Information and Communication Technologies to Provide Agricultural Advice to Smallholder Farmers: Experimental Evidence from Uganda

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Agricultural advisory services generally rely on interpersonal knowledge transfers by agricultural extension agents who visit farmers to provide information. This approach is not always effective and has proved hard to scale sustainably, particularly in highly dispersed smallholder farming systems. Information and communication technologies (ICTs) have been advanced as a promising way to overcome many of the problems associated with conventional agricultural extension. We evaluate the effectiveness of an ICT-mediated approach to deliver agricultural information in a field experiment conducted among small-scale maize farmers in eastern Uganda. Three complementary technologies designed to address both informational and behavioral constraints to technical change are considered. First, we investigate the effectiveness of audiovisual messages (video) as a means of delivering information on input use and improved maize management practices to farmers. Second, we quantify the additional impact of complementing video with an interactive voice response (IVR) service. Third, we estimate the incremental effect of time-sensitive short message services (SMS) messages designed to remind farmers about applying key practices at specific points during the season. We find that households that were shown a short video on how to become better maize farmers were performing significantly better on a knowledge test, more likely to apply recommended practices, and more likely to use fertilizer than households that did not view the video. These same households also reported maize yields about 10.5% higher than those that did not view the video. We find little evidence of an incremental effect of the IVR service or SMS reminders.

Key words: Agricultural extension, information and communication technology, interactive voice response, maize, short message services, Uganda, video.

JEL codes: O13, Q12, Q16.

Conventional approaches to agricultural extension, such as the training and visit system or farmer field schools, have met with mixed success in many developing countries (Bindlish and Evenson 1997; Anderson, Feder and Fanguly, 2006; Waddington et al. 2014).

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Information and communication technologies (ICTs) have been advanced as a promising means to overcome many of the problems associated with these approaches, such as low cost effectiveness and limited scalability (Aker 2011). An emerging literature explores the application of different ICTs to agricultural extension provision in smallholder production systems in developing countries. For instance, various studies investigate the potential for audiovisual messages as a medium to transfer agricultural extension information (eg. Gandhi et al. 2009; Van Campenhout et al. 2017; Maredia et al. 2018). Cole and Fernando (2016) evaluate the impact of a toll-free hotline among cotton farmers in Gujarat, India. Casaburi et al. (2014) test the effectiveness of short message services (SMS) messages with agricultural advice among sugarcane farmers in Kenya, and Larochelle et al. (2019) consider the use of SMS messages to promote integrated pest management among potato farmers in Ecuador.

This article investigates the effectiveness of an ICT-mediated extension approach designed to provide information about improved maize cultivation practices to smallholder farmers in Uganda. The approach consists of three complementary information technologies, tested in an incremental design. First, we look at the effectiveness of short video messages that provide detailed information on how to improve maize cultivation and were shown to farmers on tablet computers. The strength of video is that it can combine audio and visual information in an attractive way that is accessible to the potentially illiterate farmer. However, video screenings can be a passive exercise for viewers, which may increase the likelihood that farmers will forget some of the details, particularly if the lag between screening and implementation is long. Second, to address this concern, we add an IVR service that provides a follow-up with the same information. With an IVR system, a farmer calls a phone number, navigates through a menu to select a topic, and then listens to a prerecorded message with information on the selected topic. Third, we add SMS messages that remind farmers at specific points during the maize growing season about key recommendations on farming practices shown in the video and available on demand through the IVR system. Addition of the SMS reminders is motivated by the growing recognition that information alone is often insufficient to change behavior, but timely reminders have been found very effective in overcoming inertia, procrastination, competing obligations, or simple forgetfulness (Sunstein 2014), and repetition can make information more salient (Duflo, Keniston, and Suri 2014). The outcomes used to assess the effectiveness of this approach and its components include increases in knowledge about improved maize cultivation, changes in the use of improved inputs and recommended agronomic practices, and production-related changes.

We draw on a field experiment involving approximately 4,000 farm households sampled from the population of households cultivating maize across five districts of eastern Uganda. We find that providing information to farmers through a short video significantly increased their knowledge about improved agricultural input use and recommended management practices. In addition, farmers who were shown the video were also more likely to adopt a range of inputs and practices that were promoted in the video. We also find maize yields were 10.5% higher among treatment households than among control households. However, we did not find strong evidence that the IVR service generated much additional impact on knowledge, on the use of inputs or practices. We find a positive effect of the IVR only on the use of one input: hybrid maize seed. However, with less than 10% of farmers who were invited to use the IVR actually calling in, we acknowledge concerns with statistical power. In the context of our nested design, we also find no additional effects of the SMS reminders.

We contribute to the literature on how ICTs can increase the adoption of improved inputs and management practices among smallholders—a topic that has received considerable attention in recent years (Aker 2011; Nakasone and Torero 2016). Several studies, many of which are still ongoing, have hinted at positive impacts of ICTs applied to extension services. Notable examples include Cole and Fernando (2016), who found that the introduction of a toll-free hotline, through which farmers can ask questions to agricultural experts, significantly increased cumin and cotton yields among farmers in Gujarat, India. Similarly, Casaburi et al. (2014) found that in Kenya, sending SMS messages with agricultural advice to smallholder sugarcane farmers increased yields by 11.5% relative to a control group with no messages (but only in the first season). Fabregas et al. (2019) report positive results from six randomized controlled trials (RCTs) in Kenya and Rwanda that used SMS messages to increase the use of agricultural lime to reduce soil acidity and increase yields. Fu and Akter (2016) found that a multimedia mobile phone-based product linked to expert advisory services increased farmers' awareness and knowledge about specific solutions to their production constraints in Madhya Pradesh, India. Maredia et al. (2018), on the other hand, found that although mobile phone-based animated videos shown to farmers in Burkina Faso induced learning and understanding, the videos were no more effective in encouraging adoption than conventional approaches to information provision. In Uganda—the site of our study—Grameen Foundation had some success using smartphones to provide agriculture-related information to farmers through ICT-empowered community knowledge workers (Van Campenhout 2017).

The remainder of the article is organized as follows. In the next section, we briefly contextualize the study. We then present the experimental design and models that are used to assess impact. Next, the intervention and its components are described in detail. We then turn to the results, assessing the impact on knowledge, adoption, and production. This is followed by a section with additional analysis and robustness tests that examines demand for the IVR component, experimenter demand effects, heterogeneity in treatment effects, and attrition. We then reflect on cost effectiveness of the intervention and draw conclusions in a final section.

Context

The study was conducted among smallholder maize farmers in Uganda, a population that is similar to many others in eastern and southern Africa in terms of its dependence on rainfed maize cultivation and on the consumption of maize as a key dietary staple. In our study context, as in much of the wider region, maize is also an important traded commodity because of its relatively high value-to-weight ratio. Therefore, efforts to increase maize productivity at the farm-household level are an important dimension of Uganda's strategy to increase food security and reduce poverty through both consumption and income channels. Yet maize yields in Uganda are low when compared with neighboring countries and global averages. While research station trials conducted in Uganda report potential yields of about 1.6 metric tons per acre (using only improved varieties without fertilizer application), data from the Uganda National Household Survey (UNHS) 2005/06 indicate that average maize yields are much lower, at about 618 kg per acre for the main growing season.

The use of modern inputs such as inorganic fertilizer is extremely low in Uganda, even when compared to other countries in the region (Sheahan and Barrett 2017). Bold et al. (2017) report that only 9% of maize cultivating households use inorganic fertilizer. In Tanzania, this rate is almost 20%, while in Malawi, the government's input subsidy program drove it to 80%. Yet for other inputs, such as improved maize seed, there is some ambiguity as to whether use rates—between 27% and 37% of households report using improved maize seed—are lower than comparison countries such as Tanzania and Malawi, where use rates are reportedly between 30% and 50% (Bold et al. 2017; Sheahan and Barrett 2017). Maize management practices—the water, soil, and natural resource management practices that often accompany the use of these inputs—also vary considerably, driven both by changes in policy and market signals as well as changes in demographic trends, land use choices, soil health, livestock keeping, and other factors (Nkonya, Kaizzi, and Pender 2005; Ebanyat et al. 2010). At best, available data suggest that there is considerable within-country variation in input use and management practices, as well as variation in the extent to which key inputs and management practices are being used in productive combinations. Such variation is similarly observed in many of the maize-cultivation systems found in the region (Sheahan and Barrett 2017).

