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 more geographically dispersed areas. In light of the recent spread of Information and Communication Technologies (ICTs) in developing countries, ICT tools can be potentially used to provide extension services to smallholder farmers at a lower cost. In this study, we conduct a Randomized Control Trial (RCT) with four treatment arms comparing the effectiveness of three ICTs (i.e., radio program, voice response messages and a smartphone app) alongside a traditional extension training in communicating the timing of maize fertilizer application practices for diammonium phosphate (DAP) and urea fertilizers to farmers across four rural districts in Nepal. The intent to treat effects reveal that farmers in the app and the training programs are 0.084 and 0.13 times more likely, respectively, to adopt the urea fertilizer practices compared to farmers in the control group (at the 5% and 10% statistical levels of significance, respectively). We find that the app is the most effective technology to induce learning and retention of the information provided, where farmers in the app treatment achieve 7.8% higher percentage scores in the agronomic literacy test compared to control farmers, statistically significant at the 5% level. There are no statistically significant effects of the treatments on the actual adoption of the DAP fertilizer practices, as it is suspected that the advice might have come at an inappropriate time. We find statistically significant heterogeneous effects of the treatments, where female farmers are 0.094 times more likely to adopt the urea recommendations from the radio messages and 0.096 from the training programs compared to men, at the 10% and 5% statistical confidence

levels, respectively. Wealthier farmers receiving the app and attending the training are 0.109 and 0.149 times less likely, respectively, to adopt the urea recommendations compared to middle- and bottom-income farmers in these same treatments (statistically significant at the 10% confidence level). While the app succeeded at encouraging the adoption of the urea fertilizer practices among the poorest, it is found that bottom income farmers achieved 7.15% lower agronomic test scores compared to farmers above the 25th income quartile in the app treatment (statistically significant at the 10% level).

Résumé

La collecte et divulgation d'information dans le secteur agricole, particulièrement dans les zones rurales et éloignées, est coûteuse. Malgré les efforts des agents de vulgarisation et l'utilisation des réseaux sociaux par les agriculteurs pour diffuser les nouvelles technologies agricoles, ces outils laissent souvent les agriculteurs dans les zones éloignées peu informés et n'ont donc qu'un faible impact dans la transformation technologique agricole cherchant des gains de productivité. Face à ces contraintes, cette étude utilise la méthode des essais contrôlés randomisés pour mesurer l'efficacité de trois traitements utilisant des technologies de l'information et de la communication (radio, messages de réponse vocale et une application mobile) pour l'enseignement et l'adoption de nouvelles pratiques utilisant les engrais urea et phosphate de diammonium (DAP), dans le but d'augmenter les rendements du maïs au Népal, en comparaison à une formation traditionnelle de vulgarisation. Les résultats suggèrent que l'application mobile et la formation agricole traditionnelle augmentent la probabilité d'adopter les pratiques de l'urea de 0.084 et 0.13, avec une signification statistique de 5% et 10%, respectivement par rapport aux homologues non traités. L'application mobile se révèle également être le meilleur traitement pour augmenter l'apprentissage des nouvelles technologies, d'après un test agronomique montrant que les agriculteurs qui ont utilisé l'application mobile accomplissent en moyenne des résultats 7.8% plus élevés que les sujets non traités (5% de signification statistique). On ne trouve pas d'effets sur l'adoption des technologies pour l'engrais DAP. De même, on constate que les femmes ont une probabilité 0.09 fois plus élevée que les hommes d'adopter les nouvelles pratiques agricoles pour l'engrais urea à travers la radio et la formation agricole traditionnelle (signification statistique de

10% et 5% respectivement). Les agriculteurs ayant les plus haut revenus utilisant l'application mobile et la formation traditionnelle ont des probabilités 0.109 et 0.149 moins élevées d'adopter les nouvelles technologies, par rapport aux sujets à plus bas revenus, avec une signification statistique de 5% et 10% , respectivement. Finalement, nous pouvons observer que les agriculteurs aux revenus les plus bas de notre échantillon apprennent moins à travers l'application mobile, obtenant des résultats 7.15% plus bas dans le test agronomique par rapport aux agriculteurs au-dessus du 25ème quartile du revenue (signification statistique de 10%).

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Contribution of authors

I, Nicoletta Giulivi, as main author, have contributed creating and writing every chapter included in this thesis report. The views and opinions expressed in this paper represent my own and are the result of my analysis and interpretation of the study outcomes. I have produced the literature review and all quantitative and qualitative analysis presented in this study, including all regression tables, figures and appendices.

Aurélie Harou, co-author and supervisor at McGill University, edited and proof read every chapter, providing insights and guidance to my analysis. Prof. Harou shared her expertise for the design of the study and when assessing the internal validity of the results. She also helped with restructuring the order of the chapters.

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Chapter 1: Introduction

1.1. Problem statement

Agriculture continues to account for the majority of the labor force in developing countries, making increasing agricultural productivity key to promoting economic growth and food security. Despite the green revolution's success at bringing productivity gains from Mexico to India, there is still a considerable agricultural productivity gap between developed and developing countries, which has been largely attributed to low technology adoption (Nakasone et al., 2014).

The early literature review on technology adoption in developing countries by Feder et al. (1985) identifies human capital as one of the main barriers to adoption, defined as the extent of crop experience and extension services received by farmers. Access to information regarding new technologies is critical to foster adoption, but it is costly in developing countries with poor infrastructures and where farmers are located in geographically dispersed areas (i.e., high travel costs). This adds to the existing high search costs of information that come from farmers' lack of knowledge of where to search and the prevalence of low literacy rates that limit farmers' understanding of the information that is available to them (Chuang and Schechter, 2015). With the existing issue of **asymmetric information** (Jack, 2011) smallholder farmers are forced to rely mostly on their own trial and error or their social networks to obtain agricultural advice (Aker, 2011), which is the problem that the present research wishes to address.

Extension services, defined as the delivery of information inputs to farmers (Anderson and Feder, 2007), have been traditionally used to bridge the gap between research and innovations by providing information satisfying various farmers' needs including market prices, weather forecasts, recommended input applications, best cultivation and pest management practices, among others (Aker, 2011). These services have taken several forms, the most common being: 1.) Training and Visit (T&V), which involves sending extension agents (i.e., agricultural specialists or 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 contexts 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).

The provision of extension has received some criticism due to its high implementation costs and lack of accountability (i.e., hard to monitor number of trainings and attendees), introducing the principal-agent problem[1] (Anderson and Feder, 2007). Despite significant amounts of resources invested in the provision of extension programs, totaling to $1.8 billion coming just from the World Bank alone between 1965 and 1986, there are very few rigorous impact evaluations assessing the impacts of extension services on farm productivity (Birkhaeuser et al., 1991). In their review of 15 studies evaluating extension impact published between 1970 and 1989, Birkhaeuser et al. (1991) find that a large body of literature used linear regression techniques subject to potential bias in their results stemming from endogenous program placement and selection bias from non-random treatment assignment.

