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 disappointing crop yields and outputs and, eventually, dis-adoption of the improved variety. Using a field experiment, we test an information intervention among smallholder maize farmers in eastern Uganda that points out these complementarities. We find that farmers adopt less after they have been sensitized about the need to use complementary inputs to unlock the adoption premium. We rationalize this finding with a simple theoretical model where farmers have misspecified mental models of the technology production function and conclude that most farmers in our sample do indeed believe in miracle seeds.

Note: Author order is alphabetical.

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).

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).[1]

There are many reasons why farmers may not move into a state of sustained adoption of a given technology. For explanations grounded in multiple market failures such as credit constraints or imperfect labor and land markets, readers are encouraged to consult comprehensive reviews by Magruder (2018) and Suri and Udry (2022). In this paper, we take a more behavioral approach and consider the possibility that farmers' inflated expectations of new technologies explain their dis-adoption. These inflated expectations may result from farmers being unaware, failing to recognize, or downplaying the importance of 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 only the (higher) cost of seed but also of fertilizer required to achieve expected yield improvements, as well as higher costs of labor for farm tasks are associated with the cultivation of higher-yielding maize.

The impact of inflated expectations due to insufficient complementary input use on future adoption behavior is complex and depends on what the unexpected outcome is attributed to, and hence on learning. Learning about a new technology is difficult: as multiple factors simultaneously affect yields and outputs, learning about the causal impact of a new technology from a single experience is hard, 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).

Inflated expectations are likely to have a negative impact on future adoption if farmers attribute disappointing outcomes to the seed itself. However, as there are different types of seed and seed quality is known to vary, farmers may be tempted to try again at some point in the future, particularly if neighbors get better results and extension workers are promoting improved seed varieties. Alternatively, farmers may attribute disappointing outcomes to other factors such as weather events, so that they are likely to adopt again in the future. Finally, if farmers attribute disappointing outcomes to the correct cause (insufficient complementary investment), farmers may re-optimize in light of the additional cost of complementary inputs and practices.

[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.

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 (temporary) 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 gives high yields on even the poorest soil, does not suffer from lack of water, or does not need weeding due to exceptional vigor. 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).

We test the miracle seeds hypothesis in a field experiment 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 instead of unimproved 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, and manage expectations by stressing that farmers should not skimp on this input or practice because improved seed varieties are not "miracle seeds."

We first check whether farmers are able to extract the relevant information from the treatment video and find that treated farmers better select the correct answer in a quiz on the use of complementary investments. Turning to adoption behavior, we find, somewhat surprisingly, that farmers in the treatment group are less likely to adopt improved seed varieties than control group farmers. 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 weeding frequency and re-planting. We do see, however, that among treated farmers, expectations with respect to maize yield after the treatment tend to be more in line with realized output.

To explain the negative impact of our information treatment on adoption, we develop a simple model of technology adoption. In this model, farmers compare the expected returns of an improved technology (seed) to their business-as-usual choices. The new technology comes at a cost, while the unimproved technology does not. Yet, both technologies require complementary inputs and efforts that directly affect productivity, with productivity gains from the new technology—the adoption premium—only materializing when complementary inputs and practices exceed business-as-usual levels. We then introduce heterogeneity in the beliefs that farmers hold about the nature of the production function of the new technology: some farmers know that additional complementary inputs and practices are needed to obtain the adoption premium, other farmers believe in miracle seeds and think that the adoption premium is also present if they apply complementary inputs and practices as they normally would. Finally, there is a group of farmers who do not believe in any adoption premium, perhaps because they have been disappointed in the past. The model is then used to derive predictions on the treatment effect for specific subgroups, and tested by estimating the effect on subsamples of participants. Results suggest that a substantial share of our study population believes in miracle seeds: they believe improved seeds are profitable under a misspecified production function but not when all costs of complementary inputs and practices are considered.

[2]The overarching study was pre-registered at the AEA RCT registry under 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 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 effective due to cross pollination and genetic drift over multiple generations, or due to poor seed storage and handling between seasons.

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 will likely be disappointing. Often, disappointment about the performance of a technology is then erroneously attributed to the technology itself, leading farmers to continue using local seed. In the aggregate, this is likely to lead to lower than optimal adoption. Providing this information up front can save farmers from the disappointment and financial loss of failed attempts. Additionally, correcting beliefs may prompt some of these disappointed farmers to re-evaluate costs and benefits of using improved seed, which may increase adoption in the long run. Our findings also have important policy implications: 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. In Section 3, we discuss the study setup and interventions in the field experiment, and present the empirical strategy. Section 4 describes the study population and discusses baseline balance. Section 5 provides a summary of the results for the entire study population, followed by Section 6 which presents a simple theoretical model that helps explain these findings. Section 7 revisits the results to provide a more in-depth analysis and validate predictions derived from the theoretical model. Concluding remarks are provided in Section 8.

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.

Many 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 longer-term perspective, documenting significant levels of dis-adoption (for example, Ainembabazi and Mugisha, 2014), or transient technology use over time (Moser and Barrett, 2006; Chen, Hu, and Myers, 2022).

