ICT Effectiveness in Transmitting Information about Optimal Time of Fertilizer Application to Nepalese Farmers

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Getting the Message out: Comparing the Effect of Different Information and Communication Technologies in Delivering Agricultural Advice to Farmers in Nepal

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Abstract

The collection and dissemination of agricultural information in remote, rural areas is costly. Governments and other organizations have relied on extension agents and farmers' social networks to provide agricultural recommendations but have had few institutions with the capacity and resources to effectively reach farmers in geographically dispersed areas. In light of the recent spread of Information and Communication Technologies (ICT) in developing countries, ICT tools are studied as a low-cost solution to providing extension services to smallholder farmers in Nepal. We conducted a randomized control trial with four treatment arms to test the effectiveness of different ICTs (i.e., radio program, voice response messages and a phone app) alongside a traditional extension training in communicating fertilizer management practices for DAP and urea fertilizers in maize crops to farmers across four districts in rural Nepal (Surkhet, Dang, Palpa and Kavre). The intent to treat effects revealed that farmers in the app and the training programs were 0.084 and 0.13 times more likely, respectively, to adopt the urea fertilizer practices compared to farmers in the control group. The app was also the most effective technology to induce learning and retention of the information provided, increasing agronomic test percentage scores significantly by 7.8%. There were no significant effects of the

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treatments on the actual adoption of the DAP fertilizer practices, as it is suspected that the advice might have come at an inappropriate time. Heterogeneous effects showed that female farmers were 0.09 times more likely to adopt our urea recommendations from the radio messages and training programs compared to men. Wealthier farmers were 0.109 and 0.149 times less likely, respectively, to adopt the urea recommendations as a result of receiving the app and attending the training compared to middle- and bottom-income farmers in these same treatments. While the app succeeded at encouraging adoption of the urea fertilizer practices among the poorest, it was found that bottom income farmers achieved 7.15% lower agronomic test scores compared to farmers above the 25th income quartile in the app treatment.

Keywords: Technology Adoption, Agricultural Extension, ICT tools, Randomized Control Trial, Nepal

JEL Codes: O1, O13, Q1 and Q16

Introduction

Agriculture accounts for the majority of the labor force in developing countries, often providing a source of income for smallholder farmers. Increasing agricultural productivity is therefore key to contributing to economic growth and increasing the income and expenditure of the poor. Yields, however, have failed to converge to the levels achieved in developed countries for decades (Aker 2011). During the green revolution the diffusion of high-yielding varieties (HYV's) allowed certain developing countries like Mexico and India to boost their productivity in the agricultural sector. Other developing countries, however, failed to do so in part due to the low adoption of new technologies.

Critical to the successful adoption of new technologies is the diffusion of information. The dissemination of information in developing countries is particularly difficult given poor infrastructure and high search costs. Extension services delivering information inputs to farmers, has been used in several developing countries to address this gap. Agricultural extension has been used to bridge the gap between research and innovations in an attempt to increase farm productivity by providing information satisfying various farmers' needs ranging from market prices, weather forecasts, inputs, cultivation and pest management practices. Extension services have taken several forms, the most common being 1.) Training and Visit (T&V), which involves sending extension agents (i.e., agricultural specialists, trained field staff) to visit selected communities and share information with farmers; 2.) Farmers Field Schools (FFS), which are group-based trainings designed to empower individuals to experiment and gain skills to adopt more sustainable farming practices for their specific context through learning by doing, often used to teach Integrated Pest Management (IPM) practices in Asia and 3.) Fee-for-service coming from both private and public sector initiatives, whereby farmers contact agent specialists with specific information requests for a fee (Aker 2011).

However, despite these efforts, the capacity and resources to effectively reach farmers in geographically dispersed areas has remained limited and constrained by high implementation costs for sending extension agents and motivating extension staff. These shortcomings have given considerable attention to the potential of using Information Communication Technology (ICT) tools, defined as communication devices or applications that provide access to information through the transmission of signals over long distances, including radio, television, mobile phones, computers and network hardware and software. ICTs have been recognized to have the potential to be a low-cost solution for extension service delivery to smallholder farmers either as substitutes or complements to traditional extension trainings (Aker 2011).

The recent spread of ICTs in developing countries has generated two streams of studies. The first stream of literature examined the poverty reduction potential of ICTs by looking at the use of mobile phone services to facilitate farmers' access to price information in agricultural markets. Significant reductions in price dispersion were found, achieving positive welfare effects brought by leveraging farmers' arbitrage opportunities (Jensen 2007, Aker and Fafchamps 2014, Aker and Mbiti 2010, Aker 2010). Other evidence failed to corroborate the positive welfare effects brought by mobile phone services, finding no evidence of spatial arbitrage nor of any significant impacts on the quantities grown or sold by farmers (Fafchamps and Minten 2012, Aker and Ksoll 2016). However, the literature finding positive welfare effects of ICTs contributed spreading the optimism about using ICT tools for agricultural development, which gave rise to a second stream of literature examining the capacity of ICTs to enhance knowledge and adoption of new agricultural technologies (Nakasone, Torero, and Minten 2014).

The present study fits under the second stream of literature. Most rigorous studies evaluating knowledge and adoption of new technology outcomes have only focused on mobile phone-based services including one-way communication, such as text message reminders (i.e., SMS) to perform agricultural tasks in the field (Larochelle et al. 2017) or two-way communication, through mobile-based interactive platforms connecting farmers to professional agronomists for consultations regarding agricultural information (Cole and Fernando 2016, Fu and Aker 2016). Some studies have tested both types of communication (i.e., one and two-ways) separately, for example, Casaburi et al. (2014) tested one program consisting of SMS reminders to perform agricultural tasks and a second program providing a hotline service allowing farmers to call companies and receive input delivery and payment information. However these studies have not being able to compare between different mobile-based services (i.e., SMS versus hotline), or studied the effects of mobile services compared to other technologies (i.e., radio, television…), which is a gap that we wish to close in the present study.

The general results have shed positive evidence of the returns to learning and adoption of new technologies from mobile services. Larochelle et al. (2017) found that farmers who received regular SMS during the potato growing season increased their overall knowledge about Integrated Pest Management (IPM) practices by 18.4 percentage points (measured by a knowledge score from the survey responses to 23 knowledge questions) and increased the likelihood of adopting IPM practices by 6.7 percentage points compared to the control. However their messages were sent after a formal training session (the farmer field day), so the results could not be extrapolated to untrained farmers. There is however evidence of the benefits of using mobile services alone for marginal farmers, proving increased awareness, knowledge and interest in adopting new technologies from a mobile-based platform allowing farmers to use video, voice and SMS messaging features with an assistant guiding farmers (Fu and Aker (2016). Finally mobile-based services have provided evidence of positive welfare effects. Casaburi et al. (2014), showed that their SMS advice increased yields by 8% more for treated farmers compared to the control and the hotline improved efficiency in fertilizer delivery by reducing delays by 3.8 percentage points compared to the control. Cole and Fernando (2016), also reported reductions in pest losses and yield increases of cumin by 28% and of cotton by 8.6% from the Avaaj Otalo (AO) service (mobile phone-based technology allowing farmers to call a hotline, to interact with professionals and access other farmers' Q&A).

Finally, the other identified potential benefits of ICTs in the literature are spillover effects, to both recipients and non-recipients of the technologies. The advantage of ICT tools is that they can be shared among farmers allowing non-recipients to also benefit from the services. Technologies can also facilitate farmers' access to information through their social networks since they reduce the costs of communication and could link farmers to other adopters in their social networks (Aker 2011). However, the effects of social networks on the adoption of new technologies are not clear. Foster and Rosenzweig (1995) were the first paper to look at technology adoption through learning from others in the context of the green revolution, when new Mexican High Yielding Varieties (HYV) were diffused in India. They found that farmers drew on their neighbors' experiences to make appropriate decisions about the optimal input usage when adopting new technologies, but this was found to delay adoption due to free riding behaviour from farmers who knew that they neighbors were likely to adopt the technologies first. Subsequent papers have shown positive evidence that social learning fosters technology adoption for farmers with more experienced neighbors sharing similar characteristics (Conley and Udry 2010, Maertens and Barrett 2011, BenYishay and Mobarak 2018). However, heterogeneous effects can affect social learning, including social distances and gender. Beaman and Dillon (2018) found that targeting the most-connected individuals resulted in lower knowledge for woman and that greater social distance reduced the extent of information sharing. Characteristics such as gender, wealth and experience are therefore important determinants of the speed and efficiency of information spreading and who will benefit from the information. So far, the paper by Cole and Fernando (2016) found positive spillover effects from the AO service confirming the potential benefits of ICT tools for non-participants.

Given these promising effects, international and non-governmental agencies have been looking to incorporate ICT tools into their programs. For example, USAID sought to incorporate ICTs into its five-year funded initiative (2016-2021), the Nepal Seed and Fertilizer (NSAF) project run by the International Maize and Wheat Improvement Center (CIMMYT), which aims to facilitate sustainable increases in national crop productivity through extension service provision, to raise farmers' incomes and contribute to national food security. More specifically, ICTs have been used in the NSAF project to promote the adoption of the 4R Nutrient Stewardship Approach to crop nutrient management in Nepal. The "4Rs" constitute the use of the **R**ight Source of fertilizer, the **R**ight Rate of fertilizer, at the **R**ight Time, and at the **R**ight Place. In January 2018, McGill University partnered with CIMMYT's NSAF to evaluate the relative effectiveness of different ICT tools in providing farmers recommendations on soil fertility management practices for maize crops targeting one of the "4Rs", namely teaching farmers the right timing of fertilizer application for urea and DAP fertilizers.

In this study, we implement a randomized control trial with four treatment arms to test the effectiveness of radio messages, voice response messages sent to farmers via phone calls, a remotely accessible smartphone App, and a traditional extension program in delivering recommendations on when to optimally apply urea and DAP fertilizers on maize. Our first differences estimation reveals that farmers who received an app were 0.084 times more likely to split the application of urea in two doses at the right times compared to farmers in the control group with 5% significance. Furthermore, farmers in the app treatment achieved 7.841% higher agronomic test scores for questions directly related to the treatments, and 5.023% higher test scores for questions measuring general agronomic knowledge at the 5% and 10% levels, respectively, indicating that the app was more effective in disseminating information. Traditional extension training programs also appeared effective at sharing information on the timing of urea fertilizer application by an average of 0.13 at the 10% level compared to control farmers. These results suggest that farmers seem to reject more impersonal tools, since radio and voice mail messages were delivered without face-to-face interaction. However, we find no significant effects of any ICT on the use of DAP at planting, which we suspect to result from the fact that most farmers had already planted maize when they received the advice. Heterogeneous effects showed that the training and app treatments benefited middle-and-low income farmers the most compared to wealthier farmers, but the returns to learning for the poorest from the app treatment were about 7.15% lower than the rest of farmers at the 10% level. Finally, female farmers were more likely to follow the urea fertilizer timing recommendations in the radio and training programs compared to men.

This study contributes to the literature looking at the poverty reduction potential of ICTs by promoting learning and adoption of new technologies in the context of extension services (Casaburi et al. 2014, Cole and Fernando 2016, Fu and Aker 2016, Larochelle et al. 2017). Most of these studies have been optimistic in the potential of ICTs to enhance learning and adoption for farmers in developing countries, however they have restricted their analysis to mobile phone use. No study we are aware of has compared how mobile phones fare vis-à-vis other technologies. We close this gap by evaluating how four different ICTs (i.e., radio, voice response messages, phone app and traditional training) compare in delivering agricultural recommendations looking at farmers' knowledge, retention and use of the information provided. Our study allows the comparison between different ICTs in an attempt to begin identifying the specific features from the technologies that are driving the results. This is novel since most studies have only focused on assessing one intervention at a time failing to compare the utility of different delivery channels both within mobile services (i.e., voice versus SMS) and between different types of channels (i.e.: mobile phones, radio, TV, and face-to-face contact) (Baumüller 2018).

The paper is organized as follows. Section 1 provides an overview of the context and fertilizer policies in Nepal. Section 2 contains the experimental design describing the treatments and data collection process. The methods are presented in Section 3, including the empirical analysis. The results are reported in Section 4, followed by the robustness checks (Section 5). Finally, Section 6 contains the discussion and the Section 7 concludes.

1. Nepalese context

Nepal is a South Asian landlocked country whose economy predominantly relies on the agricultural sector, which accounts for 31% of the gross domestic product (GDP) and employs two-thirds of its labor force (CBS (Central Bureau of Statistics) 2014). Despite the predominance of agriculture in the country, many smallholders in Nepal have not adopted improved agricultural technologies, especially regarding best farming practices to increase their farm productivity. This is problematic since the IPC (2014) reported that more than half (54%) of the Nepalese population are affected by chronic food insecurity. Mineral fertilizer could account for a 50% increase in food production, implying that ensuring timely access to and application of adequate mineral fertilizer is key to agricultural development, food security and poverty reduction in the country (United States Agency for International Development (USAID) 2012).

Fertilizer Policies

Chemical fertilizer was first introduced in Nepal during the 1950s (Takeshima et al. 2017). In 1966, the Ministry of Agriculture implemented the Agriculture Input Corporation (AIC), which was a public-sector enterprise dedicated to importing and distributing chemical fertilizers in Nepal initially from India but later also from international markets (ibid.). The government introduced fertilizer subsidies between 1973 to 1974 with the aim to increase food production by encouraging chemical fertilizer use among farmers, this included both a price and transport subsidy for transporting fertilizers from Terai districts to Hilly districts[1] (APROSC (Agricultural Projects Services Centre) 1995). Initially the subsidy was only applied to diammonium phosphate (DAP) and muriate of potash (MoP) but was later extended to urea fertilizer.

Towards the middle of 1990s, the price of fertilizer on international markets began to increase as did domestic demand, turning the subsidy into a financial burden for the government. This resulted in the dissolution of the AIC (deregulation of fertilizer trade) and the end of fertilizers subsidies by 1999 (Takeshima et al. 2017). This allowed the private sector to import and distribute fertilizers. As a result, the government converted the AIC into the Agriculture Inputs Company Limited, responsible for the fertilizer business, and the National Seed Company Limited, responsible for the crop seed business (ibid.).