Yet despite the importance of these issues to the country's economic growth strategy, Uganda has struggled to maintain a functioning agricultural extension service for the last two decades. In 2000, the National Agricultural Advisory Services (NAADS) was established as an ambitious and innovative public-private partnership with support from various donors. After what seemed to be a successful start, NAADS became a victim of political capture and governance problems, culminating in its demise and replacement by Operation Wealth Creation (Joughin and Kjaer 2010; Benin et al. 2011; Rwamigisa et al. 2018). Operation Wealth Creation is managed by the army and primarily focused on the distribution of inputs. As a result, this public extension service currently provides little in the way of information to smallholders. The last available data obtained from the Uganda National Panel Survey (wave 2013/2014) suggest that only 20% of households received extension in the past twelve months. Recently, private initiatives and international social enterprises have started to fill the void. Examples include Viamo's 3–2-1 service, which provides agricultural information through IVR; the Market-led, User-owned ICT4Ag-enabled Information Service (MUIIS) project, which uses ICTs to facilitate farmer-to-farmer extension; and the m-Omulimisa platform, through which farmers send SMS messages with questions to agricultural extension officers. Yet it remains to be seen whether these initiatives and enterprises are a substitute for public extension or just provide a complementary function.

In our study site in eastern Uganda, where maize is a critically important crop, there are two maize cropping seasons. We concentrated on the second maize-growing season of the year 2017, which ran from approximately August 2017 to January 2018. The second growing season is characterized by a shorter period of rainfall than the first, allowing only 3–3.5 months for the complete cycle from planting to harvest. As a result, farmers tend to cultivate early-maturing but lower yielding maize varieties. Fields are prepared in August, planted in September, and harvested beginning in mid to late December and, at higher elevations, through mid January.

Experimental Design and Estimation of Treatment Effects

We evaluate the effectiveness of ICT-mediated agricultural extension using a field experiment (de Janvry, Sadoulet, and Suri 2017).[1] The experiment has four treatment arms, and the IVR and SMS treatments are incremental in design. The experimental units are the households, which were randomly assigned to one of these four arms. A total of 3,703 households were shown an agricultural extension video, while 256 households (our control group) were shown a placebo video. From the 3,703 households that were shown the extension video, 2,414 also received an IVR starter kit: a flyer containing a toll-free phone number and instructions on how to use it. From the 2,414 households that were shown the video and received the IVR encouragement, 1,113 households were also allocated to the SMS treatment.[2]

We sampled from five districts in eastern Uganda known for their maize production: Bugiri, Mayuge, Iganga, Namayingo, and Namutumba. From these districts, we removed town councils and also two subcounties that consisted of islands in Lake Victoria. We used two-stage cluster sampling to obtain a representative sample of this population, as follows. From the five districts, we first selected fifty parishes randomly and in proportion to the number of villages within each parish. Within each village in the selected parishes, we then listed all households, from which we randomly selected ten households to participate in the study. In each village, one of the ten households was randomly allocated to the control group. The remaining nine households were all shown the intervention video (detailed below). We then added the IVR treatment randomly to two-thirds of the households that were allocated to the video intervention and further randomly allocated half of the households assigned to the IVR encouragement to the SMS treatment.[3] The resulting

[1] This study is part of a larger study that also examined the role of gender in video-mediated agricultural extension. The overall study took the form of a 3^3 factorial design (plus a separate pure control group), where one factor corresponds to the information technology and the other two factors varied the gender of the person to whom the video was shown within the household and the gender of the person providing the information in the video. In this study, we restrict attention to the first factor; for an analysis of the other factors, we refer to Lecoutere, Spielman, and Van Campenhout (2019). More information on the overall study can also be found in the pre-analysis plan, which was preregistered and publicly available from the American Economic Association's registry for randomized controlled trials (AEARCTR-0002153).

[2] Ex ante, we expected the largest effect size for the video intervention, and power calculations indicated that we only needed about 250 observations in each group to detect this. Much smaller effects were expected from adding the other two technologies (as essentially no new information was given, see section 3), so a larger sample was needed to retain statistical power. Power calculations were based on an elaborate set of comparisons using different outcomes to power the complete 3^3 factorial design. We used simulation techniques that allowed us to sample from actual data on outcome variables instead of from a theoretical distribution with an assumed mean and standard deviation. Apart from the sample size in the control group, sample size in other treatment arms are the result of binding constraints for minimal sample size needed to test differences in two other factors of the design. Detailed information on the power calculations can be found in the pre-analysis.

[3] Following on from footnote 1, we also experimentally varied who provided the information in the video (a man alone, a woman alone, or a couple [man+woman]) as well as to whom the video was shown within the household (a man alone, a woman alone, or a couple [man+woman]). In the context of a factorial design with two factors with each three levels, this corresponded to nine treatment combinations. We thus used villages as blocs and randomly assigned the nine potential treatment combinations to the

sample is representative of maize-cultivating households in these five districts of eastern Uganda. The sample is also potentially relevant to similar populations in the eastern and southern Africa region where we observe rainfed maize cultivation systems, consumption of maize as the primary staple food, and shared constraints to both the production and marketing of maize. Of course, significant policy and institutional differences exist between and among countries in this region, such that the sample cannot be strictly representative of these otherwise similar populations.

To evaluate the effectiveness of these different ICT treatments, we start by comparing average household-level outcomes among households that were shown the extension video to average outcomes of households in the control group. This gives us the average treatment effect for the video intervention. To obtain the additional effect of the IVR treatment, we compare average outcomes of households that were shown the video and were also allocated to the IVR treatment with households that were only shown videos. Finally, the additional effect of the SMS campaign is obtained by comparing outcomes of households that were shown the video, were encouraged to use IVR, and also received eight SMS reminders with outcomes of households that were shown the video and received the IVR system information but did not receive the SMS reminders. In practice, this is estimated using an ordinary least squares (OLS) regression of the form:

$$(1) \quad y_i = \alpha + \beta_1 video_i + \beta_2 .IVR_i + \beta_3 .SMS_i + \varepsilon_i$$

with y_i the outcome used to assess impact as reported by household *i*; $video_i$ a dummy variable that is one if household *i* was shown a video and zero otherwise; $IV\ R_i$ a dummy variable that is one if household *i* was given an IVR starter kit and zero otherwise; SMS_i is a dummy variable that is one if household *i* was allocated to the SMS treatment and zero otherwise. In this regression, α is then the average outcome in the control group, β_1 provides an estimate of the effect of having been shown a video, β_2 provides an estimate of the incremental effect of also having been allocated to the IVR intervention, and β_3 provides an estimate of the incremental effect of also having been allocated to the SMS intervention.

We collected some information prior to the experiment's rollout to investigate balance. The choice of variables was based on those used by similar studies in their orthogonality tests. In particular, we looked at variables used in studies that investigate the adoption of yield-improving technologies and practices using RCTs, including Duflo, Kremer, and Robinson (2011); Karlan et al. (2014); Ashraf, Gine, and Karlan (2009) and Bulte et al. (2014). We collected household characteristics such as household size, age, education level of household head, and housing conditions (number of bedrooms), as well as more specific information related to maize farming, such as acreage and quantities produced in the last season, and distance to the nearest agro-input shop. In addition, we collected data on whether the household had received agricultural extension services, used improved maize varieties, and applied inorganic fertilizer to maize. As mobile phone ownership is directly relevant to the IVR and SMS interventions, we also collected data on household access to and ownership of a mobile phone.

In table 1, we provide descriptive statistics and balance tests for the comparisons among the three components of the intervention. Averages for the control group are reported in the first column. We observe that few households included in our study had access to agricultural extension in the previous year (about 11%). We also observe that only about 17% of households reported using any fertilizer in the previous season, and about 34% reported using improved seed bought from a shop or agro-input dealer during the most recent cropping season. This suggests ample scope to increase intensification investments through the provision of information and extension. We also find that farmers produced on average only 268 kg of maize per acre in the first cropping season of 2017. This is substantially lower than the average yield of 618 kg per acre we find in data from the 2005/06 Uganda National Household Survey. It is worth noting that these low yield figures from our sample may reflect the devastating impact of the fall armyworm outbreak and adverse weather conditions that plagued East Africa in 2017 (Stokstad 2017).