Such a pattern of adoption and dis-adoption is consistent with a model of learning failures, where farmers have inflated expectations about the returns of a new technology but fail to uncover the true form of the production function through experience, leading to disappointment and subsequent dis-adoption. Indeed, heterogeneity in farmer characteristics implies that farmers need to learn 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; see Lybbert and Bell, 2010; Bold et al., 2017; Ashour et al., 2019), or the social, psychological, and behavioral attributes of farmers and their learning processes (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 (for example, 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 would be 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 adoption decisions. The effect of incorrect expectations about future returns on decision-making has largely been studied in the context of investments in education, but is readily applicable to technology adoption 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 informing Ugandan farmers about the returns on intensification investments in rice growing improves practices and increases input use and production.[4]

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 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 Ugandan students who watched "Queen of Katwe," a feel-good Disney movie 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 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 were shown a placebo 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 using data from a two-year randomized experiment and find that it increases farmers' adoption of improved agricultural technologies.

In the present study, we also use a video as the main conduit for information transfer. In the video presented to the treatment group, we emphasize the crucial role of complementary inputs and efforts in maximizing the benefits of improved seed varieties. We also show a video that promotes best practices in maize growing using improved seed varieties to the control group but do not explicitly point out the interaction with complementary inputs and efforts. Our study hence contributes to this literature by testing whether videos are also effective in conveying subtle messages.

[4]Note that across these studies, it is assumed that the individual underestimates the returns in question. In our study, as farmers fail to appreciate the importance of complementary inputs, they are in a sense overestimating returns to a new technology, leading to over-investment in technologies, and subsequent disappointment.

3 Field Experiment

To test whether providing information about the need for additional inputs and practices when using improved seed varieties affects farmer behavior, we conduct a field experiment with almost 3,500 maize farmers in eastern Uganda. The intervention entails 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. In this section, we provide a detailed description of the intervention and the empirical strategy used to answer the research question.

3.1 Intervention

At the heart of the field experiment is a video that opens with a woman and a man standing in a well-kept maize plot inspecting their crop. The couple explains that while they have been farmers for more than ten years, 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 to 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 improved seed varieties such as hybrid seed or open pollinated varieties (OPVs) 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 to 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.

We obtained experimental variation by recording two versions of this intervention video. The control group viewed the video as described above: it shows different recommended inputs and practices like row planting and inorganic fertilizer application but does not comment on the importance of combining them with improved seed varieties. The treatment group viewed a similar video, but now it is made explicit that, for each individual recommended input or practice, significant complementarities exist when using improved varieties.[5] Generally, the treatment video focuses on the *benefits* of complements instead of the *need* for complements. Except for these messages, the videos are identical, no scenes are replaced or modified. The control video can be found at https://vimeo.com/781882803. The treatment video can be found at https://vimeo.com/781882930.

By randomizing which video is viewed by our sampled farmers, we can isolate the causal effect of making salient that improved varieties do not substitute for inputs or efforts, but in fact require more investments. 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 participants could provide information to participants in the control group—a common issue 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 planted in August

[5]For example, in the control video, the farmer explains that: "At planting time, I paid attention to recommended spacing, carefully measuring one foot between plants and 2.5 feet between rows. I first dug a 4-inch deep hole and added one water bottle cap of Di-Ammonium Phosphate (DAP). Then I added some soil. Afterwards, I put one 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?" Often, we also added a few sentences that aim to correct inflated expectations. For instance, when discussing the use of inorganic fertilizer, we warn the viewer that "Improved seed are not miracle seeds! They also need proper fertilizer application to get the higher yields." For the practice of gap filling two weeks after planting, we warn: "Do not assume that just because you used an improved seed variety, all seeds will germinate!"

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. The intervention was repeated just before planting in August 2021, and post-treatment data was collected in January and February 2022.

3.2 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. We use a standard Analysis of Covariance (ANCOVA) regression framework and estimate the following equation:

$$Y_{ij} = \alpha + \beta_T T_j + \beta_O \left(O_j - \bar{O}\right) + \beta_X T_j \left(O_j - \bar{O}\right) + \delta Y_{ij}^B + \varepsilon_{ij} \tag{1}$$

where Y_{ij} is the outcome of interest (knowledge, adoption, complementary input use, and correct expectations) of farmer i in village j, and Y_{ij}^B is the corresponding outcome at baseline. T_j is the treatment indicator, so that β_T is the parameter estimate of interest. Furthermore, as this study was part of a larger project with additional cross-randomized treatments, controls are included for the orthogonal treatments (O_j). These controls enter the equation demeaned and fully interacted with the main (video) treatment (Lin, 2013; Muralidharan, Romero, and Wüthrich, 2023).

Standard errors are clustered at the village level, the level of randomization. For outcome families with more than one variable (knowledge, adoption, and complementary input use), we compute outcome indices to account for multiple hypothesis testing. We follow Anderson (2008), so that 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 are switched where necessary so that the positive direction always indicates a "better" outcome.

4 Study Population

4.1 Sample

The field experiment was conducted in southeastern Uganda, an area known for its smallholder maize production where maize is considered both a food and a cash crop. Because it was organized as part of a larger study on maize seed supply chains, farmers were drawn from the market-sheds of agro-input shops. These shops sell agricultural inputs and technologies in countries with large smallholder farmer populations living in remote areas with relatively poor infrastructure. A reasonably dense network of semi-formal agro-input dealers provides access to seeds, fertilizers, agro-chemicals, and tools, and sometimes to services like agricultural advisory and credit.

