Miracle seeds: Biased expectations, complementary input use, and the dynamics of smallholder technology adoption

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Abstract

To fully benefit from new agricultural technologies like improved seed varieties, significant investment in complementary inputs such as fertilizers and pesticides, and practices such as systematic planting, irrigation, and weeding are also required. Farmers may fail to recognize the importance of these complements, leading to unsatisfactory crop yields and outputs and, eventually, dis-adoption of the variety. We provide a simple model of biased expectations, complementary input use and technology adoption and test its predictions using a field experiment among smallholder maize farmers in eastern Uganda. We find that pointing out the importance of complementary investments using a short, engaging video effectively deters some farmers from using commercial improved varieties. Consistent with the theoretical model, we find some evidence that this behavior change emanates from increased knowledge and expectations that are more in line with realized outcomes.

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

JEL Codes: O33, D84, Q16

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1 Introduction

To feed a growing population in an environmentally sustainable manner and in the midst of a long-term climate crisis, farmers throughout the developing world are expected to grow more food on less land with greater efficiency (Tilman et al., 2011; Garnett et al., 2013). To achieve this goal, much is expected from new technologies, especially from higher-yielding varieties that are resilient to pests, diseases, and other biotic stresses and are tolerant of droughts, floods, heat, and other abiotic stresses (Evenson and Gollin, 2003; Lybbert and Sumner, 2012).

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Unfortunately, the adoption of such technologies is lagging in areas where they may have the largest impact. Recent trends in agricultural productivity growth in Africa show that technological progress has largely stagnated on the continent (Suri and Udry, 2022). However, significant heterogeneity underlies this general stagnation. For instance, at the micro level, we often observe dis-adoption patterns and trends, where farmers choose to switch back to technologies and inputs they have been using for decades after trying out a new technology once or twice (Moser and Barrett, 2006; Chen, Hu, and Myers, 2022). In many cases, these patterns and trends cannot be explained by a lack of awareness or information about, for example, improved cultivars or inorganic fertilizers (Sheahan and Barrett, 2017).[1]

There are many reasons why farmers may not move into a state of sustained adoption of a given technology. An obvious one is that farmers cannot access the technology through local markets or other means of supply, or may have enjoyed access only for a limited time as part of a promotional campaign or project intervention (Shiferaw et al., 2015). Another reason may be that farmers 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 technology, coupled with the fact that it is often difficult to assess quality prior to purchase or application, may also result in dis-adoption (Bold et al., 2017; Miehe et al., 2023). Farmers that face credit or liquidity constraints, or additional uninsured risk may also reconsider past adoption behavior and tend towards dis-adoption (Karlan et al., 2014). In the longer run, general equilibrium effects that accrue as more farmers adopt a new technology, thereby increasing supply of the commodity and reducing output prices, may also lead farmers with higher marginal costs to exit the market and dis-adopt (Cochrane, 1958).

In this paper, we consider the possibility that farmers hold inflated expectations of new technologies as an explanation for their dis-adoption. These inflated expectations result from the possibility that farmers may be unaware (or fail to recognize) the need for substantial complementary investment. Indeed, for the new hybrid seeds suitable for East African maize farmers that came on the market a few decades ago, the promise to double or even triple yields could typically only be achieved in favorable climatic conditions and with the addition of fertilizer and other inputs (Quiñones, Borlaug, and Dowswell, 1997). Chen, Hu, and Myers (2022) show that farming with improved maize varieties is far more costly than farming with unimproved maize varieties. The additional production costs include not just the (higher) cost of seed but also higher fertilizer costs required to achieve expected yield improvements, as well as higher costs of labor for farm tasks that are associated with the cultivation of higher-yielding maize.

Inflated expectations about technology performance can have lasting impacts on adoption if farmers attribute poor outcomes to the technology, instead of to insufficient complementary inputs and effort. This learning failure is often understandable: if multiple factors simultaneously affect yields and outputs, then learning about the causal impact of a new technology from a single experience is difficult, especially if the technology performs only under specific or stochastic circumstances such as abiotic stress (Lybbert and Bell, 2010), or if the farmer is unable to learn in a Bayesian manner because it is too cognitively taxing (Gars and Ward, 2019), pays attention to the wrong attributes of the technology (Hanna, Mullainathan, and Schwartzstein, 2014), or is unable to sufficiently complement own experience with social learning (Foster and Rosenzweig, 1995; Conley and Udry, 2010).

This paper was motivated by evidence suggesting that many farmers are unaware that agricultural technologies such as improved varieties require substantial complementary inputs and efforts to reap benefits. Indeed, it is theoretically possible and quite reasonable to believe that farmers overestimate the returns to a technology and are disappointed when they compare realized yields with what they expected at the time of planting. Because it is hard for farmers to learn about the yield response

[1] For simplicity, we use the term "technologies" to refer to agricultural technologies such as improved varieties, which are genetic innovations embodied in seed. We use the term "inputs" to refer to organic and inorganic fertilizers and pesticides, and we use the term "practices" to refer to labor and management effort such as precision planting, irrigation, and weeding. Of course, we recognize that these terms can be used interchangeably—seed is also an input, while fertilizers and precision practices can also be technologies—and that each figures differently into our understanding of the conventional agricultural production function.

of a single input, farmers may decide that the technology itself is to blame. This is consistent with the observation that farmers think inputs are often counterfeit or of low quality, even when objective assessments of input quality find them to be acceptable (Barriga and Fiala, 2020; Michelson et al., 2021).

Many researchers working in developing-country agriculture will have their own anecdotal evidence of inflated expectations that illustrate the presence of biased expectations, sub-optimal complementary investments, and subsequent dis-adoption when disappointing outcomes are attributed to the technology itself. For instance, researchers may be familiar with farmers' belief that using inorganic fertilizer for one cropping cycle will lead to long-lasting soil fertility improvements. Others may be familiar with another common belief among farmers—often promoted by extension agents and agro-dealers—that an improved variety is a "miracle seed" that can be planted without additional inputs or management to achieve exceptional harvests. Entire narratives—some with more nuance than others—have been written on the singular power of genetic improvement, from the semi-dwarf "Green Revolution" varieties of wheat and rice to genetically modified crops (Lipton and Longhurst, 1989; Tripp, 2002; Sumberg, Keeney, and Dempsey, 2012). An example the learning failure and its consequences was provided by extension agents we worked with. Seed of improved maize varieties need a lot of nutrients, often leaving soil more depleted than when farmer-saved seed is used. In the areas where our research is situated, Striga (*Striga hermonthica*), a parasitic weed that feeds on the roots of maize plants and cause stunted growth, is a serious problem. Unfortunately, Striga proliferates in poor soils and as a result some farmers now believe that improved seed varieties are responsible for increased Striga infestations on their fields.