In 2002, the National Fertilizer Policy (NFP) was implemented, with two missions: first, providing policy and infrastructure for increased fertilizer use, and, second, to promote an Integrated Plant Nutrient Management System (IPNS) encouraging the efficient and balanced

[1] Nepal consists of diverse agroecological belts, Terai with flat terrain and Hills with rugged terrain.

use of fertilizers. The NFP continued to encourage policies for the deregulation of fertilizers however, with time, the rise in fertilizer prices and the increased perception of adulteration of fertilizers traded in private markets became a concern. In 2009 the government therefore reintroduced chemical fertilizer and transport subsidies in an attempt to contain prices and ensure fertilizer quality (Takeshima et al. 2017). Currently, most of the formal-sector channel supplying fertilizer is subsidized and government-owned, through the Agriculture Inputs Company Limited and the National Salt Trading Corporation (Pandey 2013). Currently, subsidized fertilizers are the same as in the past — urea (58% subsidy), diammonium phosphate (DAP, 38% subsidy) and muriate of potash (MoP, 2% subsidy). Farmers who own at most 0.75 ha of agricultural land in the Hills and 4 ha in the Terai are eligible to receive the fertilizer subsidy for three crops a year (Paudel and Crago 2017). Together they provide the NPK (nitrogen N, phosphorus P, and potassium K) macro-nutrients needed to maximize plant yields. Urea provides nitrogen (N), DAP is a mix between phosphorus (P) and a little nitrogen (N), and MOP provides potassium (K).

The government of Nepal partnered with the Asian Development Bank (ADB), USAID and other donors to prepare a 20-years strategy to foster agricultural sector development in Nepal through its Agricultural Development Strategy (ADS). As a result, in 2012, the United States Agency for International Development (USAID) (2012) made an assessment of fertilizer usage and management practices in Nepal through qualitative and quantitative surveys conducted in 11 districts involving 855 farmers in 47 cooperatives with the aim of presenting policy options to increase productivity from fertilizer use in Nepal and maximizing the government's investment in the fertilizer sector. They found that most of the farmers in Nepal have little to no knowledge of fertilizers. Despite previous government efforts to encourage the efficient and balanced use of fertilizers through the IPNS initiative, there is an observed tendency for farmers to apply more nitrogenous fertilizer since it delivers a quicker response. A higher ratio of nitrogen is against the principle of balanced fertilizer use, and can be a matter of concern for sustainable soil fertility management since large applications of N (nitrogen), especially coming from urea, can present management risks including the degradation of soil structure, increased soil acidity, and imbalance of crop nutrients (ibid.).

2. Experimental Design

Selected Districts

Between May and October 2018, CIMMYT and McGill tested the effectiveness of Information and Communication Technologies (ICT) tools by conducting a randomized control trial (RCT) in four districts in Nepal: Kavrepalanchok, Surkhet, Dang and Palpa. These four districts were selected among the 25 districts targeted by the NSAF project to ensure that they were located in the maize pockets and had access to mobile coverage (figure 1: Mobile coverage Nepal[2]).

Data collection

[2] Collins Bartholomew's Mobile Coverage Explorer is a polygon vector dataset, which represents the area covered by mobile communication networks around the world. The data is created from submissions made directly to Collins Bartholomew or the GSMA from the mobile operators.

In each of the four districts, a census of all the cooperatives planting maize, and with a majority of farmers having access to the radio and a smartphone, was collected. From this census, 15 cooperatives were randomly sampled per district, giving us a total of 60 cooperatives in the maize pockets. Randomization into the treatment arms was done at the cooperative level: 10 cooperatives were randomly assigned to each one of our four treatments and 20 cooperatives were allocated to the control group, in which farmers received no information on fertilizer application timing (figure 2). In each cooperative we randomly sampled 15 farmer participants, giving us a full sample of 900 participants who were interviewed at baseline (pre-treatment) in May 2018 and end line (post treatment) at the end of September 2018, post maize harvest. All treatments were delivered the last week of May, from the 28th onwards (before the beginning of the maize planting season). Randomly selected respondents were only interviewed if they consented to participate in the study and satisfied the criteria of planting maize in the 2018 season and had access to both the radio and a smartphone. Access to a smartphone was defined as directly owning a device or indirectly accessing it from a neighbor or other household member at least 3 times a week. This rule was applied to achieve a more representative sample of participants.

Treatments

The treatments provided agricultural recommendations regarding the optimal timing for fertilizer application of urea and DAP fertilizers on farmers' maize crops. The advice was shared either via a remotely accessible smartphone App, a traditional extension training, radio messages, or IVR (Interactive Voice Response) messages sent through phone calls.

The content of the advice for each treatment was the same and consisted of applying DAP fertilizer only at planting and splitting the application of urea fertilizer in two doses, one at vegetative stage 6, when the maize plant has six fully grown leaves (v6), and then at vegetative stage 10, when the maize plant has ten fully grown leaves (v10). The right timing of fertilizer application, at these two specific stages of maize plant growth (v6 and v10), was proven to exhibit maximum absorption of nutrients, leading to less fertilizer waste and increased yields by up to an additional 2 tons/hectare, according to CIMMYT's field trials. Farmers were therefore informed to use all DAP fertilizer they were planning on using for the season at planting stage and then to split their urea for the season in two doses, one at v6 and the second at v10. Regarding urea application, farmers were also given detailed information on how to identify if the plants were ready for the application of each dose of urea. In order to identify whether the plots were ready for the first urea application, farmers were told to pick five plants at random in their main maize plot and count their leaves. If at least three out of those five plants had six fully formed leaves, this was to be interpreted as a sign to apply the first half of the urea application (v6 stage). The same rule applied for the second application of urea; farmers were told to apply the second dose of urea when most plants had achieved ten fully formed leaves (v10 stage). The proper technique to count leaves was to start with the 1^{st} leaf at the top of the maize plant and only count the leaves turned downwards including the leaves that had already fallen.

a) App

Our partners, Geokrishi, a private innovation company with the mission to bridge the gap between research and traditional farming practices, specializing in providing technological based crop advice for remote farmers, developed the smartphone App used for the treatment. The App was called M Krishi after the Nepali word for agriculture, “Krishi”. The design of the App was simple and easy to use, it contained static slides with illustrations on the techniques on how to count leaves to apply urea fertilizers at specific stages of maize plant growth, as well as supporting text and an option to press the audio to listen to voice recordings reading the text out loud for illiterate people. The slides used in the App where the same as the ones presented during the extension training given by CIMMYT’s field staff, to ensure comparability between both treatments. The App was also designed to be remotely accessible (offline), meaning that it did not require Internet access to be shared between devices. The app was shared to farmers using the google app “SHAREit”, a cellular data free app allowing to transfer files between devices. For that, CIMMYT staff contacted each of the 15 randomly selected participants assigned to receive the app treatment and informed them that they had been randomly selected to receive a free App containing information regarding fertilizer management practices for maize crops. Each farmer was then invited to meet at a specific location to redeem the App during a group meeting with the rest of the randomly selected farmers assigned to the App treatment in each cooperative. CIMMYT staff did not deliver a training on how to use the App, staff only assisted in the process of sharing and uploading the application on farmers’ devices. After receiving the App, farmers were given time to go over the App on their phones individually to check that everything was working properly on the technical side. No comments or additional information regarding the fertilizer recommendations provided by the app were discussed in the meeting, so as not to bias their interpretations of the information provided. In certain cooperatives, farmers were too busy to come to the meeting, so CIMMYT staff visited farmers' houses individually to share the App at their earliest convenience.

b) Traditional Extension Training

The traditional extension training was delivered by CIMMYT's field staff in each respective randomly selected cooperative and consisted of a verbal explanation teaching farmers the new farming practices using printed paper slides, the same slides as for the App, which contained illustrations for the techniques discussed as well as text descriptions. The presentation was followed by a field demonstration on a sample plot where farmers saw the technique to count leaves being applied in practice as well as how to measure the distance and depth of fertilizer application from the maize plants. The training was conducted in farmers' cooperatives or designated locations in the villages. Randomly selected farmers in each cooperative received a call with an invitation to attend the trainings at specified times and common locations. Since the study aim is to compare the effectiveness of each treatment in delivering agricultural advice to farmers, an attempted to increase treatment comparability was made. Given that the ICTs give farmers a higher frequency of exposure to the information provided, farmers assigned to the in person training received a paper printed poster summarizing the main information delivered by the training (DAP application at planting and the technique to count leaves to split the application of urea at v6 and v10). It was anticipated that the poster would allow farmers to refer back to the training materials as many times as needed, increasing the frequency of access to the information.

c) Radio Program

The radio treatment was created in partnership with a media agency called V-Chitra who specializes in providing marketing and advertising services. The agricultural recommendations were aired through the second most popular radio stations in each district in order to minimize contamination so that farmers who were not in the radio treatment would be less likely to tune into the radio stations airing the messages. To encourage treated farmers to tune into the radio at the right times, farmers were sent voice response message reminders sent by VIAMO, a global social enterprise company aiming to connect individuals and organizations to improve lives via mobile. Farmers received these reminder calls to tune into the radio every other day (between the 1st and 17th of June and between the 27th of June to the 16th of July).

V-Chitra contacted each individual local FM radio station per district to record and air the messages. The radio messages were recorded in Kathmandu using a man and a woman's voice having an interactive dialogue to discuss the agricultural advice (people from two different genders were used to differentiate the speakers). All radio messages were aired as a dialogue between the same man and woman, using local names for the characters in the dialogue to ensure continuity in the information and allow farmers to better remember the story. The approximately one-minute message discussed between the man and woman is a summary of the recommendations provided by the treatments, recommending farmers to apply DAP only at planting and to split the application of urea fertilizer in two doses when plants have 6 and then 10 fully formed leaves[3]. Two follow-up approximately one-minute radio messages, one for v6 and the other for v10, contained detailed explanations on how to count leaves and randomly select plants to identify v6 and v10 stages of maize plant growth. The first generic radio message was

[3] The full dialogue script can be found in Appendix 1.

aired from the 28th of May until the 4th of June. The two additional radio messages were synchronized to the approximated dates when farmers' maize plots would be ready for the first application of urea at v6 stage (between the 4th of June until the 18th of June), and for the second application of urea at v10 stage (between the 2nd of July to the 16th of July) given farmers' planting dates. The messages were aired during the add breaks after popular radio programs at five different times during the day (7:15-7:30am 8:15 to 8:30am and in the evening at 6:15-6:30 pm, 8:15-8.30pm and 9:15-9:30pm), which were the most common times at which farmers listen to the radio, according to the baseline survey data.

d) IVR (Interactive Voice Response) messages

The IVR treatment was tested as an alternative method of communication with the potential of reaching illiterate farmers. Farmers randomly assigned to this treatment received a phone call containing an automatic response message that was programmed to play as soon as farmers picked up the phone. The calls were also sent by VIAMO. Again, a local toll-free number was used to inspire trust in the ID caller. There were three main calls sent through the IVR treatment, a general call and two follow up calls to remind farmers to apply urea fertilizers at v6 and v10 stages of plant growth. The first call contained the same dialogue as the radio messages, but with an introduction letting farmers know that it was an automatic voice response message delivered by CIMMYT and USAID regarding agricultural recommendations on optimal timing of fertilizer application (cf. Appendix 1 for full script). The follow-up message calls contained the same information as the radio messages but had an additional interactive feature asking farmers questions in which they could use the keypad to answer. This was meant to engage farmers during the calls and check their understanding of the information. The first message call contained a question after the introduction, asking whether farmers were free to listen to the information or if they wanted to be called the following day. The follow up calls asked farmers whether they remember when to apply the first and second doses of urea, giving them options and asking them to use their keypad to respond to the questions. Depending on their answer a message would play giving detailed information on how to count leaves in their plots and reminding them of the proper distance for fertilizer application. The information was synchronized by groups of farmers' planting dates to make sure the information would come at an appropriate time.

VIAMO sent the first call (1-minute-long), followed by the second call (1:60 minutes long) leaving one-day break in between the calls. These calls went off from the 1st of June to the 17th of June. The last call was sent from the 29th of June until the end of July depending on farmers' planting dates, leaving two days break in between each call since the third call (1:60 minutes long) did not have a follow up call.

3. Methods

Regression Estimation

The effects of the different treatments outlined above were estimated using the following first difference equation:

$$(Yendline_{ic} - Ybaseline_{ic}) = \alpha_c + \beta_1 App_{ic} + \beta_2 IVR_{ic} + \beta_3 Radio_{ic}$$

$$+\beta_4 Training_{ic} + \gamma X_{ic} + \Delta\varepsilon_{ict} \qquad (1)$$

where the parameter α_v is the constant capturing the village fixed effects, $Yendline_{ic}$ is the outcome variable of interest for farmer i in cooperative c at end line and $Ybaseline_{ic}$ is the outcome variable of interest at baseline for farmer i in cooperative c. The left-hand side of the equation is therefore the first difference in the outcome variables, explained in more detail below, between end line and baseline. All of the models were estimated using a linear probability model (OLS), including the adoption outcomes, where the dependent variable is binary to ease the interpretation of the results (a logit model is presented in the robustness checks). When there are only two time periods, it is possible to choose the model specification based on assumptions about the functional form, which is here that the joint effect pattern between exposure and time is additive. The treatment variables are denoted by $App_{ic}, IVR_{ic}, Radio_{ic}\ and\ Training_{ic}$ and take the value of 1 if an individual i in cooperative c was randomly assigned to that treatment or 0 if the individual did not receive that treatment. The main parameters of interest are the β coefficients, which show the intent to treat effect of the treatments on the outcome variables of interest, namely knowledge and adoption rates. Equation (1) is estimated both with and without controls. The vector of controls is denoted by X_{ic} and includes all the imbalanced characteristics identified at baseline (discussed further below). Finally, $\Delta\varepsilon_{ivt}$ is the error term. All the regressions include village fixed effects and were clustered at the cooperative level.

Outcome variables

The study aimed to measure the effectiveness of information communicated through different ICT channels on two main outcome variables: (i) adoption of new agricultural technologies and

(ii) knowledge about these new farming practices. Both variables were collected through self-reported data during the household surveys using questions evaluating farmers' retention of the information provided and enquiring about adoption of the recommendations.

At baseline, farmers were asked whether they applied urea and DAP fertilizers to their maize crops and the techniques they used to determine if the soil was ready for fertilizer application (timing of fertilizer application) in the 2017 monsoon season. Farmers were then asked the same questions for the 2018 season at end line (post intervention and immediately after harvesting time). The survey options included an option on whether they split their application of urea fertilizer in two doses following the technique of counting leaves at v6 and v10 stages of maize plant growth, and another asking them whether they had only applied DAP fertilizer at planting.