Balance is tested by assessing the significance of coefficient estimates in a regression

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remaining nine households in each village. We then added the IVR treatment randomly to two-thirds of the households in each treatment cell. Among those that were allocated the IVR in each treatment cell, we then randomly allocated half of the households to the SMS treatment. As such, the treatment cells created by the interaction of the two other factors were used as blocs in the randomization of IVR and SMS treatments. Exactly the same sampling procedure was used in the permutation algorithm that was used to judge significance through randomization inference.

Table 1. Balance Tests

	Mean	Video	+IVR	+SMS	N
Maize yield (kg/ac)	267.93 (230.20)	17.41 (18.97)	7.57 (11.30)	−9.15 (11.93)	3,959
Age of HH head (years)	40.50 (14.33)	−1.05 (0.88)	0.87* (0.52)	−0.73 (0.55)	3,910
HH head finished primary school	0.37 (0.48)	−0.01 (0.03)	0.02 (0.02)	0.00 (0.02)	3,959
HH size	7.72 (3.17)	−0.30 (0.22)	0.42*** (0.13)	−0.21 (0.14)	3,959
Number of bedrooms	2.32 (1.21)	−0.12 (0.08)	0.10** (0.05)	−0.09* (0.05)	3,959
Access to extension last year	0.11 (0.31)	0.00 (0.02)	0.00 (0.01)	0.01 (0.01)	3,959
Has used fertilizer last season	0.17 (0.37)	0.04 (0.03)	0.01 (0.02)	−0.01 (0.02)	3,959
Has used improved seed last season	0.34 (0.47)	0.04 (0.03)	0.01 (0.02)	−0.01 (0.02)	3,959
Distance nearest agro input shop (km)	5.18 (4.89)	0.17 (0.36)	0.13 (0.22)	0.34 (0.23)	3,959
HH owns mobile phone	0.76 (0.43)	0.01 (0.03)	0.01 (0.02)	0.01 (0.02)	3,959
HH has access to a mobile phone	0.84 (0.36)	−0.01 (0.02)	0.02 (0.01)	−0.01 (0.02)	3,959
F-test		0.820	1.186	1.143	
P-value		0.621	0.291	0.323	

Note: First column reports control group means (and standard deviations below); Column 2 reports differences between placebo (control) and video treatment (and standard error below), column 3 between video only and video+ivr, column 4 between video+ivr and video+ivr + SMS; the last column is sample size; ***, ** and * denote that the difference is signficantly different from zero at the 1%, 5% and 10% level, respectively.

(equation (1)) and with a joint significance test (F-test). The second column in table 1, denoted "Video," compares baseline characteristics between households that were shown the placebo video (control group) and households that were shown the intervention video (β_1 in equation (1)). For example, we see that yields prior to the intervention were about 17 kg per acre higher in the group that was shown the intervention video than in the group that was shown the placebo video. However, this difference is not significantly different from zero. In fact, for the placebo video versus intervention video comparison, none of the differences in baseline characteristics are significant at the 10% significance level, and the F-statistic cannot be rejected. The third column shows differences in baseline characteristics between households that received the intervention video and households that received the IVR starter kit in addition to the video (denoted "+IVR"; corresponding to β_2 in equation (1)). Here, we see that, at baseline, households in the latter group were significantly larger than households that only saw the video. They also had significantly more bedrooms and the household head was slightly older. However, we cannot reject the null hypothesis that jointly, baseline characteristics were unrelated to the treatment group for this comparison. For the final comparison (comparing households that received video and IVR to those that additionally received SMS messages; reported in column 4 and denoted "+SMS" and corresponding to β_3 in equation (1)), we find that treatment households had slightly fewer bedrooms, but the figure is only significant at the 10% level, and the joint test does not reject overall balance.

We find that about 84% of households had access to a mobile phone prior to the intervention. This is encouraging, as the usefulness of IVR depends on access to a mobile phone. Further, we find that there was no difference in this percentage between the various treatment groups. The incidence of mobile phone ownership was also high, with about three-quarters of households reporting they own a mobile phone. Again, this is important as the potential effect of the SMS intervention depends on being able to receive the messages.

ICT Intervention

Our ICT-mediated extension approach consisted of three ICT interventions: a short video, an encouragement to use an IVR system, and a series of eight SMS messages. The videos were shown on 10-inch Android tablet computers and screened by a trained field enumerator during one-to-one meetings with either an individual farmer or the male and female co-heads of household.[4] The control group received a placebo treatment, which was a music video of traditional dancing that contained no information related to farming

[4] In particular, the person or persons within the household to whom the video was shown was dictated by one of the other factors in the factorial design, and were either the man co-head within the household alone, the woman co-head within the household alone, or the man and woman co-heads as a couple together. As this factor was orthogonal to the factor corresponding to the information technologies in the factorial design, it does not matter who within the household the video is shown to, and the treatment effect corresponds to the average impact at the household level.

or maize (Bernard et al. 2015). Videos (treatment or placebo) were screened twice with the households in the sample, once prior to maize planting (August 2017) and once at planting time (September 2017).

The information contained in the treatment groups' video is expected to influence maize yields positively by encouraging the adoption of several improved technologies and practices. The topics included in the video script were obtained from qualitative interviews with key informants—experts from Uganda's agricultural research and extension community—that were conducted in May 2017. The key informants included maize farmers, traders, maize breeders, extension workers, district agricultural officers, and other government staff and experts.

A significant portion of the videos focuses on technical information regarding seed choice, soil nutrient management (including the promotion of both organic and inorganic fertilizer application), weeding (with particular attention paid to fighting striga, a parasitic weed that feeds off the roots of the maize plant), timely planting, and plant spacing, which were ranked by our key informants as the top challenges facing farmers. We made sure to include information that was likely to be unknown to the farmer, because information is likely to be most valuable when individuals learn about a new technology or institutional innovation. However, other studies also provide evidence of behavioral change occurring through the compounding or re-emphasis of common knowledge that, through repetition, becomes more salient to the individual (Duflo, Keniston, and Suri 2014; Hanna, Mullainathan, and Schwartzstein 2014). Therefore, the video also contains information that farmers likely know but do not seem to act upon.

That said, not all constraints to maize productivity improvement are associated with information deficiencies directly related to the use of inputs, technologies, and crop management practices. Often, missing information problems manifest indirectly, as uncertainty about a range of variables affecting the farm household's profit function, which farmers may simply be unable to conceptualize or measure. This includes uncertainty about the correlations between expected and actual returns, the intertemporality of income streams, estimates of fixed and variable costs, hidden transactions costs, and probabilities of adverse events. Thus, a significant portion of the video also focuses on evaluating the costs and benefits of the different technologies and practices being promoted. In addition, the videos encourage long-term thinking, advising farmers to (a) start small and grow their farm enterprise over time, and (b) combine technologies and practices rather than investing all their money and effort into one single input, practice, or technology.

We also pay attention to how the information is packaged. For instance, prior studies have found that farmers find communicators who face agricultural conditions and constraints most comparable to their own to be more persuasive than other communicators (BenYishay and Mobarak 2018). Several studies point out the importance of role models in shaping aspirations and future-oriented behavior (Bernard et al. 2015). A growing strand of the literature investigates how non-cognitive farmer characteristics such as aspirations, locus of control, and self-esteem can lead to behavioral change such as technology adoption (Abay, Blalock, and Berhane 2017). Therefore, in our video, the message is conveyed by individuals who are readily recognized as "peer farmers" and who provide information that is framed as a success story. Note that these peer farmers featured in the video represent the key source of information, while the enumerator charged with screening the video is neither an extension agent nor representing him or herself as an extension agent. However, the enumerators' level of education, training on the intervention, and understanding of the content make them a reasonable stand-in for extension agents in that they provide a consistent and complementary signal to the messaging in the video.