The sampling frame was developed as follows. First, we listed all agro-input shops in eleven 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 are similarly distributed across treatment and control groups.

Next, field supervisors compiled household lists for each village and ten maize-cultivating households per village were selected using systematic random sampling (nth name selection technique). 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. 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. Since we have more than 3,400 observations in about 350 clusters, we use the original form of the sandwich estimator (Liang and Zeger, 1986).

Baseline data were collected in April 2021, prior to the second agricultural season of 2021, which runs from August to December. A follow-up survey was conducted post treatment in January and February 2022, after the maize harvest from the second season of 2021.[6] Detailed information on the full range of data and outcome variables collected is available in the pre-analysis plan, mock report, and midline report, all accessible through the AEA's registry for RCTs.

4.2 Descriptive Statistics and Balance

Table 1 provides descriptive statistics from the baseline farmer survey. The first column reports sample means (and standard deviations below). For example, we see that household heads are 49 years old on average, and that 78 percent are male. The average household consists of almost nine members and uses 3.3 acres of land for crop production. About half of the farmers in our sample indicate that they used seed of an improved maize variety (OPV or hybrid) on at least one plot in the season preceding the baseline survey, and 33 percent bought this seed at an agro-input shop. We further asked farmers to rate the general quality of the maize seed they planted in the previous season on a scale of one (poor) to five (excellent) and see that they rate it fairly high (3.4 out of 5). Organic fertilizer use at baseline is very low and the average farmer harvested 500 kg of maize per acre. About half of the farmers in our sample also sold maize.

Table 1 also serves to demonstrate baseline balance on a set of pre-registered variables. The second column shows the differences between treatment and control group means (and standard errors below—they are clustered at the village level). We find only one significant difference (at the 10-percent significance level) which is expected when ten comparisons are made, hence we conclude that the randomization was successful.

5 Results

Figure 1 summarizes the impact of the intervention on four families of outcomes: farmer knowledge about the importance of using complementary inputs and practices when using improved seed, adoption of seed of an improved variety, use of complementary inputs and good agronomic practices, and a measure of how well expected maize yields align with realized yields on the farmer's field.

We test farmer knowledge about the importance of using complementary inputs and practices through a short quiz where enumerators asked a number of questions read a set of alternative answers to farmers who then selected the response that they felt most appropriate. More details are provided in Subsection 7.1 where we look at detailed results for each question; here we restrict attention to a knowledge index that is constructed from the individual questions following Anderson (2008). Figure 1 shows that farmers that were made aware of the importance of using complementary inputs and practices when using seed of an improved variety do significantly better on the quiz than farmers who were not made aware of the importance of using additional inputs and practices.

A second key outcome is the adoption of seed of an improved variety. We use three related and even partly overlapping variables to capture this, details on these outcomes are again deferred to Subsection 7.2; here we use a summary index. Figure 1 shows that farmers who were made aware of the importance of using additional complementary inputs and practices when using seed of an improved variety are less likely to adopt seed of an improved variety than farmers who were not made aware of this (and the difference is significant at the 10 percent level).

[6]We collected an additional round of post-treatment data from farmers in July and August 2022, following the harvest of the first season of 2022. This second follow-up aimed to address other hypotheses within the overarching research design (see Footnote 2). For this study, however, we primarily rely on data from the first follow-up, collected in January and February 2022.

Table 1: Descriptive statistics and orthogonality tests

	mean	difference T-C
Farmer's age in years	48.62	-0.247
	(13.38)	(0.561)
Farmer is male	0.777	0.022
	(0.421)	(0.022)
Number of household members	8.69	0.118
	(3.98)	(0.171)
Land for crop production in acres	3.35	0.172
	(4.32)	(0.180)
Farmer used improved maize seed for any field last season	0.492	-0.012
	(0.500)	(0.022)
Farmer bought improved maize seed from agro-input shop	0.325	-0.009
	(0.468)	(0.021)
Farmer's rating of maize seed quality (1=poor to 5=excellent)	3.38	0.083^{+}
	(1.03)	(0.050)
Farmer used organic manure	0.074	-0.009
	(0.262)	(0.011)
Land productivity in kg/acre	499.52	44.08
	(771.17)	(31.48)
Farmer sold maize	0.513	0.023
	(0.500)	(0.025)

Note: Column (1) reports sample means at baseline and standard deviations below; columns (2) reports differences between treatment and control group means and standard errors below; they are clustered at the level of randomization; **, *, and + denote significance at the 1, 5, and 10 percent levels. The number of observations is 3,470.

