed of an improved variety and farmer-saved seed respectively. Farmer-saved seed is assumed to be free, while the amount of seed of an improved variety s_{it} is procured at a cost $b_t > 0$. In both profit functions, the cost of a range of complementary inputs and cultivation practices, further referred to as inputs, are deducted, which are summarized in the vector X_{it} with corresponding factor prices w_t.

Farmers adopt improved varieties if they expect that using this seed is more profitable than using farmer-saved seed, that is, if $E\left(\pi_{it+1}^{H}\right) > E\left(\pi_{it+1}^{L}\right)$ or:

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

where we normalize by output price.[2]

Equation 3 shows that adoption decisions fundamentally depend on yield comparisons. We assume that yield for farmer-saved seed is a function of inputs used:

$$Y_{it+1}^{L} = Y_{it}\left(X_{it}^{L}\right) \tag{4}$$

and this relationship is assumed to be positive with decreasing returns to scale: $\frac{dY_{it}}{dX_{it}} > 0$ and $\frac{d^2Y_{it}}{dX_{it}^2} < 0$.

Yield for seed of improved varieties follows the same function as yield for farmer-saved seed, but adds a positive and constant adoption premium $(A > 0)$. However, the adoption premium only applies when the farmer uses at least the same amount of complementary inputs as they would do when using farmer-saved seed $\left(X_{it}^{H} \geq X_{it}^{L}\right)$:

$$Y_{it+1}^{H} = A\left(X_{it}^{H} \geq X_{it}^{L}\right) + Y_{it}\left(X_{it}^{H}\right) \tag{5}$$

[2] We assume farmers have only one plot and model the decision to adopt as a binary process, instead of expressing s_{it}in kilograms of seed used. As such, b_t refers to the cost of planting an entire field with seed of an improved variety.

If farmers would be able to, at least on average, predict yields in *t+1*, such that $E\left(Y_{it+1}\right) = Y_{it+1} + \varepsilon$ and $\varepsilon \sim N(0, \sigma)$, their decision to adopt would depend on the difference in yield between seed of an improved variety and farmer-saved seed, on the relative prices of the inputs, and on the yield responses of the inputs. We introduce farmer heterogeneity into the model by assuming that at least some farmers are not aware of the true relationship between Y_{it}^{H} and X_{it}, but instead believe that the adoption premium is always there, that is $E\left(Y_{it+1}^{H}\right) = A + Y_{it}\left(X_{it}^{H}\right)$. As a result, some farmer will use seed of improved varieties but not enough complementary inputs, leading to disappointing outcomes.

The model leads to different farmer types based on their dynamic profile and knowledge, as summarized in Table 1. First, there is a group of farmers that is knowledgeable about the true relationship between Y_{it}^{H} and X_{it} in equation 5, and as a result these farmers make correct investment choices. For at least some of these farmers, referred to as type 1 farmers in Table 1, the marginal cost of adoption will be lower than the expected marginal return in equation 3, and as a result they adopt (and will continue to do so in the future unless there is a change in fundamentals such as the cost of seed). For another subset of these farmers , referred to as type 2 farmers in Table 1, the marginal cost of adoption will be higher than the expected marginal return, so they will not adopt (and are unlikely to adopt in the near future).

Another group of farmers is not knowledgeable about the true relationship between Y_{it}^{H} and X_{it} and believes there is always an adoption premium. A subset of these farmers may adopt prior to the intervention because their marginal cost of adoption is lower than their expected marginal returns. We refer to these farmers in Table 1 as type 3 farmers. Another subset of this second group of farmers that is not knowledgeable about the true relationship between Y_{it}^{H} and X_{it}, referred to as type 4 farmers in Table 1, does not adopt at baseline because, even though they have inflated expectations of the improve seed variety yields, the marginal cost of adoption still exceeds the expected marginal returns.

Another group of farmers is also not knowledgeable about the true relationship between Y_{it}^{H} and X_{it}. But unlike type 3 and 4 farmers, these farmers underestimate the adoption premium (much like the rice farmer underestimate the returns to intensification investments in Van Campenhout (2021)), perhaps due to a disappointing experience in the past. Some of these farmers, type 5 in Table 1, adopt at baseline as the expected marginal return may still be larger than the marginal cost of adoption, even if they underestimate the return. For another fraction of farmers that underestimate the adoption premium, referred to as type 6 in Table 1, the expected marginal return will be smaller than the marginal cost of adoption, so that they do not adopt prior to the intervention.