Agronomic literacy was measured through an agronomic test conducted during both baseline and end line surveys. The agronomic test contained 11 multiple-choice questions measuring general agronomic knowledge regarding fertilizers, seed varieties and pest disease. Among these questions, 6 of them were specifically related to the information provided by our treatments, regarding optimal timing of urea and DAP application, as well as the distance to apply fertilizers from the maize plants. Two percentage scores were constructed from these agronomic tests. The first was a *general agronomic knowledge score*, assigning 2 points for each right answer, and 1 point for each partially right answer. The second percentage score called the *relevant agronomic knowledge score*, was created following the same procedure except it only included the 6 relevant questions related to the treatments (the questions asked to generate both scores can be found in Appendix 2). Knowledge scores represented the percentage of questions answered correctly. The relevant agronomic knowledge score is the main focus of this study since it captures the knowledge coming directly from the information provided by the treatments. We kept the general agronomic knowledge score, to see if overall agronomic literacy could also be improved as a result of increased knowledge in fertilizer management practices.

Intent to Treat Effects (ITT), Compliance, Contamination and Attrition

Equation (1) above measures the intent-to-treat (ITT) effect since we estimate the coefficients for all the respondents who were randomly assigned to the treatments, regardless of whether they used the treatments or not. Compliance rates for this study are presented in table 1; the data in column (2) of table 1 describes the number of farmers who actually received the treatments, as opposed to those who were randomly assigned to receive it (column 1). This data was gathered through attendance lists that recorded how many farmers showed up to the meetings to receive the trainings or get the app. For example, out of the 150 farmers who were invited to receive the training, only 105 of them actually attended the training event. Similarly, 106 farmers out of 150 came to the meeting to get the app installed on their phones after being invited. The radio and IVR treatment data were gathered by the company VIAMO, who recorded data on whether farmers picked up the calls or not, independently of whether they listened to the full length of the call. The data for the IVR presented in the second column of table 1 is for the first IVR call that farmers received, which included all of the fertilizer recommendations summarized (apply urea in two doses at v6 and v10 and DAP only at planting). Farmers randomly assigned to the radio treatment received IVR reminders to tune into their selected district radio stations at specific times of the day. Table 1 captures how many of them picked up the radio reminder calls.

Contamination rates were estimated using data from the end line survey, respondents were asked to recall whether they had received agricultural recommendations regarding the optimal timing of fertilizer application in maize plants from CIMMYT, and through which specific technology. The possible spillover of the radio treatment to other treatments is a concern since the radio messages were broadcasted several times during the day, and it was impossible to exclude non-treated farmers from possibly hearing the information if they tuned into the radio at the time the messages were broadcasted. To minimize contamination, selected farmers into the radio treatment also received voice response message reminders to tune into the radio at specific times of the day. However, as anticipated, there were some farmers in other treatment groups and the control group that heard the radio messages. A total of 16 respondents from other groups claimed to have heard the radio messages[4] (3 people pertained to the control group, 3 people were from the training group and the remaining 10 farmers belonged to the IVR treatment). In addition to the radio treatment 1 person from the control claimed to have accessed the app. In summary, cross treatment spillover effects were low with only 13 respondents from other treatments having heard the radio messages and 4 people in the control accessed the treatment information.

Finally, because a total of 14 respondents from baseline, representing 1.55% of the total sample of 900 participants, dropped out of the study, we do not account for the possible attrition bias. We drop these 14 baseline respondents from the final analysis, leaving a sample of 886 respondents.

[4] The question asked was "Where any of the CIMMYT radio messages you listened regarding maize optimal timing of fertilizer application (which fertilizers to apply, when and how to apply them)?"

Balanced test

Before estimating the regressions, a balanced test table (table 2) was produced to ensure that the intervention and control groups were equivalent with regards to a set of baseline observable characteristics. Columns (1) to (4) of table 2 report the mean and standard errors for each one of the treatments testing whether the randomization achieved balance between the given treatment compared to the rest of the treatments and the control group (column (5)).

As observed from table 2, marriage status, smartphone ownership in the household, maize yields from the main maize plot (kg/ha), area of the main maize plot (ha) and land ownership (ha) are all balanced across treatments. Variables such as age, education levels, whether the household head is a female, political participation and the dependency ratio are however imbalanced. All of these imbalanced characteristics were therefore included as regression controls, X_{ic}, in equation 1 above[5]. From table 2, it is also visible that farmers assigned to the App treatment were applying significantly more fertilizers after planting in 2017 compared to the treatments and control groups. Similarly, farmers randomly assigned in the Training treatment group applied significantly less fertilizers at planting compared to the rest of the groups.

To proxy wealth, three separate indices were created using factor analysis: a durables index, a livestock index and a productive index (see Appendix 3 for the Summary Statistics and Factor Loading for the Wealth Asset Indices). An aggregate wealth asset index is created by summing the three indices together and is used to control for differences in wealth across

[5] For the outcome variables capturing adoption rates, the vector X_{ic} was augmented by three dummy variables on whether farmers hired extra labour, used irrigation and agro-machinery, which could be associated with the adoption of the recommended farming practices since applying fertilizers by plant can be time consuming and technologies used in the plots can increase efficiency making it more likely for farmers to adopt the advice.

treatments. Asset data was collected at baseline survey asking farmers to state their ownership of livestock, durables and productive assets and was used to build the indices since it carries fewer measurement problems and has a lower likelihood of recall bias than expenditure or income data (Moser and Felton 2007). It also provides a better indication of living standards since assets have been accumulated over time whereas income is a more volatile and a seasonal measurement. Factor analysis was chosen as the selected method to construct the asset indices following the same methodology as in Sahn and Stifel (2000).

We also check whether the outcome variables of interest outlined above were balanced between the treatments and control group at baseline, reported in table 3. It appears, from table 3, that general agronomic literacy, urea applied at v6 and v10, and DAP applied at planting are not balanced across treatments. Regarding agronomic literacy, this imbalance does not affect the analysis since we are most interested in the knowledge acquired through the treatments, which is captured by the relevant agronomic score, which is perfectly balanced. Concerning the adoption outcomes, farmers in the App and Radio treatments seemed to be already splitting urea application in two doses, at v6 and v10, before the intervention compared to the rest of the treatments. Similarly, farmers randomly assigned to the Training and IVR treatments seemed to be already following the provided DAP recommendations. The variable capturing whether farmers applied urea at v6 and v10 in the 2017 season is a dummy variable taking the value of 1 if farmers declared splitting the application of urea at v6 and v10, and 0 otherwise. A similar dummy variable was created for whether farmers applied DAP only at planting.

The allocation of farmers in the treatments was done randomly to prevent selection bias. Nonetheless, differences at pre test are observed in two of the outcome variables of interest. The advice on DAP is more commonly used in traditional farming practices and therefore was not expected to be as novel as the recommendations regarding urea. Traditionally, the most progressive farmers would split the application of urea in two doses and focus on the height of the plants to determine when to apply the doses of urea fertilizer, usually when plants would reach knee and shoulder height. However, height varies from plant to plant and can only be an imprecise measurement to determine whether the plants have reached v6 and v10 stages of plant growth. The appropriate technique to determine if plants are ready for urea application is to count the leaves. However, most farmers are not aware of this novel technique so it was therefore highly unanticipated that there will be any imbalances in the urea outcome variable. In fact, table 4 shows that the urea imbalance is being driven by very few observations, 11 farmers in the App and 5 in the Radio treatments, which indicates that few farmers were counting leaves to identify v6 and v10 stages prior to receiving the treatments. A baseline imbalance should however be distinguished from selection bias. Random allocation removes selection bias, however as Fives et al. (2013) points out, not all random allocations are meant to ensure baseline equality and it is possible that for a single particular randomization the groups might result imbalanced, which is the case in this study. Since there is no particular reason to believe that some farmers might have been more prone to know about the advice than others *a priori*, this will be deemed as an unlucky outcome in the randomization process, but is taken into account when interpreting and discussing the results.

4. Results

Agronomic literacy scores

The results measuring the effects of the treatments on agronomic knowledge are found in table 5. Columns (1) and (2) of table 5 contain the regressions on general agronomic knowledge and columns (3) and (4) the estimations for relevant agronomic knowledge. Starting with general agronomic knowledge, the app treatment increases general agronomic test scores by approximately 5%, statistically significant at the 10% confidence level. More pertinently, when isolating the questions related to the treatment information, the results reveal that the app increases relevant test scores by about 7.8%, significant at the 5% level (column (4)). In column (3), the training treatment also increases relevant test scores by 6.993%, significant at the 10% level. However, this result disappears when we add controls.

Adoption rates

Table 6 presents the effects of the treatments on the actual adoption of the recommended practices for DAP fertilizer application at planting (columns (1) and (2)), and the timed urea application at V6 and V10 (columns (3) and (4)). Again, both the app and the training are positive and statistically significant (at the 5% and 10% confidence levels, respectively). These results are consistent and robust across all specifications, columns (3)-(4). Farmers randomly assigned to the app treatment were 0.084 more likely to adopt the urea recommendations provided on their maize plots compared to farmers in the control group. The training increased the likelihood of adoption of urea recommendations by 0.13 on average compared to farmers in the control group. The IVR and the radio treatment do not have a statistically significant effect in inducing adoption of the recommended urea practices. Finally, none of the treatments are shown significant in inducing the application of DAP fertilizer only at planting (columns (1) and (2)).

4.1 Heterogeneous effects

Gender

We are also interested in whether the positive effect of the app and training persists across female and male-headed households. To do so, we estimate (2) below, where we interact a dummy variable on gender with the treatments. The dummy variable is called $female_{ic}$ and takes the value of 1 if the respondent is a female or 0 if the respondent is male.

$$(Yendline_{ic} - Ybaseline_{ic}) \ = \alpha_v + \beta_1 App_{ic} + \beta_2 IVR_{ic} + \beta_3 Radio_{ic}$$
$$+\beta_4 Training_{ic} + \beta_5 (App_{iv} * female_{ic}) + \beta_6 (IVR_{ic} * female_{ic}) +$$
$$\beta_7 (Radio_{ic} * female_{ic}) + \beta_8 (Training_{ic} * female_{ic}) + \gamma X_{ic} + \Delta\varepsilon_{ict} \qquad (2)$$

The effects of the treatments on agronomic test scores by gender are presented in columns (1) and (2) of table 7. The gender effects by treatments on adoption rates are displayed in column (3) for urea recommendations and (4) for DAP recommendations (table 7). We see that the app again has a positive and statistically significant effect on agronomic knowledge across all regressions (columns (1)-(3)), confirming our previous results. However, we find no statistically significant differential effect between male- and female-headed farmers (table 7, columns (1)-(2)).

When looking at the interaction terms in the regressions measuring change in adoption rates, on the other hand, it appears that women who listened to the radio treatment messages and women who attended the training treatment were approximately 0.09 more likely to adopt our recommendations on urea compared to men assigned to these two same treatments (table 7, column (3)). These relationships are significant at the 10% and 5% levels, respectively.

Regarding the adoption of the recommended practices for DAP fertilizer, as above, none of the interaction terms are statistically significant (table 7, column (4)).

Wealth

The same specification as in equation (2) is used to measure the treatment effects of the poorest and richest farmers, measured by estimating a general asset index. The effects on asset index are depicted in table 8, where the treatments are interacted with a dummy variable for farmers pertaining to the poorest income quartile (Yes=1), and table 9, interacting the treatments with a dummy variable denoting farmers in the richest income quartile (Yes=1). Looking at the regression in column (2) of table 8, the effect of the app treatment measured by the relevant agronomic knowledge percentage test scores are about 7.15% lower for the poorest farmers compared to the rest of farmers (above the 25th income quartile). The training appears to have favored learning among the richest farmers since returns to learning among the richest has a positive coefficient (table 9, column (2)) and a negative one among the poorest (table 8, column (2)), however these relationships are not statistically significant.

Regarding the income effects on the adoption of urea recommendations, the richest farmers in the app treatment were found to be 0.109 times less likely to split the application of urea as suggested, compared to the rest of the farmers who received the app and pertained to a lower income quartile (significant at the 10% level (table 9, column (3))). Similar effects are found for the training treatment, the richest farmers were on average about 0.149 times less likely to adopt urea recommendations as a result of attending the training compared to the rest of farmers who attended the training and were below the 75th income quartile (significant at the

10% confidence level, table 9, column (3)). Finally, the IVR treatment had a negative effect on inducing the adoption of the urea recommendations among the poorest farmers relative to farmers in higher income quartiles who also received this treatment. They were also found to be about 0.058 times less likely to adopt them at 10% significance (table 8, column (3)). Again, we see that both the app and training treatments have consistently positive and statistically significant effects in inducing adoption of urea recommendations (table 8 and 9, column (3)), but again there are no observable significant effects of the treatments by income on DAP application confirming the previously discussed findings.

5. Robustness Checks

As seen from columns (1) to (6) of table 10, similar magnitudes in the coefficients and statistical significance is found, confirming the previously presented results. The app appears to have significantly increased general and relevant agronomic test scores by 4.759% and 6.163%, respectively, at the 10% significance level (columns (2) and (4)). Farmers in the training (10% significance) and the app (5% significance) treatments were approximately 0.1 times more likely to adopt our urea recommendations than the control group (columns (5) and (6)). These results are also validated by the logit models (table 11), although the app treatment loses statistical significance when adding controls (column (2)). In columns (7) and (8) of table 10, it appears that farmers in the IVR treatment were 0.139 and 0.103 times more likely to apply the DAP recommendations, respectively, compared to farmers in the control group at the 10% significance level. However, this finding was not corroborated by the first difference estimations (table 6), so it is not deemed robust evidence of the impacts of the IVR.

Tables 12-14 present the robustness checks for the heterogeneous effects. Table 12, confirms that female farmers were about 0.08 to 0.09 times more likely to adopt the urea practices than men for those who received the radio and the training treatments at the 10% significance level (columns (5) and (6)). From table 13, the regressions for the poorest farmers confirmed that they achieved around 6.331% lower relevant agronomic test scores in the app treatment compared to wealthier farmers at the 10% level (column (4)). Concerning the effects for the richest farmers, columns (5) and (6) of table 14, confirms that richer farmers were less likely to follow the urea recommendations from the app treatment, however evidence that the training also discouraged adoption of the urea recommendations among the richest is only statistically significant at the 10% level in the regression with controls (column (6)) and appears negative but non-significant in the regression without controls (column (5)).

