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[¶]

March 6, 2023

Abstract

Farmers that try out agricultural technologies, such as improved seed 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 in the short run, our message scares farmers away from commercial seed, back to local farmer-saved seed. There is further suggestive evidence that at least some farmers adjust expectations and move back into adoption in the longer run. We conclude that policy makers and industry should focus on technology adoption as a package of complementary inputs and efforts, instead of marketing a single technology.

JEL Codes: O33, D84, Q16

Keywords: agricultural technology adoption, expectations, perceptions, learning (failures), complementary inputs, seed systems, Uganda

[*]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, seed 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.[1] 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 hybrid seed is far more costly than farming with traditional seed. The extra production costs include the cost of seed, but also fertilizer costs as hybrid farming requires more chemical fertilizers

[1] 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 improvements in soil fertility. However, these fertilizers need to be applied in 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” which they can just broadcast on their least fertile plots without further management and still get exceptional harvests.

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, improved maize seed 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 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, 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 improved seed varieties.

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

We then look at some secondary outcomes to explore mechanisms at work behind the intervention. First, we test if the intervention has an effect on the use of complementary inputs such as fertilizer and pesticides, as well as on best practices in crop management such as row planting and weeding. We would have expected a positive impact here, at least in the longer run when farmers are given sufficient time realign their production decisions to the new knowledge, but we do not; statistical power may be an issue. Second, 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 seed varieties by smallholder farmers. Governments should provide (free or subsidized) innovation packages that include complementary inputs as well, instead of focusing on a single technology such as 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 6 provides some descriptive statistics and illustrates the dynamics of seed adoption. Section 7 looks at results, with subsections for knowledge, adoption, and impact pathways. A final Section 8 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 "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 the reverse: Farmers consider improved seed to be miracle seed and thus overestimate returns, leading to too much investment. Correcting these believes is expected to lead to less adoption in the short run, but more stable adoption for part of the farmer population in the long run.

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*.[2] In line with Suri (2011), we assume that farmers are risk-neutral and choose a seed type, an improved seed (a high-yielding cultivar, i.e. an OPV or hybrid variety) or local farmer-saved seed, to maximize their profits per area of land. In particular, they compare the expected profit functions of improved seed ${\pi_{it}^*}^H$ and farmer-saved seed ${\pi_{it}^*}^L$ which are defined as:

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

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

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

where E is an expectations operator and $E(p_{t+1})$ is the expected price at which output is valued, assuming that consumers do not differentiate between maize obtained from improved seed 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 improved and farmer-saved seed respectively. Farmer-saved seed is assumed to be free, while the amount of improved seed s_{it} is procured at a cost b_t. 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 seed if they expect that using it is more profitable than using farmer-saved seed, that is, if $E\left(\pi_{it+1}^H\right) > E\left(\pi_{it}^L\right)$ or:

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

where we normalize by output price.[3]

Equation 3 shows that adoption decisions based on profit functions 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 improved seed follows a similar 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 $X_{it}^H \geq X_{it}^L$:

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

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

$$Y_{it+1}^H = Y_{it}\left(X_{it}^L - \frac{b_t s_{it}}{w_t}\right) \tag{6}$$

If farmers would be able to, at least on average, predict yields in *t+1*, such that $E(Y_{it+1}) = Y_{it+1} + \varepsilon$ and $\varepsilon \sim N(0, \sigma)$, their decision to adopt would depend on the difference in yield between improved 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

[3] We model the decision to adopt as a binary process, where farmers adopt on entire fields, instead of expressing s_{it}in kilograms of seed used. As such, b_t refers to the cost of planting an entire field with improved seed varieties.

not aware of the true relationship between Y_{it}^H and X_{it}, but instead believe that $E\left(Y_{it+1}^H\right) = A + Y_{it}\left(X_{it}^L\right)$. The credit constrained farmer's expected yield will then be:

$$E\left(Y_{it+1}^H\right) = A + Y_{it}\left(X_{it}^L - \frac{b_t s_{it}}{w_t}\right) \tag{7}$$

and as a result, the farmer will use too much improved seed and not enough other inputs.

The model leads to different farmer types based on their dynamic profile and knowledge, see 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. Providing information about the true relationship between Y_{it}^H and X_{it} will have no effect on these farmers.