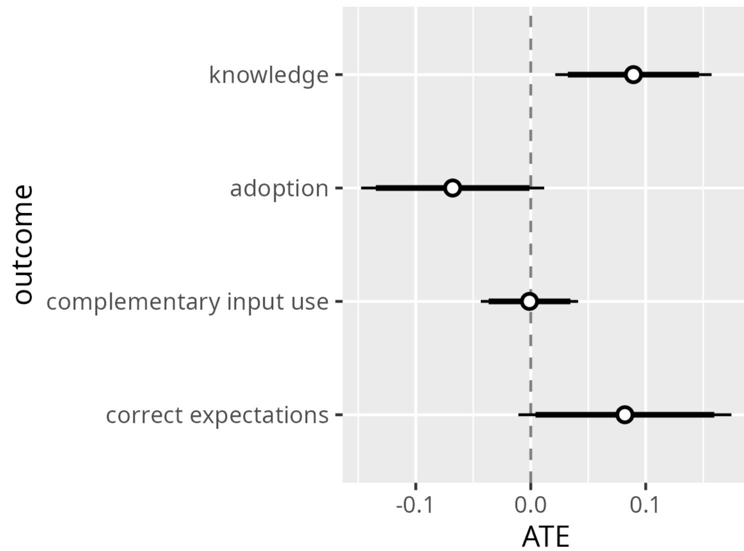

Figure 1: Impact of treatment on outcomes

The third key outcome we compare between treatment and control households measures the use of inputs and recommended agronomic practices by the farmer. Subsection 7.3 provides details on the four inputs and six practices we included in the index to assess the impact of the treatment. Figure 1 shows no difference between treatment and control groups.

Finally, we look at the impact on expectations. To do so, we simply asked farmers if the yield that they obtained in the previous season was what they expected (yes/no). Figure 1 shows that a higher share of farmers indicate that yields were according to their expectations in the treatment group, but the difference is significant only at the 10 percent level.

The negative impact on adoption may seem counter-intuitive at first glance. Indeed, when we set up the experiment, we did not intend to reduce the adoption of seed of improved varieties. However, after considering the fact that the treatment may lead to different effects for different types of farmers, we realize that the impacts we observe in Figure 1 are in fact consistent with the miracle seeds hypothesis, which we will explain in the theoretical model in the next section.

6 A Simple Model of Technology Choice with Biased Expectations

We describe farmers as solving an inter-temporal problem in which they allocate resources at t in order to maximize profits at $t+1$.[7] 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 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,[8] to maximize their profits per area of land. In doing so, they compare the expected profit functions of Variety H $\left(\pi_{it}^{*H}\right)$ and Variety L $\left(\pi_{it}^{*L}\right)$ which are defined as:

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

[8]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 OPV, etc.

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

$$E\left(\pi_{it+1}^{L}\right) = E\left(p_{t+1}Y_{it+1}^{L}\right) - \sum w_t X_{it}^{L} \tag{3}$$

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.[9] $E\left(Y_{it+1}^{H}\right)$ 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 seed of Variety H, s_{it} is procured at a cost $b_t > 0$.[10] 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:

$$\left(E\left(Y_{it+1}^{H}\right) - \sum \frac{w_t}{E(p_{t+1})} X_{it}^{H}\right) - \left(E\left(Y_{it+1}^{L}\right) - \sum \frac{w_t}{E(p_{t+1})} X_{it}^{L}\right) > \frac{b_t}{E(p_{t+1})} s_{it}^{*} \tag{4}$$

where we normalize by output price.[11]

Equation 4 shows that if farmers use the same inputs irrespective of seed choice, adoption decisions fundamentally depend on yield comparisons. We assume that yield for Variety L is a function of inputs used:

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

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 Variety H follows the same function, but adds a positive farmer specific adoption premium $(A_i > 0)$. However, the adoption premium only applies if the farmer uses more complementary inputs $\left(X_{it}^{H}\right)$ than they would when using Variety L $\left(X_{it}^{H} > X_{it}^{L}\right)$:

$$Y_{it+1}^{H} = A_i\left(X_{it}^{H} > X_{it}^{L}\right) + Y_{it}\left(X_{it}^{L}\right) \tag{6}$$

Next, we introduce farmer heterogeneity in the beliefs they hold about the relationship between yield obtained from using seed of an improved variety $\left(Y_{it+1}^{H}\right)$ and the inputs needed to realize this yield (X_{it}).

A first group of farmers—also referred to as type 1 farmers below—knows that, for the adoption premium to materialize, additional complementary inputs and practices are needed. These farmers will adopt if the value of the expected adoption premium $\left(E\left(p_{t+1}A_i\left(X_{it}^{H} > X_{it}^{L}\right)\right)\right)$ exceeds the cost of the seed and additional complementary inputs needed $\left(\sum w_t X_{it}^{H} - \sum w_t X_{it}^{L} + b_t s_{it}\right)$. Informing these farmers about the true shape of the production function will not have an effect on adoption of improved seed, or any other outcome we consider in Figure 1.

A second group of farmers—also referred to as type 2 farmers below—thinks that the adoption premium is not dependent on the use of complementary inputs and practices. They believe that

[9] In a country like Uganda, where most grain is aggregated, 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.

[10] 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 3, so that the adoption decision in Equation 4 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.

