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 varieties, significant investment is often required in complementary inputs such as fertilizers and pesticides, and management such as systematic planting, irrigation, and weeding practices. 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, in turn reducing complementary input use. 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. Our findings have important implications for the dynamics of technology adoption, as disappointment about the performance of a technology that is erroneously attributed to the technology itself may lead to dis-adoption. We argue that smallholders' information sources such as private input dealers and public extension agents may not be sufficiently able to communicate the importance of applying complementary inputs and implementing required management practices. We conclude that policymakers, extension providers, and agri-input companies need to focus more on the design of more holistic and thoughtful packages—inclusive of recommendations on timing, labor, cost, and effort—for smallholders, rather than the marketing of single "miracle" technologies and inputs.

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1 Introduction

To feed a growing population in a 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 biotic

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stresses (pests and disease) and tolerant of droughts, floods, heat, and other abiotic stresses (Lybbert and Sumner, 2012; Evenson and Gollin, 2003).

Unfortunately, the adoption of such technologies is lagging in areas where they may have the largest potential. 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 may not be due to a lack of awareness of information about, for example, improved cultivars or inorganic fertilizer (Sheahan and Barrett, 2017).[1]

There are many reasons why farmers may not move into a state of sustained adoption of a given technology. One obvious reason 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 may be learning 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 (Miehe et al., 2023; Bold et al., 2017). Farmers that face credit or liquidity constraints, or face 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. For instance, 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, and 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 output, 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 Ward, 2019), pays attention to the wrong attributes of the technology (Hanna, Mullainathan, and Schwartzstein, 2014), or is unable to capitalize on social learning (Foster and Rosenzweig, 1995; Conley and Udry, 2010).

This paper was motivated by evidence suggesting that many farmers are unaware that many agricultural technologies such as improved varieties require substantial complementary inputs and effort 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 of a single input, farmers may decide that the technology itself is to blame. This is consistent with the observation that many farmers think inputs are often counterfeit or of low quality, even when

[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.

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 a 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; Sumberg, Keeney, and Dempsey, 2012) (Tripp 2002).

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 input use exceeds 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 know 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. While we do not find treatment effects that differ significantly from zero, we see that all coefficients move in the expected direction. Turning to adoption behavior, we find that farmers in the treatment group are less likely to use an improved variety. If we confine our attention to only farmers that adopted at baseline, we find further indications of dis-adoption by treated farmers between baseline and follow-up. We find no evidence that the intervention increased 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 farmers, expectations became more in line with realized output.

Our findings have implications for the dynamics of smallholder technology adoption. Disappointment about the performance of a technology that is erroneously attributed to the technology itself may lead to dis-adoption which, in the long run, may actually encourage farmers to form more realistic expectations and, from a public welfare point of view, increase efficiency in production and other positive externalities (Ledgerwood and Boydstun, 2014; Hornik et al., 2015). Our findings also imply

[2]The overarching study that this paper was pre-registered at the AEA RCT registryunder RCT ID 0006361. That study 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 (OPVs) 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 performant due to cross pollination and genetic drift over multiple generations, or due to poor seed storage and handling between seasons.

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 inputs. Concluding remarks are provided in Section 7.

2 Related literature

The role of technology adoption in agriculture 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 is 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 (Chen, Hu, and Myers, 2022; Moser and Barrett, 2006).

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 if 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). 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 credence good nature) (Ashour et al., 2019; Bold et al., 2017; Lybbert and Bell, 2010), or the social, psychological, and behavioral attributes of the farmer and her learning process (Hanna, Mullainathan, and Schwartzstein, 2014; Foster and Rosenzweig, 1995). Our study contributes to this literature by...

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 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 potentially synergistic interactions 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. It seems unlikely that farmers would follow a sequential learning path that allows for all possible interactions between the different technologies. Furthermore, farmers may face certain behavioral constrains 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...