The few robust existing studies provide mixed evidence. Owens et al. (2003) use panel data with fixed effects to look at the impact of receiving two extension training visits a year on farm productivity in Zimbabwe and find significant crop production increases of 15%. The effects

[1] In this analogy, the principal is the Government or NGO financing the extension service, and the agent the extension agent, responsible for delivering the information to farmers.

persist even after controlling for farmers' ability and plot characteristics, but these results are not consistent over different crop years. Godtland et al. (2004) use propensity score matching to estimate the effects of FFS among potato farmers in Peru and find increases in knowledge measured by IPM test scores. However, their results are not corroborated by Feder et al. (2003), who do not find impacts from FFS on yields and reduction of pesticides use in Indonesia neither for farmers who attended the trainings nor for their neighbors. Finally, the heterogeneity of the results is also significant varying by farmers' initial yield productivity and farm size, suggesting that extension programs can be improved by targeting the information to meet specific farmers' needs (Cerdán-Infantes et al., 2008).

Practitioners and policy-makers have therefore looked at other ways of disseminating information, for instance, using farmers' social networks. Foster and Rosenzweig (1995) are the first to explore social learning in the context of technology adoption of high-yielding varieties (HYV's) during the green revolution in rural India. They do not collect explicit data on social networks but using household level panel data they find that farmers with experienced neighbors are significantly more profitable than farmers with inexperienced neighbors, and naturally adopt more of the new varieties on their plots. These findings have been corroborated by subsequent papers showing that farmers learn which inputs to use (i.e., water, soil, fertilizers, pesticides…) from their more experienced neighbors sharing similar characteristics to themselves (BenYishay and Mobarak, 2018; Conley and Udry, 2010).

Programs encouraging farmer-to-farmer diffusion, however, need to provide the appropriate incentives for farmers to spread the information with their peers. This has not been successfully achieved so far, resulting in poor influence on other farmers' behavior and adoption (Feder et al., 2004; Kondylis et al., 2017). Alene and Manyong (2005), suggest that additional trainings teaching farmers how to communicate information with others, are also needed to make peer learning more effective. Further considerations include the choice of targeting strategy since it determines who will benefit from the information. For instance, Beaman and Dillon (2018) find that targeting central nodes within a network excludes women from the information sharing process and that greater social distance reduces the reach of information for people who are far from the initial recipients.

However, relying on social learning does not always speed up technology adoption, especially if farmers are seen to delay their adoption to free-ride on the learning of others to save the cost of experimentation (Bandiera and Rasul, 2006; Foster and Rosenzweig, 1995; Liverpool-Tasie and Winter-Nelson, 2012). Social learning can also be limited by “incomplete learning”, since farmers get information from what they can observe or learn from their neighbors, which might not be precise in terms of quantities, methods for input use and actual yields (Maertens and Barrett, 2012). Finally, social learning is also subject to measurement problems due to hidden characteristics (i.e., ability, plot conditions…) and difficulties in collecting reliable social network data, which prevents researchers from properly assessing the returns from social learning, which are often overstated (Maertens and Barrett, 2012; Munshi, 2004).

1.2. Study Objectives

Given the previously mentioned shortcomings of traditional extension trainings and social networks, increasing attention has been given to Information and Communication Technologies (ICTs) as a low-cost solution to substitute or complement extension service delivery to smallholder farmers in developing countries (Aker, 2011). Our study wishes to evaluate how different ICT tools impact farmers’ knowledge and adoption of new fertilizer management practices when used to deliver agricultural advice to farmers. For this we implement a Randomized Control Trial (RCT) in 60 cooperatives across four districts in rural Nepal (i.e., Kavre, Palpa, Dang and Surkhet). The RCT comprises four treatments to test the relative 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 our fertilizer recommendations. More specifically, we wish to understand the differences in the delivery channels and how they affect retention and adoption of information.

This study is a pilot research project that fits into a wider strategy called the Nepal Seed and Fertilizer (NSAF) project, run by the International Maize and Wheat Improvement Center (CIMMYT). NSAF began in 2016 as a five-year funded initiative by USAID aiming to facilitate sustainable increases in national crop productivity through extension service provision, to raise farmers' incomes and contribute to national food security. We aim to be able to evaluate the effectiveness of the preceding mentioned ICT tools to see if they could be effectively incorporated into the NSAF's strategy 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 conduct the present study testing ICT tools to provide farmers with 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 diammonium phosphate (DAP) fertilizers on maize plants.

1.3. Contributions

Past studies have investigated the capacity of ICTs to enhance knowledge and adoption of new agricultural technologies (Nakasone et al., 2014). Overall, ICTs have shown to have positive effects on learning and adoption of new technologies (Fu and Aker, 2016; Larochelle et al., 2017), as well as positive welfare effects from increases in yields (Casaburi et al., 2014; Cole and Fernando, 2016) and even improved the efficiency of fertilizer deliveries (Casaburi et al., 2014). Additionally, some studies find also positive effects from spillovers of learning from recipients to non-recipients of the technologies (Cole and Fernando (2016).

However, these studies have restricted their analysis to mobile phone-based services and tested two types of communications. The first is one-way communication, such as text message reminders (i.e., SMS) to perform agricultural tasks in the field (Larochelle et al., 2017) and the second is 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 the effectiveness of both types of communication but have not compared between the two. For example, the study by Casaburi et al. (2014) tests one program consisting of SMS reminders to perform agricultural tasks and a second separate program providing a hotline service allowing farmers to call companies to receive input delivery and payment information.

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 and use of the information provided. We focus on one-way communication for the app and the IVR treatments unlike Cole and Fernando (2016) and Fu and Aker (2016) who examine the effect of two-way communication. One implication of this is that the effects of the app and IVR in our study likely underestimate the potential for these technologies.

Indeed, we expect interactive features to better address individual farmers' needs. Additionally, in the long-run, the lack of interactive features could reduce farmers' interest in using the technologies. However, on the other hand, the more straight-forward information provided in a simple uni-directional app may be more easily understood potentially inducing higher levels of knowledge and adoption. Therefore, the difference between uni- and two-way communication is not directly obvious.

In summary, our study allows for the comparison between different ICTs in an attempt to begin identifying the specific features from the technologies that are most conducive to learning and adoption. This allows us to contribute to the literature by comparing 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, and face-to-face contact) (Baumüller, 2018).

1.4. Summary

Our first difference estimation reveals that farmers who received the app are 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% statistical significance. Furthermore, farmers in the app treatment achieve 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 of statistical significance, respectively, indicating that the app is most effective in disseminating information. Traditional extension training programs also appear effective at sharing information on the timing of urea fertilizer application by an average of 0.13 at the 10% confidence 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 interactions.

However, no significant effects of any ICT on the use of DAP at planting are found, which we suspect results from the fact that most farmers had already planted maize when they received the advice. Heterogeneous effects show that wealthier farmers are less likely to adopt our urea recommendations from the training and app treatments compared to middle-and-low income farmers, and that poorest farmers achieve on average 7.15% lower test scores in the app treatment compared to the rest of farmers at the 10% statistically significant level. Finally, female farmers are more likely to follow the urea fertilizer recommendations in the radio and training programs compared to men.