Heterogeneity in terms of prior knowledge and adoption behaviour will lead to different impacts of an intervention aimed at correcting incorrect beliefs about the relationship between input use and effort and the returns to improved seed varieties. In some cases, such as for adoption, effects for different subgroups may go in opposite directions, potentially canceling out an overall average treatment effect. In other cases, such as for knowledge, some groups may not be affected,

Table 1: Farmers types and model predictions

farmer type	baseline expectations	baseline adoption	effect on knowledge	effect on adoption	effect on expectations	effect on efforts
1	correct expectations of adoption premium	yes	none	none (always adopt)	none (correct at baseline)	none
2	correct expectations of adoption premium	no	none	none (never adopt)	none (correct at baseline)	none
3	inflated expectations of adoption premium	yes	yes ++	dis-adopt due to decreased exp. marg. return	more realistic	decrease +
4	inflated expectations of adoption premium	no	yes +	none (never adopt)	none (correct at baseline)	none
5	reduced expectations of adoption premium	yes	yes ++	none (always adopt)	more realistic	increase +
6	reduced expectations of adoption premium	no	yes +	adopt due to increased exp. marg. return	none (correct at baseline)	increase ++

++ indicates large predicted effect, + indicates small predicted effect.

diluting the overall treatment effect. The model and the different farmer types summarized in Table 1 allow us to make predictions on the impact of an intervention designed to increase knowledge about the true relationship between performance of improved seed varieties and complementary inputs and efforts (described in detail in the next section) on four key outcome areas:

1. Impact on knowledge: As type 1 and type 2 farmers are assumed to be already knowledgeable about the true relationship between Y_{it}^{H} and X_{it}, the intervention will have little effect on these farmers.[3] Types 3 to 6 are assumed to be unaware about the true relationship between seed of improved varieties and complementary inputs; the intervention will thus increase knowledge. The knowledge effect will be larger for farmers that adopt at baseline (types 1, 3, 5) since this removes "never adopters" who are likely to be less interested in the information (types 2 and 4) from the sample.

2. Impact on adoption: We expect opposing effects on adoption behavior for farmer types 3 and 6. Providing type 3 farmers with information may lead them to dis-adopt if the new information reduces their expected marginal return below the marginal cost. For type 6 farmers, the intervention may increase expectations of the return, and they may start adopting in response to the treatment if the increase is sufficiently high. Reducing expectations of farmers that do not adopt at baseline even though they have inflated expectations will not change their mind as this will reduce their expected returns even more (type 4). Similarly, we do not expect the intervention will change adoption of farmers that already adopt even though they underestimate potential yield effects (type 5); these farmer will keep adopting as the intervention increases their expected returns to seed of improved varieties. Finally, as for knowledge, farmers that are aware of the correct relationship between inputs and improved seed varieties (types 1 and 2) are not expected to change adoption behavior in response to the intervention. The direction of the effect of the intervention of adoption will thus depend on the relative size and effects of group 3 and group 6 respectively. Note that if we only consider farmers that adopt at baseline, the expected effect on adoption will be negative as this excludes type 6 farmers from the analysis.

3. Effect on expectations: Expectations are defined as the difference between what the farmer expected and what was realized on the farm. We predict that the intervention results in expectations that are more in line with realized outcomes. This will likely only be the case for farmers that are unaware of the true relationship and so we again do not expect an effect for types 1 and 2. Furthermore, since our intervention aims to correct perceptions only for seed of improved varieties, expectations of farmers that use farmer-saved seed at baseline are unlikely to be affected (as it

[3] Note that we do not know which farmers are knowledgeable and which are not as we only measure knowledge at endline to avoid priming effects.

is assumed that the production function of farmer-saved seed is common knowledge). Therefore, we only expect an impact on farmers that plant seed of improved varieties at baseline and also have incorrect expectations (types 3 and 4). Again, we expect this positive effect to be stronger if we restrict the sample to farmers that adopt at baseline.

4. Impact on use of complementary inputs and effort: Some farmers that were unaware of the true relationship between seed of improved varieties and complementary inputs and receive new information about the importance of using complementary inputs and effort may invest more effort and increase use of complementary inputs. This will be especially the case for type 6 farmers who stared adopting (potentially after disadopting due to disappointing outcomes) and will put the new knowledge into practice. To a lesser extent, farmers that consider adoption to be profitable despite low yield expectations may try to further increase yields by increasing effort (type 5). For type 3 farmers, we expect a negative effect, with farmers using less complementary inputs if the fall back to farmer-saved seed. For input use and effort, the effect is not clear a-priori, even if we confine ourselves to impact in the sub-group of farmers that adopt at baseline.