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 Jensen (2010) and Nguyen (2008) find that providing accurate information about the returns to education significantly increased investment in schooling (in the Dominican Republic and Madagascar respectively). After appropriately modeling spillover effects, 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. Across these studies, it is assumed that expected returns are underestimated by the individual. Our study contributes to this literature by unpacking this strong assumption, and exploring the possiblity that individuals may be capable of both over- and under-estimating returns to a new technology, leading to over-investment and under-investment in complementary input use, respectively.

Finally, we build on another 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 changing 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 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 those we use in the present study were performing significantly better on a knowledge test, and 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 control group. In Ethiopia, Abate et al. (2023) assess the impacts of video-mediated agricultural extension service provision on farmers' adoption of improved agricultural technologies and practices in Ethiopia using data from a two-year randomized experiment. Our study contributes to this literature by testing whether a short and engaging video is effective in transmitting salient information.

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 an improved variety or is farmer-saved seed, to maximize their profits per area of land. In doing so, they compare the expected profit functions of seed of an improved variety ${\pi_{it}^{*}}^{H}$ against farmer-saved seed ${\pi_{it}^{*}}^{L}$ which are defined as:

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

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

where E is an expectations operator and $E\left(p_{t+1}\right)$ is the expected price at which output is valued, assuming that the end commodity, maize grain, is indistinguishable to consumers by variety.[5] $E\left(Y_{it+1}^{H}\right)$

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

[5] In Uganda, where most grain is combined, milled, and sold without varietal denomination, this is a reasonable assumption. In other countries such as Mexico and Malawi, where consumers have distinct varietal preferences related

and $E\left(Y_{it+1}^{L}\right)$ reflect the expected yield for seed of an improved variety and farmer-saved seed respectively. Farmer-saved seed is assumed to be free, while seed of an improved variety s_{it} is procured at a cost $b_t > 0$. In both profit functions, the cost of a range of complementary inputs and management practices, referred to as inputs, are deducted and summarized by the vector X_{it} with corresponding factor prices w_t.

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

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

where we normalize by output price.[6]

Equation 3 shows that adoption decisions fundamentally depend on yield comparisons. We assume that yields for farmer-saved seed 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 $\frac{d^2Y_{it}}{dX_{it}^2} < 0$.

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

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

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 an improved variety and farmer-saved seed, on the relative prices of inputs and costs of management, and on the yield responses to the inputs and management.

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 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 seed of improved varieties 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. The first type of farmers are those that 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 second group of farmers that is not knowledgeable about the true relationship between Y_{it}^{H} and X_{it}, referred to as Type 4 farmers in Table 1, does not

to taste, texture and color, this assumption might not always hold.

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

Table 1: Farmers types and model predictions

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

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

adopt at baseline because, even though they have inflated expectations of the improve variety'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, these farmers underestimate the adoption premium (much like the rice farmer underestimate the returns to intensification investments in Van Campenhout (2021)), perhaps due to a disappointing experience in the past. Some of these farmers, Type 5 in Table 1, adopt at baseline as the expected marginal return may still be larger than the marginal cost of adoption, even if they underestimate the return. For another fraction of farmers that underestimate the adoption premium, referred to as Type 6 in Table 1, the expected marginal return will be less than the marginal cost of adoption, such that they do not adopt.

Heterogeneity in terms of prior knowledge and adoption behavior will lead to different effects of an intervention aimed at "correcting" incorrect beliefs about the relationship between input use and effort and the returns to improved varieties. In some cases, such as for adoption, effects for different subgroups may go in opposite directions, potentially canceling out an overall average treatment effect. In other cases, such as for knowledge, some groups may not be affected, diluting the overall treatment effect. The model and the different farmer types summarized in Table 1 allow us to make predictions on the impact of an intervention designed to increase knowledge about the true relationship between performance of improved seed varieties and complementary inputs and efforts (described in detail in the next section) on four key outcome areas:

1. Impact on knowledge: As Type 1 and Type 2 farmers are assumed to be already knowledgeable about the true relationship between Y_{it}^{H} and X_{it}, the intervention will have little effect on these farmers.[7] Types 3 to 6 are assumed to be unaware of the true relationship between improved varieties and complementary inputs; the intervention will thus increase knowledge. The knowl-

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

edge effect will be larger for farmers that adopt at baseline (Types 1, 3, 5) since this removes "Never Adopters" who are likely to be less interested in the information (Types 2 and 4) from the sample.