1.5. Organization of the research

Chapter 2 provides an overview of the context of the study and fertilizer policies in Nepal. Chapter 3 reviews the relevant literature related to ICT tools used for extensions service delivery in light of recent evidence demonstrating their positive welfare effects in agricultural markets, as well as their potential to reduce communication costs when facilitating learning and adoption of new technologies. Chapter 4 describes the experimental design and data collection providing a detailed description of the treatments. The methods of the study are presented in Chapter 5, which includes the empirical analysis used for the regressions. Chapter 6 contains the results and robustness checks. Finally, Chapter 7 discusses the results, and Chapter 8 concludes the research.

Chapter 2: Background

2.1. 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). Nepalese agriculture is dominated by small-holder farmers following traditional farming practices, regarded as low yielding technologies (Adhikari et al., 2018). This is problematic since the IPC (2014) reported that more than half (54%) of the Nepalese population is affected by chronic food insecurity. According to the Development Strategy (2015-2034), the major reasons for low agricultural productivity is low use of fertilizers. The twenty-year Agriculture Perspective Plan (APP), implemented since 1997, mentions that chemical fertilizer could account for a 50% increase in food production (Adhikari et al., 2018). Ensuring timely access to and application of adequate mineral fertilizer is therefore key to agricultural development, food security and poverty reduction in the country (USAID, 2012). The APP has aimed to increase fertilizer usage and set a target to increase it from 31 kg nutrient/hectare of the base year 1995 to 131 kg nutrient/hectare by 2017. However, since Nepal does not produce any fertilizers, meeting the demand depends on formal and informal imports coming from India and other countries (Shrestha, 2010). The Government's priority has therefore been to ensure adequate and timely supply of quality fertilizers through the Ministry of Agricultural Development (MoAD) fertilizer subsidy programs that focus on small-holder farmers (Adhikari et al., 2018).

2.2. Fertilizer Policies

Fertilizer policy history in Nepal has evolved following three main phases, it started with the introduction of the first subsidy policy scheme (1973-1974), followed by the deregulation of fertilizer supply in 1997/8, until the recent re-introduction of the subsidy scheme (since 2009 to present).

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 (Shrestha, 2010). The government introduced the first fertilizer subsidies between 1973 to 1974 with the aim of increasing food production by encouraging chemical fertilizer use among farmers. The subsidy included both a price and transport subsidy for transporting fertilizers from Terai districts to Hilly districts[2] (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.

However, 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.).

With time, the rise in fertilizer prices and the increased perception of adulteration of fertilizers traded in private markets became a concern. As a response to contain prices and ensure fertilizer quality, the government re-introduced the chemical fertilizer and transport subsidy in

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

2009 (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, the subsidized fertilizers are— 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). Cooperatives are the only place where farmers can purchase subsidized fertilizers. The current chemical fertilizer distribution structure is summarised in Figure 1, where cooperatives enter the distribution chain as a non-government entity and can therefore set their own rules regarding the retail prices of fertilizers, transportation arrangements, distribution and sales.

2.3. Optimal fertilizer management practices

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 use of fertilizers. The currently subsidized fertilizers (i.e., urea, DAP and MOP) provide the NPK macro-nutrients needed to maximize plant yields, nitrogen (N) from **urea**, phosphorus (P) from DAP, and potassium (K) from MOP.

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 that revealed a lack of knowledge of the principles of balanced fertilizers, farmers tend to over apply nitrogenous fertilizers (i.e., urea) since it is cheaper and delivers a quicker response but can eventually lead to soil degradation. CIMMYT's NSAF has been acting as a facilitator to build capacity for government agencies through Research and Development and promoting the appropriate use of fertilizer technologies, based on the **4R Nutrient Stewardship Approach** by working with farmers' cooperatives to share relevant extension information through formal and informal channels. Cooperatives provide extension services to farmers and organize agricultural trainings for its members. In our sampled 60 cooperatives, 60% of them claimed to have conducted an agricultural training and 30% of them delivered information regarding fertilizer best management practices in the past 12 months.

Chapter 3: Literature Review

The recent spread of Information and Communication Technologies (ICTs) in developing countries has generated an interest in studying their potential to foster agricultural development (Nakasone et al., 2014). As a result, two streams of literature have emerged, the first looking at ICT tools to provide crop price information and connect farmers and traders in agricultural markets, and the second focusing on the scope of using ICTs to enhance knowledge and adoption of new agricultural technologies, which is the research area this study contributes to. The present chapter will follow the structure proposed by Nakasone et al. (2014), starting by a review of the literature on the potential welfare effects brought by using ICT tools in agricultural markets, followed by a review of their role in extension service delivery.

3.1. ICTs and welfare effects in agricultural markets

Jensen's (2007) pioneer study on the impact of the introduction of mobile phone towers in South India is among the first to find positive welfare effects brought by allowing fisherman to search price information and perform spatial arbitrage. The introduction of mobile phone towers results in increases in fishermen's profits, reducing price dispersion in the sardines' fish market and overall market efficiency also increases dramatically since fisherman start selling their fish not only at their local markets but also in other markets, reducing fish waste due to over-catching and shortage of demand in the markets (since fish is a perishable commodity it cannot be stored). Both of these effects contribute to providing positive welfare impacts for both buyers and sellers. The author claims that the concerns of a digital divide benefitting the wealthiest who can afford to access ICT technologies[3] are attenuated thanks to spillover gains coming from the overall improved functioning of markets.

Two subsequent studies carried out by Aker and Mbiti (2010) and Aker and Fafchamps (2014), study the effects of mobile phone coverage on price dispersion for grain markets in Niger. Their results partly corroborate the findings in Jensen (2007) but the magnitude of their results is not as high. Aker and Fafchamps (2014) find that mobile phone coverage reduced intra-annual producer price variations by 6% for cowpeas but has no significant effects on millet or sorghum prices. In their study, 30% of surveyed farmers own a mobile phone and use it for trading operations; however, less than 5% of the villages have network coverage, which reduces the power of the inferences drawn from the dataset. Aker and Mbiti (2010) also find reductions in price dispersion in grain crops exploiting the introduction of mobile phone coverage in Niger in a quasi-experiment using propensity score matching, but, again, find a smaller magnitude in the impacts compared to Jensen's (2007) findings. Even though markets in non-perishable commodities, such

[3] The initial cost of acquiring a mobile phone was as high as $100 allowing only the wealthiest fisherman to purchase them.

as grains, are often not well integrated spatially, this evidence suggests that price information seems to provide greater gains for perishable commodities.