4 Intervention

The model predictions were tested using a field experiment. The field experiment itself was part of a larger project on quality related constraints to technology adoption that also had interventions at the agro-input dealer level. The pre-analysis plan for the larger study, which has a section for the farmer level intervention we focus on in this paper, was pre-registered at the AEA RCT registry under RCT ID 0006361.

The treatment was based on short, engaging videos, shown to the farmers on tablet computers. Based on extensive interviews with experts (extension agents, seed breeders, seed producers, government officials, etc.) 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 well-kept maize field inspecting their crops. The man narrates that they have been farmers for more than ten years but that their 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 on less land. The secret of their success, they continue, lies in the adoption of improved technologies and best practices, such as the use of organic fertilizer, optimal plant spacing, and reduced seed rates. Furthermore, they argue that the use of seed from an improved variety and the use of inorganic 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 have some marketable surplus that they can sell on the market. The viewer is then invited to become equally successful in farming by paying close attention as the role model farmers explain in detail the most important inputs and practices that transformed their lives in the remainder of the video.

The treatment was implemented in the form of two variations of this 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 seed of improved varieties. The only difference between the treatment and control video is thus that the former makes explicit the fact that significant complementarities exist between seed of improved varieties and recommended inputs and practices such as inorganic fertilizers and row planting.[4] The control video is about eight minutes long and can be found here. The treatment video is about twelve minutes long and can be found here, indicating four extra minutes of material (the other eight minutes are equal to the control video, no scenes are replaced or modified).

By randomizing who among our sample of farmers gets to see the video, we can isolate the causal effect of making salient the fact that improved varieties do not substitute for complementary inputs and effort, but in fact need more investment. The use of a control video also has the additional advantage is that it is not immediately clear what is the treatment and what is the control, reducing the likelihood that results are driven by experimenter demand effects (Bulte et al., 2014). Randomization was done at the village level to reduce the likelihood that treated households would provide information to households in the control group, which has been found to happen in information treatments using video (Van Campenhout, 2021).

The experiment targeted the second agricultural season of 2021, where maize planting happens in August and September and maize harvesting in November and December. We decided to implement the treatment well before the start of the season, in April 2021, to make sure that farmers had the necessary information before deciding which kind of seed to use. At this point in time, we also collected baseline data. The treatment was repeated just before planting in August 2021. Post-treatment data was collected in January and February 2022. The intervention was repeated in the first season of 2022 with a final round of data collection in July and August 2022. However, most of this paper, and particularly the impact assessment of the intervention, will focus on the 2021 agricultural season. We only use data from the 2022 agricultural season to look at some descriptive statistics on the dynamics of improved seed variety adoption.[5]

[4]To give an example, the farmer narrates in the control video that: "At planting time, I paid attention to recommended spacing, carefully measuring 1 foot between plants and 2,5 feet between rows. I first dug a 4 inches deep hole and added 1 water bottle cap of DAP. Then I added some soil. Afterwards I put 1 maize seed in and covered it with soil." The treatment video shows the same scene but then the farmer adds: "Did you know that recommended spacing and using DAP is even more important when using improved seeds?"

[5]Impact in 2022 of the treatment was limited, probably due to nature of the treatment where once you receive knowledge additional treatment is unlikely to have a lot of impact.

5 Data and empirical strategy

5.1 Sample

The field experiment was conducted in southeastern Uganda, an area known for its maize production where maize is considered both a food and a cash crop. Our sample consists of about 3,500 smallholder maize farmers. As this study is part of a larger project that investigates maize seed supply chains, farmers were drawn from the catchment areas of agro-input shops. We started by listing all shops in eleven districts in southeastern Uganda, which roughly correspond to the Busoga kingdom, an exercise that let to about 350 agro-input dealers. We then asked these dealers about the villages where most of their customers come from. Enumerators were instructed to randomly sample ten households that grow maize in these locations. Confining attention to farmers that were interviewed in all survey rounds, we remain with a balanced panel of 3,400 farmers. Given our sampling strategy, we expect farmers would have reasonable access to improved maize varieties is they would choose to adopt them.

5.2 Adoption

In this section, we illustrate the dynamics of the adoption of seed from improved varieties by smallholder farmers. We define smallholder adoption of improved maize varieties as follows: We ask farmers on how many fields they cultivated maize in the preceding season. From these plots, we randomly select one field, on which detailed questions about input use and cultivation practices are asked. A farmer is defined to be an adopter if he/she used non-recycled seed of a hybrid variety or an OPV that was recycled less than four times.