For the additional treatments—the IVR system and the SMS reminders—we collaborated with Viamo, a social enterprise. We set up an IVR system that provided the same information as was presented in the video. Farm households that were allocated the IVR treatment were encouraged to call a toll-free number that explained the IVR system. The caller was invited to select the number corresponding to a topic on which he or she wanted more information (e.g., "Press 1 for seed selection, 2 for spacing and seed rate, 3 for soil nutrient management, 4 for advice on weeding"). Depending on the number selected, the IVR then played an audio message of a conversation between two farmers, in which one farmer explains the recommended practice to the other farmer.

We set up the SMS system by first recording telephone numbers for the mobile phones owned by the household head at the time of the experiment's rollout. Households that were allocated to the SMS treatment were sent eight SMS messages to the phone number in our records over the course of the two months following the first video screening. The messages all followed a similar structure: farmers were first reminded about an important technology or practice that was relevant at the particular time that the message was sent and then reminded about the IVR service. The reminders were related to technologies and practices that were promoted in the video and IVR recommendations. For example, the first message, which was sent out around planting time, read "You will get much more maize if you use hybrid seed instead of recycled seed. Call the maize hotline on 0200522420 free for more advice!" About one month into the growing season, the following message was sent: "When your maize is knee high, apply one water bottle cap of urea around each plant. Call the maize hotline on 0200522420 free for more advice!" All content was produced in the local language (Lusoga).

Following implementation of the field experiment, 342 households (or 8.63% of the sample) could not be tracked or could not be persuaded to complete the endline survey. Given the relatively short time between baseline and endline, this is quite a large loss. Attrition was 7.03% in the control group; 8.74% in the group that was shown the video; 8.90% in the group that was shown the video and received the IVR encouragement; and 7.45% in the group that also received SMS messages in addition to the IVR encouragement and the video. We examine this attrition and find no differences between and among our various treatment and control groups to suggest bias. A complete analysis including balance tests and Manski bounds is presented in a separate section in the online supplementary appendix. Although we do find that the lower and upper bounds do change signs for some outcomes, Manski bounds are conservative. Overall, results suggest that attrition is unlikely to drive results reported below.

Results

We now turn to the results. We estimate intent-to-treat (ITT) effects for the (incremental) impact of the three information technologies on a range of outcomes related to knowledge, adoption of improved inputs and recommended practices, and production.

Impact on Knowledge

Knowledge outcomes were measured with a short quiz (Feder, Murgai, and Quizon 2004a, 2004b; Masset and Haddad 2015) consisting of four multiple-choice questions that were asked during the endline survey to each of the two spouses in the farm household separately. For each question, three possible answers were read out to the respondent, who was then asked to indicate which answer he or she thought was correct (which may differ from what he or she recalled from the video). The respondent was also allowed to indicate if he or she did not know the correct answer. The household was considered knowledgeable on a particular topic if at least one of the spouses could indicate the correct answer.

The first question was related to technical knowledge about planting. In our video, we recommended a spacing of 75 cm × 30 cm with one seed per hill, and this was the correct option. Other possible answers included a spacing of 75 cm × 60 cm with two seeds per hill, which is standard for many farmers and recommended by many extension agents in Uganda, and an intermediate alternative of 75 cm × 30 cm with two seeds per hill. Because our video recommended a technique that deviates from what is considered to be standard spacing, we assumed that the recommended practice was new to most of the farmers. This question thus tests a traditional theory of change, which holds that extension generates knowledge, which leads to increased adoption and subsequently boosts yields.

The second question was related to viewing farming as a business enterprise. In the video, we paid ample attention to promoting an approach where farmers start small and grow over time by reinvesting, and we emphasized the benefits of combining inputs rather than investing only in one input, for example, improved seed. To examine whether farmers internalize the advice provided, we asked them what a successful farmer would do if he or she had only UGX 40,000 (Ugandan shillings).[5] The correct answer was to "use this

[5] At the time this study was conducted, the exchange rate was approximately UGX 3,628 per USD.

amount to purchase improved seed and fertilizer and start intensified farming on a small area." Alternative options were to "use all the money to buy hybrid seeds, because without good seeds, yields will be low" and "use all the money to buy fertilizer, because with poor soils, yields will be low."

For the third question, we asked if farmers knew when weeding is most important. The video showed that weeding is most important during the first four weeks after planting, as maize is a poor competitor for light and nutrients. We assumed that most farmers would know the correct answer to this question given that weeding is part of well-established management practices in the study area. Alternative answers were: "when the maize is knee high" and "when the maize is at tasseling stage." This question suggests a theory of change directly related to the saliency effect of ICT-mediated information provision (Duflo, Keniston, and Suri 2014; Hanna, Mullainathan, and Schwartzstein 2014).

Finally, we asked if farmers knew when spraying against fall armyworm is most effective. No information was given about combating fall armyworm in the intervention video, so unless our intervention unexpectedly encouraged farmers to search for additional information, we do not expect any impact. For this question, the correct option was "during the evening, as fall armyworm eats during night," while the other options were: "early in the morning when it is still cool" and "at noon because sunlight increases chemical performance."

To guard against over-rejection of the null hypothesis due to multiple inference, outcomes of the knowledge questions were combined into an index, constructed as the weighted mean of the individual standardized outcomes, using as weights the inverse of the covariance matrix of the transformed outcomes (Anderson 2008). However, we also see value in examining the impact on the questions individually, as they attempt to measure different aspects of the information intervention. To control the family-wise error rate (FWER) when examining results for each question individually, we use re-randomization to construct the joint null distribution for the family of outcomes we are testing. From this family-wise sharp null, we can obtain the corresponding FWER-consistent significance thresholds by determining which cut offs yield 10%, 5%, and 1% significant hypothesis tests across all tests and simulations.

Table 2 shows results for the three incremental levels of ICT-mediated information delivery using different information technologies.[6] The first column reports mean scores in the control group (with standard deviations reported below in parentheses). For the four individual questions, this is simply the proportion of households in the control group that answered the particular question correctly. For instance, we find that in almost 16% of the households in the control group, at least one of the spouses indicated the correct option among the response alternatives to the question on optimal maize seed spacing. This relatively low rate of correct responses is likely due to the fact that this is a fairly new recommendation that deviates from what farmers were taught in the past and have been doing for decades. We find that in about 91% of control households, at least one spouse knew inputs were best combined, and in more than 95% of control households it was known that weeding is most important during the first four weeks. In about one-third of households, at least one spouse knew how to fight fall armyworm. For the knowledge index, the mean is harder to interpret, as it is the result of a weighted mean after standardization of the individual components of the index.

In the second column, we report the impact of having been shown the video (with standard errors of the estimated coefficients reported below in parentheses). We find that having viewed the video increases the likelihood that at least one spouse knows the recommended spacing by 13.2% points. This difference is significantly different from zero at the 1% FWER-adjusted significance level (randomization inference-based p-values are shown in the third column; asterisks denote significance as compared to FWER-adjusted thresholds). We also find that the video increases the likelihood that at least one spouse knows that inputs are best combined for optimal results by 4.5% points. This difference is statistically significant at the 5% FWER-adjusted significance level. For the question on weeding, the video does not seem to have had a significant effect. However, this result should be interpreted with care due to limited variation in

[6] As we found only limited imbalance in baseline covariates in table 1, we do not include baseline variables as control here. However, we also did the analysis with controls, results of which can be found in the Online Appendix Tables 6 through 9. Results are not sensitive to inclusion of baseline variables.