2. Impact on adoption: We expect opposing effects on adoption behavior for farmer Types 3 and 6. Providing Type 3 farmers with information may 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 the intervention will change the adoption behavior of farmers who already adopt even though they underestimate potential yield effects (Type 5): these farmer will keep adopting as the intervention increases their expected returns to the improved variety. Finally, as for knowledge, farmers that are aware of the correct relationship between inputs and improved varieties (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: Expectations are defined as the difference between what the farmer expected and what was realized on the farm. We predict that the intervention results in expectations that are more in line with realized outcomes. This will likely only be the case for farmers that are unaware of the true relationship and so we again do not expect an effect for Types 1 and 2. Furthermore, since our intervention aims to "correct" perceptions only for improved varieties, expectations of farmers that use farmer-saved seed at baseline are unlikely to be affected (as it is assumed that the production function of farmer-saved seed is common knowledge). Thus, we only expect an impact on farmers that plant improved varieties at baseline and also have incorrect expectations (Types 3 and 4). Again, we expect this positive effect to be stronger for farmers that adopt at baseline.

4. Impact on use of complementary inputs and management effort: Some farmers that were unaware of the true relationship between improved varieties and complementary inputs and receive new information about the importance of using complementary inputs and effort may invest more effort and increase use of complementary inputs. This will be especially the case for Type 6 farmers who adopted (potentially after dis-adopting due to disappointing outcomes) and will put the new knowledge into practice. To a lesser extent, farmers that consider adoption to be profitable despite low yield expectations may try to further increase yields by increasing effort (Type 5). For Type 3 farmers, we expect a negative effect, with farmers using less complementary inputs if the fall back to farmer-saved seed. For input use and effort, the effect is not clear *a priori*, even not for 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 was the screening of short, engaging videos about best practices in maize cultivation. The videos were shown individually to participating farmers on a tablet computer by specially trained field enumerators. The content of the video's script 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 couple (a man and woman) 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 this 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.

For example, the video addresses commonly held belief among farmers in Uganda that improved varieties directly lead to increases in infestations of Striga (*striga hermonthica*), a parasitic weed that feeds on the roots of maize plants and cause stunted growth infestations. Indeed, because improved maize varieties require more nutrients than more conventional varieties sown by farmers, it is often the complementary application of inorganic fertilizer that stimulates Striga growth. As such, the video encourages farmers to invest more effort in timely weeding practices when cultivating improved maize.

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/even more important when you are using seed of an improved variety". [8] The control video is about eight minutes long and can be found here. The treatment video is about twelve minutes long and can be found here, indicating four extra minutes of material (the other eight minutes are equal to the control video, no scenes are replaced or modified).

By randomizing 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 complementary inputs and effort, but in fact require more investment. The use of a control video has the 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 sampled 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

[8] 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 inches deep hole and added 1 water bottle cap of DAP. Then I added some soil. Afterwards, I put 1 maize seed in and covered it with soil." 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?"

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, and where maize is considered both a food and cash crop. Because this experiment was conducted as part of a larger study on maize seed supply chains, farmers were drawn from the catchment areas (marketsheds) 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 about 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 (or not 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, our field enumerators compiled household lists for each village and randomly sampled ten maize-cultivating households per village. The 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. There were no large farms in the study villages, so no exclusion criterion was needed to ensure the sampling of smallholder farmers. 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 find no evidence of attrition bias among the drop-outs, and thus focus our analysis on a balanced panel of 3,407 farmers.

5.2 Adoption

In this section, we explore the dynamics of improved maize variety adoption by smallholder farmers in our study area. We define smallholder adoption of improved maize varieties as follows. First, we asked farmers how many plots they cultivated maize on 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."[9]

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 45 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 50 percent and, by Survey 3 in July/August 2022, to about 54 percent.