Figure 1 provides a visual representation of the evolution of varietal adoption among farmers over different survey rounds using this definition. We see that the share of adopters slowly increases over time: At survey 1 (the baseline survey), we find that about 45 percent of farmers report to have adopted an improved maize variety on the randomly selected plot. At the end of the first season, at the time of our second survey in early 2022, this figure has already increased to about 50 percent. After a second season, when we interviewed farmers one last time in July/August 2022, the share of adopters further increased to 54 percent.

The figure also shows interesting dynamics. At the top, we see a substantial share of households (22 percent) that adopted in all three survey rounds. These could be considered "always adopters". At the bottom of the chart, we find an equally substantial share (23 percent) that can similarly be categorized as "never adopters". However, we also see that a large group of farmers that adopts during the first survey reverts to farmer-saved seed at the time of the second survey (16 percent) or still adopts at the time of the second survey but eventually dis-adopts at the time of the third survey (7 percent). Fortunately, large groups of households also enter into adoption. We see that 19 percent of non-adopting households are adopting at the time of the second survey and twelve percent of households that are not adopting at both first and second survey become

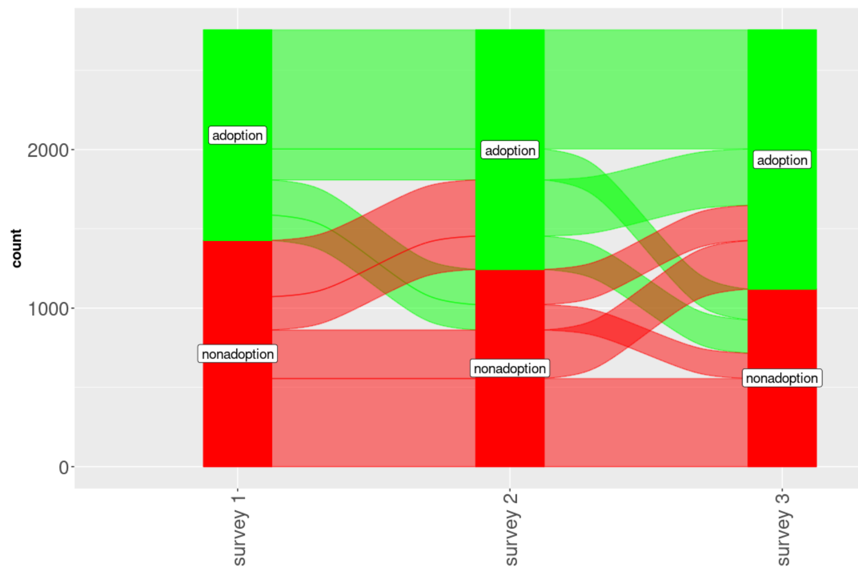

Figure 1: Dynamics of varietal adoption

adopters in the third survey. 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, we find that a significant share of farmers that adopted at the time of the first survey seems to be disappointed. Baseline data shows that 30 percent of farmers indicated that were not satisfied with the quality of the planting material that they used. One in four indicates that they will not use it again in the future.

5.3 Empirical strategy

Due to the random assignment to treatment and control groups, comparing outcome variable averages of treated and control participants provides unbiased estimates of the average treatment effects. We follow common practice and do this in an Analysis of Covariance (ANCOVA) regression framework, where we regress outcomes of interest (knowledge, adoption, input use and effort, and expectations) on an indicator variable that takes the value of one if the household was in the treatment group (and zero otherwise) and include baseline values of the outcome variables as controls (McKenzie, 2012). Furthermore, as this study was part of a larger project with additional cross-randomized treatments, controls are included for the orthogonal treatments (demeaned and interacted with the main treatment (Lin, 2013; Muralidharan, Romero, and Wüthrich, 2019)).

Standard errors are clustered at the village level as this is the level of randomization used. Since we have almost 3500 observations in 350 clusters, the original form of the sandwich estimator (Liang and Zeger, 1986) is used. For each of the four outcome families (knowledge, adoption, input use and effort, and expectations), we compute outcome indices, which is a common way to also account for multiple hypothesis testing. To do so, we follow Anderson (2008), where each index is computed as a weighted mean of the standardized values of the outcome variables. The weights are derived from the (inverse) covariance matrix, such that less weight is given to outcomes that are highly correlated with each other. For these indices, signs of outcomes were switched where necessary so that the positive direction always indicates a "better" outcome.