Another group of farmers is not knowledgeable about the interaction effect, but instead believes in miracle seed and thinks that there is always an adoption premium. A subset of these farmers without knowledge about the true relationship between Y_{it}^H and X_{it} does adopt prior to the intervention because their marginal cost of adoption is lower than their expected marginal returns. Providing these type 3 farmers with information may lead them to dis-adopt, at least in the short run, when this new information reduces their expected marginal return below the marginal cost. As these farmers stop adopting improved varieties and start using cheaper farmer-saved seed, their yield expectations will also become more in line with reality. As type 3 farmers dis-adopt, we do not expect an impact on efforts in response to the treatment for this subgroup.

Another subset of this second group of farmers that is not knowledgeable about the interaction effect, referred to as type 4 farmers in Table 1, does not adopt at baseline because, even though the have inflated expectations of the seed, the marginal cost of adoption still exceeds the expected marginal returns. Providing these farmers with information will not have an effect on their adoption decision because it will only decrease their expected marginal return which was already too low to adopt prior to the intervention. As they were already planting local seed, their expectations will also not be affected by the intervention, nor do we expect an effect on their efforts.

Farmers may also underestimate the adoption premium. For some, type 5 in Table 1, 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. These farmers keep adopting as the intervention increases their expected marginal return, but they may adjust their efforts and expectations in response to the treatment. For another fraction of farmers that underestimate

Table 1: Types of farmers

	prior knowledge	internal comparison	baseline adoption	effect on adoption	effect on exp.[1]	effect on efforts
1	know true probability of adoption premium	true exp. marg. return > marg. cost of adoption	yes	none (always adopt)	none (correct at baseline)	none (correct at baseline)
2	know true probability of adoption premium	true exp. marg. return < marg. cost of adoption	no	none (never adopt)	none (correct at baseline)	none (correct at baseline)
3	overestimate probability of adoption premium	biased exp. marg. return > marg. cost of adoption	yes	dis-adopt due to decreased exp. marg. return	more realistic	none (no adoption)
4	overestimate probability of adoption premium	biased exp. marg. return < marg. cost of adoption	no	none (never adopt)	none (correct at baseline)	none (no adoption)
5	underestimate probability of adoption premium	biased exp. marg. return > marg. cost of adoption	yes	none (always adopt)	more realistic	increase
6	underestimate probability of adoption premium	biased exp. marg. return < marg. cost of adoption	no	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 improved seed, these expectations deal with the yield of improved seed. If a farmer plants local seed, these expectations deal with the yield of local seed.

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. However, as the intervention increases their expectation of the return, they may start adopting in response to the treatment and also invest more efforts. There will be no impact on expectations because the type 6 farmers do not adopt at baseline and therefore have correct expectations about their yield prior to the intervention.

The model leads to the following testable predictions:

1. Some farmers that acquire new information related to the interaction effects between improved seed varieties and complementary inputs (types 3 and 6) will change their adoption behavior. The effect on adoption in the next season could be positive or negative, depending on how many farmers can be categorized as type 3 and type 6. If there are more type 3 than type 6 farmers, the effect on adoption will be negative. If there are less type 3 than type 6 farmers, the effect on adoption will be positive. However, it is likely that these two opposing effects cancel each other out. 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.

2. Not knowledgeable farmers that acquire new information related to the interaction effects between improved seed varieties and complementary inputs *and plant improved seed after the treatment* (types 5, 6) will use more complementary inputs and invest more effort. The effect will be larger for farmers that adopt at baseline (types 1, 3, 5) since this removes "never adopters" (types 2 and 4) from the sample.

3. Farmers that acquire new information related to the interaction effects between improved seed varieties and complementary inputs *and plant improved seed at some point in time but not at baseline* (types 3, 5) will adapt their expectations. The effect will be larger for farmers that adopt at baseline (types 1, 3, 5) since this removes many farmers that have correct expectations at baseline (types 2, 4, 6) from the sample.

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. We describe the study population and the treatments below.