To develop our theory of inflated expectations, we present a simple model of technology adoption that incorporates the ideas discussed above. In this model, farmers compare the expected returns of an improved technology to their business-as-usual choices. The new technology comes at a cost, while the unimproved technology does not. Both technologies, though, require complementary inputs and efforts that directly affect productivity, with productivity gains from the new technology only materializing when complementary inputs and practices exceed business-as-usual levels for the unimproved technology. Further, recognizing that farmers may be heterogeneous, we define several farmer types and derive predictions about how they might behave if they learn about the true shape of the production function of the new technology.

We test our model's predictions using a field experiment conducted with almost 3,500 maize farmers in eastern Uganda.[2] At the heart of the field experiment is a light-touch information intervention that highlights the importance of complementary investments when using improved maize varieties.[3] Specifically, we show all farmers in our sample a short, engaging video about the use of improved inputs and recommended management practices for maize cultivation. In the treatment group, we show the same video, except that in certain points in the narration—for instance when the use of inorganic fertilizers is demonstrated or when weeding is explained—we highlight the particular importance of using additional inputs and performing certain management practices in conjunction with the improved variety.

We begin by testing whether farmers are able to extract the relevant information from the treatment video. We see that all coefficients move in the expected direction, and find treatment effects that differ significantly from zero for a subset of farmers. Turning to adoption behavior, we find evidence of treated farmers dis-adopting between baseline and follow-up. We find no evidence that the intervention affected the use of complementary inputs such as fertilizers and pesticides, or recommended practices for maize management such as row planting and intensive weeding. We also see that among treated

[2] The overarching study was pre-registered at the AEA RCT registryunder RCT ID 0006361. It was primarily designed to examine quality-related constraints to technology adoption with a series of interventions at the agro-input dealer level. This paper makes use of farmer-level interventions that were introduced alongside the main design and described in the pre-analysis plan.

[3] We use the term "improved variety" throughout this paper to refer to both maize hybrids and open pollinated varieties marketed and sold in our study areas, as opposed to farmer-saved seed or seed obtained through farmer-to-farmer exchanges which, in the specific context of maize, may be less effective due to cross pollination and genetic drift over multiple generations, or due to poor seed storage and handling between seasons.

farmers, expectations become more in line with realized output.

These findings have implications for our understanding of smallholder technology adoption dynamics. If farmers do not use appropriate complementary inputs and practices when using improved maize varieties because they believe in "miracle seeds", their yields are likely to be disappointing. Often, disappointment about the performance of a technology is then erroneously attributed to the technology itself, potentially leading to dis-adoption. "Correcting" incorrect beliefs about the needed inputs and efforts may result in farmers dis-adopting technologies in the short run. However, if farmers' expectations become more realistic, the ones that keep adopting (or start adopting in light of the new information) will be less likely to be disappointed in the future, leading to sustained adoption, which in turn could lead to efficiency gains and positive spillover effects. Our findings also imply that public and private actors in the agriculture sector need to promote new technologies as highly site- and context-specific combinations of technologies, inputs, practices, and efforts instead of single "miracle seeds".

The remainder of the article is organized as follows. In Section 2, we provide a brief overview of the related literature. Section 3 provides a simple theoretical framework and derives testable hypotheses. In Section 4, we discuss the intervention we will use to test model predictions. Section 5 provides some descriptive statistics and illustrates the dynamics of varietal adoption in our sample, while also presenting our empirical strategy. Section 6 explores our results, with subsections focusing on outcomes related to knowledge, adoption, expectations, and complementary investments. Concluding remarks are provided in Section 7.

2 Related literature

Agricultural technology adoption is at the heart of a rich body of research on food security, poverty reduction, economic development, and structural transformation. Studies on the economics of technical change in agriculture go back to at least Griliches (1957) and are reviewed in widely cited articles such as Feder, Just, and Zilberman (1985) and Sunding and Zilberman (2001). More recently and with the proliferation of field experiments and randomized controlled trials, economic theories that explore alternative drivers of technology adoption have received greater empirical attention.

Most of these studies (implicitly) assume that some kind of graduation model underlies the technical change process, wherein farmers switch from a low-level equilibrium to a high-level equilibrium in which technology use is sustained once initial conditions—typically, access to information or finance—are satisfied or binding constraints removed (Karlan et al., 2014; Shiferaw et al., 2015; Abate et al., 2016). Yet most of these studies follow farmers across a limited number of agricultural seasons, and are unable to fully appreciate the dynamics of technology adoption over time. Only a few studies offer a long-term perspective, with several documenting significant levels of dis-adoption (e.g. Ainembabazi and Mugisha, 2014), or transient technology use over time (Moser and Barrett, 2006; Chen, Hu, and Myers, 2022).

At the core of our theoretical framework described in Section 3 is a model of learning failures where farmers have inflated expectations about the returns to a new technology, but fail to uncover the true form of the production function through experience, leading to disappointment and subsequent dis-adoption. Indeed, heterogeneity in farmer characteristics implies that farmers need to learn whether using a new technology is optimal for their specific context given costs and benefits (Suri, 2011). Farmers learn through a combination of own experiences and observing others (Foster and Rosenzweig, 1995; Conley and Udry, 2010). However, learning about a new technology is often difficult for reasons related to the technology's complexity and the observability of its quality or performance (i.e., its experience good nature) (Lybbert and Bell, 2010; Bold et al., 2017; Ashour et al., 2019), or the social, psychological, and behavioral attributes of the farmer and her learning process (Foster and Rosenzweig, 1995; Hanna, Mullainathan, and Schwartzstein, 2014).