Figure 1 also illustrates the dynamics of adoption in our sample. At the top, we see a substantial share of households (22 percent) that adopted in all three survey rounds. These could be considered "Always Adopters" or Type 1 and 5 farmers, as described earlier. At the bottom of the chart, we find an equally substantial share (23 percent) that can similarly be categorized as "Never Adopters" or Type 2 and 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 (16 percent) or still adopts at the time of Survey 2 but eventually dis-adopts at the time of Survey 3 (7 percent). During this same period, large numbers of households also adopt. We see that 19 percent of non-adopting households adopt at the

[9] We acknowledge that this definition of adoption is not perfect. Seed of an open pollinated variety that had been recycled (saved) up to four times could still count as improved and farmers using this seed could still count as adopters. However, smallholder expectations are likely to be biased because they pay a higher price for hybrids and open pollinated varieties, which is less the case for farmer-saved seed, which 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.

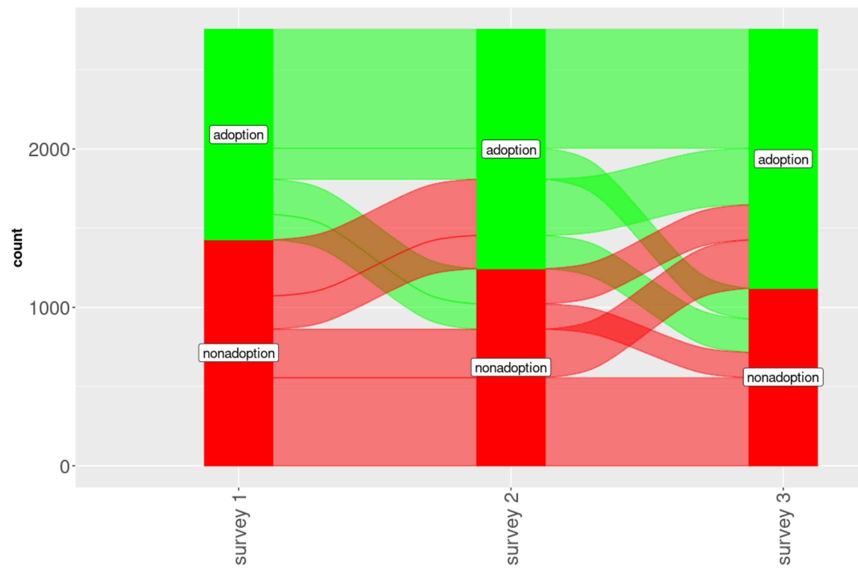

Figure 1: Dynamics of varietal adoption

time of Survey 2 and 12 percent of households that are not adopting in both Surveys 1 and 2 do adopt by Survey 3. Finally, we find that the some households 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 substantial share of farmers that adopted at the time of the first survey seems to be disappointed. Baseline data shows that 30 percent of farmers indicated that were not satisfied with the quality of the planting material that they used. One in four indicates that they will not use it again in the future.

5.3 Empirical strategy

Due to the random assignment 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 (McKenzie, 2012). Furthermore, as this study was part of a larger project with additional cross-randomized treatments, controls are included for the orthogonal treatments (demeaned and interacted with the main treatment (Lin, 2013; Muralidharan, Romero, and Wüthrich, 2019)).

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 (our 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 also account for multiple hypothesis testing. To do so, we follow Anderson (2008), where each index is computed as a weighted mean of the standardized values of the outcome variables. The weights are derived from the (inverse) covariance matrix, such that less weight is given to outcomes that are highly correlated with each other. For these indices, signs of outcomes were switched where necessary so that the positive direction always indicates a "better" outcome.

6 Results

6.1 Impact on knowledge

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

The quiz begins with a general question that asks whether farmers think recommended cultivation practices like weeding and application of fertilizer is less, equally, or more important when using an improved variety. This is followed by a more specific multiple-choice question on the appropriate weeding practice when cultivating an improved variety. Response options are: (1) You do not need to weed and remove Striga because seed of a hybrid variety of varieties are treated to resist weed infestation; (2) You do not need to weed and remove Striga in the first four weeks because seed of a hybrid variety is better at competing for sun, nutrients, and water than normal seed; and (3) You need to weed and remove Striga just as you would with normal seed because maize seed does not compete well for sunlight, water, and nutrients.