[11] 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.

the adoption premium is always present $\left(Y_{it+1}^{H}=A_i+Y_{it}\left(X_{it}\right)\right)$. These farmers will use the same inputs for both varieties (hence $\sum w_t X_{it}^H=\sum w_t X_{it}^L$) and adopt if the value of the (misspecified) expected adoption premium $E\left(p_{t+1}A_i\right)$ exceeds the cost of seed ($b_t s_{it}$). Informing this group of farmers about the need for complementary inputs will presumably reduce the likelihood of adoption, as it increases the cost of obtaining the premium by the cost of the additional complementary inputs $\left(\sum w_t X_{it}^H-\sum w_t X_{it}^L\right)$.[12] For these farmers, we thus expect a positive effect of the intervention on knowledge and a negative effect on adoption. Furthermore, we do not expect a change in the use of complementary inputs and practices. We expect that farmers' expectations become more in line with reality.

A third group of farmers—also referred to as type 3 farmers below—also use misspecified mental models of the production function. This group of farmers does not believe that seed of an improved variety is any better than local seed, hence $Y_{it+1}^H=Y_{it}\left(X_{it}\right)$. This could be farmers who used to believe in miracle seeds, but after a negative experience with improved seed (either through own experimentation or through learning from peers) adjusted their expectations downward. Informing this group of farmers about the need for complementary inputs could increase the likelihood of adoption if they update their beliefs and, after doing so, the expected adoption premium $E\left(p_{t+1}A_i\left(X_{it}^H>X_{it}^L\right)\right)$ exceeds the cost of the seed and additional complementary inputs needed $\left(\sum w_t X_{it}^H-\sum w_t X_{it}^L+b_t s_{it}\right)$. For these farmers, we would expect an increase in knowledge, an increase in adoption, and an increase in the use of complementary inputs and practices. For this group of farmers, we do not expect a change in expectations.[13]

The different (and sometimes opposing) effects of the intervention on these different groups imply that Figure 1 shows net results that depend on the shares of the three groups of farmers. Furthermore, the treatment effect is also affected by the technology itself, as farmers compare the additional returns to adoption to the costs. In the next section, we revisit the results and partition our sample to study these heterogeneous treatment effects.

7 Subgroup Analysis

In this section, we provide a more detailed analysis than in Section 5. We run regressions on the entire sample, as in Section 5, and additionally on sub-samples to sharpen estimates and test model predictions. In particular, we condition on two variables. First, we attempt to remove farmers who already use complementary inputs from our sample, as we do not expect an effect for these farmers (which would be in the first group in our model of Section 6).[14] This leads to a more homogeneous subsample of individuals who are potentially responsive to the treatment and an effect size that is not diluted due to the presence of non-responders' outcomes—considering the entire sample brings the treatment group's average closer to the control group's average.

Second, we attempt to identify farmers who believe in miracle seeds (to zoom in on the second group in our model of Section 6). We do this by looking at the distribution of expected maize yields at baseline. Farmers in the highest 33 percent of the distribution are then categorized as potentially

[12] Only if the misspecified adoption premium is large enough (i.e., exceeding the cost of additional complementary inputs needed (including the seed and normalized by the price)), type 2 farmers who adopted under the misspecified model will also adopt after having been informed about the need to use complementary inputs. As such, the average treatment effect does not only depend on the share of farmers who hold correct or incorrect beliefs, but also on the technology and associated costs.

[13] This is because virtually all these farmers will be using local seed in the control group and so they know that they can expect low yields. In the treatment group, these farmers are sensitized about the true relationship between inputs and yields, so also in this group there should be no surprises.

[14] One challenge with this strategy is that there are different complementary inputs and practices, and some farmers may adopt some while not adopting others. As such, it is not immediately clear which complementary inputs should be selected to condition on. To deal with this, we created an index of the ten inputs and practices that are featured in the video (and measured at baseline; these are also considered as outcomes in Subsection 7.3 when measured post intervention). The index is again computed according to Anderson (2008) and weighs its components by the inverse variance covariance matrix. As the components are standardized, the index is on average approximately zero, and so we simply define adopters of complementary inputs and practices as farmers that have a baseline index above zero.

overestimating the yield premium (while those in the lowest 33 percent of the distribution may have been disappointed in the past).

7.1 Impact on Knowledge

We start by re-examining whether the treated participants are able to pick up the relevant information from the treatment video. According to our model in Section 6, we expect a positive effect of the treatment on farmers' knowledge, and this effect should become increasingly stronger when farmers who use complementary inputs are removed from the sample and when we zoom in on farmers that are likely to overestimate yields.

As indicated above, we test farmer knowledge using a short quiz. The quiz begins with a general question asking farmers whether they think recommended cultivation practices like weeding and fertilizer application are (1) less, (2) equally, or (3) 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 because seed of improved varieties is treated to resist weed infestation; (2) you do not need to weed 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 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 about a key input as well—fertilizer—when cultivating an imatproved 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 seed of an improved variety also needs nutrition; and (4) you should use more fertilizer than you would normally use. We also combine all outcomes in an overall index following Anderson (2008).

Estimates of the average treatment effects on knowledge can be found in Table 2. Column (1) provides the means 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, which is likely to reduce statistical power for these comparisons. For example, 38 percent of farmers in the control group know that recommended inputs and cultivation practices like weeding or applying fertilizer are even more important when using improved varieties.