However, the welfare implications of mobile phone services remain ambiguous. Fafchamps and Minten (2012) test the effects of providing farmers in India a free one-year subscription called Reuters Market Light (RML) sending regular SMS with farming information on prices, weather forecasts, new crop varieties and cultivation practices. They find no evidence of an increase in sale prices of farmers' crops, nor reduced crop losses, nor changes in crop varieties and cultivation practices from the intervention. The study involves both perishable (i.e., tomatoes, pomegranates and onions) and non-perishable commodities (i.e., wheat and soybeans) with two treatments, one where RML is provided to the full sample of randomly assigned participants, and the second where only part of the assigned participants are given the RML to evaluate spillover effects. Their results reveal statistically significant but small effects on farmers willingness to share information with others. Although they observe that farmers sought arbitrage gains from the RML, this does not lead to an increase in the price received by farmers nor does it reduce price variations. Despite the rigorous methodology, i.e., a randomized control trial design, the low or lack of significant findings makes them conclude that there might be other market frictions preventing spatial arbitrage to increase farmers' sale prices, e.g., segmented and non-organized markets, comparative advantage of producers selling in nearby markets, spatial concentration of markets. They also discuss potential trust issues from farmers who might be afraid of being cheated if they switch markets.

Finally, Aker et al. (2012) demonstrate the learning benefits from using ICT tools in the context of an educational program. They introduce a mobile phone component to be shared among five people in an adult educational program called the ABC program (i.e., ABC= Alphabetisation de Base par Cellulaire) conducted by an NGO in Niger. The authors compare the program with and without the mobile phone component using a randomized control trial design. They find that the ABC program increases writing and math test scores compared to the non-ABC programs, but only math scores are statistically significant at the 5% level. The authors are able to exclude potential group effects, thereby attributing learning to the technology alone. Their findings suggest that the use of the mobile phones outside the classroom fosters better retention by practicing writing text messages and/or making calls (i.e., learning by doing). Aker and Ksoll (2016) exploit the same setting and conduct another randomized control trial to measure the effect of mobile phones in agricultural production and crop prices, comparing villages under the ABC educational program (i.e., ABC villages) to villages in the non-ABC educational program (i.e., non-ABC villages). The evidence reveals that farmers in ABC villages increase the diversity of crops cultivated compared to non-ABC villages, but this does not significantly impact the quantity grown nor sold by farmers.

3.2. ICTs used for extension service delivery

Most studies to date find positive evidence that ICTs can effectively be used to encourage learning and adoption of new farming practices. However, the literature is still at its very early stages. Although a wide array of projects have started studying the use of ICTs in developing countries to deliver agricultural recommendations, there are few evaluations of these projects (Nakasone et al., 2014). A larger stream of papers and conference presentations on the topic have presented mainly descriptive statistics, failing to establish causality in their results (Balasubramanian et al., 2010; Mittal, 2015; Pede et al., 2018; Veeraraghavan et al., 2009).

More rigorous studies measuring the effects of ICTs for extension service delivery are needed, which is the gap in the literature that the present research aims to fill. One commonality observed among the few rigorous studies, using inferential analysis, is that they focus mainly on mobile-based programs (Casaburi et al., 2014; Cole and Fernando, 2016; Fu and Aker, 2016; Larochelle et al., 2017). More studies comparing mobile phone technologies with other technologies, like the radio, TV or face-to-face interactions, are needed (Baumüller, 2018). The present study aims to add on to this missing piece by conducting an impact evaluation using a Randomized Control Trial (RCT) with four treatment arms, testing three different ICTs including the radio and two mobile-based services (i.e., voice response messages and smartphone app), as well as a traditional extension training.

Cole and Fernando (2016) are the first to create a study design comparing the effects of an ICT intervention (Avaaj Otalo (AO) service) with a traditional training. The AO service is a mobile-based service sending weekly voice messages about agricultural information with a voice platform that allows farmers to call a hotline and record questions and answers (Q&A) interacting with other farmers and agronomists as well as listening to the Q&A forum. They conduct a randomized control trial with two treatments and a control group. The first treatment provides toll-free access to AO in addition to the traditional extension training and the second contains only the AO service. Their preliminary results find reductions in pest-related losses leading to yield increases of 28% for cumin and 8.6% for cotton, relative to the control. They also find positive spillover effects from the treatments using social network data collected at baseline. However, they do not find any learning effects from the treatments -- knowledge regarding basic agricultural questions is low at baseline and does not change throughout midline and end line surveys.

Casaburi et al. (2014) evaluate two interventions, but do not compare them to each other, by conducing two separate randomized control trials: one tests the impact of sending text message reminders around the time farmers need to perform agricultural tasks on their plots, and the second intervention tests the effect of a hotline service allowing farmers to call a helpline regarding issues with input deliveries and payments related to sugar cane production. They find that farmers who access the SMS advice achieve 8% higher yields than the control group average, and that the hotline improves efficiency in fertilizer delivery by reducing delays by 3.8 percentage points compared to the control, extending these benefits to non-mobile phone owners. Their study does not exploit differences in the voice (i.e., hotline) and visual (i.e., SMS) features of their treatments that could have been interesting to identify the delivery channels through which technologies foster learning and adoption of new practices.

The evaluation of different delivery channels within mobile services (e.g., voice versus SMS) has to date not been explicitly studied (Baumüller, 2018). However, Fu and Aker (2016) examine the effect of a mobile-based initiative, 'Knowledge Help Extension Technology Initiative' (KHETI) in India, which provided customized advice to farmers with an assistant person (i.e., a Munna) guiding farmers to use the technologies and seek advice from agronomists. Their quasi-experimental design with difference-in-differences estimation reveals that the program benefited the poorest farmers and increased awareness for new technologies and general agricultural knowledge. They also find heterogeneous effects by gender and age. Women are less likely to get the information and benefit from it and older farmers tend to have greater knowledge and awareness of agricultural techniques. However, knowledge was calculated through an awareness-knowledge index (AKI) created merging questions from self-perception in general agricultural knowledge and new technology awareness, and as noted by the authors, there could be a bias since farmers might be inclined to give a positive response to the experimenters.

Larochelle et al. (2017) use a randomized control trial among potato farmers in Ecuador to evaluate the effects of text message reminders following a three-day long farmer field day (FFD) on integrated pest management (IPM) practices. They test knowledge by creating two test scores, one made of 23 general questions and a second test score containing 15 directly related questions to the information provided by the treatments. Treated farmers receive regular text messages at the appropriate timing they need to perform IPM practices on their plots. They find that farmers who receive regular SMS during the potato growing season increase their overall knowledge about Integrated Pest Management (IPM) practices by 18.4 percentage points and increase the likelihood of adopting IPM practices by 6.7 percentage points compared to the control. The adoption of time-sensitive and complex IPM practices also increases in the treatment group, and there is evidence that the increase in knowledge is driven by the questions related to the IPM practices, which indicates that the text messages induce behavioral change through knowledge building. However, as the authors note in their limitations, their message reminders were sent to farmer participants after attending a three-day Farmer Field Day (FFD) training, which does not allow extrapolating the technology effects of the text messages alone. Our study wishes to build upon this study by specifically separating the impact of different ICTs and compare their performance to a traditional extension training.