6 Results

6.1 Impact on knowledge

First we check if smallholder farmers are able to pick up the subtle messages in the treatment video. According to prediction 1, we expect a positive effect of the treatment on farmers' knowledge. We test farmer knowledge by means of a short quiz where a number of questions were asked and enumerators read a set of alternative answers to farmers who then select the response that they felt most appropriate.

We started with a general question, asking if farmers think recommended cultivation practices like weeding and application of fertilizer is less, equally, or more important when using quality maize seed like OPV or seed of a hybrid variety. This is followed up by a more specific question, asking the farmer to indicate what applies for weeding when they are using seed of a hybrid variety. The options from which the farmer can choose are: 1) You do not need to weed and remove Striga because seed of a hybrid variety of varieties are treated to resist weed infestation; 2) You do not need to weed and remove Striga in the first four weeks because seed of a hybrid variety 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 seed of a hybrid variety is 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 seed of an improved maize variety grows faster 3) You need to use the amount of fertilizer that you would with normal seed because also seed of an improved variety 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 seed of an improved variety on. The options here are 1) that it is best to save seed of an improved variety for poor plots, as these need less nutrients; 2) that is best to use your seed of an improved variety for plots that are furthest away from the home, as seed of an improved variety need less care than normal seed; and 3) that the decision on what plot to plant seed of an improved variety should not be affected by the seed type that is used.

Another question tests if farmers think it is better to combine inputs, or to 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 question, 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 two and a half foot between rows with one seed per hill; 2) One foot between plants and two and a half foot between rows with two seeds per hill; and 3) Two foot between plants and two and a half foot between rows with two seeds per hill. The four outcomes (excluding the control question) are also combined in an index following Anderson (2008).

The average treatment effects on knowledge can be found in Table 2. The first column (1) provides the mean in the control group, mainly to get an idea of effect sizes of the intervention. We see that knowledge is already high: 88 percent of farmers in the control group know that recommended cultivation practices like weeding or applying fertilizer are also important when using seed of improved varieties.

The second column (2) shows the estimated difference between the treatment and control group for outcomes after the intervention, while the third column (3) also reports this difference, but only for the subset of farmers that adopted an improved variety at baseline. The rationale for restricting is explained in 3: as it keeps farmers for whom the treatment effect is likely to be largest, we expect a larger effect in column (3) than in column (2).

We see that knowledge, as measured by the quiz questions, has increased for all questions, and generally more so for the subset of farmers that used seed of an improved variety at baseline. For instance, the share of farmers that knows complementary inputs and practices are at least as important when using seed of improved varieties increased from 87.1 to 89.4 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 73.5 to 75.7 percent. If we only consider farmers that adopted at baseline, the increase over the control amounts to almost five percentage points. However, 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 were already 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 which translates in the index in column (3) coming closes to significance with a p-value

Table 2: Average treatment effects on knowledge

	(1)	(2)	(3)
Farmer knows inputs and practices are important when using an improved variety	0.871	0.022	0.021
	(0.336)	(0.015)	(0.018)
Farmer knows weeding is important when using an improved variety	0.790	0.025	0.034
	(0.407)	(0.022)	(0.026)
Farmer knows applying fertilizer is important when using an improved variety	0.835	0.009	0.005
	(0.371)	(0.016)	(0.020)
Farmer knows plot selection should be independent of using an improved variety	0.792	0.007	0.007
	(0.406)	(0.025)	(0.030)
Farmer knows it is best to invest in different inputs instead of putting all eggs in one basket	0.735	0.022	0.044
	(0.441)	(0.023)	(0.027)
Farmer knows recommended seed spacing and rate	0.687	0.029	0.020
	(0.464)	(0.024)	(0.029)
Knowledge index	0.015	0.046	0.064
	(0.580)	(0.036)	(0.042)
Observations	1707	3441	1570

Note: Column (1) reports control group means post-intervention (and standard deviations below); column (2) reports difference between treatment and control post-intervention; column (3) reports difference between treatment and control post-intervention 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.

of 0.125.

6.2 Impact on adoption

We now test the main hypothesis of this paper: Do farmers that were made aware of the fact that seed of improved varieties needs substantial complementary inputs and proper agronomic management behave differently in terms of seed use in subsequent seasons than farmers that were not exposed to this information. To this end, we asked farmers which maize variety they planted on the randomly selected maize field in the season prior to the survey. We again define adoption as the use of fresh seed of an improved variety, i.e. seed of a hybrid variety which was not recycled and seed of an OPV which was not recycled too often (the same definition used in Figure 1 to illustrate the dynamics of varietal adoption). In addition, we investigate other outcomes that are related or even partly overlapping. For instance, we test if there are differences in the use of recycled seed between the treatment and control group, where we define recycled seed as seed that a farmer has saved themselves or obtained from another farmer who saved it (neighbor, relative, etc.). Note that seed of an improved variety and seed that was recycled are not exact opposites, as seed of an OPV can be recycled for a couple of seasons and still count as seed of an improved variety. Another related outcome is the share of farmers that report to have bought seed from an agro-input shop. The three outcomes are also combined in an index following Anderson (2008).