Regarding the initial outcome variable imbalance identified at baseline, it seemed that more farmers in the app and radio treatments were applying the urea recommendations prior to receiving the treatment compared to the rest of farmers in other treatments. It is therefore suspected that the coefficients for the app treatment are downward biased, since despite the positive imbalance, improvements in adoption rates were still observed from this treatment. The rates of prior exposure to phone apps at baseline are not significantly higher in the app and radio treatments compared to the rest of the treatments. This excludes the possibility of farmers being more responsive to this treatment due to higher exposure to this technology at baseline. There were also observed baseline differences in the general agronomic literacy test scores, however our main variable of interest was the relevant test score which was perfectly balanced across treatments and confirmed the beneficial effects of the app in fostering retention of new agricultural practices. These two results combined provide enough evidence of the success of the app treatment to encourage both learning and adoption of new farming practices in the Nepalese context.

6. Discussion

The app treatment was the most successful technology to foster knowledge and adoption of new agricultural practices among farmers. There are many reasons that can explain the success of this technology vis-a-vis the rest of the treatments and to better understand them a comparison of the features characterizing each treatment (table 15) will be discussed next.

Visual vs Auditive Features

Each treatment attributes are presented in table 15, the main difference that distinguishes the app and the training from the other two treatments (radio and IVR) is the visual component, which might have helped farmers better understand the information provided and feel more confident to adopt the recommendations. The app contained the same slides that were presented in the training and the training had an additional plot demonstration where farmers were shown how to implement the given advice on a sample plot. The radio and the IVR treatments, in contrast, only explained the information verbally, without providing any visual support to aid farmers' learning. The recommendations for urea fertilizer were deemed more complex than the DAP recommendations since they entailed an understanding of the technique to properly count the leaves and for farmers to be able to determine if the field was ready for the first dose of urea by randomly selecting five plants in their plots. In Cole and Fernando (2016), farmers were given a similar treatment to our IVR treatment, however instead of voice response messages, farmers had the option to call a landline to obtain agricultural advice. Their limitations were, however, similar: the authors also recognized that the information provided by this treatment was limited to what could be shared and explained by voice, since there was no visual feature. Indeed, 16% of farmers who did not follow the recommendations in the IVR treatment declared that it was because the instructions provided in the messages were not clear and easy enough to implement on their plots. This is evidence that perhaps auditive features are not good enough to explain complex practices but might be useful to explain simple practices like the DAP recommendations. Indeed, the robustness checks using cross sectional estimates for the DAP fertilizer recommendations presented in table 10_(column (4)) showed that farmers in the IVR treatment were about 0.103 times more likely to adopt the DAP fertilizer recommendations compared to farmers in the control at the 10% significance level. However, this is not robust evidence since these results were not validated by the first difference regressions presented in table 6. Additionally, exposure and usage of mobile phone technologies have been found to improve test scores and motivate adult students to learn more, which might explain why the app was more successful than the training to encourage learning and retention of the recommended practices. This was the case in the paper by Aker, Ksoll, and Lybbert (2012), who observed that introducing a mobile phone to an educational program for adults in Niger increased math test scores with statistical significance, compared to participants in villages who received the same educational program without the mobile phone component .

In person delivery

The second main difference that separates the app and the training from the rest of the treatments aside of the visual component is the in-person delivery that was used to share the app and training treatments with farmers. The radio and IVR treatments, were sent directly to farmers without meeting them in person. The information was perhaps not adopted when delivered through the radio and IVR channels because farmers were not given the possibility to interact with CIMMYT staff. Sulaiman V et al. (2012) discuss the reasons behind the ICT failure to encourage adoption in the Indian context and conclude that a horizontal interaction that connects both academics, with NGOs and farmers would be more efficient to foster adoption than simply sending the advice to farmers, since technologies should provide a means to interact and exchange information that goes two ways and not just in one direction. Although the app was shared without explaining the contents of the messages, farmers were still able to ask questions regarding how to use the technology and met a representative from the CIMMYT team, which might have induced more trust and motivation to follow the recommendations. Finally, the IVR treatment might not have worked because farmers did not understand the purpose of the calls. This was a very novel treatment, more than half of farmers in the whole sample (58.62%) had never received voice response calls according to baseline data. While delivering this novel treatment, there were questions in the IVR script meant to engage farmers. However, the data reveal that a lot of farmers did not use the keypad options to answer the questions during the calls or hung up before the end of the calls. To better understand the non-responsiveness of the IVR treatment, a few randomly selected farmers in this group were called by a CIMMYT representative to gather some feedback about this treatment around the end of June. Farmers stated to be confused since they did not know the person who was calling and the purpose of the calls. Most of them thought it was a real person speaking rather than a voice recording. Looking at the data on IVR for usage we see that most farmers picked up the phone calls and stayed on the line and even sometimes heard the messages several times on a row, however this was after several calls and attempts, and there is little evidence of their understanding of the information provided since the majority did not use the keypad to answer the questions asked during the calls. For a few subsets of farmers, a positive learning curve was observed, where farmers showed to have learnt from the voice response messages. It was observed that some of them were initially pressing the wrong keypad options to answer the questions and then started pressing the right option in subsequent calls. Perhaps this treatment would have worked if introduced by a person in charge of explaining the purpose of the calls prior to sending them, like was done with the app and the training treatments.

Timing is key

Finally, it is important to discuss the timing of fertilizer advice. When gathering feedback about the treatments, one of the main causes explaining lack of adoption of the recommended practices as declared by farmers, was that the information did not come at the appropriate time, despite having synchronized the information with farmers' planting dates. In this regard, the IVR and Radio treatment were the most challenging treatments, especially the radio since all farmers had planted at very different times and it was not possible to customize the messages individually. The information was broadcasted around the times that would suit a majority of farmers. The IVR treatment was customized by groups of farmers with similar planting dates however the main challenge for this treatment was that farmers were confused about the purpose of the calls and they did not always respond or stayed on the line to listen to the information. Some farmers only listened to the full message after the 3rd or 5th call or even stopped responding after receiving several calls without ever listening to the messages entirely. This limited the reach of the treatment, but also made it less likely that farmers would receive the information on time, since they had to be called several times before picking up. The training was the least flexible treatment, since it only occurred once, this is why we also provided a paper poster at the end of the training that allowed farmers to refer back to the training materials. The end line data revealed that as many as 70% of farmers in the training treatment referred to the poster around the relevant months for fertilizer application, from June-August. Farmers in the app treatment also consulted the information in the app around the time they needed to apply fertilizers in their plots (June-August). Timing was therefore an important determinant of usage in this study as well as for the study by Larochelle et al. (2017), where the authors found increased adoption from text message reminders but only for time-sensitive and complex practices. A potential reason why there was no significant observed effect from the treatments on the adoption of the DAP recommendations might have been that advice came too late and most farmers had already planted. However, it is also true that much more emphasis was put on the urea recommendations, deemed more complex, which might have also negatively affected the retention of the simple information that could have been quickly forgotten in the effort to remember the complex advice. Another aspect to consider is that urea is the more popular fertilizer used among farmers, while DAP fertilizer came second in our sample.

Heterogenous effects and the Digital divide?

While technological progress is an essential component to growth in developing countries, there are growing concerns about the possibility of a "digital divide," in which the poorest or least educated would face barriers in accessing the information through the new technologies. This hypothesis was tested using two dummy variables for whether farmers were in the poorest and richest quartiles, as well as a dummy variable reflecting the gender of the maize plot decision-maker (Female=1). It seems that females were more likely to adopt the urea recommendations from the radio and the training compared to men, which are the most traditional technologies. However, there are no significant effects from the treatments to discuss the impact of the app on women's understanding and adoption of the recommended practices. Evidence in Africa has proven that there are benefits of introducing mobile phones to women in agriculture. Female farmers were found to plant more diversified crops compared to men (Aker and Ksoll 2016). The present study sheds light on the app's positive impacts for the whole sample but did not find any statistically significant evidence to discuss the specific effects of the app treatment on women, which calls for further research.

Regarding income quartiles, it seems that farmers above the 75th quartile were less likely to adopt the new farming practices for urea in the app and training treatments, suggesting that the success of these treatments is driven by farmers in lower income quartiles. This might be because the advice was too simplistic for richer farmers who expected more detailed information and were already doing better off so seemed less interested in trying it. Indeed, the end line surveys revealed that the second main cause for not adopting the recommendations aside of poor timing, was that the information was not complex or detailed enough, this answer was found particularly prominent among wealthier farmers. This should not be interpreted as a rejection for the technologies, but rather a demand for more diversified agricultural information and advice coming from these ICT tools (especially from the smartphone app). Fu and Aker (2016) found similar results in India, in their research needy farmers gained more from the intervention than those who were better off since wealthier farmers had access to better services. In the present study the app was built to be straightforward to use and accessible to illiterate farmers (voice recordings available), and farmers in bottom income quartiles were still able to adopt the advice and benefited from the app despite not having an assistant guiding them to interpret the information provided by the app, like in the study by Fu and Aker (2016). This however does not exclude the possibility that assistance will not be needed if the app becomes more sophisticated and starts demanding more technical skills.

Regarding learning, it seems that the poorest retained less information form the app compared to other farmers in higher income quartiles when asked to recall the information post-harvest at the end line survey. However, the results still revealed that the app was effective in encouraging adoption of the recommended urea practices for this group. It is therefore suspected that retention rates for the poorest were lowest due to this groups' lower ability to recall the information when taking the agronomic test, but not due to a lack of understanding of the information provided. This is plausible since farmers only referred to the information at the time of fertilizer application between June-August, so it is possible that this was enough exposure to remember the information that was asked at the end of September, when the end line interviews were conducted.

Spillover effects

The end line surveys collected data on spillover effects coming from farmers' social networks and treated farmers were asked whether they had shared any of the recommendations provided with their friends, neighbors or relatives. It was found that approximately 36.22% of them did, which provides evidence of peer effects in information spreading and the potential for technologies to reach a vast majority at a lower cost. Most farmers (75.61%) accessed the app on their own smartphone but the remaining 24.39% of farmers accessed the information from the smartphone owned by a member of the household or neighbor, which provides evidence that the benefits extended even to non-smartphone holders.

7. Conclusion

The present study found evidence that technologies are not complete substitutes to face-to-face interactions; both the app and the trainings used intermediation in order to be shared with farmers. The success of the app among the technologies has important policy implications since it has proven that smartphone apps can add value to existing extension services. Our heterogeneous effects showed that richer farmers were less likely to adopt our recommendations on urea fertilizers from the app and the training compared to the rest of farmer. However, the end line surveys allowed understanding that it was not due to a lack of interest in the technology but rather a higher demand for more complex and detailed agricultural advice, particularly coming from wealthier farmers. Finally, female farmers seemed to have been more motivated to adopt the urea recommendations compared to men in the training and radio treatments, which are the most traditional technologies. However, no statistically significant evidence was found to comment on the specific effects of the app for this particular group, which calls for further investigation.

References

Aker, Jenny C. 2010. "Information from Markets Near and Far: Mobile Phones and Agricultural Markets in Niger." *American Economic Journal: Applied Economics* 2 (3):46-59. doi: 10.1257/app.2.3.46.

Aker, Jenny C. 2011. "Dial "A" for agriculture: A review of information and communication technologies for agricultural extension in developing countries." doi: 10.1111/j.1574-0862.2011.00545.x.

Aker, Jenny C., and Marcel Fafchamps. 2014. "Mobile Phone Coverage and Producer Markets: Evidence from West Africa". Working Paper.

Aker, Jenny C., and Christopher Ksoll. 2016. "Can mobile phones improve agricultural outcomes? Evidence from a randomized experiment in Niger." *Food Policy* 60:44-51. doi: 10.1016/j.foodpol.2015.03.006.

Aker, Jenny C., Christopher Ksoll, and Travis J. Lybbert. 2012. "Can Mobile Phones Improve Learning? Evidence from a Field Experiment in Niger." *American Economic Journal: Applied Economics* 4 (4):94-120. doi: 10.1257/app.4.4.94.

Aker, Jenny C., and Isaac M. Mbiti. 2010. "Mobile Phones and Economic Development in Africa." *Journal of Economic Perspectives* 24 (3):207-232. doi: 10.1257/jep.24.3.207.

APROSC (Agricultural Projects Services Centre). 1995. Nepal Agriculture Perspective Plan. Kathmandu, Nepal: Agricultural Projects Service Centre.

Baumüller, Heike. 2018. "The Little We Know: An Exploratory Literature Review on the Utility of Mobile Phone-Enabled Services for Smallholder Farmers." *Journal of International Development* 30 (1):134-154. doi: 10.1002/jid.3314.

Beaman, Lori, and Andrew Dillon. 2018. "Diffusion of agricultural information within social networks: Evidence on gender inequalities from Mali." *Journal of Development Economics* 133:147-161. doi: 10.1016/j.jdeveco.2018.01.009.

BenYishay, A., and A. M. Mobarak. 2018. "Social Learning and Incentives for Experimentation and Communication." *The Review of Economic Studies* 86 (3):976-1009. doi: 10.1093/restud/rdy039.

Casaburi, L., M. Kremer, S. Mullainathan, and R. Ramrattan. 2014. "Harnessing ICT to Increase Agricultural Production: Evidence from Kenya. " Working Paper.

CBS (Central Bureau of Statistics). 2014. National Household Survey 2012/2013. Kathmandu: National Planning Commission Secretariat, Government of Nepal.

Cole, Shawn A. , and A. Nilesh Fernando. 2016. "´Mobile'izing' Agricultural Advice: Technology Adoption, Diffusion and Sustainability." Working Paper. Harvard Business School.

Conley, Timothy G., and Christopher R. Udry. 2010. "Learning about a New Technology: Pineapple in Ghana." *American Economic Review* 100 (1):35-69. doi: 10.1257/aer.100.1.35.

Fafchamps, Marcel, and Bart Minten. 2012. "Impact of SMS-Based Agricultural Information on Indian Farmers." *The World Bank Economic Review* 26 (3):383-414. doi: 10.1093/wber/lhr056.

Fives, A., D. W. Russell, N. Kearns, R. Lyons, P. Eaton, J. Canavan, C. Devaney, and A. O'Brien. 2013. "The Role of Random Allocation in Randomized Controlled Trials: Distinguishing Selection Bias from Baseline Imbalance." *Journal of MultiDisciplinary Evaluation* 9 (20):33-42.

Foster, A. D., and M. Rosenzweig. 1995. "Learning by Doing and Learning from Others: Human Capital and Technical Change in Agriculture." *Journal of Political Economy* 103 (6):1176-1209.

Fu, Xiaolan, and Shaheen Aker. 2016. "The Impact of Mobile Phone Technology on Agricultural Extension Services Delivery: Evidence from India." *The Journal of Development Studies* 52 (11):1561-1576. doi: 10.1080/00220388.2016.1146700.

IPC. 2014. IPC Chronic Food Insecurity Situation in Nepal. Kathmandu: Integrated Foos Security Phase Classification, MoAd and FAO.

