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

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

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Abstract

Farmers that try out agricultural technologies, such as seeds of improved varieties obtained from agro-input dealers, may hold unrealistic expectations about these technologies. 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 fertilizers or pesticides and reduce management practices such as 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 test its 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 our message scares farmers away from commercial seed, back to farmer-saved seed. There is further suggestive evidence that treated farmers adjust expectations: they are also more likely to report to have harvested as much as they expected. 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.

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[*]Development Strategy and Governance Division, IFPRI, Belgium - corresponding author: bjorn.vancampenhout@cgiar.org

[†]LICOS, KU Leuven, Belgium

[‡]Development Strategy and Governance Division, IFPRI, Uganda

[§]Development Economics Group, Wageningen University and Research, Netherlands

[¶]Development Strategy and Governance Division, IFPRI, Rwanda

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 diseases 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). 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. An obvious one 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 (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 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 inputs as an explanation for their dis-adoption. These inflated expectations have their origin in the fact that monetary outlays are necessary for improved technologies, and farmers may consider this as a signal that modern inputs are substitutes for other investments they would typically make. In reality, however, for improved technologies to reach their full potential, equal or even additional complementary investments are necessary. 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 the reduced use of 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).

Over the years, we uncovered many anecdotes in a variety of contexts 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, fertilizer need to be applied for 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. However, seed of improved maize varieties needs a lot of fertilizer, 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 the improved variety is responsible for increased Striga infestations on their fields.

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 efforts that directly affect productivity, yet for farmers that experiment with the new technology, this technology is considered to be a substitute for some of the other inputs.

We test the predictions of the model using a field experiment among 3500 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 efforts. 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 remains important to use additional inputs and to perform management practices when using seed of an improved variety.

We start with testing if farmers are able to extract the relevant information from the treatment video by testing 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 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 farmer-saved seed, and less likely to use seed of an improved variety such as a 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. Finally, even in the absence of adjustments in complementary input use and practices, the intervention may still have lasting impacts if farmers' expectations become more realistic, and 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 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 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. The Data Section 5 provides some descriptive statistics and illustrates the dynamics of varietal adoption. Section 6 looks at results, with subsections for knowledge, adoption, complementary inputs, and expectations. 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 contains 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 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 and Berkeley's Center for Effective Global Action (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). 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). Our study takes a similar dynamic approach and differentiates "always adopters" and "never adopters" from "new adopters" and "dis-adopters".

At the core of our theoretical framework presented in the next Section 3 is a learning failure that leads to dis-adoption. Indeed, heterogeneity in farmer characteristics implies that farmers need to learn if a technology is suitable for their specific case (Suri, 2011). Generally, 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 interventions are presented as a package often 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 in subsequent adoption. 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) finds 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 different reactions of different groups of farmers: A group of farmers considers seed of improved varieties to be miracle seed and thus overestimate returns, leading to too much investment. Another group underestimates returns 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 video 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 Disney's feel-good movie Queen of Katwe about a chess prodigy 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. 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 (index 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.

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

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

$$\left(E\left(Y^H_{it+1}\right) - \sum \frac{w_t}{E(p_{t+1})} X^H_{it}\right) - \left(E\left(Y^L_{it+1}\right) - \sum \frac{w_t}{E(p_{t+1})} X^L_{it}\right) > \frac{b_t}{E(p_{t+1})} s^*_{it} \tag{3}$$

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:

$$Y^L_{it+1} = Y_{it}\left(X^L_{it}\right) \tag{4}$$

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

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 $\left(X^H_{it} \geq X^L_{it}\right)$:

$$Y^H_{it+1} = A\left(X^H_{it} \geq X^L_{it}\right) + Y_{it}\left(X^H_{it}\right) \tag{5}$$

However, there may be reasons why farmers reduce input use when switching to improved varieties. For instance, if they face a budget constraint, then inputs will be reduced by the cost of seed, resulting in lower yields:

$$Y^H_{it+1} = Y_{it}\left(X^H_{it}\right) = Y_{it}\left(X^L_{it} - \frac{b_t s_{it}}{w_t}\right) \tag{6}$$

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^H_{it} and X_{it}, but instead believe that $E\left(Y^H_{it+1}\right) = A + Y_{it}\left(X^H_{it}\right)$. The credit constrained farmer's expected yield will then be:

$$E\left(Y^H_{it+1}\right) = A + Y_{it}\left(X^L_{it} - \frac{b_t s_{it}}{w_t}\right) \tag{7}$$

and as a result, the farmer will use seed of improved varieties but not enough complementary inputs.