Chapter 4: Experimental Design

4.1. Selected Districts

Between May and October 2018, CIMMYT and McGill tested the effectiveness of different Information and Communication Technologies (ICTs) 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 farmers had access to mobile coverage (Figure 2: Mobile coverage Nepal[4]).

4.2. Data collection

In each of the four districts, a census of all the cooperatives planting maize, 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 3). The randomization was done at cooperative level for three reasons. First, cooperatives are one of the primary sources of extension information for farmers in Nepal, so it was administratively convenient to provide the extension services at the cooperative-level. Second, cooperatives encapsulate farmers' social networks where agronomic information is often shared, which is desirable to prevent treatment contamination. Lastly, NSAF operates at the cooperative-level to ensure logistical efficiency (i.e., higher farmer reach), making the interventions logistically more feasible if treatments occurred at the cooperative-level. Fifteen farmer participants were randomly

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[4] 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.

sampled from each cooperative, 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 having access to both a 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.

4.3. 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) (see Figure 4). 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 1st leaf at the top of the maize plant and only count the leaves turned downwards including the leaves that had already fallen.

4.3.1. App

The smartphone app, called M Krishi, where “Krishi” means agriculture in Nepali, was developed by Geokrishi, a private innovation company specializing in providing technological based crop advice for remote farmers. 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 were the same as the ones presented during the extension training given by CIMMYT’s field staff (see Appendix A), 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 and was shared to farmers using the google app “SHAREit”, a cellular data free app allowing to transfer files between devices. 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 their cooperative. CIMMYT staff did not deliver a training on how to use the app, nor additional information regarding the fertilizer recommendations not to bias farmers' their interpretations of the information provided. After receiving the app, farmers were given time to go over the app on their phones to check that everything was working properly on the technical side. In certain cooperatives, farmers were too busy to come to the meeting, so CIMMYT staff visited farmers' houses individually to share the app with them at their earliest convenience.

4.3.2. 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[5]. The presentation was followed by a field plot demonstration where farmers saw the techniques applied in practice. 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 specific times and common locations. Given that ICTs provide farmers with a higher frequency of exposure to the information compared to a one-time training, farmers assigned to the in-person training also received a paper printed poster (see Appendix B). This allowed them to refer back to the training materials when

[5] The slides can be found in Appendix A.

convenient, increasing the frequency of access to information in an attempt to increase treatment comparability.

4.3.3. 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 treatment radio stations. 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 providing mobile based services to connect individuals and organizations in developing countries. 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).

The radio messages were recorded in Kathmandu by the company Equal Access Nepal and used 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)[6]. 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] The full dialogue can be found in Appendix C.

6 and then 10 fully formed leaves. 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 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.

4.3.4. 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[7]. 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. The

[7] The full dialogue script can be found in Appendix D.

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 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 a 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.

Chapter 5: Methods

5.1. Regression Estimation

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

$$\Delta Y_{ic} = \alpha + \beta_1 App_{ic} + \beta_2 IVR_{ic} + \beta_3 Radio_{ic}$$

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

ΔY_{ic} denotes the difference between the outcome variable of interest, defined further below, for farmer *i* in cooperative *c* between end line and baseline. All of the models are 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 as a robustness check in

Chapter 6). 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 $Training_{ic}$ take the value of 1 if individual i in cooperative c was randomly assigned to that treatment or 0 otherwise. 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. 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). d_v captures the village fixed effects. Finally, $\Delta\varepsilon_{ic}$ is the error term, which we cluster at the cooperative level.

5.2. Outcome variables

The study aims 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 harvest 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 contains 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. A 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 E). Knowledge scores represent 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. The general agronomic knowledge score measures whether overall agronomic literacy was also improved as a result of increased knowledge in fertilizer management practices.

5.3. Intent to Treat Effects (ITT) and Compliance

Equation (1) above measures the intent-to-treat (ITT) effect and is used to 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 used the treatments, as opposed to those who were randomly assigned to receive them (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 was 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.

5.4. Radio Spillovers and Social Networks

There are possible concerns regarding potential spillover effects coming from the radio treatment since the messages were broadcasted several times during the day, and it was impossible to exclude non-treated farmers from listening to the local radio stations. To estimate the extent of the spillovers, at end line, farmers were asked whether they had heard the radio messages[8]. Aside of farmers initially assigned to the radio treatment, 16 other farmers answered positively (3 control farmers, 3 farmers form the training and 10 farmers from the IVR treatment).

The end line survey collected additional data on spillover effects coming from farmers' social networks. Treated farmers were asked whether they had shared any of the recommendations provided with their friends, neighbours or relatives[9]. We find that approximately 36.22% of them

[8] 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)?"

[9] Did you share any of the recommendations regarding maize timing of fertilizer application provided by CIMMYT with your friends and neighbors? By app, radio, voice response messages or training.

did, which provides evidence of potential peer effects in information spreading. Most farmers (75.61%) access the app on their own smartphone but the remaining 24.39% of farmers accessed the information from a smartphone owned by a member of the household or neighbour, proving that the benefits from the app treatment can be extended to non-smartphone holders.

5.5. Attrition

Only 14 respondents from baseline, representing 1.55% of the total sample of 900 participants, dropped out of the study. These 14 baseline respondents were dropped from the final analysis, leaving a sample of 886 respondents.

5.6. Balanced test for controls

To ensure the population was properly randomized, the balance of key variables of interest at baseline was checked (Table 2) to ensure that the intervention and control groups were equivalent. 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, whether the survey respondent is a female, political participation and the dependency ratio are, however, imbalanced. All of these imbalanced characteristics are therefore included as regression controls, X_{ic}, in equation (1) above[10]. Note that since respondent gender

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[10] For the outcome variables capturing adoption rates, the vector X_{ic} was augmented by three dummy variables on

and head of household gender are highly correlated, we only include head of household gender in the regression estimations. 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.

We proxy wealth with an asset index. The use of assets data to measure household welfare has become more common over the last decade, since it carries fewer measurement problems and has a lower likelihood of recall bias than consumption, expenditure or income data (Moser and Felton, 2007). It also provides a better indication of longer-term living standards since assets have been accumulated over time whereas income is a more volatile measure that often suffers from seasonal variation and nonremunerated self-employment (Moser and Felton, 2007; Sahn and Stifel, 2000). Several studies have indeed shown a strong link between household productive assets and subsequent poverty rates (Barrett et al., 2006). To construct an asset index, the choice of weights to assign to each asset within an asset category is required. The weights are then multiplied to the assets and the index constitutes the sum of all weighted assets for a given category. Commonly used weights include prices, unit values, or parameter estimates from principal components analysis (PCA), factor analysis (FA), multiple correspondence analysis, or polychoric PCA (Moser and Felton, 2007). Since obtaining asset prices is difficult due to imperfect market prices that might not accurately reflect the value of an asset in rural areas, another method is to assign each asset a binary value of zero or one, if the respondents own that asset or not and summing the number of assets within a category. Sahn and Stifel (2000) use FA to aggregate several binary asset ownership

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.

variables into a single index instead of PCA, arguing that FA offers more flexibility because it does not force all the components to explain the correlation structure between the assets. We follow the FA method to create the asset indices. I constructed the asset indices following the same methodology as in Sahn and Stifel (2000), using data collected at baseline regarding farmers' ownership of livestock, durables and productive assets.