Jensen, R. 2007. "The digital provide: information (technology), market performance, and welfare in the South Indian fisheries sector." 122 (3):879-924. doi: 10.1162/qjec.122.3.879.

Larochelle, Catherine, Jeffrey Alwang, Elli Travis, Victor Hugo Barrera, and Juan Manuel Dominguez Andrade. 2017. "Did You Really Get the Message? Using Text Reminders to Stimulate Adoption of Agricultural Technologies." *The Journal of Development Studies* 55 (4):548-564. doi: 10.1080/00220388.2017.1393522.

Maertens, A., and C. B. Barrett. 2011. "Measuring Social Networks' Effects on Agricultural Technology Adoption." *American Journal of Agricultural Economics* 95 (2). doi: 10.2139/ssrn.2024678.

Moser, C, and A Felton. 2007. "Intergenerational Asset Accumulation and Poverty Reduction in Guayaquil Ecuador (1978-2004)." doi: 10.1093/acprof:oso/9780199557547.003.0005.

Nakasone, Eduardo, Maximo Torero, and Bart Minten. 2014. "The Power of Information: The ICT Revolution in Agricultural Development." *Annual Review of Resource Economics* 6 (1):533-550. doi: 10.1146/annurev-resource-100913-012714.

Pandey, S. 2013. "Role of Fertilizer in Transforming Agricultural Economy in Nepal." Unpublished report prepared for RESAKSS-ASIA, Washington, DC.

Paudel, J., and C. L. Crago. 2017. "Fertilizer Subsidy and Agricultural Productivity: Empirical Evidence from Nepal." Agricultural & Applied Economics Association, Chicago, Illinois, July 31- August 1.

Sahn, D, and D Stifel. 2000. "Poverty Comparisons over Time and across Countries in Africa." *World Development* 28 (12):2123-2155.

Sulaiman V, Rasheed, Andy Hall, N. J. Kalaivani, Kumuda Dorai, and T. S. Vamsidhar Reddy. 2012. "Necessary, But Not Sufficient: Critiquing the Role of Information and Communication Technology in Putting Knowledge into Use." *The Journal of Agricultural Education and Extension* 18 (4):331-346. doi: 10.1080/1389224x.2012.691782.

Takeshima, Hiroyuki, Rajendra Prasad Adhikari, Sabnam Shivakoti, Basu Dev Kaphle, and Anjani Kumar. 2017. "Heterogeneous returns to chemical fertilizer at the intensive margins: Insights from Nepal." *Food Policy* 69:97-109. doi: 10.1016/j.foodpol.2017.03.007.

United States Agency for International Development (USAID). 2012. Nepal Fertilizer Demand and Plant Nutrient Assessment. Washington, DC.

Figures

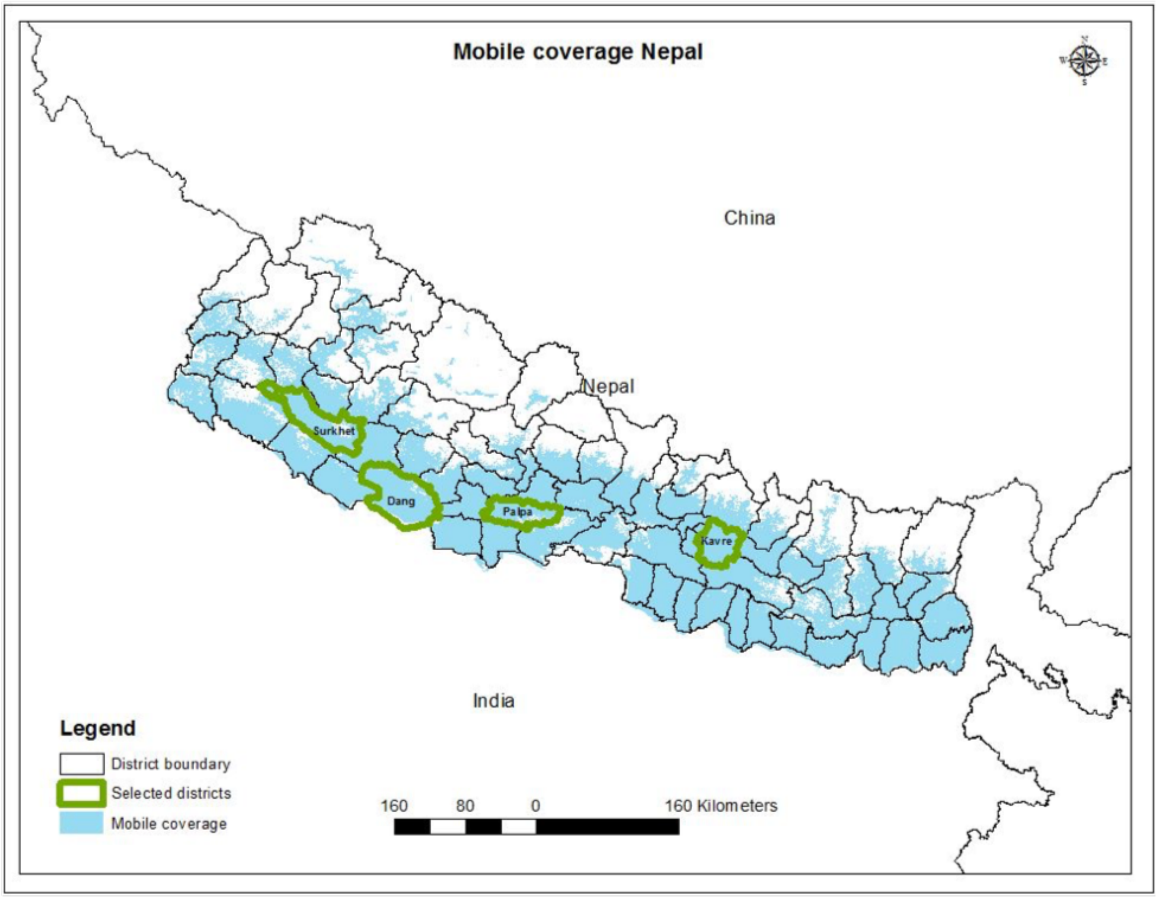

Figure 1: Mobile coverage Nepal

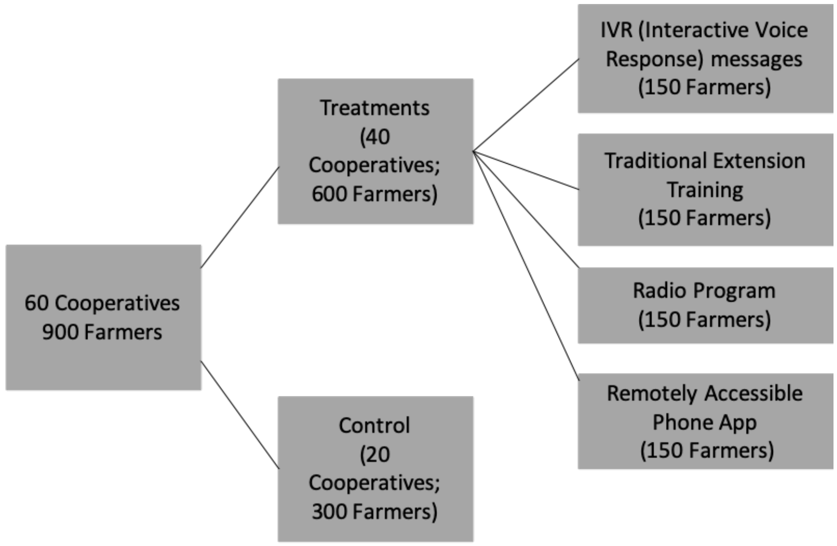

Figure 2: Treatment randomization

Tables

Table 1: Treatment Compliance Rates

Treatments	Farmers randomly assigned to the treatments (1)	Farmers who actually received the treatments (2)
1. IVR	150	124
2. Radio	150	110
3. Extension training	150	105
4. Phone App	150	106
TOTAL	600	445

Table 2: Balanced Test Table

Variables	Radio (1)	App (2)	Training (3)	IVR (4)	Constant (5)	N
Age of respondent	-0.8205	0.249	-3.3695**	-0.4575	44.8***	881
	(1.3378)	(1.3471)	(1.3229)	1.3378	(0.7697)	
High School and above (Yes=1)	0.1423***	0.0581	0.1062**	0.1194	0.311***	900
	(0.0484)	(0.0485)	(0.0483)	(0.0483)**	(0.0280)	
No education (Yes=1)	-0.0008	-0.0797*	-0.0952**	-0.0489	0.2542***	900
	(0.0411)	(0.0412)	(0.0411)	(0.0411)	(0.0238)	
Female Head (Yes=1)	-0.0208	-0.0797	-0.1482***	-0.0423	0.2542***	900
	(0.0402)	(0.0403)**	(0.0401)	(0.0401)	(0.0232)	
Political Participation (Yes=1)	0.0629	0.1448***	-0.0444	0.141***	0.1371***	900
	(0.0385)	(0.0386)	(0.0384)	(0.0384)	(0.0223)	
Dependency Ratio	-0.0447**	-0.0681***	-0.086***	-0.0469**	0.42***	885
	(0.0216)	(0.0217)	(0.0214)	(0.0216)	(0.0124)	
Married (Yes=1)	0.0204	0.0198	0.0143	0.0143	0.893***	900
	(0.0295)	(0.0296)	(0.0294)	(0.0294)	(0.0170)	
Fertilizer at planting (Yes=1)	-0.0102	0.0034	-0.1026***	0.0034	0.9966***	886
	(0.0141)	(0.0142)	(0.0140)	(0.0141)	(0.0081)	
Fertilizer after planting (Yes=1)	0.014	0.1253**	-0.0409	0.0208	0.5574***	886
	(0.0497)	(0.0500)	(0.0493)	(0.0497)	(0.0286)	
Irrigation (Yes=1)	0.0632**	0.1042***	0.0492*	0.0757**	0.0502***	900
	(0.0297)	(0.0298)	(0.0296)	(0.0296)	(0.0172)	
Hired Labour (Yes=1)	-0.0852*	-0.0082	-0.1148**	-0.0287	0.5518***	900
	(0.0500)	(0.0501)	(0.0498)	(0.0498)	(0.0289)	
Agro machinery(Yes=1)	0.0852*	0.1894***	0.1544***	-0.0707	0.4548***	900
	(0.0493)	(0.0494)	(0.0492)	(0.0492)	(0.0285)	
Smartphones owned by the household	0.0966	0.1846	0.0032	-0.0895	2.01***	900
	(0.1201)	(0.1204)	(0.1198)	(0.1198)	(0.0694)	
Maize yields from main maize plot 2017 (kg/ha)	1447.155	1095.414	193.85	-256.131	3530.826**	898
	(1.93)	(1.46)	(0.26)	(0.34)	(8.19)	
Area main maize plot 2017	-0.031	0.045	0.056	0.014	0.565**	900
	(0.77)	(1.09)	(1.36)	(0.34)	(23.85)	
Land ownership (ha)	-0.0318	0.0397	0.0123	-0.0541	0.5694***	886
	(0.0425)	(0.0427)	(0.0421)	(0.0425)	(0.0245)	
Wealth asset index	0.1401	-0.22**	0.0023	0.1538	-0.0076	886
	(0.1005)	(0.1010)	(0.0996)	(0.1005)	(0.0579)	
Durables index	-0.0432	-0.3518***	-0.079	0.1236	0.0653	886
	(0.0998)	(0.1002)	(0.0989)	(0.0998)	(0.0575)	
Livestock index	-0.218**	-0.0641	0.1175	-0.0596	0.0389	886
	(0.1008)	(0.1012)	(0.0999)	(0.1008)	(0.0581)	
Productive index	-0.171*	0.0038	-0.1226	-0.1434	0.0694	886
	(0.1010)	(0.1015)	(0.1001)	(0.101)	(0.0582)	

*p<0.1; **p<0.05; *** p<0.01

Standard errors in brackets below coefficients.

Table 3: Balanced Test for Outcome Variables

Variables	Radio (1)	App (2)	Training (3)	IVR (4)	Constant (5)
Relevant agronomic score (%)	1.4877	1.881	-0.537	2.5081	35.3604***
	(2.0233)	(2.0326)	(2.0053)	(2.0233)	(1.1655)
General agronomic score (%)	1.5285	3.3322**	1.9477	1.7759	24.6929***
	(1.5407)	(1.5478)	(1.527)	(1.5407)	(0.8875)
urea applied at v6 and v10 (Yes=1)	0.0273*	0.0691***	-0.0068	0	0.0068
	(0.0144)	(0.0145)	(0.0143)	(0.0144)	(0.0083)
DAP applied at planting (Yes=1)	0.0179	-0.0009	-0.0588*	0.0587*	0.125***
	(0.0336)	(0.0337)	(0.0333)	(0.0336)	(0.0193)

*p<0.1; **p<0.05; *** p<0.01

Standard errors in brackets below coefficients.

Table 4: Number of Farmers who applied urea at V6 and V10 Prior to Receiving the Treatments

Outcome Variable	Treatments				
	Radio	App	Training	IVR	Control
Farmers who applied urea at v6 and v10 at baseline	5	11	0	1	2

Table 5: Impact of Treatments on Agricultural Knowledge

Explanatory Variables	General Agronomic Literacy Test Scores		Relevant Agronomic Literacy Test Scores	
	(1)	(2)	(3)	(4)
Phone App	4.143	**5.023***	**6.619***	**7.841****
	(2.206)	**(2.161)**	**(3.029)**	**(2.899)**
Radio	2.132	1.32	2.435	1.375
	(2.054)	(1.962)	(2.924)	(3.025)
IVR	-0.678	-0.466	-4.864	-4.847
	(2.125)	(2.201)	(2.937)	(2.82)
Training	4.515	3.926	**6.993***	6.261
	(2.767)	(2.968)	**(3.343)**	(3.56)
No educ (Yes=1)		1.505		2.069
		(1.58)		(2.19)
High school and above (Yes=1)		1.194		1.631
		(1.21)		(1.857)
Female head (Yes=1)		0.127		-0.423
		(1.581)		(2.097)
Political (Yes=1)		-0.774		-3.188
		(1.778)		(2.582)
Fertilizer was applied at planting 2017 (Yes=1)		-4.768		1.043
		(3.12)		(4.768)
Fertilizer was applied after planting 2017 (Yes=1)		**-3.749***		-5.044
		(1.709)		(2.539)
Dependency_ratio		**-6.077***		**-9.996***
		(2.772)		**(4.180)**
Assets (full)		1.415		1.156
		(0.973)		(1.208)
Age_respondent		0.099		0.109
		(0.05)		(0.072)
Constant	2.687	6.82	0.301	0.85
	(1.368)	(4.217)	(1.769)	(5.858)
Controls	NO	YES	NO	YES
Clustered se at Cooperative level	YES	YES	YES	YES
Village Fixed effects	YES	YES	YES	YES
R2	0.010	0.03	0.02	0.04
N	886	880	886	880

* p<0.1, ** p<0.05, *** p<0.01.