Results are in Table 3. The first column (1) shows sample means of the four outcomes at baseline and standard deviations in brackets below. For instance, we see that 48 percent of farmers use fresh seed of improved varieties and that one third of farmers reports that the seed that they planted on the randomly selected plot was obtained from an agro-input dealer. The second column (2) illustrates pre-treatment balance between treatment and control groups. We see that the randomization was successful, as there is no significant difference in varietal adoption behavior between farmers that will be exposed to the treatment and those that will not.

The third column (3) shows the difference between treatment and control for outcomes after the intervention. Our theory suggests that in response to being sensitized about the importance of using complementary inputs and cultivation practices when using seed of an improved variety, some farmers (types 3 and 6) will change their adoption behavior (prediction 2 in Section 3). A share of farmers that initially underestimated the returns to improved seed varieties (type 6) will start adopting as their expected marginal return is increased by the treatment. Another share of farmers that initially overestimated the probability of an adoption premium (type 3) will dis-adopt as their expected marginal return is reduced by the treatment. Dis-adoption implies that farmers will be less likely to plant fresh seed of an improved variety and seed bought at agro-input shops, but more likely to use recycled farmer-saved seed. As these two opposing effects cancel each other out, we find few effects on the entire sample. However, we find that all coefficients go in the direction of dis-adoption and a significant difference for the share of farmers that planted recycled seed post-intervention.

The comparisons in the third column is for all farmers, while the fourth column (4) restricts the sample to farmers that adopted at baseline. We see that effects become stronger if we restrict attention to this subgroup (and exclude type 6 farmers from the analysis). Farmers that were exposed to the treatment are almost seven percentage points less likely to adopt fresh seed of an improved variety. We see a particularly strong increase in the share of farmers that uses seed recycled from the previous harvest in the treatment group and a somewhat lower but still significant reduction in farmers that bought seed from an agro-input dealer. For the subgroup of farmers that adopted at baseline, the treatment also has a significant and negative effect on the adoption index.

6.3 Impact on expectations and harvest

As the intervention is designed to affect farmer behavior by correcting farmers' expectations, we confirm this impact pathway by testing if post intervention, farmers feel their expectations in terms of yield were met. As mentioned in prediction 3 in Section 3, we think this is particularly the case if we restrict the sample to farmers that adopt at baseline. We also measure harvest related

Table 3: Average treatment effects on adoption

	(1)	(2)	(3)	(4)
Farmer planted seed of an improved variety	0.479	0.010	-0.036^{+}	-0.069**
	(0.500)	(0.023)	(0.021)	(0.026)
Farmer planted seed from agro-input shop	0.328	-0.004	-0.022	-0.065*
	(0.469)	(0.020)	(0.020)	(0.027)
Farmer planted seed that was recycled	0.569	0.020	0.032	0.077**
	(0.495)	(0.022)	(0.021)	(0.027)
Adoption index[1]	0.008	0.006	-0.064	-0.125*
	(0.923)	(0.041)	(0.039)	(0.051)
Observations	3242	3242	2941	1408

Note: Column (1) reports means at baseline (and standard deviations below); column (2) reports difference between treatment and control at baseline; column (3) reports difference between treatment and control post-intervention; column (4) reports difference between treatment and control post-intervention 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. [1]For this index, signs of outcomes were switched where necessary so that the positive direction always indicates adoption of improved varieties.

outcomes on a randomly selected maize field. We look at production and yield (dividing production of the plot by the size of the plot). The three outcomes are also combined in an index following Anderson (2008).

Results can be found in Table 4. We again report baseline means and balance in the first two columns (1) and (2). However, we did not ask if expectations were met at baseline, and so we report the control group average post-intervention and do not test for baseline balance for the expectations variable. Note that a large majority of farmers indicated that they harvested less than expected.

The third column (3) shows that, in line with expectations, in the treatment group a significantly higher share of farmers say that they produced what they expected. The effect is larger for the subset of farmers that adopted at baseline, see column (4). This suggests that a subset of farmers indeed started out with inflated expectations, which were corrected after they learned that seed of improved varieties is not miracle seed.