[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.

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 always adopt. 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 never adopt.

Another group of farmers is not knowledgeable about the true relationship between Y_{it}^H and X_{it} and believe 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, the marginal cost of adoption still exceeds the expected marginal returns. Type 3 and 4 farmers are those that believe in "miracle seed".

Another group of farmers is also not not knowledgeable about the true relationship between Y_{it}^H and X_{it}. But unlike type 3 and 4 farmers, these farmers hold expectations of the adoption markup that are too low. This could be because they had a disappointing experience with an improved variety in the past, as they used to believe in miracle seed and over-adopted as described above. 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 probability of realizing an adoption premium. 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 false beliefs about the relationship between input use and effort and the return on improved seed varieties. In some cases, such as for adoption, effects for different subgroups may go in different directions, potentially canceling out an overall average treatment effect. In other cases, like for knowledge, some groups may not be affected, 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

[3]Note that we do not know which farmers are knowledgeable and which are not as we only

Table 1: Types of farmers

	baseline expectations	baseline adoption	effect on knowledge	effect on adoption	effect on exp.[1]	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	increase +
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 ++

Note: [1]Correct expectations are defined as the farmer harvesting as much maize from their field as expected. If a farmer plants seed of an improved variety, these expectations deal with the yield of seed of an improved variety. If a farmer plants farmer-saved seed, these expectations deal with the yield of farmer-saved seed.

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 this 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. Reducing expectations of farmers that do not adopt at baseline even though they believe in miracle seed 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 event 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 wil thus depend on the relative size of group 3 and group 6 respectively. Note that if we only consider farmers that adopt at baseline, the 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 expect that the intervention results in expectations that are more in line with realize 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 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 maize varieties at baseline and also have incorrect expectations (types 3 and 4). So again, we expect a positive effect, particularly 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

measure knowledge at endline to avoid priming effects.

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). Finally, as we mentioned above, also we expect a positive treatment effect for type 3 farmers, as in the control group there are farmers that still believe improved seed varieties are miracle seed and so apply less inputs and put in less effort than they would if they would use farmer saved seed (while in the treatment group most farmers revert to farmer saved seed). For input use and effort, we thus expect a positive effect, and whether the effect is more pronounced for baseline adopters only depends on the relative importance of the groups and the effect sizes.

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.

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 complementarity exists between seed of improved varieties and recommended inputs and practices such as inorganic fertilizers and row planting. 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?" 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 also need inputs and effort, that they are not miracle seed. An 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).

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 descriptives statistics on the dynamics of improved seed variety adoption.[4]

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. As a matter of fact, much of the maize that is used as food aid in Sudan is sourced from here. 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,

[4]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.

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. As such, farmers should have reasonable access to improved maize varieties.

5.2 Adoption

In this section, we illustrate the dynamics of the adoption of seed from improved varieties by smallholder farmers. We define smallholders' 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 for 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 suvey), we find that about 45 percent of farmers report to have adopted an improved maize variety on the randomly selected plot at baseline in April 2021. 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 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. Almost 30 percent indicate 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.

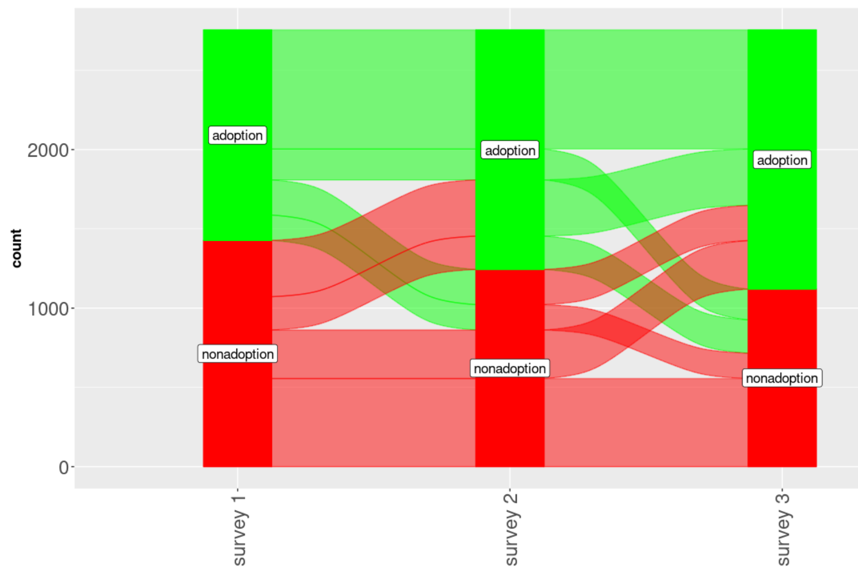

Figure 1: Dynamics of varietal adoption

5.3 Empirical strategy

Due to the random assignment to treatment and control groups, comparing outcome variable means of treated and control participants provides unbiased estimates of the average treatment effects. Differences are estimated in a regression framework. To increase power, we condition the estimates on baseline values of the outcome variables.[5]