Column (2) shows the estimated difference between the treatment and control groups for outcomes after the intervention on the entire sample. Column (3) also reports this difference, but in the more homogeneous subset of farmers who did not already use complementary inputs and good agronomic practices at baseline. Finally, column (4) further reduces the sample to only those that overestimate yields in an attempt to isolate the second group of farmers in our model of Section 6.

Looking at the summary index, we find that the treatment increases the likelihood that farmers answer correctly. The difference is particularly significant for the individual question about the use of fertilizer. This could be because the recognition that complementary inputs are necessary to reap the benefits of improved seed may become more salient when this complementary input comes at a substantial pecuniary cost. Effect sizes become larger with increasingly specific samples, as predicted by the theoretical model in Section 6.

7.2 Impact on Adoption

We now turn to the main hypothesis of this paper: whether farmers who were told that improved varieties need substantial investment in complementary inputs and management practices behave differently in terms of seed use in subsequent seasons than farmers who were not similarly informed.

First, we determine if farmers adopted improved maize varieties. To do so, 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

Table 2: Average treatment effects on knowledge

	(1)	(2)	(3)	(4)
Farmer knows inputs and practices are important	0.357	0.049^{+}	0.029	0.048
when using an improved variety	(0.479)	(0.025)	(0.030)	(0.055)
Farmer knows weeding is important	0.790	0.024	0.016	0.013
when using an improved variety	(0.407)	(0.022)	(0.027)	(0.047)
Farmer knows applying fertilizer is important	0.379	0.053*	0.066*	0.180**
when using an improved variety	(0.485)	(0.023)	(0.027)	(0.053)
Knowledge index	-0.024	0.089*	0.077^{+}	0.164*
	(0.635)	(0.035)	(0.041)	(0.073)
Observations†		3256	1615	361

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 whose use complementary inputs and practices at baseline; column (4) reports differences between treatment and control post-intervention for farmers whose use of complementary inputs and practices was below average at baseline and are in the top 33% of the distribution of expected maize yields at baseline; **, *, and + denote significance at the 1, 5, and 10 percent levels; standard errors are clustered at the village level. †These are the numbers of observations in the regression with the index, regressions with individual outcomes have more observations.

practices.[15] 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 either a hybrid or an open-pollinated variety. All others were defined as "Non-adopters."[16] A second related outcome we consider is the use of recycled seed, which is defined as seed that farmers have saved themselves or obtained from other farmers who saved it (for example, neighbors or relatives). A third related outcome is the share of farmers who report having purchased seed from an agro-input shop. We also combine all outcomes in an overall index following Anderson (2008).

Results are summarized in Table 3. Column (1) shows the sample means of the outcomes at baseline with standard deviations in the brackets below. We find that 44 percent of farmers use fresh seed of improved varieties, and one third reports that the seed that they planted on the randomly selected plot was obtained from an agro-input dealer. Column (2) 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 will change their adoption behavior (the second and third group in Section 6). A relatively large share of farmers who initially overestimated the probability of an adoption premium (the second group) may not adopt as their expected marginal return is reduced by the treatment. A share of farmers who initially underestimated the returns to improved varieties

[15] The decision to ask detailed questions on only one (randomly selected) plot as opposed to asking details on all plots was made because there is generally high correlation between technology use, input use, and management practices within a household. As such, we decided to increase the number of farmers at the expense of the number of plots as this would increase statistical power. That said, one may be worried that farmers use different seed on different plots, and if the "wrong" plot is chosen, a farmer that is actually an adopting farmer is categorized as a non-adopter. We investigated this issue further by using a different variable for adoption status, namely if the farmer used seed of an improved variety on any field, and results were very similar.

[16] We acknowledge that this definition of adoption is not perfect. Seed of an OPV that has been recycled (saved) up to four times could still be considered improved, and farmers using this seed could still be counted as adopters.

Table 3: Average treatment effects on adoption

	(1)	(2)	(3)	(4)
Farmer planted seed of an improved variety	0.435	-0.042*	-0.058*	-0.134**
	(0.496)	(0.021)	(0.026)	(0.051)
Farmer planted seed from agro-input shop	0.328	-0.022	-0.022	-0.099*
	(0.469)	(0.020)	(0.025)	(0.046)
Farmer planted seed that was recycled	0.569	0.032	0.035	0.122*
	(0.495)	(0.021)	(0.026)	(0.048)
Adoption index	0.009	-0.068+	-0.085+	-0.248**
	(0.942)	(0.041)	(0.050)	(0.095)
Observations†		2941	1449	336

Note: Column (1) reports means at baseline (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 whose use of complementary inputs and practices was below average at baseline; column (4) reports differences between treatment and control post-intervention for farmers whose use of complementary inputs and practices was below average at baseline and are in the top 33% of the distribution of expected maize yields at baseline; **, *, and + denote significance at the 1, 5, and 10 percent levels; standard errors are clustered at the village level. †These are the numbers of observations in the regression with the index, regressions with individual outcomes have more observations.

(the third group) may adopt if they decided adopting is profitable after updating their beliefs and comparing costs to benefits.

In Section 5, we showed that adoption, as measured by the index, significantly decreases as a result of the treatment. Table 3 further shows that this is driven by a lower likelihood that the farmer plants seed of an improved variety. Reducing the sample to a more homogeneous sample of farmers who did not already use complementary inputs and good agronomic practices at baseline increases the effect size, albeit only marginally, see column (3).