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 adopting the entire package at once (e.g., Byerlee and De Polanco, 1986). Leathers and Smale (1991) argue that this occurs when farmers employ a Bayesian approach to learning in which they try to isolate the impact of one component of the package at a time. However, there are circumstances under which this strategy is not optimal because it can prevent farmers from identifying potential synergies between technologies, inputs, and practices. Indeed, the reason why many interventions are presented as a package is because 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 can lift yield gains above 20 percent. If many complementarities like this exist, it seems unlikely that farmers are in a position to follow a sequential learning path that allows for all possible interactions between the different technologies within a reasonable time frame. Furthermore, as mentioned above, farmers may face certain behavioral constraints that inhibit their ability to learn about interaction effects if, for example, they pay attention to minor or tangential attributes of the package and miss the more important attributes (Hanna, Mullainathan, and Schwartzstein, 2014). Our study contributes to this literature by providing additional evidence on the limits of Bayesian learning in the context of agricultural technology adoption.

Another strand of the literature addresses the technology learning process in terms of how farmers compare realized yields against expected yields to inform their subsequent, longer-term adoption decisions. The effect of incorrect expectations about future returns on decision-making has been studied most in the context of education, but is readily applicable to learning in agriculture. For example, both Nguyen (2008) and Jensen (2010) find that providing accurate information about the returns to education significantly increases investment in schooling (in Madagascar and the Dominican Republic respectively). Van Campenhout (2021) finds that a video intervention that informs Ugandan farmers about the returns on intensification investments in rice growing improved practices and increased input use and production. Note that across these studies, it is assumed that the individual underestimates the returns in question. In our study, as a result of under-investment in complementary inputs, farmers are in a sense overestimating returns to a new technology, leading to over-investment in technologies.

Finally, the intervention we use to test our hypothesis builds on a strand of the literature that focuses on the role of video-mediated messaging to convey salient information to farmers. This literature explores the ways in which informational videos can change behavior in a variety of settings and through a range of mechanisms. Ferrara, Chong, and Duryea (2012) show how telenovelas have an impact on fertility in Brazil. Riley (2022) finds that in Uganda, students that watched a Disney feel-good movie called “Queen of Katwe” about a chess prodigy growing up in the slums of Kampala do 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 those we use in the present study perform significantly better on a knowledge test, and are more likely to apply recommended practices and fertilizers than households that did not view the video. These same households also report maize yields 10.5 percent higher than the control group. In Ethiopia, Abate et al. (2023) assess the impacts of video-mediated agricultural extension service provision on farmers’ adoption of improved agricultural technologies and practices using data from a two-year randomized experiment. Our study uses a light touch intervention where treatment and control videos were very similar, expect for one small piece of information. Our study thus contributes to this literature by testing if videos are also effective in conveying subtle messages.

3 Theoretical framework

In our theoretical framework, we describe farmers as solving an intertemporal problem in which they allocate resources at t in order to maximize profits at $t+1$.[4] In line with Suri (2011), we assume that farmers (indexed i in the model below) are risk-neutral and choose to plant seed which is either of a

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

Variety H, a new variety that is stochastically dominant in yield and other attributes in all states, or of a Variety L, an old variety that is stochastically inferior in yield and other attributes in all states,[5] to maximize their profits per area of land. In doing so, they compare the expected profit functions of Variety H π_{it}^{*H} and Variety L π_{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 the end commodity, maize grain, is indistinguishable to consumers by variety.[6] $E\left(Y_{it+1}^{H}\right)$ and $E\left(Y_{it+1}^{L}\right)$ reflect the expected yield for seed of Variety H and L respectively. Seed of Variety L is assumed to be free, while for seed of Variety H, s_{it} is procured at a cost $b_t > 0$.[7] In both profit functions, the cost of a range of complementary inputs and management practices, referred to as inputs, are deducted and summarized by the vector X_{it} with corresponding factor prices w_t.

Farmers adopt the stochastically dominant Variety H if they expect it to be more profitable than using the stochastically inferior Variety L, that is, if $E\left(\pi_{it+1}^{H}\right) > E\left(\pi_{it+1}^{L}\right)$ or:

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

where we normalize by output price.[8]

Equation 3 shows that adoption decisions fundamentally depend on yield comparisons. We assume that yield for Variety L is a function of inputs used:

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

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

Yield for Variety H follows the same function, 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 when using Variety L $\left(X_{it}^{H} \geq X_{it}^{L}\right)$:

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

If farmers are able to predict yields—at least on average—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 Variety H and L, on the relative prices of inputs, and on the yield responses to the inputs.

Next, we introduce farmer heterogeneity into the model by assuming that at least some farmers are not aware of the true relationship between Y_{it}^{H} and X_{it}, but instead believe that the adoption premium

[5]The model is applicable to a variety of cases as Variety H and Variety L can be interpreted as improved and unimproved, farmer-saved and commercially-purchased, modern and traditional, newer and older, hybrid and open pollinated varieties, etc.

[6]In a country like Uganda, where most grain is combined, milled, and sold without varietal denomination, this is a reasonable assumption. In other countries such as Malawi or Mexico, where consumers have distinct varietal preferences related to taste, texture, and color, this assumption might not always hold.

[7]Seed of Variety L may not be free but have a shadow price of at least the grain price, which could be subtracted from the expected revenue in Equation 2, so that the adoption decision in Equation 3 would not only depend on yield comparisons but also on cost comparisons. Suri (2011) takes this into account but also notes that the cost of, in her case, farmer-saved seed is likely to be low, if not zero. Rather than complicating the model by explicitly modeling the price of the stochastically inferior variety, we decide to set it to zero. Setting it to a small positive value would not change the predictions derived from the model.

[8]For simplicity, we assume that 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 plot with seed of Variety H.

is always present, that is $E\left(Y_{it+1}^{H}\right) = A + Y_{it}\left(X_{it}^{H}\right)$. As a result, some farmer will use Variety H but not enough complementary inputs, leading to disappointing outcomes.

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

Another group of farmers is not knowledgeable about the true relationship between Y_{it}^{H} and X_{it} and believes there is always an adoption premium. A subset of these farmers may adopt because their marginal cost of adoption is lower than their expected marginal return. We refer to these farmers in Table 1 as Type 3 farmers. Another subset of this 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 Variety H's yield, the marginal cost of adoption still exceeds the expected marginal return.