Standard errors are clustered at the village level, the level of randomization. Since we have almost 3500 observations in 130 clusters, the original form of the sandwich estimator (Liang and Zeger, 1986) is used. We account for multiple hypothesis testing by aggregating different outcomes within each domain into summary indices, following (Anderson, 2008).[6] For these indices, signs of outcomes were switched where necessary so that the positive direction always indicates a "better" outcome.

[5]As this study was part of a larger project with additional treatments at the agro-input dealer level, controls are included for the orthogonal treatments (demeaned and interacted with the main treatment (Lin, 2013; Muralidharan, Romero, and Wüthrich, 2019)).

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

6 Results

In this section, we present impact of the treatment using simple differences between outcomes in treatment and control villages.[7]

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, the treatment increases farmers' knowledge. In a short quiz, enumerators read a set of alternative answers to farmers who then select the response that they feel is most appropriate. This quiz was only implemented after the intervention because we were wary of priming.

We test if farmers know that when using seed of an improved maize variety like an OPV or a hybrid variety: a) recommended cultivation practices like weeding or applying fertilizer are equally or even more important than when using lower quality seed, that they should b) weed and remove Striga as often c) apply the same amount or even more fertilizer, d) use equally good plots as they would if they would use lower quality seed, e) buy both seed of an improved variety and fertilizer when investing their money in agriculture, combine these different inputs instead of putting all their eggs in one basket. We also include one control question about the optimal seed rate and plant spacing, where we do not expect a difference between treatment and control because the correct answer featured in both videos. The six outcomes 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. We look at treatment heterogeneity at this level because it is likely that the treatment is not relevant for all smallholders: some farmers may not adopt because of other reasons than the ones we conjecture. For instance, improved varieties may not be profitable in their specific case, or access to credit may be their primary constraint. This substantial share of "never adopters" is excluded from the analysis if we only look at farmers who adopt at baseline. Hence we expect the effect to be larger for the remaining share of farmers (see prediction 1).

[7] Even though we did collect data at base-, mid- and endline, we only report midline results because we expect the effect to be largest right after the intervention. For this reason and to make the paper easy to read, we decided to not present the endline results. The same analysis on endline data is available from the authors upon request.

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.

We see that knowledge, as measured by the quiz questions, has increased for all questions. 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 to 89.2 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 74 to 76.2 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. Furthermore, even though farmers may possess the knowledge, there is still a difference between knowing and acting. We suspect that our intervention does not only increase knowledge, but also nudges farmer to practice what they know. Such aspirational effects are common in other studies that use videos featuring role models (Bernard et al., 2015; Riley, 2022).

6.2 Impact on adoption

We now test the main hypothesis of this paper: if farmers that were made aware of the fact that seed of improved varieties also needs complementary inputs behave differently in terms of seed use in subsequent seasons. To this end, we asked farmers which maize variety they planted on the randomly selected maize field last season. In particular, we look at 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, our key adoption indicator that was also 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. We define recycled seed as seed that a farmer has saved him- or herself 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. 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 reports 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 five 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. As constructing the index involves standardization, its average is zero. The second column (2) illustrates balance and compares treatment and control outcomes at baseline. 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). A share of farmers that initially underestimated the probability of an adoption premium (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 predicted, these two opposing effects cancel each other out and we see almost no significant coefficients. 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, indicating that there are more type 3 than type 6 farmers in our sample.

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	0.332	-0.005	-0.022	-0.067*
	(0.471)	(0.021)	(0.020)	(0.028)
Farmer planted seed that was recycled	0.576	0.018	0.033	0.075**
	(0.494)	(0.022)	(0.021)	(0.028)
Adoption index[1]	0.004	0.007	-0.063	-0.122*
	(0.927)	(0.042)	(0.039)	(0.052)
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.

The comparisons in the third column hold 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 (as expected, see prediction 2). 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 input use and efforts

In this subsection, we investigate how the intervention affects efforts and the use of inputs other than seed, as these are important variables in our theoretical framework in 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 and 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).