Our model of Section 6 reveals that differences in expected yields (farmer types 2 and 3) may lead to opposing effects of the treatment on adoption, which is likely to mute the overall effect. To separate the two opposing effects, we further restrict the sample to farmers who overestimate the adoption premium in column (4). Consistent with model predictions, we find that after doing so, the negative effect on adoption becomes much stronger. Type 2 farmers who were exposed to the treatment are thirteen percentage points less likely to adopt fresh seed of an improved variety. This is matched by an increase in the share of farmers that uses seed recycled from the previous harvest in the treatment group. We also find an almost ten percent reduction in farmers who bought seed from an agro-input dealer. Results thus indicate that in the subgroup of farmers with inflated yield expectations, the intervention induces farmers to turn away from improved seed varieties toward local low-cost, low-yielding alternatives.[17]

[17] For the adoption outcomes in Table 3, we also analyzed the subgroup of farmers who did not use complementary inputs and underestimated the returns to improved varieties at baseline. To identify this subgroup, we reversed the approach used for over-estimators, focusing on farmers in the lowest 33 percent of the baseline distribution of expected maize yields. As anticipated, the significant negative impact of the intervention disappears, and for most variables, the sign reverses. The lack of a significant increase in improved seed adoption for this group suggests that abandoning a plan upon receiving new information is easier than committing to a new one—potentially due to credit constraints, input accessibility challenges, risk aversion, or similar factors.

7.3 Impact on Use of Inputs and Practices

Next, we investigate how the intervention affects the use of inputs (other than seed) and practices. Recall from our theoretical model in Section 6 that we expect a positive impact, but only for a particular subgroup, so the overall effect is likely to be muted.

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. 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 because 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 diammonium 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. Official recommendations are to weed at least three times per season. Furthermore, invasive insects such as the fall armyworm (*Spodoptera frugiperda*) or maize stalk borer (*Busseola fusca*) can severely reduce yields. 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 4. As in previous tables, column (1) reports means and standard deviations for outcomes at baseline. Column (2) shows that farmers do not invest more inputs or efforts in response to the intervention. In column (3), we confine attention to farmers whose use of complementary inputs and practices was below average at baseline, which does not affect findings, except for the fact that the negative effect on row planting becomes stronger. Finally, in column (4), we isolate the effect on type 2 farmers and, as expected, we establish a null effect. Overall, the finding of no impact of the intervention on the use of inputs and practices suggests that type 2 farmers dominate in our sample.

7.4 Impact on Expectations

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 are met on the randomly selected maize plot. As indicated in Section 6, this will mainly be the case for farmers who overestimated the adoption premium (type 2 farmers).

Results are in Table 5. Column (1) reports control group means and standard deviations as we did not ask this question at baseline. Note that a large majority of farmers indicated that expectations were not met. Column (2) shows that yield expectations have been significantly affected by the intervention, albeit only at the 10-percent level. The share of farmers who indicate that expectations were in line with realized outcomes increases to almost five percentage points if we zoom in on type 2 farmers, but the effect is not significantly different from zero (probably due to the reduced sample size). Taken together, this provides suggestive evidence that a subset of farmers indeed started out with inflated

Table 4: Average treatment effects on use of inputs and practices

	(1)	(2)	(3)	(4)
Row-planting	0.243	-0.070*	-0.107**	-0.095+
	(0.429)	(0.027)	(0.032)	(0.056)
Reduced seed rate	0.237	0.009	0.012	-0.070
	(0.425)	(0.019)	(0.025)	(0.052)
Organic fertilizer use	0.075	-0.013	-0.006	0.024
	(0.263)	(0.017)	(0.022)	(0.043)
DAP/NPK use	0.251	-0.029	-0.026	-0.016
	(0.434)	(0.019)	(0.023)	(0.052)
Urea use	0.076	0.002	-0.008	0.034
	(0.265)	(0.015)	(0.017)	(0.032)
Weeding frequency	2.56	-0.021	-0.058+	-0.008
	(0.650)	(0.027)	(0.035)	(0.069)
Pesticide etc. use	0.412	0.003	-0.009	-0.010
	(0.492)	(0.023)	(0.026)	(0.056)
Re-sowing	0.482	0.013	0.031	0.023
	(0.500)	(0.022)	(0.028)	(0.051)
Early planting	0.008	-0.001	-0.006	0.033
	(0.400)	(0.022)	(0.026)	(0.051)
Early weeding	0.606	0.026	0.017	0.047
	(0.489)	(0.021)	(0.026)	(0.049)
Inputs index	0.008	-0.001	-0.006	0.033
	(0.400)	(0.022)	(0.026)	(0.051)
Observations†		2970	1547	349

Note: Column (1) reports means at baseline (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 whose use of complementary inputs and practices was below average at baseline; column (4) reports differences between treatment and control post-intervention for farmers whose use of complementary inputs and practices was below average at baseline and are in the top 33% of the distribution of expected maize yields at baseline; **, *, and + denote significance at the 1, 5, and 10 percent levels; standard errors are clustered at the village level. †These are the numbers of observations in the regression with the index, regressions with individual outcomes have more observations.