Figures in brackets are standard errors and z-scores.

Table 6: Impact of Treatments on Adoption Rates

Explanatory Variables	DAP at planting		Urea at v6 and v10	
	(1)	(2)	(3)	(4)
Phone App	0.053	0.016	**0.079****	**0.084****
	(0.041)	(0.04)	**(0.026)**	**(0.029)**
Radio	0.021	0.007	0.04	0.055
	(0.044)	(0.046)	(0.033)	(0.035)
IVR	0.065	0.04	0.047	0.041
	(0.052)	(0.047)	(0.04)	(0.04)
Training	0.059	0.035	**0.12***	**0.13***
	(0.065)	(0.052)	**(0.046)**	**(0.051)**
No educ (Yes=1)		-0.004		-0.023
		(0.03)		(0.025)
High school and above (Yes=1)		-0.014		-0.035
		(0.03)		(0.026)
Female head (Yes=1)		-0.028		-0.026
		(0.025)		(0.017)
Political Participation (Yes=1)		0.044		-0.006
		(0.029)		(0.023)
Fertilizer was applied at planting 2017 (Yes=1)		-0.046		**0.159****
		(0.076)		**(0.047)**
Fertilizer was applied after planting 2017 (Yes=1)		**0.078***		0.025
		(0.033)		(0.025)
Dependency_ratio		0.011		-0.044
		(0.043)		(0.042)
Comprehensive asset index		**-0.046****		0.021
		(0.015)		(0.015)
Age_respondent		-0.001		0
		(0.001)		(0.001)
Irrigation (Yes=1)		**0.11***		0.058
		(0.043)		(0.035)
Agro Machinery (Yes=1)		0.039		-0.019
		(0.029)		(0.023)
Hired labour (Yes=1)		0.047		0.002
		(0.031)		(0.018)
Constant	**0.075****	0.072	0.014	-0.094
	(0.028)	(0.078)	(0.016)	(0.061)
Controls	NO	YES	NO	YES
Clustered SE at Cooperative level	YES	YES	YES	YES
Village Fixed Effects	YES	YES	YES	YES
Pseudo R2	0.010	0.060	0.020	0.050
N	886	880	886	880

* p<0.1, ** p<0.05, *** p<0.01.
Figures in brackets are standard errors and z-scores.

Table 7: Impact of Treatments by Gender (Female; Yes=1)

Explanatory Variables	**Dependent Variables**			
	General Agronomic Literacy (1)	**Relevant Agronomic Literacy (2)**	**Urea at v6 and v10 (3)**	**DAP at planting (4)**
Phone App	**5.762***	**9.066****	**0.109****	0.01
	(2.439)	**(3.182)**	**(0.036)**	(0.048)
Radio	0.379	0.521	0.013	0.043
	(2.541)	(3.267)	(0.036)	(0.054)
IVR	0.293	-3.581	0.06	0.082
	(2.66)	(3.997)	(0.046)	(0.06)
Training	4.434	7.144	**0.108***	0.036
	(3.246)	(3.616)	**(0.045)**	(0.064)
App*Female	-1.641	-2.759	-0.048	0.024
	(2.249)	(4.313)	(0.036)	(0.047)
Radio*Female	1.83	1.757	**0.094***	-0.055
	(2.568)	(3.169)	**(0.038)**	(0.045)
IVR*Female	-1.724	-2.884	-0.038	-0.104
	(4.831)	(7.046)	(0.039)	(0.065)
Training*Female	-1.528	-2.651	**0.096****	0.013
	(3.536)	(4.821)	**(0.036)**	(0.067)
No educ (Yes=1)	1.673	2.434	-0.028	0.005
	(1.692)	(2.377)	(0.025)	(0.029)
High school and above (Yes=1)	1.074	1.384	-0.032	-0.02
	(1.13)	(1.764)	(0.027)	(0.032)
Female head (Yes=1)	0.263	-0.097	-0.031	-0.02
	(1.651)	(2.251)	(0.018)	-(0.025)
Political Participation (Yes=1)	-0.78	-3.214	-0.009	0.043
	(1.776)	(2.586)	(0.022)	(0.029)
Fertilizer was applied at planting 2017 (Yes=1)	-5.076	0.455	**0.182****	-0.045
	(3.389)	(5.034)	**(0.052)**	(0.087)
Fertilizer was applied after planting 2017 (Yes=1)	**-3.746***	-5.025	0.021	**0.076***
	(1.701)	(2.543)	(0.025)	**(0.034)**
Dependency_ratio	**-6.003***	**-9.877***	-0.042	0.01
	(2.811)	**(4.181)**	(0.043)	(0.042)
Comprehensive asset index	1.401	1.133	0.02	**-0.045****
	(0.981)	(1.242)	(0.015)	**(0.015)**
Age_respondent	0.09	0.09	0	-0.001
	(0.059)	(0.083)	(0.001)	(0.001)
Irrigation (Yes=1)			0.054	**0.113***
			(0.034)	**(0.043)**
Agro Machinery (Yes=1)			-0.02	0.042
			(0.024)	(0.029)
Hired labour (Yes=1)			0.005	0.046
			(0.018)	(0.031)
Constant	7.427	2.073	-0.13	0.082
	(4.718)	(6.403)	(0.066)	(0.088)
Clustered SE at Cooperative level	YES	YES	YES	YES
Village Fixed Effects	YES	YES	YES	YES
Pseudo R2	0.03	0.04	0.06	0.06
N	880	880	880	880

* p<0.1, ** p<0.05, *** p<0.01.
Figures in brackets are standard errors and z-scores.

Table 8: Impact of Treatments by Poorest Income Quartile (Poorest; Yes=1)

Explanatory Variables	**Dependent Variables**			
	General Agronomic Literacy (1)	**Relevant Agronomic Literacy (2)**	**Urea at v6 and v10 (3)**	**DAP at planting (4)**
Phone App	**5.13***	**9.796****	**0.075***	0.047
	(2.459)	**(3.213)**	**(0.032)**	(0.046)
Radio	1.667	1.65	0.059	0.006
	(2.269)	(3.166)	(0.039)	(0.048)
IVR	-0.01	-5.412	0.056	0.048
	(2.539)	(3.191)	(0.039)	(0.053)
Training	5.037	7.283	**0.141***	0.04
	(3.76)	(4.666)	**(0.059)**	(0.055)
App*Poorest	-0.939	**-7.15***	0.019	-0.129
	(3.725)	**(2.899)**	(0.054)	(0.07)
Radio*Poorest	-1.314	-1.274	-0.018	-0.028
	(4.435)	(5.032)	(0.054)	(0.047)
IVR*Poorest	-2.029	1.461	**-0.058***	-0.05
	(4.261)	(5.945)	**(0.029)**	(0.077)
Training*Poorest	-4.21	-3.713	-0.044	-0.026
	(4.405)	(5.833)	(0.047)	(0.056)
No educ (Yes=1)	1.49	2.256	-0.025	-0.003
	(1.576)	(2.178)	(0.025)	(0.03)
High school and above (Yes=1)	1.344	1.867	-0.034	-0.01
	(1.233)	(1.931)	(0.027)	(0.031)
Female head (Yes=1)	0.188	-0.344	-0.025	-0.027
	(1.581)	(2.104)	(0.017)	(0.025)
Political Participation (Yes=1)	-0.731	-2.979	-0.006	0.049
	(1.766)	(2.599)	(0.023)	(0.029)
Fertilizer was applied at planting 2017 (Yes=1)	-4.758	0.834	**0.162****	-0.045
	(3.078)	(4.69)	**(0.047)**	(0.078)
Fertilizer was applied after planting 2017 (Yes=1)	**-3.768***	**-5.226***	0.026	**0.075***
	(1.695)	**(2.522)**	(0.025)	**(0.033)**
Dependency_ratio	**-6.038***	**-9.583***	-0.046	0.016
	(2.768)	**(4.210)**	(0.043)	(0.042)
Comprehensive asset index	0.92	0.467	0.016	**-0.059****
	(1.177)	(1.486)	(0.016)	**(0.018)**
Age_respondent	**0.103***	0.11	0	-0.001
	(0.051)	(0.072)	(0.001)	(0.001)
Irrigation (Yes=1)			0.062	**0.109***
			(0.035)	**(0.041)**
Agro Machinery (Yes=1)			-0.02	0.043
			(0.023)	(0.029)
Hired labour (Yes=1)			0.003	0.045
			(0.017)	(0.031)
Constant	6.594	0.822	-0.1	0.07
	(4.278)	(5.917)	(0.061)	(0.077)
Clustered SE at Cooperative level	YES	YES	YES	YES
Village Fixed Effects	YES	YES	YES	YES
Pseudo R2	0.03	0.05	0.05	0.06
N	880	880	880	880

* p<0.1, ** p<0.05, *** p<0.01.
Figures in brackets are standard errors and z-scores.

Table 9: Impact of Treatments by Richest Income Quartile (Richest; Yes=1)

Explanatory Variables	**Dependent Variables**			
	General Agronomic Literacy (1)	**Relevant Agronomic Literacy (2)**	**Urea at v6 and v10 (3)**	**DAP at planting (4)**
Phone App	**5.009***	**8.858****	**0.103****	0.013
	(2.240)	**(2.919)**	**(0.031)**	(0.043)
Radio	1.263	2.148	0.048	0.027
	(2.047)	(2.855)	(0.035)	(0.049)
IVR	-1.948	-6.443	0.053	0.036
	(2.657)	(3.612)	(0.049)	(0.041)
Training	3.579	5.769	**0.179****	0.046
	(3.803)	(4.88)	**(0.059)**	(0.062)
App*Richest	-2.744	-10.677	**-0.109****	0.012
	(5.064)	(8.535)	**(0.033)**	(0.046)
Radio*Richest	-1.551	-6.174	0.003	-0.101
	(3.466)	(6.193)	(0.033)	(0.11)
IVR*Richest	4.691	5.129	-0.039	0.008
	(3.901)	(5.208)	(0.044)	(0.103)
Training*Richest	0.882	1.215	**-0.149***	-0.044
	(4.949)	(6.749)	**(0.060)**	(0.083)
No educ (Yes=1)	1.336	1.81	-0.023	-0.006
	(1.592)	(2.199)	(0.024)	(0.031)
High school and above (Yes=1)	1.175	1.521	-0.04	-0.016
	(1.211)	(1.824)	(0.026)	(0.03)
Female head (Yes=1)	0.121	-0.377	-0.028	-0.026
	(1.602)	(2.117)	(0.017)	(0.025)
Political Participation (Yes=1)	-0.813	-3.237	-0.005	0.047
	(1.764)	(2.555)	(0.023)	(0.029)
Fertilizer was applied at planting 2017 (Yes=1)	-4.478	1.421	**0.163****	-0.041
	(3.198)	(4.888)	**(0.046)**	(0.077)
Fertilizer was applied after planting 2017 (Yes=1)	**-3.631***	-4.842	0.028	**0.08***
	(1.728)	(2.539)	(0.024)	**(0.032)**
Dependency_ratio	**-6.014***	**-9.849***	-0.037	0.013
	(2.736)	**(4.180)**	(0.043)	(0.043)
Comprehensive asset index	1.305	1.499	**0.036***	**-0.038***
	(1.142)	(1.356)	**(0.018)**	**(0.017**
Age_respondent	0.107	0.121	-0.001	-0.001
	(0.052)*	(0.074)	(0.001)	(0.001)
Irrigation (Yes=1)			0.058	**0.112***
			(0.034)	**(0.043**
Agro Machinery (Yes=1)			-0.02	0.038
			(0.024)	(0.029)
Hired labour (Yes=1)			0.002	0.047
			(0.017)	(0.031)
Constant	6.293	0.108	-0.094	0.069
	(4.305)	(5.948)	(0.059)	(0.078)
Clustered SE at Cooperative level	YES	YES	YES	YES
Village Fixed Effects	YES	YES	YES	YES
Pseudo R2	0.03	0.05	0.06	0.06
N	880	880	880	880

* p<0.1, ** p<0.05, *** p<0.01.
Figures in brackets are standard errors and z-scores.

Table 10: Robustness Checks

Explanatory Variables	Dependent Variables (cross sectional estimates)							
	General Agronomic Literacy		Relevant Agronomic Literacy		Urea at v6 and v10		DAP at planting	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Phone App	**5.984***	**4.759***	**6.876***	**6.163***	**0.098****	**0.102****	0.022	-0.012
	(2.457)	**(2.248)**	**(2.733)**	**(2.553)**	**(0.03)**	**(0.034)**	(0.051)	(0.048)
Radio	0.537	-1.14	0.041	-1.335	0.039	0.054	0.049	0.033
	(2.753)	(2.21)	(3.014)	(2.923)	(0.033)	(0.036)	(0.062)	(0.057)
IVR	1.884	-0.277	-0.445	-2.229	0.048	0.044	**0.139***	**0.103***
	(2.541)	(2.334)	(3.038)	(2.911)	(0.04)	(0.04)	**(0.057)**	**(0.048)**
Training	4.251	1.585	3.859	1.631	**0.12****	**0.131***	0.078	0.05
	(3.346)	(3.376)	(3.256)	(3.435)	**(0.045)**	**(0.049)**	(0.055)	(0.045)
No educ (Yes=1)		**-4.578****		-3.379		-0.027		-0.034
		(1.385)		(1.817)		(0.025)		(0.029)
High school and above (Yes=1)		**6.545****		**4.612****		-0.042		0.019
		(1.048)		**(1.405)**		(0.026)		(0.033)
Female head (Yes=1)		-1.998		-2.844		-0.029		0.007
		(1.44)		(1.718)		(0.018)		(0.022)
Political Participation (Yes=1)		0.401		0.03		-0.003		0.012
		(1.308)		(1.415)		(0.024)		(0.031)
Fertilizer was applied at planting 2017 (Yes=1)		-6.048		-6.551		**0.16****		-0.038
		(3.782)		(3.743)		**(0.046)**		(0.068)
Fertilizer was applied after planting 2017 (Yes=1)		1.339		3.148		0.024		**0.134****
		(1.591)		(1.824)		(0.025)		(0.04)
Dependency_ratio		**-6.895***		**-6.763***		-0.037		-0.002
		(2.613)		**(2.866)**		(0.045)		(0.056)
Comprehensive asset index		-0.795		0.317		0.024		-0.035
		(0.871)		(1.039)		(0.015)		(0.019)
Age_respondent		**0.162****		**0.162***		-0.001		0.001
		(0.053)		**(0.071)**		(0.001)		(0.001)
Irrigation (Yes=1)						0.059		**0.142****
						(0.035)		**(0.042)**
Agro Machinery (Yes=1)						-0.013		0.02
						(0.025)		(0.029)
Hired labour (Yes=1)						-0.001		0.039
						(0.018)		(0.036)
Constant	**28.389****	**29.169****	**36.696****	**37.364****	0.013	-0.091	**0.115****	0.02
	(1.702)	**(5.205)**	**(1.812)**	**(5.582)**	(0.017)	(0.06)	**(0.036)**	(0.094)
Control	NO	YES	NO	YES	NO	YES	NO	YES
Clustered SE at Cooperative level	YES	YES	YES	YES	YES	YES	YES	YES
Village Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
Pseudo R2	0.01	0.09	0.02	0.06	0.03	0.05	0.01	0.07
N	886	880	886	880	886	880	886	880

* p<0.1, ** p<0.05, *** p<0.01.