4.1 Study population

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

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

4.2 The treatment

The treatment was implemented using short, engaging videos, shown to the farmers on tablet computers. Based on extensive interviews with experts, we developed a script that served as a basis for a video about best practices in maize cultivation. The video starts off with a couple (man and woman) in a healthy maize field inspecting their crops. The man narrates that they have been farmers for 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. The secret of their success, they continue, lies in the adoption of improved technologies and best practices, such as the use of organic fertilizer, and optimal plant spacing and reduced seed rates. Furthermore, they argue that the use of improved seed and fertilizer also contributed significantly to increased production. They conclude this introduction by stating that they are proud to be successful farmers that can feed their families and even have some marketable surplus that they can sell on the market. The viewer is then invited to become a successful farmer as well by paying close attention as the role model farmers explain in detail the most important inputs and practices that 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 improved seed varieties. The only difference between the treatment and control video is thus that the former makes explicit the fact that significant complementarity exists between improved seed varieties and the recommended inputs and practices. The treatment video is about twelve minutes long and can be found here. The control video is about eight minutes long and can be found here. Half farmers in half of the villages are randomly assigned to the control group, the other half to the treatment group.

5 Empirical strategy

6 Data

6.1 Sample

The 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 3500 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. Consequently, about 3500 smallholders were sampled. 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. Baseline data was collected in April 2021, midline data in January and February 2022, and endline data in July and August 2022.

6.2 Adoption

We define smallholders' improved maize seed adoption 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 not recycled hybrid seed or an OPV that was recycled less than four times.

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

The figure also shows interesting dynamics. At the top, we see a substantial share of households (22 percent) that adopted according to 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 at baseline reverts to local farmer-saved seed at midline (16 percent) or still adopts at midline but eventually dis-adopts at endline (7 percent). Fortunately, large groups of households also enter into adoption. We see that 19 percent of non-adopting households are adopting at midline and twelve percent of households that are not adopting at both base- and midline become adopters at endline. Finally, there are also some households that seem to be moving in and out of adoption (8 percent) or moving out and back into adoption (9 percent).

Furthermore, we find that a significant share of farmers that adopted at baseline 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.

7 Results

In this section, we present impact of the treatment at mid- and endline using simple differences between outcomes in treatment and control villages.[4]

7.1 Impact on knowledge

First we check if smallholder farmers are able to pick up the subtle messages in the treatment video. In a short quiz, enumerators read a set of alternative an-

[4]Differences between treatment and control are estimated in a regression framework where standard errors are clustered at the level of the intervention (village level). As this study was part of a larger study with also treatments at the agro-input dealer level, controls are included for orthogonal treatments (demeaned and interacted with the main treatment (Lin, 2013)).

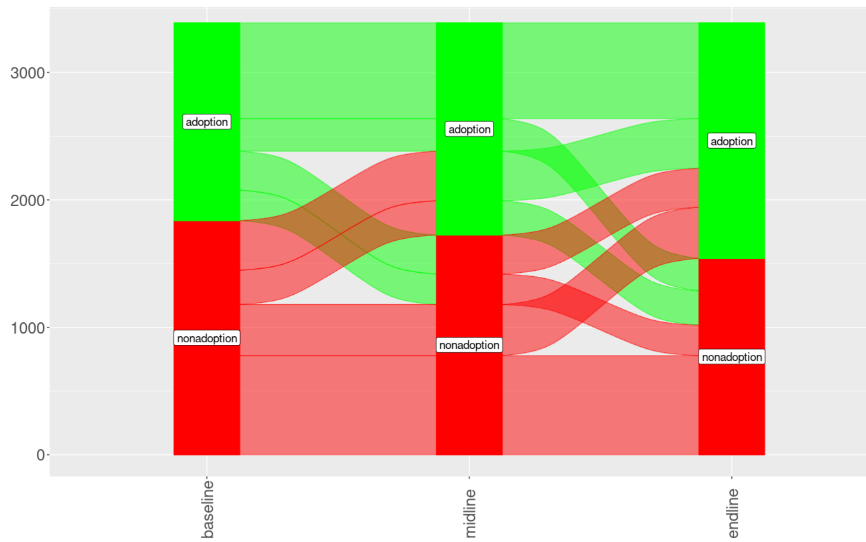

Figure 1: Dynamics of varietal adoption

swers to farmers who then select the response that they feel is most appropriate. This quiz was only implemented at endline because we were wary of priming.

We test if farmers know that when using improved maize seed like open-pollinated or hybrid seed: 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 improved seed 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 improved seed. The only outcome with significant scope for improvement appears to be the control question.