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

Heterogeneity in terms of prior experiences, expectations, and adoption behavior will lead to different effects of an intervention aimed at "correcting" incorrect beliefs about the relationship between the returns to Variety H and investments in inputs and practices (described in detail in the next section). In some cases, such as for adoption, effects for different farmers may go in opposite directions, potentially canceling out an overall average treatment effect. In other cases, such as for knowledge, some farmers may not be affected, diluting the overall 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 the performance of a stochastically dominant variety and complementary efforts on four key outcome areas:

1. Effect on knowledge: As Type 1 and 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 them.[9] Types 3 to 6 are assumed to be unaware of the true relationship between Variety H and complementary inputs and practices; 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. Effect on adoption: We predict opposing effects on adoption behavior for farmer Types 3 and 6. Providing Type 3 farmers with information may cause them to dis-adopt if the new information reduces their expected marginal return below their marginal cost. For Type 6 farmers, the intervention may increase expectations of the return, and they may start adopting in response to the treatment if the increase is sufficiently high. Reducing expectations of farmers that do not adopt at baseline even though they have inflated expectations will not change their mind as this will reduce their expected returns even more (Type 4). Similarly, we do not expect that

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

Table 1: Farmer types and model predictions

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

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

the intervention will change the adoption behavior of farmers who already adopt even though they underestimate potential yield effects (Type 5): these farmers will keep adopting as the intervention increases their expected returns to the stochastically dominant variety. Finally, as for knowledge, farmers that are aware of the correct relationship between inputs and Variety H (Types 1 and 2) are not expected to change adoption behavior in response to the intervention. The direction of the intervention's effect on adoption will thus depend on the share of Type 3 and 6 farmers respectively. Note that if we only consider farmers that adopt at baseline, the expected effect on adoption will be negative as this excludes Type 6 farmers from the analysis.

3. Effect on expectations: We predict that the intervention results in expectations that are more in line with realized outcomes. This will likely only be the case for farmers that are unaware of the true relationship, and so we again do not expect an effect for Types 1 and 2. Furthermore, since our intervention aims to "correct" perceptions only for Variety H, expectations of farmers that use Variety L at baseline are unlikely to be affected (as it is assumed that the production function of stochastically inferior varieties is common knowledge). Thus, we only expect an impact on farmers that plant the stochastically dominant variety at baseline and also have incorrect expectations (Types 3 and 5).

4. Effect on use of inputs and practices: Some farmers that were unaware of the true relationship between Variety H and complementary inputs and practices and receive new information about the importance of these complements may start investing more. This will be especially the case for Type 6 farmers who adopt due to the intervention (potentially after previously dis-adopting due to disappointing outcomes in the past) 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). Hence, for inputs and efforts, we expect a positive effect that becomes less strong if we restrict ourselves to farmers that adopt at baseline.

4 Intervention

The model predictions were tested using a field experiment conducted with almost 3,500 maize farmers in eastern Uganda. The intervention consisted of screening short, engaging videos about best practices in maize cultivation. The videos were shown individually to participating farmers on tablet computers by specially trained field enumerators. The content of the video scripts was developed following extensive interviews with experts, including agricultural extension agents, plant breeders, seed producers, government officials, and farmers themselves.

The video opens with a woman and a man standing in a well-kept maize plot inspecting their crop. The couple explains that they have been farmers for more than ten years but that their fields have not always been productive. They recount 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, the couple continues, 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 explain that the use of an improved variety and inorganic fertilizer contributed significantly to increased production. They conclude this introduction by stating that they are proud to be successful farmers who can feed their families and even produce surpluses that they can sell in the market. The viewer is then invited to become equally successful in farming by paying close attention as the featured (role model) farmers explain in detail the most important technologies, inputs, and practices that transformed their lives.

The treatment was implemented in the form of two variations of this video. The control group viewed the video as described above. The treatment group viewed a similar video that differed slightly in terms of content. Specifically, we added subtle recommendations for inputs and practices that are particularly important when cultivating improved maize varieties. The only difference between the control and treatment videos is that the latter makes explicit the fact that significant complementarities exist between improved varieties and recommended inputs and practices such as inorganic fertilizers and row planting. In effect, the treatment and control videos are identical, except that, after each practice or input that is shown, the treatment video explicitly mentions that the practice or input is "[...] particularly or even more important when you are using seed of an improved variety".[10] The control video is about eight minutes long and can be found at https://vimeo.com/781882803. The treatment video is about twelve minutes long and can be found at https://vimeo.com/781882930, indicating four extra minutes of material. The other eight minutes are equal to the control video, no scenes are replaced or modified.

By randomizing which video is viewed by our sampled farmers, we can isolate the causal effect of making salient the fact that improved varieties do not substitute for inputs and effort, but in fact require more investment. The use of a control video has an additional advantage: since it is not clear to farmers or enumerators which video is the treatment and which is the control, we reduce the likelihood that results are driven by experimenter demand effects (Bulte et al., 2014). Furthermore, to reduce the likelihood that treated households could provide information to households in the control group—a common problem in video-mediated information treatments (Van Campenhout, 2021)—randomization was conducted at the village level in a manner that ensured reasonable geographic and social distance between villages.

The experiment targeted the second agricultural season of 2021, where maize is sown in August and September and harvested in November and December. We implemented the treatment in April 2021, well before the start of the season, to ensure that farmers had the necessary information before making decisions on seed and input use. At this point in time, we also collected baseline data on our sample households.

The intervention was repeated just before planting in August 2021, and post-treatment data was collected in January and February 2022. The intervention was again repeated in the first season of 2022, with a final round of data collection conducted in July and August 2022. Note that this paper focuses on outcomes following the 2021 agricultural season since we do not expect significant results from continuing the intervention (i.e., providing farmers with the same information) in 2022. However, we do explore descriptive results from 2022 to provide insight into patterns of sustained adoption among treated farmers.

5 Data and empirical strategy

5.1 Sample

The field experiment was conducted in southeastern Uganda, an area known for its maize production by smallholder farmers, and where maize is considered both a food and cash crop. Because it was conducted as part of a larger study on maize seed supply chains, farmers were drawn from the catchment areas (market-sheds) of agro-input shops. The sampling frame was developed as follows: first, we listed all agro-input shops in 11 districts in southeastern Uganda, resulting in the identification of 347 agro-input dealers. We then asked these dealers to identify the villages where most of their customers come from. This sampling frame allows us to assume that sampled farmers have both reasonable and similar access to improved maize varieties if they choose to adopt as a result of our intervention, and that other constraining factors such as seed quality, credit access, or individual preferences were similarly distributed across our treatment and control groups.