Table 5: Average treatment effects on expectations

	(1)	(2)	(3)	(4)
Farmer harvested as much maize as expected	0.138	0.029^{+}	0.018	0.048
	(0.345)	(0.017)	(0.020)	(0.036)
Observations		3185	1572	347

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 whose use of complementary inputs and practices was below average at baseline; column (4) reports differences between treatment and control post-intervention for farmers whose use of complementary inputs and practices was below average at baseline and are in the top 33% of the distribution of expected maize yields at baseline; **, *, and + denote significance at the 1, 5, and 10 percent levels; standard errors are clustered at the village level.

expectations, which were corrected after they learned that improved varieties are not "miracle seeds."

8 Conclusion

This paper was motivated by the observation that farmers often seem to be unaware that many agricultural technologies such as improved seed varieties require substantial complementary inputs, better management practices, and greater effort for their benefits to realize. In a sense, farmers thus overestimate the returns to a technology and may be disappointed when they compare expectations to actual yields. Because learning about a new technology is hard, farmers may attribute the disappointing results to the technology itself and refrain from adopting in subsequent seasons. 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 test the hypothesis that farmers think of improved varieties as "miracle seeds," we conducted a field experiment built around a short, engaging video on recommended input use and management practices for maize cultivation in eastern Uganda. More in particular, we produced two versions of the video that differ only in terms of the presence of explicit messaging about the importance of using complementary inputs like fertilizers and practices such as weeding when using improved seed. 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 before and after the intervention to uncover any changes in their knowledge about best practices in maize cultivation as well as their seed or variety choices, their yield expectations, and their use of complementary inputs and management practices.

We find that sensitizing farmers about the fact that improved seed varieties require substantial complementary inputs and practices to obtain yield benefits increases their knowledge and brings their expectations more in line with realized outcomes. However, somewhat paradoxically, we find that the treatment led to a reduction in the adoption of seed of a new variety and had no effect on the use of complementary inputs and practices. We rationalize this finding through a model that features a heterogeneous response to the treatment caused by differences in ex-ante beliefs about the production function. Type 1 farmers understand the true shape of the production function and the treatment will not affect their behavior. Type 2 farmers have inflated expectations about the yield gains from improved seed, and the intervention reduces these expected benefits (or equivalently raises the cost of obtaining these benefits). For these farmers, our model predicts a negative effect on adoption. Type 3 farmers do not believe that improved seed performs better than normal seed. Correcting this false belief may induce at least some farmers to start adopting.

We find that the negative effect on adoption outweighs a positive impact, which seems reasonable in the Ugandan context. First, it is likely that the share of type 2 farmers is larger than the share of type 3 farmers. Low adoption rates in the study population imply limited opportunities to become disappointed and switch from believing in miracle seeds to believing that improved seed does not work. Second, even if type 2 farmers tried out seed without complementary inputs and experienced a disappointing outcome, they may not always adjust expectations and become type 3 farmers. Indeed, learning about a new technology from own experimentation is hard (given the many stochastic processes that enter a production function like weather events, pests, and diseases) and farmers may attribute a disappointing outcome to a bad draw from a good distribution (and they keep believing in miracle seeds). Third, the net treatment effect also depends on the nature of the production function. Indeed, as we saw in Section 6, type 3 farmers will only adopt if the updated beliefs about the adoption premium exceed the cost of the seed and additional complementary inputs needed. Given the high cost of complementary inputs in the context of potentially resource constrained farmers, the share of farmers who begins to adopt due to the treatment is likely to be small.

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.[18] 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.

Our findings have implications for the understanding of technology adoption dynamics. If disappointment about the performance of a technology is erroneously attributed to the technology itself and this learning failure is not corrected—for instance, by pointing out that the seed is good and that the problem is the lack of complementary input use—farmers potentially move into long periods of consistent under-adoption even if adoption would be profitable for them.[19] Furthermore, as negative experiences tend to stick more and negative news may travel faster, exaggerated expectations and subsequent dis-adoption may further complicate (social) learning (Ledgerwood and Boydstun, 2014; Hornik et al., 2015). All this is likely to lead to lower than optimal adoption in the aggregate. Informing farmers about the need for complementary inputs up front can save them from the disappointment and financial loss of failed attempts. Additionally, correcting beliefs may prompt some of these disappointed farmers to re-evaluate costs and benefits of using improved seed, which may increase adoption in 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 are able to try out all possible combinations of inputs to learn about these interactions in a Bayesian fashion, at least within a reasonable time frame. This suggests an important role for agricultural extension and advisory services when introducing new technologies.

Our findings also 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, this will result in sub-optimal levels of adoption due to the learning errors

[18] 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.

[19] Note that new varieties are introduced now and then, and extension workers and successful neighbors may convince farmers to try again. So, farmers are likely to adopt again after some seasons but generally only to be disappointed again if they are still not aware about the importance of complementary inputs and practices.

described above. 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 in part encourage farmers' learning processes and "correct" their perceptions (for example, with unique standalone technologies, see 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. Thus, our findings suggest that agricultural development programs, extension providers, and agro-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.

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