Table 2. Impact of ICT Treatments on Knowledge Outcomes

	Mean	Video	P-value	+IVR	P-value	+SMS	P-value	N
Knows optimal spacing (yes = 1)	0.155 (0.363)	0.132*** (0.030)	0.000	−0.020 (0.018)	0.227	0.010 (0.019)	0.571	3,629
Knows inputs best combined (yes = 1)	0.908 (0.290)	0.045** (0.018)	0.011	−0.016 (0.011)	0.114	0.009 (0.011)	0.416	3,629
Knows optimal time for weeding (yes = 1)	0.954 (0.210)	−0.017 (0.017)	0.323	0.009 (0.010)	0.357	−0.002 (0.011)	0.811	3,629
Knows how to fight armyworm (yes = 1)	0.336 (0.473)	−0.018 (0.031)	0.590	−0.017 (0.019)	0.503	0.019 (0.020)	0.310	3,629
Knowledge index	−0.075 (0.565)	0.089*** (0.041)	0.002	−0.021 (0.025)	0.335	0.056 (0.026)	0.561	3,629

Note: In the first column, means (and standard deviations) in the control group are presented for each variable. Column 2 reports differences between placebo and video treatment (and standard error) with its corresponding p-value in column 3; column 4 reports differences between video only and video+ivr (and standard error) with its corresponding p-value in column 5; column 6 reports differences between video+ivr and video+ivr + SMS (and standard error) with its corresponding p-value in column 7; sample size is reported in column 8. Reported p-values are based on randomization inference (10,000 permutations); ***, ** and * denote that the difference is signficant at the 1%, 5% and 10% level, respectively, after correcting for multiple hypothesis testing using a family-wise sharp null (10,000 permutations). All specifications control for the other orthogonal factors in the factorial design. The knowledge index is based on the first three knowledge questions only, as the hypothesis was that there would be no effect on the fourth knowledge question.

the outcome.[7] Finally, on the fall armyworm question, we find that households that were shown the video are no more likely than control households to know when one should spray to control the pest. This suggests that the videos did not encourage farmers to actively search for information on topics that were not explicitly covered. Overall, and as confirmed by the knowledge index, we conclude that the agricultural extension videos increased knowledge at the household level and that this increase seems especially pronounced for novel information provided in the videos.

The fourth column (+IVR) shows the incremental effect of IVR (with standard errors of the estimated coefficients reported below in parentheses and corresponding randomization inference-based p-values in the fifth column). We see that the IVR encouragement does not additionally affect knowledge about the new recommended spacing. Similarly, there is no additional effect on knowledge related to the optimal time for weeding nor on combating fall armyworm. The fact that there is no supplementary effect of the IVR encouragement on knowledge is confirmed by the nonsignificant difference in the knowledge index. The sixth column (+SMS) reports the additional effect of the SMS reminders on the various questions and the index (with randomization inference-based p-values reported in the seventh column). Similar to the impact of IVR, we do not find an additional effect of the SMS campaign on any of the questions. We also do not find an effect of the SMS campaign as judged by the knowledge index. The fact that the IVR and SMS components have no additional knowledge effects is perhaps not surprising, as they did not provide new information.

Adoption Effects

Next, we consider changes in household-level adoption of recommended farming practices as a result of the intervention. In the endline survey, we collected detailed information on practices employed on household maize plots. Mean adoption rates in the control group for different practices are reported in the first column of table 3. For instance, the video

[7] In fact, our pre-analysis plan specifies that we would drop from the analysis variables where 95% of outcomes are the same value.

Table 3. Impact of ICT Treatments on Adoption of Recommended Practices

	Mean	Video	P-value	+IVR	P-value	+SMS	P-value	N
Planted immediately after start rains (yes = 1)	0.366 (0.483)	−0.001 (0.033)	0.966	0.008 (0.020)	0.673	−0.002 (0.021)	0.919	3,509
Used recommended seed spacing/rate (yes = 1)	0.026 (0.158)	0.062*** (0.019)	0.001	−0.003 (0.011)	0.776	0.013 (0.012)	0.236	3,572
Removed striga early on (yes = 1)	0.689 (0.464)	0.057* (0.030)	0.030	−0.005 (0.018)	0.819	0.020 (0.019)	0.240	3,572
First weeding after eighteen–twenty days (yes = 1)	0.430 (0.496)	0.015 (0.034)	0.682	0.012 (0.021)	0.560	−0.006 (0.022)	0.789	3,572
Recommended practices index	−0.083 (0.473)	0.077*** (0.036)	0.006	0.009 (0.022)	0.670	0.039 (0.023)	0.378	3,509

Note: In the first column, means (and standard deviations) in the control group are presented for each variable. Column 2 reports differences between placebo and video treatment (and standard error) with its corresponding p-value in column 3; column 4 reports differences between video only and video+ivr (and standard error) with its corresponding p-value in column 5; column 6 reports differences between video+ivr and video+ivr + SMS (and standard error) with its corresponding p-value in column 7; sample size is reported in column 8. Reported p-values are based on randomization inference (10,000 permutations); ***, ** and * denote that the difference is signficant at the 1%, 5% and 10% level, respectively, after correcting for multiple hypothesis testing using a family-wise sharp null (10,000 permutations). All specifications control for the other orthogonal factors in the factorial design.

recommends that farmers start planting maize immediately after the start of the rains. We find that 37% of households in the control group reported that they started planting within one day after the start of the rains on at least one plot—a relatively high rate of adoption for this practice that indicates the extent to which it is likely known among farmers. We also find that only 2.6% of households in the control group applied the recommended plant spacing of 75 cm × 30 cm with a reduced seed rate of one seed per hill. This low rate in the control group is not surprising given that this was a new recommendation. Almost 69% of control households reported removing striga before it flowered to reduce damage early on and prevent the weed from spreading. Finally, about 43% of control households reported first weeding after eighteen–to twenty days, a practice that was also recommended in the video.

The second column in table 3 again reports the difference in the adoption of practices between households that were shown the intervention video and households that were given the placebo treatment (with standard errors of the estimated coefficients in parenthesis below and corresponding randomization inference-based p-values in column 3). We find that for the first recommended practice, timely planting, there is no impact from the video treatment. However, the likelihood that households adopt the recommended 75 cm × 30 cm spacing with a reduced seed rate increases significantly after having viewed the video: while only 2.6% of households in the control group reported adopting this practice on at least one plot, this figure increases to 8.8% among households that were shown the video. This difference is significant at the 1% FWER-adjusted significance level. Similarly, we find that the proportion of households that removed striga early on increased from 68.9% to 74.6% as a result of viewing the video (with a randomization inference-based p-value of 0.030, significant at the 10% FWER-adjusted significance level). Finally, while the proportion of households that reported having started weeding after eighteen to twenty days is higher among households that were shown the video than those in the control group, the difference is not significantly different from zero. Estimation results for the index that summarizes the different practices confirms that overall, we can conclude that the videos significantly increased the adoption of recommended practices.

The fourth and fifth columns of table 3 report results for the additional effect of the IVR encouragement, with estimates reported in column 4 (and the corresponding randomization inference-based p-values in column 5). We do not find any significant additional effect of the IVR treatment on any of the recommended practices. The sixth column reports estimates for the additional effect of the SMS campaign (with the corresponding randomization inference-based p-values in column 7). Although we do find that the proportion of households that reported having removed striga before flowering is 20% points higher in the treatment group, and we also find a small positive effect on seed spacing and seed rate, the differences are not significant. The fact that both the IVR encouragement and the SMS campaign have no additional impact on adoption of practices is confirmed by the indices.

Next, we examine results related to the use of agricultural inputs. Results are reported in table 4. In the top panel, we examine results separately for the three types of fertilizer that were recommended in the video and again use an index to assess changes in overall fertilizer use. The first column in table 4 reports mean adoption rates in the control group. We find that 26% of control households reported that they used DAP or NPK on at least one of their maize plots, while the use of urea was less widespread with only 5.1% of control households reporting urea use on at least one plot. Among control households, 16.2% reported using organic fertilizer on at least one plot.

The impact of showing the video on fertilizer use is reported in column 2 and 3 of table 4. We see that the video treatment increased the use of urea by 5% points (with a randomization inference-based p-value of 0.011, and significance at the 5% FWER-adjusted significance level). We also find that the use of organic fertilizer increased by about 7.3% points as a result of the video treatment. Summarizing the three types of fertilizer in an index shows a positive difference between treatment and control, with the difference significant at the 5% level.

The incremental impact of the IVR encouragement is reported in columns 4 and 5 of table 4. While the difference between treatment and control is positive for both types of inorganic fertilizer, the effects are not significant. However, we do find that the IVR encouragement reduced the proportion of households that reported using organic fertilizer by 3.8% points. The opposing effects result in an insignificant index. The additive effect of the SMS campaign is reported in columns 6 and 7 of table 4, and it suggests no effect of the SMS campaign on fertilizer use.