Next, field supervisors compiled household lists for each village and randomly sampled ten maize-cultivating households per village using systematic sampling (nth name selection technique). The

[10] For example, in the control video, the farmer explains 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-inch deep hole and added 1 water bottle cap of Di-Ammonium Phosphate (DAP). Then I added some soil. Afterwards, I put 1 maize seed in and covered it with soil." In the treatment video, the farmer narrates the same scene but adds a pointed comment at the end of the exposition, stating: "Did you know that recommended spacing and using DAP is even more important when using improved seeds?"

enumerators interviewed 3,470 farmers using a household survey instrument that contained a wide range of questions about the individual, their household, and their farm. From an initial sample of 3,470 farmers who were interviewed in the baseline survey round, only 63 farmers dropped out in the subsequent survey round. We did not find that attrition differed significantly between treatment and control group, and thus proceed with the analysis on a balanced panel of 3,407 farmers.

5.2 Adoption

In this section, we explore the dynamics of improved variety adoption by smallholder farmers in our study area. We define adoption of improved maize varieties as follows. First, we asked farmers on how many plots they cultivated maize during the preceding season. From these plots, we randomly selected one plot and asked detailed questions about seed and varietal use, input use, and management practices. Based on the information collected, we then defined a farmer as an "Adopter" if they used either non-recycled (newly purchased, not saved) seed of (a) a hybrid or (b) an open pollinated variety. All others were defined as "Non-adopters".[11]

Figure 1 illustrates 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 (baseline), about 43 percent of farmers report to have sown an improved maize variety on the randomly selected plot. At the end of the first season, at the time of Survey 2 in April 2022, this figure increased to about 49 percent and, by Survey 3 in July and August 2022, to about 52 percent.

Figure 1 also illustrates the dynamics of adoption in our sample. At the top, we see a substantial share of households (19 percent) that adopted in all three survey rounds. These could be considered "Always Adopters" or Type 1 and Type 5 farmers, as described earlier. At the bottom of the chart, we find an equally substantial share (22 percent) that can similarly be categorized as "Never Adopters" or Type 2 and Type 4 farmers. However, we also see that a large group of farmers that adopts during Survey 1 reverts to farmer-saved seed at the time of the second survey (13 percent) or still adopts at the time of Survey 2 but eventually dis-adopts at the time of Survey 3 (6 percent). During this same period, large numbers of households also start adopting. We see that 19 percent of non-adopting households adopt at the time of Survey 2 and 10 percent of households do not adopt in both Surveys 1 and 2 but do adopt by Survey 3. Finally, we find that the some households seem to be moving in and out of adoption (7 percent) or moving out and back into adoption (6 percent).

Another indication of the dynamic nature of adoption is the fact that a substantial share of farmers that adopted at the time of the first survey seemed to be disappointed. Baseline data shows that 30 percent of farmers indicated that were not satisfied with the quality of the planting material that they used; one in four indicated that they will not use the seed again in the future.

5.3 Empirical strategy

Due to the random assignment of participants to treatment and control groups, comparing outcome variable averages of treated and control participants provides unbiased estimates of the average treatment effects. Using an Analysis of Covariance (ANCOVA) regression framework, we regress outcomes of interest (knowledge, adoption, input use and effort, and expectations) on an indicator variable that takes the value of 1 if the household was in the treatment group and 0 otherwise, and include baseline values of the outcome variables as controls. Furthermore, as this study was part of a larger project with additional cross-randomized treatments, controls are included for the orthogonal treat-

[11] We acknowledge that this definition of adoption is not perfect. Seed of an open pollinated variety that has been recycled (saved) up to four times could still be considered as improved, and farmers using this seed could still be counted as adopters. However, we expect the problem of incorrect beliefs about "miracle seeds" and biased expectations to be most pronounced when smallholders do not have experience with the seed. If farmers recycle and use seed several times, their beliefs about the relationship between efforts and the returns to improved varieties will become closer to reality as they learn from season to season. That is why this stricter definition is useful to answer the questions raised in this paper. Also, most of our results remain robust to different definitions of adoption.

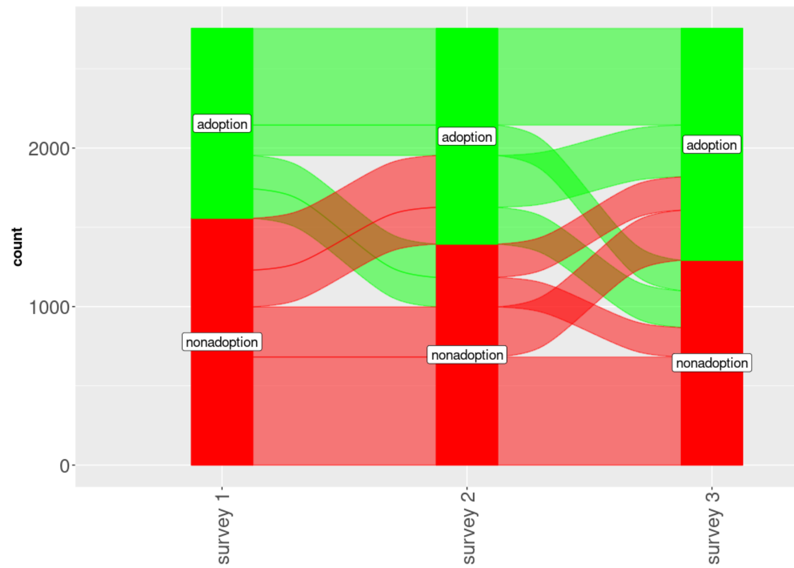

Figure 1: Dynamics of varietal adoption

ments (demeaned and interacted with the main (video) treatment (Lin, 2013; Muralidharan, Romero, and Wüthrich, 2019)).

Since we have almost 3,500 observations in about 350 clusters, the original form of the sandwich estimator (Liang and Zeger, 1986) is used, with standard errors clustered at the village level, the level of randomization. For each of the four outcome families (knowledge, adoption, input use and effort, and expectations), we compute outcome indices, which is a common way to account for multiple hypothesis testing. To do so, we follow Anderson (2008), where each index is computed as a weighted mean of the standardized values of the outcome variables. The weights are derived from the (inverse) covariance matrix, such that less weight is given to outcomes that are highly correlated with each other. For these indices, signs of outcomes were switched where necessary so that the positive direction always indicates a "better" outcome.

6 Results

We look at impact on knowledge, adoption, expectations and harvest, and inputs and practices in separate subsections.