Finally, the table shows that the average farmer cultivates about 460 kilograms of maize on the random plot. The randomly selected field seems to be slightly larger than one acre on average, so that yield is about 440 kilograms per acre. The intervention does not seem to have any impact on production or productivity.

6.4 Impact on input use and efforts

Finally, we investigate how the intervention affects effort and the use of inputs other than seed. For input use and effort, the effect is ambigious, even if we restrict attention to the subsample of baseline adopters (see prediction 4 in

Table 4: Average treatment effects on expectations and harvest

	(1)	(2)	(3)	(4)
Yield as expected	0.15		0.029^{+}	0.054^{*}
	(0.36)		(0.017)	(0.023)
Production in kg	463.702	16.444	2.562	-8.864
	(399.319)	(18.004)	(12.713)	(18.666)
Yield in kg/acre	436.332	9.559	6.790	17.644
	(280.790)	(12.128)	(12.129)	(15.579)
Harvest index	-0.004	0.006	0.026	0.045
	(0.755)	(0.038)	(0.035)	(0.047)
Observations	2496	2496	3185	1460

Note: Column (1) reports means at baseline (and standard deviations below); column (2) reports difference between treatment and control at baseline; column (3) reports difference between treatment and control post-intervention; column (4) reports difference between treatment and control post-intervention 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.

Section 3).

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

Reducing the seed rate, i.e. the number of seeds used, is our second outcome. Farmers often plant more seed than necessary because they fear that it may not germinate. However, using more than two 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 need to engage in gap filling after one week if seed fails to germinate.

The next three outcomes look at fertilizer use. The application of organic fertilizer is important for soil structure, while Di-Ammonium Phosphate (DAP) or Nitrogen, Phosphorus, and Potassium (NPK) and Urea are used to provide essential nutrients at particular points in time. The cost of organic fertilizer is mainly in terms of labor, while both DAP and Urea need to be bought from an agro-input shop and applied during planting (DAP) and at early stages of growth (Urea).

Farmers should weed within the first week after planting and as often as possible. Official recommendations are to weed at least three times. Furthermore, invasive insects such as the fall armyworm (*Spodoptera frugiperda*) or maize stalk borer (*Busseola fusca*) can severely reduce yields. Pesticides, herbicides, fungicides, and insecticides, are widely available in agro-input shops under commercial names such as Rocket, Lalafos and Dudu acelamectin. While weeding requires labor, pesticides come at a pecuniary cost.

Finally, we look at differences in re-sowing or gap-filling. This involves revisiting the field after planting and inspecting the hills for seed germination. If a seed did not germinate, a new seed is planted in that location. Re-sowing, reduced seed rate and row-planting are thus likely to be correlated. We also combine all outcomes in an overall index following Anderson (2008).

Results are reported in Table 5. As in the previous table, the first two columns (1) and (2) report means and orthogonality for outcomes before the treatment. We find an imbalance for the number of times that a farmer reports to have weeded and the likelihood that farmers re-sow after one week. Note that the imbalance goes in different directions, which makes it less likely that it is caused by a structural difference between treatment and control group such as consistently lower efforts in one group, and more likely to be the result of chance.

The third column (3) shows that farmers do not invest more inputs or efforts after the intervention. On the contrary (and especially if we only consider a subset of farmers that adopted at baseline, see column (4)) farmers appear to be less likely to plant in rows and to use DAP. This suggests that there is an important group of farmers that adopts at baseline, perhaps using some inputs and practices such as inorganic fertilizer and row planting. However, after being made aware that all complementary inputs are equally important, they may decide it is not optimal to use improved seed varieties, and they may turn back to farmer saved seed, in turn reducing input use and some practices like row planting.

7 Conclusion

This paper was motivated by qualitative evidence suggesting that many farmers are unaware that many agricultural technologies such as seed of improved varieties require substantial complementary inputs and effort to get the most out of it. As a result, farmers overestimate the returns from the technology and are disappointed when they compare realized yields with what they expected at the time of planting. As it is hard for farmers to learn about the yield response of a single input, farmers may decide that the technology itself is to blame. This is consistent with the observation that many farmers think inputs are often counterfeit or of low quality, but objective assessments of quality of inputs find quality to be acceptable (Barriga and Fiala, 2020; Michelson et al., 2021).