The quiz contains a similar questions for fertilizer application when cultivating an improved variety. The options here are: (1) You do not need to use inorganic fertilizer because you already bought seed; (2) You can use less fertilizer than you normally would since seed of an improved maize variety grows faster; (3) You need to use the amount of fertilizer that you would with normal seed because also seed of an improved variety need nutrition; and (4) You should use more fertilizer than you would normally use.

The quiz also contains questions that checks if farmers use sub-optimal plots by asking which plots are best suited to cultivate an improved variety on. Response options are: (1) that it is best to save seed of an improved variety for poor plots, as these need less nutrients; (2) that is best to use your seed of an improved variety for plots that are furthest away from the home, as seed of an improved variety need less care than normal seed; and 3) that the decision on what plot to plant seed of an improved variety should not be affected by the seed type that is used.

Another question explores how farmers think about their investment choices with respect to inputs, i.e., whether to invest their resources in a single input or a combination of inputs. The question simply asks how to best invest money in agriculture. 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 between treatment and control groups because the answer 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 foot between rows with one seed per hill; (2) One foot between plants and two and a half foot between rows with two seeds per hill; and (3) Two foot between plants and two and a half foot between rows with two seeds per hill. The four outcomes (excluding the control question) are also combined in an index following Anderson (2008).

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, 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 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,

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	3441	1424

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

we expect a larger effect in Column (3) than in Column (2).

We find that knowledge, as measured by the quiz questions, increases for all questions, 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 89.4 percent. Furthermore, the share of farmers that recommends investing in different inputs (as opposed to investing all their money in only one input), increases from 73.5 to 75.7 percent. If we only consider farmers that adopted at baseline, the increase over the control amounts to almost five percentage points. However, after adjusting standard errors for clustering at the village level, none of the differences are statistically significant at conventional levels. 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. At the same time, we note that all coefficient estimates are moving in the same direction, which translates in the index in Column (3) approaching significance with a p-value of 0.125.

6.2 Impact on adoption

We now test the main hypothesis of this paper, whether farmers who were informed with subtle, salient messaging 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

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	3242	3242	2941	1275

Note: Column (1) reports means at baseline (and standard deviations below); column (2) reports difference between treatment and control at baseline; column (3) reports difference between treatment and control post-intervention; column (4) reports difference between treatment and control post-intervention for farmers that adopt at baseline; **, * and + denote significance at the 1, 5 and 10 percent levels; standard errors are clustered at the village level. [1]For this index, signs of outcomes were switched where necessary so that the positive direction always indicates adoption of improved varieties.

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 48 percent of farmers use fresh seed of improved varieties and that one third of farmers reports that the seed that they planted on the randomly selected plot was obtained from an agro-input dealer. 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 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. Dis-adoption implies that farmers will be 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 these two opposing effects cancel each other out, we find limited effects on the entire sample. However, we do find that all coefficients move in the direction of dis-adoption; we also find a significant difference in the share of farmers that planted recycled seed post-intervention.

While the comparisons in Column (3) includes all farmers in our sample, Column (4) restricts the sample to farmers that adopted at baseline. 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 seven percentage points less likely to adopt fresh seed of an improved variety. We see a particularly strong increase in the share of farmers that uses seed recycled from the previous harvest in the treatment group and a somewhat lower but still significant reduction in farmers who 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.

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	2496	2496	3185	1324

Note: Column (1) reports means at baseline (and standard deviations below); column (2) reports difference between treatment and control at baseline; column (3) reports difference between treatment and control post-intervention; column (4) reports difference between treatment and control post-intervention for farmers that adopt at baseline; **, * and + denote significance at the 1, 5 and 10 percent levels; standard errors are clustered at the village level.

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 expectations of yield were met. As mentioned in Prediction 3 in Section 3, we think this is particularly the case if we restrict the sample to farmers that adopt at baseline. We also measure harvest-related 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 (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 randomly selected plots is slightly larger than one acre on average, such that yields are about 440 kg per acre. Thus, the intervention does not seem to have any impact on maize production or yield.