In the lower panel of table 4, we report results for the use of improved seed. We differentiate between maize hybrids and open-pollinated maize varieties. Use rates are about the same for both types. We find that the video treatment does not change these percentages (columns 2 and 3). However, we do find an effect from the IVR encouragement: the percentage of households that reported having used hybrid seed on a least one plot was 4.1% points higher in the treatment group. Apparently, providing farmers with a tool that allows them to actively seek out information about a new input or technology increases the likelihood that they also adopt hybrid maize seed.[8] The impact of the IVR treatment on improved seed use is confirmed by the seed index. The SMS campaign appears to counteract the effect of the IVR on hybrid seed use. This is somewhat surprising and may indicate that the effect of IVR on seed is driven by noise.

Production Effects

Finally, we turn to the intervention's effects on production-related outcomes. We first examine household-level maize production. In the endline survey, we asked both spouses separately to estimate how much maize was harvested from each maize plot. These quantities were then summed over the different maize plots assessed by each spouse and the average between the two spouses was taken as the final estimate of household-level maize production.

The first column in table 5 shows mean values for the production indicators for the control group. On average, control households produce (log[kg]) 5.825 or about 440 kg of maize. This was cultivated on (log[acre]) 0.019 or about 1.19 acres on average. It also shows that for the average household in the control, maize yields (log[kg/acre]) equal 5.846 or about 430 kg/acre. This is much higher than yields recorded at baseline

[8] Consistent with this interpretation, we find that among farmers that called the IVR service and selected the topic on seed selection, 38% reported that they used hybrid seed. This rate is only 35% among those that called but did not select this topic. However, the difference is not statistically significant.

Table 4. Impact of ICT Treatments on Fertilizer and Improved Seed Use

	Mean	Video	P-value	+IVR	P-value	+SMS	P-value	N
	Fertilizer use							
Used DAP/NPK? (yes = 1)	0.260 (0.439)	−0.043 (0.029)	0.119	0.022 (0.017)	0.159	−0.007 (0.018)	0.699	3,572
Used urea? (yes = 1)	0.051 (0.221)	0.050** (0.020)	0.011	0.013 (0.012)	0.277	−0.023 (0.013)	0.071	3,572
Used organic fertilizer? (yes = 1)	0.162 (0.369)	0.073** (0.028)	0.007	−0.038* (0.017)	0.024	0.030 (0.018)	0.070	3,572
Fertilizer index	−0.056 (0.548)	0.065** (0.040)	0.038	−0.003 (0.024)	0.887	0.016 (0.025)	0.953	3,572
	Improved seed use							
Used hybrid maize seed? (yes = 1)	0.294 (0.456)	0.003 (0.031)	0.925	0.041** (0.019)	0.028	−0.049* (0.020)	0.009	3,572
Used open pollinated varieties? (yes = 1)	0.298 (0.458)	−0.027 (0.031)	0.410	0.012 (0.019)	0.493	0.025 (0.020)	0.393	3,572
Seed index	0.032 (0.693)	−0.068 (0.046)	0.551	0.059** (0.028)	0.025	0.016 (0.029)	0.429	3,572

Note: In the first column, means (and standard deviations) in the control group are presented for each variable. Column 2 reports differences between placebo and video treatment (and standard error) with its corresponding p-value in column 3; column 4 reports differences between video only and video+ivr (and standard error) with its corresponding p-value in column 5; column 6 reports differences between video+ivr and video+ivr + SMS (and standard error) with its corresponding p-value in column 7; sample size is reported in column 8. Reported p-values are based on randomization inference (10,000 permutations); ***, ** and * denote that the difference is signficant at the 1%, 5% and 10% level, respectively, after correcting for multiple hypothesis testing using a family-wise sharp null (10,000 permutations). All specifications control for the other orthogonal factors in the factorial design.

(290 kg/acre) for the previous season, possibly because rainfall patterns were better during the season of our intervention and farmers may have given greater attention to combating fall armyworm. Still, compared to figures recorded in FAOSTAT (1,000 kg/acre) or figures from other household survey data (typically around 600 kg/acre), yields in our sample were below what might be considered "normal" in Uganda. This low yield level is also confirmed by the fact that in less than 40% of households at least one spouse reported that yields were better than a typical year on at least one plot. We also look at labor use. The average household spent about seventy-two person-days on maize farming, which includes labor that was hired in. This translates to a labor productivity of 6.73 kg of maize per hour worked.

In the second column of table 5, we report the impact of the video treatment (with corresponding randomization inference-based p-values in column 3) for the various production-related outcomes. We see that there is no impact on (log) maize production. However, we do see that households in the video treatment produced this same amount of maize on an area that is about 10.5% smaller than the area used for maize production by control households. As a result, we also find that among households in the video treatment, yields are about 10.5% higher than among the control group. This difference is significant at the 10% FWER-adjusted significance level. The fact that the video intervention has a clear effect on production-related outcomes is also reflected in the significant difference in the production index (aggregating amount produced, area cultivated, labor used, and a subjective assessment of maize yield) between treatment and control. That said, we do not find that households in the video treatment were more inclined to feel that yields were better than normal than were households in the control group.[9]

Results are again consistent with the content provided in the video. In particular, the video advised that farmers experiment on a small part of their field with modern inputs, following recommended practices, and advised against using improved seed on their

[9] Farmers may have confused yields with production. Consistent with our recommendation to start small and combine technologies, and the results that yield effects are due to producing the same amounts on smaller plots, farmers may indicate that on the plot the same amount of maize was produced when part was left fallow or planted with another crop.

Table 5. Impact of ICT Treatments on Production Outcomes

	Mean	Video	P-value	+IVR	P-value	+SMS	P-value	N
Maize production (log(kg))	5.825 (0.754)	−0.017 (0.059)	0.747	0.045 (0.034)	0.316	0.042 (0.036)	0.351	3,347
Maize area (log(acre))	0.019 (0.579)	−0.100* (0.045)	0.020	−0.010 (0.026)	0.683	0.023 (0.028)	0.390	3,339
Maize yield (log(kg/acre))	5.846 (0.658)	0.100* (0.049)	0.025	0.039 (0.028)	0.292	−0.002 (0.030)	0.935	3,301
Yield better than normal (yes = 1)	0.387 (0.488)	0.023 (0.034)	0.496	0.001 (0.020)	0.971	0.035 (0.021)	0.133	3,572
Labor (log(mandays))	4.134 (0.580)	−0.010 (0.042)	0.786	−0.010 (0.024)	0.706	0.036 (0.026)	0.122	3,381
Labor productivity (log(kg/mandays))	1.650 (0.719)	0.024 (0.056)	0.649	0.073 (0.033)	0.062	−0.009 (0.035)	0.750	3,346
Production index	−0.050 (0.364)	0.043** (0.025)	0.024	0.007 (0.015)	0.607	0.026 (0.016)	0.565	3,297

Note: In the first column, means (and standard deviations) in the control group are presented for each variable. Column 2 reports differences between placebo and video treatment (and standard error) with its corresponding p-value in column 3; column 4 reports differences between video only and video+ivr (and standard error) with its corresponding p-value in column 5; column 6 reports differences between video+ivr and video+ivr + SMS (and standard error) with its corresponding p-value in column 7; sample size is reported in column 8. Reported p-values are based on randomization inference (10,000 permutations); ***, ** and * denote that the difference is signficant at the 1%, 5% and 10% level, respectively, after correcting for multiple hypothesis testing using a family-wise sharp null (10,000 permutations). All specifications control for the other orthogonal factors in the factorial design.

entire field if this does not leave sufficient money for complementary inputs such as fertilizer. Further, the video advised farmers to cultivate a more commercial mindset, paying ample attention to the idea of starting small and growing over time through re-investing. Columns 4 and 5 report the additive effect of the IVR treatment on production-related outcomes. As with previous outcomes, there seems to be little impact from this treatment. Similarly, we do not find additional effects on production-related outcomes from the SMS treatment.

Additional Analysis and Robustness Tests

Although we find significant effects from the video intervention, we find limited additional effects from the IVR and SMS treatments. In this section, we explore potential reasons for this. We further show that experimenter demand effects are unlikely to drive our results. In the online supplementary appendix, we also explore heterogeneity in treatment effects.