The second column (2) shows the estimated difference between the treatment and control group for outcomes at endline, while the third column (3) also reports this difference, but only for the subset of farmers that adopted improved seed 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 seed 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.

We see that knowledge, as measured by the quiz questions, has increased for all questions except for the control question. For instance, the share of farmers that knows complementary inputs and practices are at least as important when using improved seed increased from 88 to 90.2 percent. Furthermore, the share of farmers that recommends investing in different inputs (as opposed to investing all their money in only one input), increases from 75 to to 77.2 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).

7.2 Impact on adoption dynamics

We now test the main hypothesis of this paper: if farmers that were made aware of the fact that improved seed also needs complementary inputs behave differently in terms of seed use in subsequent seasons. In particular, we look at the use of fresh improved seed varieties, i.e. hybrid seed which is not recycled and open-pollinated seed which is 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 look at the use of farmer-saved seed, as using farmer-saved seed is to some extent the opposite of technology adoption (but not completely because many farmer also recycle hybrid seed because they are not aware that it is not suited for recycling). We also test if there are differences in the use of recycled seed between the treatment and control group. A related outcome is the share of farmers that buy from agro-input dealers. The four outcomes are also combined in an index following Anderson (2008).

Results are in Table 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 46 percent of farmers use fresh improved seed varieties and that one third of farmers report that the seed that they planted on the randomly selected plot was obtained from an agro-input dealer. As constructing the index involves standardization, its average is zero. The second column (2) illustrates

Table 2: Average treatment effects on knowledge

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

Note: Column (1) reports control group means at endline (and standard deviations below); column (2) reports difference between treatment and control at endline; column (3) reports difference between treatment and control at endline for farmers that adopt at baseline; **, * and + denote significance at the 1, 5 and 10 percent levels; standard errors are clustered at the village level.

balance and compares treatment and control outcomes at baseline. We see that the randomization was successful, as there is no significant difference in seed 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 at midline, after households in the treatment group received treatment once. Our theory suggests that in response to being sensitized about the importance of using complementary inputs and cultivation practices when using improved seed varieties, a share of farmers will dis-adopt as their expected marginal return is reduced by the treatment (prediction 1). Dis-adoption implies that farmers will be less likely to plant fresh improved seed varieties and seed bought at agro-input shops, but more likely to use recycled and farmer-saved seed. We find that all coefficients go in the expected direction, however, we only find a significant difference for the share of farmers that planted recycled seed at midline.

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 (as expected, see prediction 1). Farmers that were exposed to the treatment are almost six percentage points less likely to adopt fresh improved seed varieties, and five percentage points more likely to revert to farmer-saved seed. 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.

The fifth column (5) shows the difference between treatment and control for outcomes at endline, after treatment households were treated a second time, while the sixth column (6) repeats this analysis for farmers who reported adopting at baseline. At endline, differences seem to have disappeared, suggesting that the dis-adoption effect is only temporary. This may be because farmers have moved to a new equilibrium where they know the true adoption premium and are more likely to become "always adopters".

7.3 Causal mechanisms

In this section,we investigate how the interventions affect the use of inputs and cultivation practices other than improved seed varieties, and expectations, as these are important variables in our theoretical model of Section 3.

7.3.1 Complementary inputs use and cultivation practices

The effect of making farmers aware that improved seed needs the same complementary inputs and effort than normal seed on the actual use of complementary inputs and practices is not clear a-priori. On the one hand, the intervention advocates for the use of complementary inputs and practices, and so one may

Table 3: Average treatment effects on adoption

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

Note: Column (1) reports control group 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 at midline; column (4) reports difference between treatment and control at midline for farmers that adopt at baseline; column (5) reports difference between treatment and control at endline; column (6) reports difference between treatment and control at endline for farmers that adopt at baseline; **, * and + denote significance at the 1, 5 and 10 percent levels; standard errors are clustered at the village level.

expect that adopters increase use in the future as they adjust their practices to this new knowledge. However, we see that the first order response of the average farmer is to reduce the use of improved seed, which may offset the increased use of complementary inputs, at least in the short run. However, in subsequent seasons, when farmers adopt again, one would expect that at least some treatment farmers now also use more complementary inputs and put in more effort.