Three asset indices were generated, a durables asset index (bicycle, gas cooker, radio, television, etc.), a livestock asset index (goats, sheep, buffalo, etc.), and a productive asset index (barrel, chain saw, sickle, etc.), in addition to a comprehensive wealth asset index, aggregating all three together, which is the one that was included to control for differences in wealth in the regressions. Factor summary statistics for each asset owned by the respondents comprising the asset indices are reported in Appendix F, Table F.1. The estimated factor loadings and summary statistics for each asset index by percentiles are also available in Appendix F, Tables F.2 and F.3, respectively.

The anticipated direction of the relationships between the controls and dependent variables are presented in Table 3. Education is expected to be positively correlated with all outcomes, implying that higher education will have a positive impact on learning and adoption since literate farmers are expected to be able to better understand the messages (Cole and Fernando, 2016). Additional variables such as political participation, application of fertilizer at planting and after planting, and age of the respondents should also be positively correlated to the outcomes. The involvement of the respondent in the community (political participation) is a proxy for farmers' social networks, and more contacts would make it more likely for farmers to share and discuss the information, which can result in social learning (Conley and Udry, 2010; Foster and Rosenzweig, 1995). Farmers who applied fertilizers in the 2017 season might be more likely to re-apply it in the 2018 season and therefore can be more interested in the information provided, as opposed to farmers who do not utilize fertilizers. The age of the respondent reflects experience, and is expected to be therefore positively correlated with the dependent variable, whereas being a female farmer is expected to be negatively correlated with the outcomes since women are in charge of more domestic tasks and are therefore less likely to access information before men (Fu and Aker, 2016). The wealth asset index is expected to be positively correlated with both learning and adoption (Feder et al., 1985). Use of irrigation, agro-machinery and hired labor increase crop productivity and are also indicators of wealth, so they are expected to increase adoption of new technologies. Finally, the dependency ratio is also an indicator of household wealth (Larochelle et al., 2017), the larger the poorest is the household, so it is expected to be negatively correlated with learning and adoption.

5.7. Balanced test for outcome variables

We also checked whether the outcome variables of interest outlined above were balanced between the treatments and control group at baseline. It appears, from Table 4, that general agronomic literacy, urea applied at v6 and v10, and DAP applied at planting were not balanced across treatments at baseline. Regarding agronomic literacy, this imbalance does not affect the analysis since we are most interested in the knowledge acquired through the treatments, captured by the relevant agronomic score, which is perfectly balanced. The variables capturing whether farmers applied urea at v6 and v10 and DAP only at planting in the 2017 season are dummy variables taking the value of 1 if farmers declared following those specific practices and 0 otherwise. We observe that 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, and similarly, farmers randomly assigned to the Training and IVR treatments seemed to be already following the provided DAP recommendations (Table 4).

The allocation of farmers to the treatments was done randomly to prevent selection bias. Nonetheless, the randomization did not prevent the observed differences at pre-test for two of our 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. It must be noted that 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 highly unanticipated that there would be an imbalance in the urea outcome variable. Table 5 shows indeed that the urea imbalance is being driven by very few observations, 11 and 5 farmers in the App and Radio treatments, respectively, 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) point 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 the present 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 outcome is deemed unlucky, and is taken into account when interpreting and discussing the results.

Chapter 6: Results

6.1. Agronomic literacy scores

The results measuring the effects of the treatments on agronomic knowledge are found in Table 6. Columns (1) and (2) of Table 6 contain the regressions on general agronomic knowledge and columns (3) and (4) the estimations for relevant agronomic knowledge. Starting with general agronomic knowledge, farmers in the app treatment achieved approximately 5% higher percentage scores in the general agronomic test compared to control farmers, at the 10% statistical level of significance. More pertinently, when isolating the questions related to the treatment information, the results reveal that farmers in the app treatment achieve 7.8% higher scores in the relevant agronomic test compared to control farmers at the 5% statistical significance level (column (4)). Farmers in the training treatment also achieve statistically significant increases in their test scores by approximately 6.993% compared to the control, at the 10% level (column (3)). However, this result disappears when controlling for the observable unbalanced characteristics at baseline, so we do not deem them to be robust evidence of the training's impact on knowledge.

6.2. Adoption rates

Table 7 presents the effects of the treatments on the adoption of the recommended practices for DAP fertilizer application at planting (columns (1) and (2)), and the time of urea application at v6 and v10 stages of plant growth (columns (3) and (4)). Both the app and the training increase the probability of adopting the recommended practices for urea fertilizer. Farmers randomly assigned to the app treatment appear to be on average 0.084 times more likely to adopt the urea recommendations compared to control farmers at the 5% statistical levels of significance. In turn, farmers in the training treatment have on average 0.13 higher probability of adopting the urea recommendations compared to farmers in the control group at the 10% statistical levels of significance. These results are consistent and robust across all specifications, columns (3)-(4). 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 significant in inducing the application of DAP fertilizer only at planting (columns (1) and (2)).

6.3. Heterogeneous effects

We are interested in investigating heterogenous effects to add further in-depth insights to the analysis. Given that the gender of the respondent and the wealth asset index variables are not balanced at baseline (Table 2), stratifying by gender and income would have been the most appropriate methodology to control for the observed imbalance. However, since this is not the main purpose of this research, we carry on using the current study design, and present this section as an additional analysis with some preliminary results shedding light on the heterogenous effects of the treatments using a regression specification with interaction terms. Subsequent studies explicitly designed to more rigorously investigate gender and income dynamics will be needed to corroborate the findings presented next.

6.3.1. Gender

To study whether the positive effect of the app and training persists across female and male respondents, we estimate (2) below, where we interact a dummy variable capturing respondent's 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.

$$\Delta Y_{ic} = \alpha + \beta_1 App_{ic} + \beta_2 IVR_{ic} + \beta_3 Radio_{ic}$$

$$+\beta_4 Training_{ic} + \beta_5 (App_{iv} * female_{ic}) + \beta_6 (IVR_{ic} * female_{ic}) + \beta_7 (Radio_{ic} * female_{ic}) + \beta_8 (Training_{ic} * female_{ic}) + \gamma X_{ic} + d_v + \Delta\varepsilon_{ic} \quad (2)$$

The effects of the treatments on agronomic test scores by gender are presented in columns (1) and (2) of Table 8. The gender effects by treatments on adoption rates are displayed in column (3) for urea recommendations and (4) for DAP recommendations (Table 8). 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 8, 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 are on average approximately 0.094 and 0.096 times more likely to adopt our recommendations on urea compared to men assigned to these two same treatments (10% and 5% statistical significance), respectively (Table 8, column (3)). Regarding the adoption of the recommended practices for DAP fertilizer, as above, none of the interaction terms are statistically significant (Table 8, column (4)).