Figures in brackets are standard errors and z-scores.

Table 11: Robustness Checks for the Binary Variables Measuring Adoption Rates (Logit Estimates)

Explanatory Variables	Binary Dependent Variables (logit estimates)			
	Urea at v6 and v10		DAP at planting	
	(1)	(2)	(3)	(4)
Phone App	**1.057***	0.794	0.466	0.194
	(0.496)	(0.535)	(0.48)	(0.512)
Radio	0.467	0.428	0.265	0.095
	(0.629)	(0.579)	(0.474)	(0.417)
IVR	0.467	0.372	0.048	-0.095
	(0.794)	(0.766)	(0.498)	(0.502)
Training	**1.583****	**1.751****	0.299	0.106
	(0.547)	**(0.489)**	(0.613)	(0.531)
No educ (Yes=1)		-0.251		-0.278
		(0.389)		(0.408)
High school and above (Yes=1)		-0.667		-0.112
		(0.446)		(0.316)
Female head (Yes=1)		-0.662		-0.392
		(0.432)		(0.329)
Political Participation (Yes=1)		-0.191		0.46
		(0.466)		(0.256)
Fertilizer was applied at planting 2017 (Yes=1)		**1.873***		0.373
		(0.872)		(0.929)
Fertilizer was applied after planting 2017 (Yes=1)		**1.465***		-0.043
		(0.631)		(0.25)
Dependency_ratio		-0.92		-0.116
		(0.789)		(0.411)
Comprehensive asset index		0.028		0.104
		(0.194)		(0.16)
Age_respondent		-0.008		-0.012
		(0.011)		(0.009)
Irrigation (Yes=1)		**0.883***		**1.078****
		(0.423)		**(0.276)**
Agro Machinery (Yes=1)		-0.028		0.42
		(0.389)		(0.361)
Hired labour (Yes=1)		0.383		-0.182
		(0.281)		(0.334)
Constant	**-3.462****	**-5.509****	**-2.299****	**-2.165***
	(0.411)	**(1.243)**	**(0.266)**	**(0.979)**
Control	NO	YES	NO	YES
Clustered SE at Cooperative level	YES	YES	YES	YES
Village Fixed Effects	NO	NO	NO	NO
Pseudo R2	0.0442	0.1203	0.0044	0.0451
N	886	880	886	880

* p<0.1, ** p<0.05, *** p<0.01.

Figures in brackets are standard errors and z-scores.

Table 12: Robustness Checks on the Impact of Treatments by Gender (Female; Yes=1)

Explanatory Variables	Dependent Variables (cross sectional estimates)							
	General Agronomic Literacy		Relevant Agronomic Literacy		Urea at v6 and v10		DAP at planting	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Phone App	8.131**	5.499	8.251**	6.04*	0.126**	0.124**	0.053	0.015
	(2.717)	(2.778)	(2.975)	(2.929)	(0.032)	(0.035)	(0.06)	(0.058)
Radio	3.768	-0.438	2.231	-1.552	0.003	0.013	0.092	0.062
	(2.742)	(2.433)	(3.035)	(3.128)	(0.034)	(0.037)	(0.08)	(0.079)
IVR	5.419*	1.27	2.849	-0.801	0.068	0.063	0.147*	0.1
	(2.582)	(2.533)	(3.384)	(3.349)	(0.048)	(0.047)	(0.06)	(0.057)
Training	5.907	2.384	4.436	1.451	0.1*	0.108*	0.083	0.056
	(3.623)	(3.674)	(3.355)	(3.599)	(0.039)	(0.044)	(0.059)	(0.051)
App*Female	-5.277*	-1.556	-3.056	0.751	-0.057	-0.041	-0.079	-0.068
	(2.595)	(3.256)	(2.774)	(3.446)	(0.039)	(0.042)	(0.051)	(0.054)
Radio*Female	-5.37*	-0.999	-3.226	0.835	0.08*	0.092*	-0.074	-0.052
	(2.114)	(2.622)	(2.573)	(2.876)	(0.035)	(0.038)	(0.062)	(0.061)
IVR*Female	-9.347**	-3.65	-8.499**	-3.459	-0.04	-0.04	-0.023	0.01
	(2.146)	(2.329)	(2.961)	(3.204)	(0.037)	(0.039)	(0.078)	(0.075)
Training*Female	-5.247	-2.241	-1.307	1.174	0.082*	0.094*	-0.012	-0.016
	(3.063)	(3.237)	(2.84)	(3.01)	(0.033)	(0.036)	(0.041)	(0.055)
No educ (Yes=1)		-4.074**		-3.268		-0.031		-0.028
		(1.525)		(1.955)		(0.026)		(0.029)
High school and above (Yes=1)		6.208**		4.506**		-0.039		0.015
		(1.058)		(1.421)		(0.026)		(0.033)
Female head (Yes=1)		-1.538		-2.828		-0.035		0.016
		(1.536)		(1.86)		(0.019)		(0.022)
Political Participation (Yes=1)		0.359		0.009		-0.005		0.01
		(1.29)		(1.401)		(0.024)		(0.031)
Fertilizer was applied at planting 2017 (Yes=1)		-6.647		-6.273		0.184**		-0.045
		(3.902)		(4.039)		(0.051)		(0.075)
Fertilizer was applied after planting 2017 (Yes=1)		1.353		3.045		0.02		0.136**
		(1.568)		(1.829)		(0.025)		(0.04)
Dependency_ratio		-6.827*		-6.786*		-0.035		0
		(2.665)		(2.935)		(0.045)		(0.055)
Comprehensive asset index		-0.797		0.338		0.023		-0.036
		(0.867)		(1.048)		(0.015)		(0.019)
Age_respondent		0.14*		0.16*		0		0
		(0.062)		(0.079)		(0.001)		(0.001)
Irrigation (Yes=1)						0.055		0.139**
						(0.034)		(0.042)
Agro Machinery (Yes=1)						-0.013		0.022
						(0.025)		(0.029)
Hired labour (Yes=1)						0.002		0.04
						(0.018)		(0.036)
Constant	28.363**	30.575**	36.575**	37.124**	0.009	-0.126	0.115**	0.038
	(1.661)	(5.532)	(1.806)	(6.004)	(0.017)	(0.066)	(0.036)	(0.101)
Controls	NO	YES	NO	YES	NO	YES	NO	YES
Clustered SE at Cooperative level	YES	YES	YES	YES	YES	YES	YES	YES
Village Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
Pseudo R2	0.04	0.09	0.02	0.06	0.04	0.07	0.02	0.07
N	886	880	886	880	886	880	886	880

* p<0.1, ** p<0.05, *** p<0.01.

Figures in brackets are standard errors and z-scores.

Table 13: Robustness Checks on the Impact of Treatments by Poorest Income Quartile (Poorest; Yes=1)

Explanatory Variables	Dependent Variables (cross sectional estimates)							
	General Agronomic Literacy		Relevant Agronomic Literacy		Urea at v6 and v10		DAP at planting	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Phone App	**6.217***	**5.569***	**8.934****	**8.184****	**0.1****	**0.09***	0.035	0.011
	(2.581)	**(2.476)**	**(2.921)**	**(2.773)**	**(0.03)**	**(0.034)**	(0.058)	(0.052)
Radio	-1.293	-1.699	-2.12	-2.797	0.054	0.058	0.006	0.01
	(3.031)	(2.6)	(3.114)	(3.024)	(0.037)	(0.039)	(0.058)	(0.054)
IVR	0.03	-1.193	-2.549	-3.798	0.066	0.058	**0.154***	**0.14***
	(2.521)	(2.475)	(3.092)	(3.077)	(0.04)	(0.04)	**(0.073)**	**(0.061)**
Training	2.502	1.033	3.33	1.735	**0.141***	**0.141***	0.058	0.06
	(3.967)	(4.146)	(4.079)	(4.45)	**(0.058)**	**(0.058)**	(0.057)	(0.048)
App*Poorest	-0.486	-2.234	**-6.625****	**-6.331***	-0.01	0.035	-0.058	-0.118
	(3.217)	(3.549)	**(2.404)**	**(2.767)**	(0.055)	(0.063)	(0.06)	(0.065)
Radio*Poorest	6.884	2.253	**8.353****	5.899	-0.052	-0.014	**0.134***	0.039
	(3.537)	(3.76)	**(3.031)**	(3.279)	(0.049)	(0.054)	**(0.067)**	(0.076)
IVR*Poorest	**6.863***	3.532	7.403	5.764	**-0.065***	-0.053	-0.063	-0.163
	(3.408)	(3.174)	(5.293)	(5.263)	**(0.025)**	(0.03)	(0.1)	(0.109)
Training*Poorest	5.777	2.151	1.349	-0.431	-0.074	-0.041	0.05	-0.063
	(4.278)	(4.613)	(4.728)	(5.404)	(0.056)	(0.047)	(0.044)	(0.053)
No educ (Yes=1)		**-4.443****		-3.051		-0.029		-0.034
		(1.376)		(1.822)		(0.025)		(0.029)
High school and above (Yes=1)		**6.465****		**4.55****		-0.041		0.021
		(1.118)		**(1.444)**		(0.027)		(0.032)
Female head (Yes=1)		-2.015		-2.796		-0.029		0.01
		(1.459)		(1.727)		(0.018)		(0.022)
Political Participation (Yes=1)		0.447		0.194		-0.004		0.017
		(1.307)		(1.379)		(0.025)		(0.031)
Fertilizer was applied at planting 2017 (Yes=1)		-6.248		-7.081		**0.164****		-0.033
		(3.777)		(3.798)		**(0.046)**		(0.071)
Fertilizer was applied after planting 2017 (Yes=1)		1.28		3		0.025		**0.133****
		(1.578)		(1.825)		(0.025)		**(0.04)**
Dependency_ratio		**-6.761***		**-6.454***		-0.039		-0.001
		(2.599)		**(2.895)**		(0.045)		(0.054)
Comprehensive asset index		-0.51		0.48		0.02		**-0.052***
		(1.03)		(1.288)		(0.016)		**(0.025)**
Age_respondent		**0.158****		**0.157***		-0.001		0.001
		(0.053)		**(0.07)**		(0.001)		(0.001)
Irrigation (Yes=1)						0.063		**0.147****
						(0.035)		**(0.043)**
Agro Machinery (Yes=1)						-0.014		0.021
						(0.024)		(0.029)
Hired labour (Yes=1)						0.001		0.04
						(0.017)		(0.036)
Constant	**28.471****	**29.513****	**36.825****	**38.049****	0.013	-0.096	**0.12****	0.015
	(1.635)	**(5.261)**	**(1.792)**	**(5.678)**	(0.018)	(0.06)	**(0.036)**	(0.092)
Controls	NO	YES	NO	YES	NO	YES	NO	YES
Clustered SE at Cooperative level	YES	YES	YES	YES	YES	YES	YES	YES
Village Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
Pseudo R2	0.02	0.09	0.03	0.07	0.03	0.06	0.02	0.08
N	886	880	886	880	886	880	886	880

* p<0.1, ** p<0.05, *** p<0.01.
Figures in brackets are standard errors and z-scores.