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

A second outcome is the recommendation to reduce seed rate. Farmers often plant more seed than necessary because they fear that seed may not germinate. However, using more than 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 may need to engage in gap filling after one week if seed fails to germinate.

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

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

Finally, we also look at differences in resowing or gap-filling. This involves revisiting the field after about one week and inspecting hills for seed germination. When a seed did not germinate, new seed is planted in that location. Gap-filling, seed rate and row planting are thus likely correlated. We also combine all outcomes into an overall index of practices following Anderson (2008).

Results are in Table 4. As in previous tables, the first two columns ((1) and (2)), show control group means and orthogonality tests for outcomes before the treatment. Interestingly, we find some imbalance on the number of times that farmers report to have been weeding the randomly selected plot and the likelihood that farmers resow after one week. Note that the imbalance is in different directions, which makes it less likely that the imbalance is due to structural difference between treatment and control group such as lower effort in one group, but is likely to be the result of chance.

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

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

Table 4: Treatment effects on input use

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

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

Table 5: Treatment effects on input use

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

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

7.3.2 expectations and outcomes

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

Results are reported in Table 5. We again report control group means and baseline balance in the first two columns ((1) and (2)). At baseline, we did not ask if expectations were met on the randomly selected plot. Therefore we report the average in the control group at midline and we do not test for baseline balance. Note that a large majority of farmers indicated that they harvested less than expected.

Column (3) shows that in the treatment group, a significantly higher share of farmers than in the control group say that what they produced was also what they expected. This is even more so for the subset of farmers that adopted at baseline (column (4)). At endline, there is no difference between treatment and control anymore (columns (5) and (6)). This pattern suggests that a subset of farmers indeed started out with inflated expectations, and this was corrected after they learned that improved seed is not miracle seed.

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

8 Conclusion

This paper was motivated by qualitative evidence that many farmers appear to overestimate the potential benefits of certain improved agricultural technologies. The cost of a particular modern commercial input that a farmer wants to start using, such as improved seed varieties or inorganic fertilizers, is often substantial and competes with other (complementary) agricultural inputs. Furthermore, modern inputs are generally marketed with a focus on a few dimensions (eg seed that is treated against certain types of weed), and so farmers may reduce inputs (like herbicides) and efforts (like manual weeding) related to this dimension. However, to get the most out of improved technologies, it is important to also use complementary inputs and proper agronomic practices, otherwise outcomes may be lower than expected. If farmers incorrectly attribute disappointing outcomes to the technology itself rather than improper use, this could lead to a pattern where farmers who try out a new technology switch back to local seed in the next season. In a sample of maize smallholder farmers in Uganda, we indeed see substantial dis-adoption over time. Furthermore, a large majority of farmers indicate that they expected higher yields from their plots.

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

We first tested if farmers picked up the subtle messages that lie at the heart of our light-touch information treatment. To do so, we subjected farmers to a multiple choice quiz. While we did not find average treatment effects that differed significantly from zero, we did see that all coefficients were going in the expected direction. We suspect that the lack of statistical significance may be due to the already high knowledge at baseline. However, even when most farmers already possess the knowledge, the treatment may still have made this knowledge more salient.

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

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

Our results differ from various other studies that found that improved technology increased agricultural productivity by crowding in modern inputs and cultivation practices (Emerick et al., 2016; Bulte et al., 2023). The reason for these opposite effects may be due to the fact that Bulte et al. (2023) and Emerick et al. (2016) provided the improved technology (also seed) for free as part of there experiment, potentially resulting in an income effect in the sense that money that was not used to buy seed was used to buy complementary inputs.[5] In our experiment, no free seed was provided, so when the adoption decision was made, farmers had to take the additional cost of seed and the fact that expensive complementary inputs would need to be purchased into account, leading to disadoption.

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 important interaction effects between different inputs are present, it is unlikely that farmers can try out all possible combinations of inputs to learn about these interactions in a bayesian fashion. Furthermore, if farmers can not learn about the interactions, expectations may be incorrect, leading to sub-optimal adoption patterns, further complicating learning.

Our study also has important implications for both policy markers and the private sector. When designing agricultural extension and advisory services, policy makers should highlight the complementarity of modern inputs. If not, their efforts risk to be short lived. Worse, false perceptions of poor quality may crowd out the market for quality inputs (Bold et al., 2017). Policy makers often subsidize improved technologies to scale up adoption (Jayne et al., 2018). While this may work for some stand-alone technologies (eg. Omotilewa, Ricker-Gilbert, and Ainembabazi, 2019), promoting technologies that require complementary inputs (such as the use of subsidized or even free seed trial packs) may be counterproductive.