6.1 Impact on knowledge

First, we examine whether the treated participants are able to pick up the subtle messages in the treatment video. According to Prediction 1, we expect a positive effect of the treatment on farmers' knowledge, and a larger effect for farmers that adopt at baseline. We test farmer knowledge by means of a short quiz where a number of questions were asked and enumerators read a set of alternative answers to farmers who then selected the response that they felt most appropriate.

The quiz begins with a general question asking farmers whether they think recommended cultivation practices like weeding and fertilizer application are less, equally, or more important when using improved varieties. This is followed by a more specific multiple-choice question on a particular practice—weeding—when cultivating an improved variety. Response options are: (1) you do not need to weed and remove Striga because seed of improved varieties is treated to resist weed infestation;

(2) you do not need to weed and remove Striga in the first four weeks because seed of improved varieties is better at competing for sun, nutrients, and water than normal seed; and (3) you need to weed and remove Striga just as you would with unimproved varieties because maize seed does not compete well for sunlight, water, and nutrients. The quiz contains a similar question a key input as well—fertilizer—when cultivating an improved variety. The options here are: (1) you do not need to use inorganic fertilizer because you already purchased seed; (2) you can use less fertilizer than you normally would since seed of an improved maize variety grows faster; (3) you need to use the amount of fertilizer that you would with unimproved varieties because also seed of an improved variety needs nutrition; and (4) you should use more fertilizer than you would normally use.

The quiz also contains a question that checks if farmers use sub-optimal plots to cultivate improved varieties by asking which plots are best suited. Response options are: (1) that it is best to save seed of an improved variety for poor plots, as it needs less nutrients; (2) that is best to use seed of an improved variety for plots that are furthest away from the home, as it needs less care; and (3) that the decision on what plot to plant seed should not be affected by the seed type. Another question explores how farmers think about the optimal investment in agriculture, i.e., whether to invest their resources in a single input or in a combination of inputs. The options are: (1) it is best to invest all your money in seed, because poor seed quality is the main cause of low yields; (2) it is best to invest all your money in fertilizer, because poor soil is the main cause of low yields; and (3) it is best to buy both fertilizer and seed, because good seed without fertilizer does not give good results.

Finally, the quiz includes a control question, answers to which are not expected to differ between treatment and control groups because they are featured in both versions of the video. Specifically, the question asks about the optimal spacing and seed rate for maize, with response options as: (1) one foot between plants and two and a half feet between rows with one seed per hill; (2) one foot between plants and two and a half feet between rows with two seeds per hill; and (3) two feet between plants and two and a half feet between rows with two seeds per hill. The four outcomes (excluding the control question) are also combined in an index following Anderson (2008).

Estimates of the average treatment effects on knowledge can be found in Table 2. The first column (1) provides the mean in the control group (with standard deviations in brackets below), mainly to get an idea of effect sizes. We see that knowledge is already high: 87 percent of farmers in the control group know that recommended inputs and cultivation practices like weeding or applying fertilizer are also important when using improved varieties.

Column (2) shows the estimated difference between the treatment and control groups for outcomes after the intervention, while Column (3) also reports this difference, but only for the subset of farmers that adopted an improved variety at baseline. The rationale for restricting our sample is alluded to in 3: because the restricted sample retains farmers for whom the treatment effect is likely to be largest, we expect larger estimates in Column (3) than in Column (2).

We find that knowledge, as measured by the quiz questions, increases for all variables, and generally more so for the subset of farmers that used an improved variety at baseline. For instance, the share of farmers that knows complementary inputs and practices are at least as important when using improved varieties increases from 87.1 to 89.3 percent. Furthermore, the share of farmers that recommends investing in different inputs (as opposed to investing all money in only one input), increases from 73.5 to 75.7 percent. If we only consider farmers that adopted at baseline, the increase over the control amounts to almost five percentage points.

After adjusting standard errors for clustering at the village level, none of the differences for the entire sample is statistically significant at conventional levels. However, if we only consider the subset of farmers that adopted at baseline, we see that the intervention increased knowledge, as measured by the index, significantly, probably because these farmers were more interested in this information. The overall effect is driven by increased knowledge about optimal agricultural investments among treated farmers. Even though we cannot defect a treatment effect for the entire sample, we note that all coefficient estimates are moving in the same direction. This may be due to the fact that, ex-post, it turns out that many of the farmers were already able to indicate the correct response, and hence there is little scope for further improvement. The significant results for the baseline adopters are in line with

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	0.026
	(0.336)	(0.015)	(0.019)
Farmer knows weeding is important when using an improved variety	0.790	0.025	0.028
	(0.407)	(0.022)	(0.026)
Farmer knows applying fertilizer is important when using an improved variety	0.835	0.009	0.011
	(0.371)	(0.016)	(0.021)
Farmer knows plot selection should be independent of using an improved variety	0.792	0.007	0.020
	(0.406)	(0.025)	(0.031)
Farmer knows it is best to invest in different inputs instead of putting all eggs in one basket	0.735	0.022	0.060*
	(0.441)	(0.023)	(0.028)
Farmer knows recommended seed spacing and rate	0.687	0.029	0.017
	(0.464)	(0.024)	(0.030)
Knowledge index	0.015	0.046	0.083^{+}
	(0.580)	(0.036)	(0.042)
Observations	1707	3407	1435

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

Prediction 1 in Section 3.

6.2 Impact on adoption

We now test the main hypothesis of this paper: whether farmers who were informed with subtle messages that improved varieties need substantial investment in complementary inputs and management practices behave differently in terms of seed use in subsequent seasons than farmers that were not similarly informed. To this end, we asked farmers which maize variety they planted on the randomly selected maize plot in the season prior to the survey. We again define adoption as described earlier and used in Figure 1. In addition, we investigate other outcomes that are related or even partly overlapping. For instance, we test if there are differences in the use of recycled seed between the treatment and control group, where we define recycled seed as seed that a farmer has saved themselves or obtained from another farmer who saved it (e.g., a neighbor or relative). Another related outcome is the share of farmers that report having purchased seed from an agro-input shop. The three outcomes are also combined in an index following Anderson (2008).