Table 14: Robustness Checks on the Impact of Treatments by Richest Income Quartile (Richest; Yes=1)

Explanatory Variables	Dependent Variables (cross sectional estimates)							
	General Agronomic Literacy		Relevant Agronomic Literacy		Urea at v6 and v10		DAP at planting	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Phone App	**6.966***	**5.391***	**7.782***	**7.208***	**0.109****	**0.125****	0.034	-0.007
	(2.722)	**(2.522)**	**(3.11)**	**(2.943)**	**(0.032)**	**(0.036)**	(0.05)	(0.049)
Radio	1.487	0.394	1.834	0.714	0.02	0.047	0.073	0.051
	-(2.659)	-(2.327)	(2.904)	(2.786)	(0.032)	(0.035)	(0.066)	(0.059)
IVR	3.218	0.129	0.837	-1.237	0.049	0.058	**0.163****	**0.106****
	-(2.433)	(2.374)	(2.99)	(3.039)	(0.05)	(0.05)	**(0.044)**	**(0.04)**
Training	6.386	2.691	5.116	2.86	**0.145****	**0.182****	0.098	0.056
	-(3.789)	(4.048)	(3.719)	(4.162)	**(0.051)**	**(0.056)**	(0.055)	(0.046)
App*Richest	-7.031	-3.94	-6.922	-6.27	**-0.073***	**-0.133****	**-0.079****	-0.031
	-(5.425)	(4.554)	(8.436)	(7.602)	**(0.03)**	**(0.039)**	**(0.029)**	(0.044)
Radio*Richest	-6.204	-3.993	-9.317	-9.44	0.055	0	-0.117	-0.084
	-(3.983)	(3.891)	(5.387)	(5.28)	(0.033)	(0.033)	(0.08)	(0.071)
IVR*Richest	-5.087	-1.394	-4.802	-3.296	-0.007	-0.046	-0.088	-0.011
	-(3.329)	(3.511)	(4.26)	(4.606)	(0.04)	(0.045)	(0.107)	(0.12)
Training*Richest	-7.975	-3.633	-5.391	-4.29	-0.076	**-0.157***	-0.082	-0.025
	-(4.262)	(3.989)	(3.978)	(4.385)	(0.051)	**(0.06)**	(0.062)	(0.068)
No educ (Yes=1)		**-4.602****		-3.424		-0.026		-0.035
		(1.398)		(1.825)		(0.024)		(0.03)
High school and above (Yes=1)		**6.372****		**4.352****		-0.047		0.017
		(1.024)		**(1.361)**		(0.025)		(0.033)
Female head (Yes=1)		-1.964		-2.692		-0.032		0.009
		(1.463)		(1.711)		(0.018)		(0.022)
Political Participation (Yes=1)		0.49		0.227		-0.003		0.014
		(1.314)		(1.36)		(0.025)		(0.031)
Fertilizer was applied at planting 2017 (Yes=1)		-5.9		-6.413		**0.1650****		-0.036
		(3.836)		(3.739)		**(0.045)**		(0.069)
Fertilizer was applied after planting 2017 (Yes=1)		1.471		3.329		0.027		**0.136****
		(1.565)		(1.772)		(0.024)		**(0.04)**
Dependency_ratio		**-6.717***		**-6.558***		-0.029		0
		(2.602)		**(2.888)**		(0.046)		(0.055)
Comprehensive asset index		-0.154		1.455		**0.04***		-0.027
		(0.975)		(1.161)		**(0.018)**		(0.022)
Age_respondent		**0.16****		**0.158***		-0.001		0.001
		(0.054)		**(0.071)**		(0.001)		(0.001)
Irrigation (Yes=1)						0.058		**0.143****
						(0.034)		**(0.042)**
Agro Machinery (Yes=1)						-0.013		0.02
						(0.025)		(0.029)
Hired labour (Yes=1)						-0.001		0.039
						(0.017)		(0.036)
Constant	**28.662****	**29.138****	**37.017****	**37.396****	0.013	-0.09	**0.119****	0.018
	(1.572)	**(5.281)**	**(1.73)**	**(5.59)**	(0.015)	(0.058)	**(0.035)**	(0.093)
Controls	NO	YES	NO	YES	NO	YES	NO	YES
Clustered SE at Cooperative level	YES	YES	YES	YES	YES	YES	YES	YES
Village Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
Pseudo R2	0.03	0.09	0.03	0.07	0.03	0.07	0.02	0.07
N	886	880	886	880	886	880	886	880

* p<0.1, ** p<0.05, *** p<0.01.

Figures in brackets are standard errors and z-scores.

Table 15: Treatment Attributes

Controls	Outcome Variables			
	App	Training	IVR	Radio
Visual feature	X	X		
Auditive feature	X	X	X	X
Field demonstration		X		
In person delivery	X	X		
Timely exposure*	X		X	X
Frequent access **	X		X	X
Accessible to illiterate people***	X	X	X	X

* Timely exposure refers to whether the information was accessible/delivered around the time when farmers needed to perform the tasks on their maize plots

**Frequent access refers to weekly exposure to the information in the most relevant months

*** Literacy rates in our sample were 66.22%, calulated according to whether respondents could read a complex sentence with ease or adequacy. The App was adapted for illiterate farmers (added voice feature reading the text out loud) and the training involved field staff that explained the information verbally in addition to a plot demonstration.

Appendix 1: Radio Dialogue script

Radio Spot 1 (Generic message)

Maili didi: Hello Bhim. Where are you rushing off to so early in the morning?
Bhim: I am going to Bikas agrovet to buy some fertilizer.
Maili didi: Ok, that means you are planning to apply UREA and DAP in your maize field this time.
Bhim: Yes. Everyone has been talking about more maize grain yield resulting from urea and DAP application.
Maili didi: Definitely! Infact, I got up to 66 kg per kattha* more maize grain yield last season compared to what I could earlier by applying fertilizers the correct way.
Bhim: Really? Can you explain the correct method to me?
Maili didi: Yes of course, I can. First start and apply all your DAP at planting. After planting apply half the urea that you are planning to use when your maize plants have six fully formed leaves.field?
Bhim: Aaahh….and how much distance would that be?
Maili didi: Yes, so I was saying…. apply the urea 5cm from each maize plant, 5cm deep in the soil and cover with soil.
Bhim: What about the remaining half of the urea?
Maili didi: When you see your maize plants have ten fully formed leaves, apply the remaining half of urea in the same way.
Bhim: Ok. I am glad to have benefited a lot from our encounter today. Thanks for the information, maili didi.

Note: Changed to 100 kg/ropani for the hilly language version

Radio Spot 2 (Reminder for first top dressing at V6)

Bhim: Hello Maili didi, how are you?

Maili didi: I am fine. So, how's your maize plant growing?

Bhim: They are growing fine. Now, the maize plants have six fully formed leaves.

Maili didi: Oh! This means it's time to apply the first amount of urea.

Bhim: Exactly! That's why I've come to meet you to learn more about that.

Maili didi: Alright. Start counting from 1st leaf on the top that is turned downward. Fallen leaves should also be counted in. Leafs that are turned upward must not be counted.

Bhim: Aaah….do we have to count leaves of all the maize plants in my field?

Maili didi: Not all of them. You need to pick 5 plants at random. If at least 3 plants have 6 leaves each, it's time to apply the urea.

Bhim: So how much of urea should I be applying now, didi?

Maili didi: You must apply half the urea that you are planning to use this season. Remember to apply the urea 5cm from each maize plant, 5-9 cm deep in the soil and cover with soil.

Bhim: What about the remaining half?

Maili didi: The second half of the urea is applied when the maize plants have ten fully formed leaves. If you practice as explained then you will definitely gain better yield.

Bhim: Thanks didi, I've understood it well.

Radio Spot 3 (Reminder for first top dressing at V10)

Maili didi: Hello Bhim bhai, where are you these days?

Bhim: Oh, hello didi!

Maili didi: I noticed that your maize plants are growing really well.

Bhim: Yes, I agree. The plants are growing so much better this season as I have been practicing what you'd suggested earlier regarding fertilizer application.

Maili didi: Great! I suppose the maize plants have ten leaves by now.

Bhim: I've been counting the leaves. If not all but most of the plants I've counted in my field have ten fully formed leaves.

Maili didi: Can you please explain how you counted them?

Bhim: In a similar manner that you had explained previously i.e. I counted from 1st leaf on the top that is turned downward including fallen leaves. I did not count leaves that are turned upward.

Maili didi: Wonderful! So, this means you can now start applying the remaining amount of urea you have there.

Bhim: Yes, I will. Similarly, like last time, I've dug holes of 5-9 cm approximately 5 cm away from each maize plant.

Maili didi: Excellent! Make sure you cover the holes with soil after you've applied the second half of urea.

Bhim: Ok. With your suggestions, looks like my maize field productivity will increase and result in higher yields.

Maili didi: Definitely, this is the best management practice for maize.

Appendix 2: General and Relevant Agronomic Literacy Test Questionnaire

Agronomic Literacy Test[6]:

1. Which of the following is NOT a maize variety? *Read all choices out loud and then check the ONE answered by the farmer.*
   [ ] Arun-2 [ ] Manakamana 3 [ ] Deuti
   [ ] Govinda-1 [ ] Don't know

2. What nutrients are available in UREA? *Read all choices out loud and then check the ONE answered by the farmer.*
   [ ] A lot of nitrogen and a little zinc
   [ ] A lot of nitrogen and a little phosphorus
   [ ] Nitrogen only
   [ ] A lot of nitrogen and a little potash and phosphorus
   [ ] Don't know

3. What nutrients are available in DAP? Read all choices out loud and then check the ONE answered by the farmer.
   [ ] A lot of Phosphorus and a little zinc
   [ ] A lot of Phosphorus and a little nitrogen
   [ ] Phosphorus only
   [ ] A lot of phosphorus and a little potash and nitrogen
   [ ] Don't know

4. What is the ideal time for applying UREA on maize? *Read all choices out loud and then check the ONE answered by the farmer.*
   [ ] Only at the time of planting
   [ ] After planting when the plant is of knee height
   [ ] Two doses: at planting and when silk is visible
   [ ] Two doses: After planting, when the plants have reached 6 leaves and then when plants have 10 leaves
   [ ] Two doses: After planting, when plants have reached knee height and then shoulder height
   [ ] Don't know

5. What is the ideal time for applying DAP on maize best results on maize? *Read all choices out loud and then check the ONE answered by the farmer.*
   [ ] Only at the time of planting
   [ ] After planting when the plant is knee height
   [ ] Two doses: at planting and when silk is visible

[6] The general agronomic knowledge score was built using all total 11 questions in this questionnaire. The relevant agronomic knowledge score was built using only questions 4, 5, 6, 7, 8 and 9.

[ ] Two doses: After planting, when the pants have 6 leaves and then when the plants have 10 leaves based on the number of leaves
[ ] Two doses: After panting, when the plants have reached knee height and then shoulder height
[ ] Don't know

6. In general, how do you know when to apply fertilizer after planting? Tick the one that does NOT apply.
   [ ] It depends on the rain
   [ ] It depends on the soil
   [ ] It depends on the number of leaves on the plant
   [ ] It depends on the temperature
   [ ] Other, specify_______________

7. If fertilizer is incorporated instead of being left on the soil surface then: *Read all choices out loud and then check the ONE answered by the farmer.*

   [ ] It will increase disease infestation
   [ ] It can be washed by the rain
   [ ] It is easier for the plant to absorb
   [ ] Yields will be lower
   [ ] Don't know

8. What is the best way to incorporate fertilizer (choose one):
   [ ] Apply it 5cm deep in the soil, covered with the soil
   [ ] Apply it 10 cm deep in the soil, covered with the soil
   [ ] Apply it 15 cm deep in the soil, covered with the soil
   [ ] Don't know

9. What is the best distance to incorporate fertilizer (choose one):
   [ ] Apply it 5cm from the seed/plant
   [ ] Apply it 10 cm from the seed/plant
   [ ] Apply it 15 cm from the seed/plant
   [ ] Apply it between plants, any distance
   [ ] Don't know

10. What plant nutrient do you think is deficient in the above picture of maize plant?
    [ ] Nitrogen
    [ ] Potassium
    [ ] Phosphorus
    [ ] Zinc
    [ ] Other, specify_______
    [ ] Don't know

11. What plant nutrient do you think is deficient in the above picture of maize plant?
    [ ] Nitrogen
    [ ] Potassium
    [ ] Phosphorus
    [ ] Zinc
    [ ] Other, specify_______
    [ ] Don't know

Appendix 3: Factor Analysis for the Wealth Asset Indices

A. Factor Summary Statistics

Variables (quantity)	Mean	Std. Dev.	Min	Max
Durables				
Bicycles	1.121	0.411	1	4
Motorcycles	2.491	0.860	1	3
Gas cookers	3.383	2.864	0	8
Refrigerators	1.853	0.354	1	2
Sofas	3.562	1.005	1	4
Tables and chairs	6.616	4.788	0	15
Beds	5.114	2.513	0	12
Sewing machines	2.799	0.595	1	3
TV	1.551	0.848	1	3
Computers	1.102	0.303	1	2
Radios	1.954	0.993	0	3
Solar Panels	1.822	0.383	1	2
Livestock				
Goats	8.417	6.280	1	17
Sheeps	3.419	2.861	1	12
Pigs	6.420	1.705	1	7
Chickens	634.422	532.081	1	1100
Cows	4.570	2.113	0	6
Calves	4.524	1.241	1	5
Ducks	8.500	10.095	2	35
Oxens	4.290	1.275	1	5
Buffalos	1.686	1.358	1	23
Productive				
Power Tillers	1.023	0.151	1	2
Hoes	6.700	4.286	0	12
Shovels	4.843	4.096	0	10
Chain saws	1.962	0.197	0	2
Hand saws	2.618	0.764	0	3
Wheel barrows	1.000	0.000	1	1
Tractors	1.063	0.246	1	2
Ploughs	4.220	2.236	1	6
Axes	3.878	0.588	1	6
Pesticide sprayers	1.589	0.492	1	2
Sickles	5.419	2.779	0	15
Spades	0.317	1.038	0	5

B. Estimated Factor Loadings

Variables (quantity)	All	Durables	Livestock	Productive
Bicycles	-0.123	0.087		
Motorcycles	0.435	0.651		
Gas cookers	0.421	0.507		
Refrigerators	0.321	0.621		
Sofas	0.352	0.621		
Tables and chairs	-0.031	0.108		
Beds	-0.240	-0.256		
Sewing machines	0.095	0.189		
TV	0.383	0.349		
Computers	0.336	0.537		
Radios	0.217	0.204		
Solar Panels	-0.256	-0.190		
Goats	-0.346		0.935	
Sheeps	-0.260		0.126	
Pigs	0.304		-0.924	
Chickens	-0.434		0.329	
Cows	0.208		-0.097	
Calves	0.103		-0.140	
Ducks	-0.102		-0.003	
Oxens	-0.589		0.275	
Buffalos	-0.069		0.145	
Power Tillers	0.366			-0.524
Hoes	-0.159			-0.030
Shovels	0.308			-0.145
Chain saws	-0.093			0.263
Hand saws	-0.109			0.449
Wheel barrows	0.260			-0.488
Tractors	0.139			0.046
Ploughs	-0.646			0.681
Axes	-0.066			0.195

Pesticide sprayers	0.102	0.172
Sickles	0.108	-0.380
Spades	-0.140	0.189

C. Asset index Summary Statistics, by Percentile (Baseline Data)

	Quartiles	mean	std dev.	median	min	max
Wealth asset index	Poorest quartile	-1.251	0.469	-1.108	-2.689	-0.706
	Second	-0.378	0.183	-0.380	-0.704	-0.052
	Third	0.321	0.223	0.301	-0.047	0.707
	Richest quartile	1.308	0.415	1.241	0.721	2.561
Durables asset index	Poorest quartile	-1.389	0.675	-1.167	-3.722	-0.629
	Second	-0.141	0.238	-0.112	-0.613	0.188
	Third	0.424	0.145	0.424	0.190	0.691
	Richest quartile	1.120	0.298	1.101	0.698	1.808
Livestock asset index	Poorest quartile	-1.035	0.195	-0.979	-1.694	-0.794
	Second	-0.622	0.103	-0.606	-0.793	-0.451
	Third	0.226	0.572	0.024	-0.451	1.141
	Richest quartile	1.448	0.164	1.484	1.141	1.828
Productive asset index	Poorest quartile	-1.182	0.456	-1.063	-3.221	-0.636
	Second	-0.343	0.187	-0.340	-0.636	0.043
	Third	0.365	0.144	0.391	0.054	0.576
	Richest quartile	1.164	0.862	0.791	0.579	4.613