To credibly test the hypothesis that farmers think of seed of improved varieties as "miracle seed", we set up a field experiment around an engaging video on recommended cultivation practices for maize growing. We produced two versions of the video, one for the treatment group and one for the comparison group. The treatment and control videos are identical, except that, after each practice or input that is shown, the treatment video explicitly mentions that the practice or input is "[...] particularly/even more important when you are

Table 5: Average treatment effects on input use and efforts

	(1)	(2)	(3)	(4)
Row-planting	0.243	0.025	-0.070*	-0.095**
	(0.429)	(0.022)	(0.027)	(0.032)
Reduced seed rate	0.237	0.010	0.009	-0.014
	(0.425)	(0.021)	(0.019)	(0.027)
Organic fertilizer use	0.075	-0.009	-0.013	-0.023
	(0.263)	(0.011	(0.017	(0.023
DAP/ NPK use	0.251	-0.020	-0.029	-0.050+
	(0.434)	(0.024)	(0.019)	(0.027)
Urea use	0.076	0.001	0.002	0.012
	(0.265)	(0.013)	(0.015)	(0.022)
Weeding frequency	2.561	0.084**	-0.021	-0.001
	(0.650)	(0.026)	(0.027)	(0.036)
Pesticide etc. use	0.412	0.031	0.003	-0.014
	(0.492)	(0.024)	(0.023)	(0.031)
Re-sowing	0.482	-0.046*	0.013	0.028
	(0.500)	(0.023)	(0.022)	(0.028)
Early planting	0.699	-0.018	0.012	0.034
	(0.459)	(0.024)	(0.025)	(0.029)
Early weeding	0.606	0.032	0.026	0.039
	(0.489)	(0.020)	(0.021)	(0.027)
Efforts index	0.008	0.009	-0.008	0.001
	(0.400)	(0.020)	(0.019)	(0.024)
Observations	3389	3389	3202	1470

Note: Column (1) reports means at baseline (and standard deviations below); column (2) reports difference between treatment and control at baseline; column (3) reports difference between treatment and control post-intervention; column (4) reports difference between treatment and control post-intervention 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.

using seed of an improved variety". We then randomly allocated treatment and control status to villages, where a set of farmers was shown the video a few months before the planting season, at the time when they selected the seed that they would use, and again at the start of the planting season. We revisited farmers after harvest in treatment and control villages to test if there were differences in farmer knowledge, seed use, expectations, complementary input use and agronomic practices.

While we did not find treatment effects that differ significantly from zero for knowledge, we did see that all coefficients go in the expected direction. We suspect that the lack of statistical significance may be caused by low power given an already high knowledge among farmers. Turning to the main outcome—behavior related to seed use—we found that treated farmers were less likely to use seed of improved varieties obtained from agro-input dealers and more likely to revert back to farmer-saved seed. We also found that farmers that received the treatment were more likely to report that their harvest was in line with what they expected. We found no overall effect of the treatment on input use and effort, although there is some indication that especially costly inputs and practices were reduced.

Our results differ from other studies that find that improved technologies increase 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 that Bulte et al. (2023) and Emerick et al. (2016) provided the improved technology (also seed) for free as part of the experiment, potentially resulting in an income effect in the sense that money that treated farmers did not use to buy seed was used to buy complementary inputs.[6] In our experiment, no free seed was provided, so when the adoption decision was made, farmers had to take the cost of seed combined with the cost of complementary inputs into account, further eroding the expected profitability of the improved technology.

Our study further 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 there are important interaction effects between different inputs, it seems unreasonable to assume that farmers can try out all possible combinations of inputs to learn about these interactions in a Bayesian fashion.

Our study has important implications for both policy makers and the private sector. When designing agricultural extension and advisory services, policy makers should highlight the complementarity of modern inputs. If not, their efforts risk to be short lived. Worse, incorrect perceptions of poor quality caused by misattribution may crowd out the market for quality inputs (Bold et al., 2017). Policy makers also often subsidize improved technologies to scale up adoption (Jayne et al., 2018). While this may work for some stand-alone

[6]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 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.

technologies (for example, Omotilewa, Ricker-Gilbert, and Ainembabazi, 2019), promoting technologies that require complementary inputs (such as subsidized or even free seed trial packs) without supplying these complementary inputs may be counterproductive, as farmers may not experience the expected success.

Industry can also play an important role here. As part of their marketing strategy, seed producers and agro-input dealers tend to highlight particular traits of the technology they sell, such as high yields or pest resistance. As a result, farmers may actually reduce fertilizer use or weeding. Furthermore, they may not be tempted to actively promote the use of complementary inputs if they are produced by competing companies. In both cases, short term benefits may lead to long run losses.

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