Results are summarized in Table 3 and show that the intervention decreases adoption. Column (1) shows sample means of the four outcomes at baseline with standard deviations in the brackets below. We find that 44 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. Column (2) shows pre-treatment balance between treatment and control groups. We see that the randomization was successful, as there is no significant difference in varietal adoption behavior

Table 3: Average treatment effects on adoption

	(1)	(2)	(3)	(4)
Farmer planted seed of an improved variety	0.435	-0.002	-0.042*	-0.077**
	(0.496)	(0.022)	(0.021)	(0.029)
Farmer planted seed from agro-input shop	0.328	-0.004	-0.022	-0.056*
	(0.469)	(0.020)	(0.020)	(0.028)
Farmer planted seed that was recycled	0.569	0.020	0.032	0.076**
	(0.495)	(0.022)	(0.021)	(0.028)
Adoption index[1]	0.009	-0.004	-0.068+	-0.121*
	(0.942)	(0.042)	(0.041)	(0.055)
Observations	3470	3470	3407	1435

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

between farmers that will be exposed to the treatment and those that will not.

Column (3) shows the difference between treatment and control groups for outcomes after the intervention. Our theory suggests that in response to being sensitized about the importance of using complementary inputs and management practices when using an improved variety, some farmers (Types 3 and 6) will change their adoption behavior (Prediction 2 in Section 3). A share of farmers that initially underestimated the returns to improved varieties (Type 6) will start adopting as their expected marginal return is increased by the treatment. Another share of farmers that initially overestimated the probability of an adoption premium (Type 3) will dis-adopt as their expected marginal return is reduced by the treatment. We find that adoption, as measured by the index, significantly decreases for the entire sample. Furthermore, all coefficients move in the direction of dis-adoption. This implies that farmers are less likely to use improved seed and seed bought at an agro-input shop but more likely to use farmer-saved seed in accordance with our earlier definitions of adoption. Since the two opposing effects for farmer Types 3 and 6 partly cancel each other out, the dis-adoption effect is not pronounced.

To separate the two opposing effects, we restrict the sample to farmers that adopted at baseline in Column (4). We see that the estimated effects become stronger when we restrict attention to this subgroup (and exclude Type 6 farmers from the analysis). Farmers who were exposed to the treatment are almost eight percentage points less likely to adopt fresh seed of an improved variety. We see another 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 who bought seed from an agro-input dealer. The treatment also has a significant and more pronounced negative effect on the adoption index for this subgroup of farmers that adopted at baseline.

6.3 Impact on expectations and harvest

Since the intervention is designed to affect farmer behavior by "correcting" their expectations, we explore the plausibility of this impact pathway by testing if post-intervention farmers feel their yield expectations were met. As mentioned in Prediction 3 in Section 3, we think this will particularly be the case if we restrict the sample to farmers that adopt at baseline. We also measure harvest-related

Table 4: Average treatment effects on expectations and harvest

	(1)	(2)	(3)	(4)
Yield as expected	0.15		0.029^{+}	0.052^{*}
	(0.36)		(0.017)	(0.024)
Production in kg	463.702	16.444	2.562	-4.289
	(399.319)	(18.004)	(12.713)	(19.308)
Yield in kg/acre	436.332	9.559	6.790	23.875
	(280.790)	(12.128)	(12.129)	(16.447)
Harvest index	-0.004	0.006	0.026	0.051
	(0.755)	(0.038)	(0.035)	(0.049)
Observations	3470	3470	3407	1435

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

outcomes (production and yield) on a randomly selected maize plot. The three outcomes are also combined in an index following Anderson (2008).

The results in Table 4 show that yield expectations have been significantly affected. We again report baseline means and balance in Columns (1) and (2). However, we did not ask if expectations were met at baseline, and so we report the control group average post-intervention and do not test for baseline balance for the expectations variable. Note that a large majority of farmers indicated that they harvested less than expected.

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

Finally, the table shows that the average farmer produces about 460 kg of maize on the randomly selected plot. The average size of these plots is slightly larger than one acre on average, such that yields are about 440 kg per acre. The intervention does not seem to have any impact on maize production or yield.

6.4 Impact on use of inputs and practices

Finally, we investigate how the intervention affects the use of inputs (other than seed) and practices. For inputs and practices, the effect is expected to be positive, but weak (see Prediction 4 in Section 3).

We examine a range of cultivation practices and complementary inputs in line with what is featured in both treatment and control videos. The first outcome is an indicator for single–stand row planting. Row planting is an important management practice that can lead to significant yield gains. Under row planting, space is used optimally such that plants have sufficient nutrients, sunlight, and room to grow. However, row planting increases workload, meaning farmers often engage in broadcast planting, which is less demanding on their labor.

Reducing the seeding rate (i.e., the number of seeds sown) is the second outcome of interest. 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 seeds fail to germinate.

The next three outcomes relate to fertilizer use. The application of organic fertilizer is important for soil structure, while inorganic fertilizers such as di-ammonium phosphate (DAP) or nitrogen, phosphorus, and potassium (NPK) and urea (nitrogen) are used to provide essential nutrients at particular points in time. The cost of organic fertilizer is mainly in terms of labor, whereas 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 per seasons. 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 plot after planting and inspecting the hills for seed germination. If a seed does not germinate, a new seed is planted in that location. Re-sowing, reduced seed rate, and row-planting are thus likely to be correlated. We also combine all outcomes in an overall index following Anderson (2008).

Results are reported in Table 5 and show no impact of the intervention on the use of inputs and practices. As in previous tables, 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.

Column (3) shows that farmers do not invest more effort in response to the intervention. On the contrary (and especially if we only consider the subset of farmers that adopted at baseline, see Column (4)), farmers appear to be less likely to plant in rows. The negative effect on some practices may be due to the fact that farmers may adopt some complementary inputs or practices, but in sufficient quantities and/or suboptimal combinations for the adoption premium to realize. When farmers subsequently dis-adopt, they may also stop using these inputs or practices, leading to a negative expected effect on practices for type 3 farmers in Table 1. In particular, for the case of row planting, it may be that farmers that adopt at baseline simply follow planting instructions that are typically printed on the seed bags. However, only row-planting without additional inputs such as fertilizer or pesticide use may not lead to expected yields, and disappointed farmers may dis-adopt in the next season which case they may also revert to plating methods used before adoption.

7 Conclusion

This paper was motivated by evidence suggesting that farmers are often unaware that many agricultural technologies such as improved seed varieties require substantial complementary inputs, better management practices, and greater effort for their benefits to be realized. In a sense, farmers overestimate the returns to a technology and are disappointed when they compare expectations to realized yields. As learning about a new technology is hard, farmers may attribute the disappointing results to the technology itself and dis-adopt. This is consistent with findings suggesting that farmers blame poor returns on inputs they believe to be counterfeit or of low quality even when objective quality assessments show otherwise (Barriga and Fiala, 2020; Michelson et al., 2021).