6.3.2. Wealth

The same specification as in equation (2) is used to measure the treatment effects on the poorest and richest farmers. Two dummy variables are generated using our wealth asset index, *poorest* and *richest*, separating farmers into two income categories, below the bottom 25th income quartile for *poorest* (Yes=1; 0 otherwise) and above the 75th income quartile for *richest* (Yes=1; 0 otherwise). The effects for the poorest are depicted in Table 9, where the treatments are interacted with *poorest*. Looking at the regression in column (2), the effect of the app treatment measured by the relevant agronomic knowledge percentage test scores are on average about 7.15% lower for the poorest farmers compared to the rest of farmers (above the 25th income quartile), at the 10% statistical level of significance.

Regarding the income effects on the adoption of urea recommendations, the richest farmers in the app treatment are on average 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 pertain to a lower income quartile (statistically significant at the 5% level (Table 10, column (3)). Similar effects are found for the training treatment, the richest farmers are 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 are below the 75th income quartile (statistically significant at the 10% level, Table 10, column (3)). Finally, the IVR treatment has a negative effect on inducing the adoption of the urea recommendations, decreasing the likelihood of adoption by an average of 0.058 probability among poorest farmers relative to farmers in higher income quartiles who also received this treatment with 10% statistical significance (Table 9, column (3)). Again, both the app and training treatments have consistent positive and statistically significant effects in inducing the adoption of urea recommendations (Tables 7, 8, 9 and 10 columns (3)), but again there are no observable significant effects of the treatments by income on DAP application confirming the previously discussed findings.

6.4. Village Spillover effects

It is suspected that there could have been spillovers between treatment and control cooperatives located in the same village (Table 11). Randomizing at the village-level would not have prevented these potential spillover effects since some cooperatives were also spread between two villages. In this complex terrain, district level randomization would have been the only solution to prevent geographical proximity, but this design was not appropriate to control for differences in fertilizer policies and with only four targeted districts, the power to test statistical differences would have been limited.

Nonetheless, to control for potential spillover effects in our regression results, we create a dummy variable, called “control_only_villages”, taking the value of one if one given village has only control cooperatives, and 0 if it has also treatment cooperatives. Using the regression specification in equation (1) we compare the results in pure control villages with those in villages where other treatments are also in place by checking whether there are statistically significant differences in the outcome variables between control only villages and villages with potential spillover effects (Table 12). Table 12 reveals that only the application of DAP at planting seems to differ between control villages and villages with potential spillover effects, where the probability of applying DAP at planting was on average 0.0785 times lower in control only villages compared to villages with potential spillover effects at the 5% statistical significance level. There are no detected statistically significant differences in the other mean outcomes (i.e., general agronomic literacy, relevant agronomic literacy and the urea recommendations) between control only villages and villages where other treatments are in place. However, we must note that there were only 3 villages that can be considered to be control only villages.

When controlling for differences in control only villages compared to villages with potential spillover effects (Table 12), we see that the main results are corroborated, but the app loses statistical significance in increasing the likelihood of adoption of the urea recommendations, while the training gains statistical power, increasing the probability of adopting urea recommendations by on average 0.110 probability with 1% statistical significance, compared to farmers in control villages where other treatments are also in place. We also find that farmers in the IVR group achieve on average 4.831% lower general agronomic test scores compared to farmers in the control group suffering from potential spillover effects, with 10% statistical significance. In contrast, the training seems to increase general agronomic test scores by an average of 9.077% at the 5% statistical confidence level. However, neither the training nor the IVR are found to affect relevant agronomic test scores.

6.5. Robustness Checks

As seen from columns (1) to (4) of Table 13.a and (5) to (6) of Table 13.b, similar magnitudes in the coefficients and statistical significance are found when estimating the cross-sectional effect of treatments on end line outcomes only, thereby confirming the previously presented results. The app appears to have significantly increased general and relevant agronomic test scores by on average 4.759% and 6.163%, respectively, compared to control farmers at the 10% statistical significance level (columns (2) and (4) of Table 13.a). Farmers in the training (10% statistical significance) and the app (5% statistical significance) treatments are approximately 0.1 times more likely to adopt urea recommendations than the control group (columns (5) and (6) of Table 13.b). These results are also validated by the logit models (Table 14), although the app treatment loses statistical significance in inducing the adoption of urea recommendations when adding controls (column (2)). In column (8) of Table 13.b, it appears that farmers in the IVR treatment are 0.103 times more likely to apply the DAP recommendations, compared to farmers in the control group at the 10% level of statistical significance. However, this finding is not corroborated by the first difference estimations (Table 7), so it is not deemed robust evidence of the impacts of the IVR.

Tables 15-17 present robustness checks for the heterogeneous effects, Tables 15.a-17. a comprise the robustness checks for the knowledge outcome variables (i.e., general and relevant agronomic test scores), and 15.b-17.b for the adoption outcome variables (i.e., urea at v6 and v10 and DAP at planting). Female farmers are on average 0.092 and 0.094 times more likely to adopt the urea practices than men for those who received the radio and the training treatments respectively, at the 10% statistical confidence level (column (6) of Table 15.b). From Table 16.a (column (4)), the regressions for the poorest farmers confirm that they achieve around 6.331% lower relevant agronomic test scores in the app treatment compared to wealthier farmers with 10% statistical significance. Concerning the effects for the richest farmers, columns (5) and (6) of Table 17.b, confirm that richer farmers are less likely to follow the urea recommendations from the app treatment. There is also evidence that the training discouraged adoption of the urea recommendations among richest farmers by reducing the probability of adoption by an average of 0.157 at the 10% statistically significance level in the regression with controls (Table 17.b, column (6)), however, this result loses statistical significance in the regression without controls (Table 17.b, column (5)).

Chapter 7: Discussion

We next discuss the potential explanations for the positive evidence found for the training and app treatments, especially compared to the radio and IVR treatments that appeared less effective in inducing learning and technology adoption.

7.1. Treatment Exposure

The app treatment is the most successful among the ICT tools in fostering knowledge and adoption of new agricultural practices among farmers. However, farmers seemed to be already familiar with this technology prior to our intervention which could partly explain the success of this treatment, 46.16% of farmers in our sample report using a smartphone app in the 12 months preceding the baseline survey. The IVR treatment, in contrast, was a novel technology for this population where more than half of our sample (i.e., 58.62% of farmers) had never received voice response calls prior to the intervention. Indeed, the data reveals that farmers were confused about the purpose of the calls, and some thought it was a real person calling them rather than a voice recording. The majority of farmers did not use the keypad options to answer the questions meant to test their understanding of the messages, which limits the feedback that can be obtained from this treatment.