Demand for IVR and Local Average Treatment Effects

In an encouragement design such as the IVR treatment, households self-select into the treatment. Based on the call log generated by the IVR system, we find that only a small number of households that were encouraged to use the IVR system actually called in (8.9% or 214 households). It may be instructive to look at differences in baseline characteristics between households that ultimately decided to make use of the IVR system and those that did not. Online supplementary appendix table 10 shows results from an OLS regression of an indicator that takes the value of one if the IVR system log showed that a household called in at least once using the household head's phone number that was recorded during baseline data collection, and zero otherwise, on various baseline variables (and the SMS treatment allocation). Results indicate that none of the baseline characteristics predict demand for the IVR service, except for access to a mobile phone. We also find that the SMS reminders seem to have increased the likelihood that farmers called the IVR hotline, as was intended.

Because demand for the IVR service is endogenous, we cannot simply compare outcomes of households that called into the system to those that did not. Furthermore, it may be that farmers who were provided with information about the IVR service passed this on to households that were shown the video but were not allocated to the IVR treatment. Noncompliance by the control group may lead to a downward bias of the treatment effects estimated in the previous section.[10] However, with two-sided noncompliance, local average treatment effects (LATE) can be estimated, where the random allocation to the IVR encouragement is used as an instrument for the variable that measures calling into the IVR system (Imbens and Angrist 1994).

Tables 11 to 14 in the online supplementary appendix correspond to tables 2–5 to show LATE estimates for the IVR intervention's additional effects. In all of these tables, means and standard deviations in the control group are repeated for reference in the first column. In the second column, we report the results of a two-stage least squares (2SLS) regression where we instrument a dummy variable that a household called the IVR with the random allocation to the IVR encouragement. We report point estimates together with standard errors in parentheses below; corresponding p-values are reported in the third column.

Results do not change much from those reported in the previous section. For knowledge-related outcomes and the use of recommended practices (online supplementary appendix Tables 11 and 12), point estimates for the IVR impact are generally much higher in absolute value but remain insignificant. Online supplementary appendix table 13 confirms the previous finding that the likelihood of using organic fertilizer reduces among households that called into the IVR system. For improved seed use, we find results that are again similar to the previous section, with IVR increasing the likelihood of using hybrid seed among households that called into the IVR system, although the seed index is no longer significant. Finally, few effects show up as significant when production-related outcomes are considered (online supplementary appendix table 14).

Thus, even after accounting for noncompliance, we find that additional effects from the IVR treatment are limited, particularly when assessed with outcome indices. A possible reason why we fail to find significant effects that are consistent with the effects from the video for the additional treatment may be that the partial compliance greatly reduces the power of the design. Again, only 8.9% of households that were selected for the IVR treatment also actually called in from the phone number we recorded at baseline.[11]

This low compliance rate may reflect low demand for the service.[12] However, we suspect that our indicator of take-up of the intervention is likely to significantly underestimate true compliance. In particular, our indicator of compliance is taken from the IVR system log, where recorded phone numbers are matched to phone numbers that were recorded during baseline data collection. This indicator is likely to severely underreport true compliance, as encouraged farmers may have used different phones to call the IVR.[13] Using our measure of compliance, we cannot maintain that the exclusion restriction holds, as some of the potential outcomes are directly determined by the instrument. The problem becomes apparent when we think about LATE as the Wald estimator that scales the ITT by compliance (Angrist and Pischke 2008). In our case, the ITT will be estimated on the basis of all farmers encouraged to call into the IVR system. Our measure of compliance forces the LATE estimation to work with the 214 households that show up in the IVR log and could be identified in the baseline, rather than through the 430 farmers who called in, which in the case of a positive impact would lead to an overestimate of the impact of the treatment among compliers. It is well known that especially in the

[10] However, we find that only 1% of farmers who were allocated to the control group called the IVR system. At the same time, there were also many numbers in the call log that could not be identified, see also Footnote 13.

[11] A back-of-the-envelope calculation shows that the minimum detectable effect (MDE) size for maize yields in the original IVR design would be about 6.4%. With only 8.9% compliance, the MDE increases to 71.6%.

[12] Fabregas et al. (2019) also find very low uptake of similar demand driven extension technologies in their analysis of different ICT enabled extension programs in Kenya and Rwanda. In one experiment where farmers were offered a phone call from an extension agent, only 8% of farmers requested a call during planting season. In another project, farmers also had access to a toll-free number, but only about 1% of treated farmers (thirty-five callers) used it. Cole and Fernando (2016) find 88% of farmers called a hotline, but this use rate was attained only after two years of intensive exposure to the system using bi-weekly reminders and for a study population of cotton farmers that expressed willingness to participate and owned a mobile phone.

[13] The fact that 430 unique calls to the system were recorded, representing about 18% of encouraged households, confirms this suspicion.

context of a weak first stage, the bias can become extremely large (Duflo, Glennerster, and Kremer 2007).[14] The above explanation may make interpretation of the LATE effects difficult, and we thus recommend focusing on ITT effects.

Experimenter Demand Effects

A key concern with this study is the use of self-reported survey data on key outcomes, as opposed to outcomes that are measured by a third party in a more objective way. Study participants may report what they feel is desired in that context (social desirability bias). In an RCT, social desirability bias becomes a concern if it is correlated to the treatment, which is sometimes referred to as experimenter demand effects (Zizzo 2010). Although recent research suggests that experimenter demand effects may be less problematic than initially thought (eg. De Quidt, Haushofer, and Roth 2018; Mummolo and Peterson 2019), we offer the following thoughts on why experimenter demand effects are unlikely to drive our results.

First, during the design of the endline questionnaire, we tried to minimize potential experimenter demand effects by careful formulation of the questions. Experimenter demand effects are more likely to be a concern for simple yes/no questions than for more open-ended questions. For instance, in our endline survey, we did not ask if farmers used "plant spacing of 75cm x 30cm with a reduced seed rate of one seed per hill" as recommended. Rather, we asked farmers to describe the planting process, and the enumerator was then required to select an appropriate response from a list of options that was not revealed to the farmer. For input adoption, we started from broad questions (e.g., whether fertilizer was used on a particular plot) and then asked farmers to provide further details (e.g., about fertilizer type, timing of application, quantities, and price), thereby allowing enumerators to detect inconsistencies that might signal experimenter demand effects.

Second, in our endline survey, not all outcomes are equally likely to be affected by experimenter demand effects. For instance, experimenter demand effects are probably less likely to be an issue for the multiple choice questions used to measure knowledge than for questions about implementation of recommended practices or the use of inputs such as inorganic fertilizer or improved seed. It is reassuring that there is consistency between effects found on questions that are more and less prone to experimenter demand effect.

Third, as reported in the online supplementary appendix, fertilizer adoption seemed to increase particularly for treated households that live close to an agro-input dealer. This finding reduces the possibility that results are driven by misreporting related to experimenter demand effects, as this would mean that households that have better access to improved inputs strategically decided to report their answers differently than households that have less access to inputs.

Cost Effectiveness

Cost effectiveness and scalability are often major selling points for ICT-mediated interventions such as ours. Although we did not collect detailed information on prices paid for inputs or the cost of labor, we can use the estimates above together with aggregate price data and some reasonable assumptions to formulate cost and benefit calculations. We first check if the video intervention affected profitability of the average farmer and then compare the total cost of the intervention to the total benefit derived by the farmers in our study.

In our sample, a bag of 100-kg of maize was sold at a median price of UGX 60,000. With control household reporting yields of 430 kg per acre, the corresponding value per acre is UGX 258,000. In the subsample that received the video treatment, yields increased to 475 kg per acre, corresponding to UGX 285,000. This means a difference in income of UGX 27,000 per acre, or about USD 7.7.

From this, we subtract the cost of inputs. In the intervention, we recommended two hybrid seed types, Longe 10H and UH5354 (commonly known as Bazooka). At the time of the experiment, Longe 10H sold for UGX

[14] A similar concern applies to our indicator of take-up of the SMS treatment. Here, however, we fear that compliance is overestimated and so the instrumental variable (IV) estimates will result in a downward bias of the impact of the treatment on compliers. That is, our indicator of compliance is again derived from the system logs and simply looks at message delivery to the intended phone. Probably not all farmers also opened the messages and read them. But the problem is likely to be less severe here, given a stronger first stage and a likely smaller difference between measured compliance and real compliance.