To credibly test this hypothesis—specifically, that farmers think of improved varieties as "miracle seed"—we conducted a field experiment built around a short, engaging video on recommended input use and management practices for maize cultivation in eastern Uganda. We produced two versions of the video that differ only in terms of the presence (absence) of subtle messaging about the salience of

Table 5: Average treatment effects on use of inputs and practices

	(1)	(2)	(3)	(4)
Row-planting	0.243	0.025	-0.070*	-0.093**
	(0.429)	(0.022)	(0.027)	(0.033)
Reduced seed rate	0.237	0.010	0.009	-0.007
	(0.425)	(0.021)	(0.019)	(0.028)
Organic fertilizer use	0.075	-0.009	-0.013	-0.013
	(0.263)	(0.011	(0.017	(0.023
DAP/NPK use	0.251	-0.020	-0.029	-0.045
	(0.434)	(0.024)	(0.019)	(0.028)
Urea use	0.076	0.001	0.002	0.013
	(0.265)	(0.013)	(0.015)	(0.024)
Weeding frequency	2.561	0.084**	-0.021	-0.001
	(0.650)	(0.026)	(0.027)	(0.037)
Pesticide etc. use	0.412	0.031	0.003	0.004
	(0.492)	(0.024)	(0.023)	(0.032)
Re-sowing	0.482	-0.046*	0.013	0.033
	(0.500)	(0.023)	(0.022)	(0.029)
Early planting	0.699	-0.018	0.012	0.021
	(0.459)	(0.024)	(0.025)	(0.031)
Early weeding	0.606	0.032	0.026	0.040
	(0.489)	(0.020)	(0.021)	(0.028)
Inputs index	0.008	0.009	-0.008	0.005
	(0.400)	(0.020)	(0.019)	(0.025)
Observations	3470	3470	3407	1435

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

recommended inputs and practices for the treatment (control) group. Screenings of the two versions were randomly assigned to villages in our study area, and then to maize farmers in those villages, resulting in a sample of almost 3,500 farmers who were interviewed at regular intervals to uncover any changes in their knowledge about best practices in maize cultivation as well as their seed or variety choices, their expectations of yield and output, and their use of complementary inputs and management practices.

While we do not find treatment effects that differ significantly from zero for knowledge outcomes for the entire sample, we do observe that all coefficients move in the expected direction and suspect that the lack of statistical significance may be caused by low power given an already high level of knowledge among our sampled farmers. We do find, consistent with our theory, that the intervention significantly improved knowledge for farmers that adopted at baseline, probably because they were more interested in the information.

For the main outcome of interest—behavior related to seed choices—we find that treated farmers were less likely to use improved varieties, and generally more likely to dis-adopt. We also find that farmers that received the treatment were more likely to report that their harvest was in line with what they expected. Both findings are again consistent with our theory. We found no overall effect of the treatment on input use and management practices, although there is some indication that especially costly inputs and practices were reduced. Taken together, we conclude that there are indeed indications that farmers consider improve maize seed varieties as "miracle seed" and that it is challenging to learn from own experience.

Our findings have implications for the study of technology adoption dynamics. We have seen that disappointment about the performance of a technology that is erroneously attributed to the technology itself may lead to dis-adoption. As long as this learning failure is not corrected—for instance, by pointing out that the seed is good; the problem is with complementary input use—farmers will not adopt anew. Worse, as we learned from extension workers who complain farmers blame improved seed varieties for the proliferation of the parasitic *Striga* weed, "fake news" may travel faster then correct information (Ledgerwood and Boydstun, 2014; Hornik et al., 2015) leading to dis-adoption at more aggregate levels, further complicating (social) learning.

Related to this, information about complementarities and changes in perceptions may reduce risk premia, particularly in the longer run. In this scenario, farmers try improved seed with complementary inputs and learn that outcomes are consistently in line with expectations. They may trade off this reduction in risk with with increased investment (and potentially lower margins). This seems to be what we find as well: When we revisited the farmers after one additional agricultural season, we no longer found any differences between treatment and control groups. At least some farmers who had disadopted in response to new information and more realistic expectations were, in fact, cultivating the new variety again; these may now be in for the long run.

Our study also casts some 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 technologies, inputs and practices, it seems unreasonable to assume that farmers can try out all possible combinations of inputs to learn about these interactions in a Bayesian fashion, at least in a reasonable time frame.

Our results differ from other studies that find that improved technologies increase agricultural productivity by crowding in modern inputs and cultivation practices (Emerick et al., 2016; Bulte et al., 2023). A possible explanation for our opposing results may be that Emerick et al. (2016) and Bulte et al. (2023) provided the improved technology (also an improved seed variety) for free as part of the experiment, potentially resulting in an income effect, i.e., the money that treated farmers did *not* use to purchase seed was instead allocated to the purchase of complementary inputs.[12] In our experiment, no free seed was provided, so when adoption decisions were made, farmers had to take the

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

combined cost of seed *and* cost of complementary inputs into account, further eroding the expected profitability of the improved technology.

Finally, our findings have implications for how public and private actors in the agriculture sector should promote new technologies. If smallholders' information sources such as private input dealers and public extension agents are not sufficiently able to communicate the importance of complementary inputs and practices, then lower likelihoods of sustained adoption may result. Worse, if smallholders have incorrect perceptions about poor quality caused by misattribution, the persistence of these perceptions may crowd out the market for quality inputs (Bold et al., 2017). And while the distribution of free or subsidized technologies and inputs may go some way in encouraging farmers' learning processes and "correcting" their perceptions (for example, with unique standalone technologies (Omotilewa, Ricker-Gilbert, and Ainembabazi, 2019)), this approach can break down when complementary inputs and practices are not part of the package, which may again lead to disappointment among farmers.

Our findings suggest that agricultural development programs, extension providers, and agri-input companies need to focus less on marketing single "miracle" technologies for smallholders, and more on the design and communication of comprehensive packages that include both agronomic and economic information on topics such as expected variation in yield and output, sensitivity of timing for specific farming tasks, magnitude and costs of family and hired labor, and the relative drudgery of effort, among many others. We conclude that the design and communication of comprehensive packages requires greater investment in the form and content of rural education, extension and advisory services, and agri-input marketing strategies.

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