6.4 Impact on input use and efforts

Finally, we investigate how the intervention affects effort and the use of inputs other than seed. For input use and effort, the effect is ambiguous, even if we restrict the sample to baseline adopters (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. A first outcome is an indicator for single-stand row planting. Row planting is an important management practice that can lead to significant yield gains. Under row planting, space is used optimally such that plants have sufficient nutrients, sunlight, and room to grow. However, row planting increases workload, such that farmers often engage in the alternative that is less demanding on their labor—broadcast planting.

Reducing the seeding rate, i.e., the number of seeds sown, is our 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 seed fails to germinate.

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

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

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

Results are reported in Table 5. As in the previous table, 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 inputs or efforts after the intervention. On the contrary (and especially if we only consider a subset of farmers that adopted at baseline (Column (4)), farmers appear to be less likely to plant in rows and to use DAP. This suggests that there is an important group of farmers that adopts at baseline, perhaps using some inputs and practices such as inorganic fertilizer and row planting. However, after being made aware that all complementary inputs are equally important, they may decide it is not optimal to use improved varieties, and may revert to farmer-saved seed, in turn reducing input use and key management practices like row planting.

7 Conclusion

This paper was motivated by evidence suggesting that farmers are unaware that many agricultural technologies such as improved varieties require substantial complementary inputs, better management practices, and greater effort to realize their benefits. Both theory and practice suggest that it is feasible for farmers to overestimate the returns to a technology, and may dis-adopt when disappointed with actual returns. But when following recommendations for the use of complementary inputs and practices, farmers may be unable to learn about the contribution made by each component of a package, and may ultimately attribute disappointing returns to the technology itself. 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" and may dis-adopt when results are disappointing—we conducted a field experiment built around an 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

Table 5: Average treatment effects on input use and efforts

	(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)
Efforts index	0.008	0.009	-0.008	0.005
	(0.400)	(0.020)	(0.019)	(0.025)
Observations	3389	3389	3202	1333

Note: Column (1) reports means at baseline (and standard deviations below); column (2) reports difference between treatment and control at baseline; column (3) reports difference between treatment and control post-intervention; column (4) reports difference between treatment and control post-intervention for farmers that adopt at baseline; **, * and + denote significance at the 1, 5 and 10 percent levels; standard errors are clustered at the village level.

(absence) of subtle messaging about the salience of recommended inputs and practices for the treatment (control) groups. Screenings of the two versions of the video 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/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, we do observe that all coefficients move in the expected direction. We suspect that the lack of statistical significance may be caused by low power given an already high level of knowledge among our sampled farmers.

Despite this, for the main outcome of interest—behavior related to seed choices—we find that treated farmers were less likely to use improved varieties obtained from agro-input dealers and more likely to revert to farmer-saved seed. We also found that farmers that received the treatment were more likely to report that their harvest was in line with what they expected. We found no overall effect of the treatment on input use and management practices, although there is some indication that especially costly inputs and practices were reduced.

Our findings have implications for the study of technology adoption dynamics, suggesting that disappointment about the performance of a technology that is erroneously attributed to the technology itself may lead to dis-adoption. But while farmers may have dis-adopted in the short run in response to our intervention, the possibility that farmers' expectations became more realistic may suggest that farmers that do adopt may be aligning their outlooks to a longer-run perspective, which could lead to efficiency gains and positive spillover effects (Ledgerwood and Boydstun, 2014; Hornik et al., 2015).

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.

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 Bulte et al. (2023) and Emerick et al. (2016) provided the improved technology (also an improved 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.[10] In our experiment, no free seed was provided, so when adoption decisions were made, farmers had to take the 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 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 mis-attribution, 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 uniquely standalone technologies (Omotilewa, Ricker-Gilbert, and Ainembabazi, 2019)), this approach can break down when complementary inputs and practices are not part of the package. And this, in turn, can again lead to disappointment among farmers.

Our findings suggest that agricultural development programs, extension providers, and agri-input

[10] 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.

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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