There is also a role for industry. As part of their marketing strategy, seed producers and agro-input dealers tend to highlight particular traits of the tech-

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

nology they use, such as high yields. Furthermore, they may not be tempted to actively promote the use of complementary inputs if they are produced by companies that target the same customers as they do. In both cases, short term benefits may lead to long run losses.

References

Abate, G. T., S. Rashid, C. Borzaga, and K. Getnet. 2016. "Rural Finance and Agricultural Technology Adoption in Ethiopia: Does the Institutional Design of Lending Organizations Matter?" *World Development* 84: 235–253.

Ainembabazi, J. H. and J. Mugisha. 2014. "The Role of Farming Experience on the Adoption of Agricultural Technologies: Evidence from Smallholder Farmers in Uganda." *The Journal of Development Studies* 50 (5): 666–679.

Anderson, M. L. 2008. "Multiple Inference and Gender Differences in the Effects of Early Intervention: A Reevaluation of the Abecedarian, Perry Preschool, and Early Training Projects." *Journal of the American Statistical Association* 103 (484): 1481–1495.

Ashour, M., D. O. Gilligan, J. B. Hoel, and N. I. Karachiwalla. 2019. "Do Beliefs About Herbicide Quality Correspond with Actual Quality in Local Markets? Evidence from Uganda." *The Journal of Development Studies* 55 (6): 1285–1306.

Bernard, T., S. Dercon, K. Orkin, and A. Seyoum Taffesse. 2015. "Will video kill the radio star? Assessing the potential of targeted exposure to role models through video." *The World Bank Economic Review* 29 (suppl_1): S226–S237.

Bold, T., K. C. Kaizzi, J. Svensson, and D. Yanagizawa-Drott. 2017. "Lemon Technologies and Adoption: Measurement, Theory and Evidence from Agricultural Markets in Uganda*." *The Quarterly Journal of Economics* 132 (3): 1055–1100.

Bulte, E., S. Di Falco, M. Kassie, and X. Vollenweider. 2023. "Low-Quality Seeds, Labor Supply and Economic Returns: Experimental Evidence from Tanzania." *Review of Economics and Statistics* .

Byerlee, D. and E. H. De Polanco. 1986. "Farmers' stepwise adoption of technological packages: evidence from the Mexican Altiplano." *American journal of agricultural economics* 68 (3): 519–527.

Chen, M., C. Hu, and R. J. Myers. 2022. "Understanding transient technology use among smallholder farmers in Africa: A dynamic programming approach." *Agricultural Economics* .

Cochrane, W. W. 1958. *Farm prices: myth and reality.* U of Minnesota Press.

Custodio, M. C., M. Demont, A. Laborte, and J. Ynion. 2016. "Improving food security in Asia through consumer-focused rice breeding." *Global Food Security* 9: 19–28.

Emerick, K., A. de Janvry, E. Sadoulet, and M. H. Dar. 2016. "Technological Innovations, Downside Risk, and the Modernization of Agriculture." *American Economic Review* 106 (6): 1537–61.

Evenson, R. E. and D. Gollin. 2003. "Assessing the impact of the Green Revolution, 1960 to 2000." *science* 300 (5620): 758–762.

Feder, G., R. E. Just, and D. Zilberman. 1985. "Adoption of Agricultural Innovations in Developing Countries: A Survey." *Economic Development and Cultural Change* 33 (2): 255–298.

Ferrara, E. L., A. Chong, and S. Duryea. 2012. "Soap operas and fertility: Evidence from Brazil." *American Economic Journal: Applied Economics* 4 (4): 1–31.

Foster, A. D. and M. R. Rosenzweig. 1995. "Learning by doing and learning from others: Human capital and technical change in agriculture." *Journal of political Economy* 103 (6): 1176–1209.

Garnett, T., M. C. Appleby, A. Balmford, I. J. Bateman, T. G. Benton, P. Bloomer, B. Burlingame, M. Dawkins, L. Dolan, D. Fraser et al. 2013. "Sustainable intensification in agriculture: premises and policies." *Science* 341 (6141): 33–34.