6,000 per kg, while Bazooka sold for UGX 8,500 per kg. However, our data show that the use of Bazooka was marginal and not correlated to the treatment. Thus, we only use the price of Longe 10H in the cost calculations. We further recommended two open-pollinated varieties, Longe 5 and Longe 4, of which Longe 5 is the more common variety. Both types cost about UGX 3,000 per kg. A farmer needs about 8 kg of seed to plant one acre. Inorganic fertilizers are probably the largest expense. The retail price of urea was about UGX 2,500 per kg, while DAP cost UGX 3,000 per kg. We recommended using 60 kg each of both DAP and urea per acre. We assume that organic fertilizer is free but may increase labor costs (see below). The spacing and seed rate we recommended in the intervention is unlikely to increase the costs of seed. We recommended a spacing of 75 cm × 30 cm with one seed per hill. Most farmers use 75 cm × 60 cm spacing with two seeds per hill, which requires the same amount of seed per unit of land. We thus simply multiply the cost of these inputs by the likelihood that they were applied in both control and treatment group (table 4), and subtract this from the income obtained from maize. Doing so actually increases the difference in income between treatment and control somewhat, as the likelihood that farmers use the more expensive fertilizer DAP reduces somewhat, while the likelihood that farmers use urea increases.

Changes in the cost of labor are harder to value. Table 3 shows an increase in the practice of removing striga early on, which is likely to increase labor. The new spacing recommendation also means more hills are needed, which may also have an impact on labor, as does the increased use of organic fertilizer. At the same time, in our endline data, we do not find that the video treatment is significantly correlated to the time spent on preparing the land (which includes application of inorganic fertilizer), to time spent on weeding, or to the likelihood that labor is hired in. In addition, labor is relatively low in cost at UGX 6,000 per day. Valuing work related to organic fertilizer adoption at three - days, the adoption of the new planting method at two days, and the work for weeding at ten - days (which is the time needed to weed one acre), the difference in profit between treatment and control reduces to UGX 22,464 or about USD 6.4.

The entire intervention cost close to USD 37,000. Almost 40% of this was fixed costs such as the production of the video (USD 6,300) and the cost of procuring twenty tablet computers (together totaling USD 5,600). We also trained the enumerators at a total cost of USD 2,224. Variable costs are estimated to be about USD 5.54 for the two video screenings for an average farmer in the area. This includes time for the enumerator to show the video, time for enumerator supervision, car hire with driver, and fuel needed to reach the households. We thus find that the variable cost is lower than the expected return per farmer (which is USD 6.9 as the average farmer has a plot of 1.08 acres). Including the fixed cost implies that the video intervention would only break even at about 10,000 households. If the intervention were rolled out to all 360,000 households in the five districts where it was piloted, the internal rate of return would be about 23%.[15]

Conclusion

In this study, we evaluated a comprehensive ICT-mediated agricultural extension approach consisting of three components—video, IVR, and SMS—introduced as incremental treatments to small-scale maize farmers in eastern Uganda. These components combine several distinct characteristics designed to lift both information and behavioral constraints to technical change. The video component combines information provision with packaging in a medium that relies on farmer-actors speaking in the local language in a manner relatable to the farmers viewing the video. However, the video medium tends to be passive in nature, potentially limiting information retention by viewers, especially where there is a lag between viewing and use of the information. To address this shortcoming, we introduce an IVR service, which allows the farmer to play a more active

[15] It may be possible to reduce variable costs considerably. The largest component of the variable cost was the cost of the person showing the videos to individual households. Currently, an extension worker with a bachelor's degree costs about the same as what we paid our enumerators (UGX 100,000 per day). One may argue that one does not need to have a university degree to show a video, in which case extension workers with only a diploma could be used at roughly UGX 77,000 per day. This would bring the variable cost down to about USD 2.36 for a single screening to the average farmer. Other cost savings may be obtained by showing videos to groups of farmers instead of individually, or direct streaming of videos to devices of farmers. However, this touches upon potentially important design features of the intervention than may alter outcomes and as such requires additional testing.

role in information acquisition through the navigation of menu-based choices leading to prerecorded messages containing the same information as provided in the video. Finally, given that farmers' decision making may be less related to information inefficiencies and more behavioral in nature, we introduce a series of SMS messages to remind farmers to use key inputs or apply key practices at relevant points during the season. We test this approach with nearly 4,000 smallholder maize farmers.

To assess the effectiveness of the video component, we compare outcomes for a random subset of farmers who were shown an informational video to a random subset of farmers who were shown a placebo video. From this initial treatment group, two-thirds of the farmers who were shown the video were randomly assigned to receive an IVR starter kit that encouraged them call into the IVR service. From this second treatment group, half of the farmers were then randomly assigned to receive a series of eight time-sensitive SMS reminders related to the recommended practices and technologies, along with a reminder to use the IVR service to obtain additional information. The design of this experiment allows us to estimate the effect of the video treatment as well as the additional effects of the IVR encouragement and SMS treatments. Effectiveness was measured in terms of gains in content knowledge, adoption of recommended practices, use of recommended inputs, and increases in production-related measures.

Findings indicate that in our study site and context, the video-enabled extension approach significantly affected a range of outcomes. We find evidence of increases in knowledge outcomes, particularly for new practices and technologies; increases in the adoption of recommended practices, particularly those that were new and otherwise unknown to farmers; and increases in the use of certain types of fertilizers (urea and organic). Importantly, we also find evidence of increases in maize yields on the order of 10.5%. Although we do not find effects of the additional IVR treatment on knowledge-, adoption-, or production-related outcomes, there is some evidence to suggest that farmers who received the IVR encouragement were more likely to use hybrid maize seed, which is one of several important inputs to improving on-farm productivity. Finally, we do not find effects of the additional SMS treatment on any outcomes of interest.

The significant and positive effects of the video-enabled approach found in our field experiment are encouraging for several reasons. First, they are potentially relevant not just to our study population but also to a wider population of small-scale farmers who depend on maize for both production and consumption in eastern and southern Africa. Second, they are generally consistent with other studies that make use of video. Third, they extend the body of evidence on ICT-enabled extension to a new country, context, and design, deepening the literature on this topic. It is less clear what we can learn from the null results for the additional treatments. In other studies, IVR or similar hotlines have been shown to have impact (eg. Cole and Fernando 2016), and SMS messaging has similarly been shown to be successful in a variety of contexts (eg. Fabregas et al. 2019). Therefore, the lack of evidence of impact may be specific to the nature of the incremental design and results may be quite different in, for instance, a parallel design. But even in the narrow context of our experiment, where an effort was made to study particular characteristics of the interventions such as the demand-driven nature of IVR or the ability of SMS to make information more salient, it is not clear if the lack of impact should be interpreted as significant for future work on this topic in either the same or other contexts or designs. For instance, in subsection 5.1 we argue that the low take-up of the IVR—a common characteristic of most commercial IVR services, for which low take-up is offset by the low cost of reaching large populations—is likely to reduce statistical power to such extent that any reasonable effect cannot be detected. It is possible that additional promotion of the IVR service or training of farmers on how to use the IVR service could have generated a positive effect, although it is also possible that additional promotion would have defeated the low-cost nature of the IVR system itself. Similarly, with respect to the SMS messaging, it is possible that a more comprehensive design might have generated measurable effects if we sampled only from the population of farmers who owned a mobile phone and actively used it. Even then, the assumption that everyone with a mobile phone also reads, internalizes, and acts upon the messages may be too optimistic.

In summary, we do not think that extension approaches relying on IVR or SMS should be dismissed solely on the basis of this study.

Rather, we encourage continued empirical study of the role that ICTs can play in increasing the effectiveness and decreasing the costs of information delivery to small-scale farmers, the effects that alternative design features have on behavioral dimensions of technical change, and the relevance of ICT-enabled approaches to agricultural extension systems and rural advisory services. Most importantly, we encourage replication of similar studies—alongside variations in the choice of ICTs and the experimental designs in which they are introduced to farmers—across multiple agroecological, social, and economic contexts.

Supplementary Material

Supplementary material are available at *American Journal of Agricultural Economics* online.

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