The effect of making farmers aware that seed of improved varieties needs at least the same complementary inputs and efforts as seed of other varieties is not clear a-priori (see prediction 3). On the one hand, the intervention advocates for inputs and cultivation practices, and so one may expect that some farmers (the not knowledgeable ones that plant seed of an improved variety after the intervention - types 5, 6) increase use as they adjust their practices to this new knowledge. However, in the previous Subsection 6.2 we saw that the first response of the average farmer is to reduce the adoption of improved varieties, which may lead to a simultaneous decline in other efforts, which may offset the increased use of inputs and practices by adopters.

Results are reported in Table 4. 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. However, according to the index, there is no overall effect of the intervention on complementary input use and cultivation practices.

These results could indicate that the response of smallholders to the treatment is limited to decisions related to seed. However, it may also be that we lack power as a result of heterogeneous treatment effects.

6.4 Impact on expectations and harvest

We also investigate how the intervention affects expectations and harvest related outcomes. To measure expectations, we simply asked farmers if they harvested as much maize from their field as they expected, a binary variable. If a farmer planted seed of an improved variety, these expectations deal with the yield of seed of an improved variety. If a farmer planted farmer-saved seed, these expectations deal with the yield of farmer-saved seed. We also measure harvest related 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 5. 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, so that 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 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 is what we expected in prediction 4 because it removes many farmers that have correct expectations at baseline from the sample. 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 470 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.

7 Conclusion

This paper was motivated by qualitative evidence suggesting that many farmers appear to overestimate the benefits of certain improved agricultural technologies, leading to subsequent disappointment. The cost of a particular commercial input that a farmer wants to start using, such as seed of improved varieties or inorganic fertilizer, is often substantial and competes with other (complementary) agricultural inputs. Furthermore, modern inputs are generally marketed with a focus on a few dimensions (for example, 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

Table 4: Average treatment effects on input use and efforts

	(1)	(2)	(3)	(4)
Row-planting	0.892	-0.001	-0.025^{+}	-0.024
	(0.311)	(0.026)	(0.014)	(0.019)
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	0.161	0.043	0.021	0.071
	(0.411)	(0.039)	(0.041)	(0.044)
Observations	923	923	403	264

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.

Table 5: 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.

of improved technologies, it is important to also use complementary inputs and proper agronomic practices, otherwise outcomes may be lower than expected. If farmers incorrectly attribute disappointing outcomes to the technology itself rather than their own improper management, this could lead to a pattern where farmers who try out a new technology switch back to farmer-saved seed in the next season. In a sample of smallholder maize farmers in Uganda, we indeed see substantial dis-adoption over time. Furthermore, a large majority of farmers indicate that they expected higher yields from from their fields.

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 one control version and one treatment version of the video. The treatment and control videos are identical, except that, after each practice or input that is shown, the treatment video explicitly mentions that this is "also important when you are 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 just before the planting season, at the time when they selected the seed that they would use. We revisited farmers in treatment and control villages to test if there are differences in farmer knowledge, seed use, complementary input use and agronomic practices, and expectations.

We first test if farmers picked up the subtle messages that lie at the heart of our information treatment. To do so, we subjected farmers to a multiple choice quiz. While we do not find treatment effects that differ significantly from zero, we see that all coefficients go in the expected direction. We suspect that the lack of statistical significance can be explained by the already high knowledge among control farmers, implying that knowledge was high prior to the intervention.

Turning to the main outcome - behavior related to seed use - we find that a share of farmers started adopting in the season following the treatment, and another share of farmers dis-adopted, so that these two opposing effects canceled each other out. Results indicate that the first group is larger: on average, treated farmers were less likely to use seed of improved varieties obtained from agro-input dealers and reverted back to farmer-saved seed. If we restrict attention to the first subgroup, we see a clear dis-adoption effect.

To see if the main impact pathway runs through the budget constraint, we look at complementary input use. We find little evidence that the intervention increased the use of inputs or recommended practices. Another intermediate outcome is related to expectations. We find that farmers that received the treatment were more likely to report that their harvest was in line with what they expected.

Our results differ from other studies that find that improved technology increases 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.[8] 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, leading to dis-adoption in some cases.

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, farmers can hardly try out all possible combinations of inputs to learn about these interactions in a Bayesian fashion. Furthermore, if farmers cannot learn about these interactions, expectations may be incorrect, leading to sub-optimal adoption patterns, further complicating learning.

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 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

[8] 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.

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. 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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