Griliches, Z. 1957. "Hybrid Corn: An Exploration in the Economics of Technological Change." *Econometrica* 25 (4): 501–522.

Hanna, R., S. Mullainathan, and J. Schwartzstein. 2014. "Learning Through Noticing: Theory and Evidence from a Field Experiment." *The Quarterly Journal of Economics* 129 (3): 1311–1353.

Jack, B. K. 2013. "Market inefficiencies and the adoption of agricultural technologies in developing countries." .

Jayne, T. S., N. M. Mason, W. J. Burke, and J. Ariga. 2018. "Review: Taking stock of Africa's second-generation agricultural input subsidy programs." *Food Policy* 75: 1–14.

Jensen, R. 2010. "The (Perceived) Returns to Education and the Demand for Schooling*." *The Quarterly Journal of Economics* 125 (2): 515–548.

Kabunga, N. S., T. Dubois, and M. Qaim. 2012. "Yield Effects of Tissue Culture Bananas in Kenya: Accounting for Selection Bias and the Role of Complementary Inputs." *Journal of Agricultural Economics* 63 (2): 444–464.

Karlan, D., R. Osei, I. Osei-Akoto, and C. Udry. 2014. "Agricultural decisions after relaxing credit and risk constraints." *The Quarterly Journal of Economics* 129 (2): 597–652.

Leathers, H. D. and M. Smale. 1991. "A Bayesian Approach to Explaining Sequential Adoption of Components of a Technological Package." *American Journal of Agricultural Economics* 73 (3): 734–742.

Lin, W. 2013. "Agnostic notes on regression adjustments to experimental data: Reexamining Freedman's critique." .

Lybbert, T. J. and D. A. Sumner. 2012. "Agricultural technologies for climate change in developing countries: Policy options for innovation and technology diffusion." *Food Policy* 37 (1): 114–123.

Ma, X. and G. Shi. 2015. "A dynamic adoption model with Bayesian learning: an application to U.S. soybean farmers." *Agricultural Economics* 46 (1): 25–38.

Moser, C. M. and C. B. Barrett. 2006. "The complex dynamics of smallholder technology adoption: the case of SRI in Madagascar." *Agricultural Economics* 35 (3): 373–388.

Nguyen, T. 2008. "Information, role models and perceived returns to education: Experimental evidence from Madagascar." *Unpublished manuscript* 6.

Omotilewa, O. J., J. Ricker-Gilbert, and J. H. Ainembabazi. 2019. "Subsidies for Agricultural Technology Adoption: Evidence from a Randomized Experiment with Improved Grain Storage Bags in Uganda." *American Journal of Agricultural Economics* 101 (3): 753–772.

Riley, E. 2022. "Role Models in Movies: The Impact of Queen of Katwe on Students' Educational Attainment." *The Review of Economics and Statistics* 1–48.

Shiferaw, B., T. Kebede, M. Kassie, and M. Fisher. 2015. "Market imperfections, access to information and technology adoption in Uganda: challenges of overcoming multiple constraints." *Agricultural Economics* 46 (4): 475–488.

Sunding, D. and D. Zilberman. 2001. "The agricultural innovation process: research and technology adoption in a changing agricultural sector." *Handbook of agricultural economics* 1: 207–261.

Suri, T. 2011. "Selection and comparative advantage in technology adoption." *Econometrica* 79 (1): 159–209.

Suri, T. and C. Udry. 2022. "Agricultural Technology in Africa." *Journal of Economic Perspectives* 36 (1): 33–56.

Tilman, D., C. Balzer, J. Hill, and B. L. Befort. 2011. "Global food demand and the sustainable intensification of agriculture." *Proceedings of the national academy of sciences* 108 (50): 20260–20264.

Van Campenhout, B. 2021. "The Role of Information in Agricultural Technology Adoption: Experimental Evidence from Rice Farmers in Uganda." *Economic Development and Cultural Change* 69 (3): 1239–1272.

Van Campenhout, B., D. J. Spielman, and E. Lecoutere. 2021. "Information and Communication Technologies to Provide Agricultural Advice to Smallholder Farmers: Experimental Evidence from Uganda." *American Journal of Agricultural Economics* 103 (1): 317–337.