The results find that CIMMYT's extension trainings are also effective in inducing technology adoption, which is reassuring given the large amount of resources invested in extension services. However, the success of the training could in part be attributed to the extensive expertise CIMMYT field staff has in providing quality extension services, which might not be applicable to all extension trainings. What came as a surprise, is that the radio treatment had no significant impact. Farmers in our sample listen to the radio for 64 minutes on average every day and 45.78% of them listen to the radio more than once a day according to the baseline data. However, the radio messages relied on IVR reminders for farmers to tune into the radio, so it was not possible to extrapolate its effects alone. Further research evaluating extension services delivered through radio messages is needed.

7.2. Internal Validity

The balance test for the outcome variables conducted at baseline finds that farmers in the app and radio seem to be already applying the urea recommendations prior to receiving our treatments. We suspect that the coefficients for the app treatment might be downward biased, since despite the positive imbalance, improvements in adoption rates are still observed from this treatment. The imbalance found from farmers in the radio program, is not a concern since this treatment had no significant impacts in our study outcomes.

There are also observed baseline differences in the general agronomic literacy test scores. However, our main variable of interest is the relevant agronomic literacy test score which is balanced across treatments at baseline, confirming the beneficial effects of the app to foster the retention of new agricultural practices.

7.3. Visual vs Auditive Features

To begin to disentangle why certain modes of communication might be more successful than others, we decompose treatment attributes, presented in Table 18. One difference distinguishing the app and the training from the other two treatments (radio and IVR) is its visual component, which might have helped farmers better understand and retain the information provided, fostering adoption through learning. The radio and the IVR treatments, in contrast, only explained the information verbally, which could have limited their impact. The recommendations for urea fertilizer were judged more complex than the DAP recommendations since they entail the technique to properly count the leaves and randomly selecting plants to determine if plots are ready for the first and second dose of urea. I find that among farmers who did not follow the IVR recommendations in our sample, 16% of them declare that the instructions provided in the messages were not clear and easy enough in order to adopt the recommendations provided. This is evidence that perhaps auditive features are not as good at explaining complex practices but might be useful for simpler practices, like our DAP recommendations (Table 13.a, column (4)). Additionally, the use of mobile phone technologies have been linked to improved knowledge test scores since they can motivate students throughout the learning process and allow them to better retain the information when frequently using mobile phones (Aker et al., 2012). This could explain the app's success over the training and all other ICT tools to encourage learning and retention of the recommended practices.

7.4. In person delivery

The second main difference that separates the app and the training from the rest of the treatments aside of its visual component is the in-person delivery used to share the app and training treatments with farmers. The radio and IVR treatments were sent directly to farmers without in-person meetings. Sulaiman et al. (2012) find that failure to encourage adoption in the Indian context happened because of a lack of interaction in the exchange of information by service providers. Indeed, horizontal interaction that connects both academics, with NGOs and farmers would be more efficient to foster adoption of new technologies as opposed to simply sending advice to farmers. Furthermore, technologies should provide a means to interact and exchange information that goes two ways and not just in one direction (ibid.). Meeting a CIMMYT representative in the present research might have induced more trust in the recommendations, leading to positive adoption. Perhaps the IVR and radio treatments would have worked better if introduced by a person in charge of explaining the purpose of the calls and radio reminders prior to sending them.

7.5. Timing is key

Finally, it is important to discuss the timing of fertilizer advice. Farmers cited the tardiness of receiving the information as one of the main causes for not adopting the recommended practices. In this regard, the IVR and Radio treatment were the most challenging treatments, especially the radio since all farmers planted at different dates and it was not possible to customize the messages individually. The information was broadcasted around the times that would suit the majority of farmers. The IVR treatment could only be customized by groups of farmers sharing similar planting dates, so the timing of information provision was approximate. The training (via referring to the poster) and the app treatments were, in contrast, available at any times farmers would need to consult them. The end line data reveals 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, and 100% farmers in the app consulted the information during these months. This supports previous evidence that delivering the information at the times farmers need to apply the recommendations in their plots increases the effectiveness of the treatments (Larochelle et al., 2017). This could also explain the lack of significant effects on the adoption of the DAP recommendations, perhaps the advice came after farmers had 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 DAP recommendations that could have been quickly forgotten in an effort to remember the urea advice. Another aspect to consider is that urea is the most popular fertilizer used among farmers, while DAP fertilizer comes only second.

7.6. 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 for different income levels (i.e., poorest and richest income quartiles), and for gender. Our sample data suggests that female's access to smartphones is not restricted. All female farmer participants owned a smartphone, with the exception of 5 female farmers who accessed a phone from a third party. It seems however that females are more likely to adopt the urea recommendations from the radio and the training compared to men. These results are interpreted as evidence of women's preferences for more traditional methods rather than evidence of exclusion of female farmers from the other technologies, specifically from the app treatment. Besides non restricted access, baseline survey data also show that 41.8% of smartphone app users in the sample in the 12 months preceding the survey are female. The qualitative data provides no evidence that the app results are being driven by male farmers, since the app treatment attendees are mostly female participants, which excludes the possibility of low involvement of females in the use or access to the app. The coefficient for the interaction term between the app treatment and the *female* dummy variable is however not significant, which prevents us from commenting on the specific effects of the app for female participants, calling for further investigation.

Regarding income quartiles, 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 adopting the new recommended practices. Indeed, the end line surveys reveal 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 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) find similar results in India, in their research needy farmers gained more from the intervention than those who are better off since wealthier farmers likely had access to better services. In the present study the app was built to be straightforward to use and accessible to illiterate farmers (i.e., voice recordings available), so that farmers in bottom income quartiles could also benefit from the app.

However, it seems that the poorest retain less information from the app compared to other farmers in higher income quartiles when asked to recall the information post-harvest. However, the results still reveal that the app was effective in encouraging the adoption of the recommended urea practices for this group. It is therefore suspected that retention rates for the poorest are 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 the fertilizer application between June-August, so it is possible that this was not enough exposure to remember the information by the end of September, at end line.

Chapter 8: Conclusion

8.1. Summary

The present study tests whether ICT tools can be used as substitutes or complements to traditional extension services by comparing the performance of three technologies (i.e., radio, IVR, smartphone app) and a traditional extension training in teaching and encouraging the adoption of new fertilizer management practices. Findings reveal that technologies are not complete substitutes to face-to-face interactions. Indeed, the app and the training treatments, which both required intermediation in order to be shared with farmers (i.e., field staff visits), appear to be the best tools in inducing knowledge and adoption of the new recommended practices. The app is the only consistently robust treatment across all regression specifications (i.e., first differences, cross sectional estimates, logit estimates and controlling for village spillover effects), that is found to increase knowledge of new management practices, measured through farmers' agronomic test scores. Similarly, the training is also the only systematically robust treatment across all specifications in inducing adoption of the urea recommendations. However, both the training and the app appear to positively increase knowledge test scores as well as increasing the probability of adoption for the urea recommendations in most specifications, confirming their overall positive impact on the outcomes of interest. The radio treatment is not found to have any statistically significant impact on the outcomes of interest (i.e., knowledge and adoption) and although we find statistically significant effects of the IVR treatment in inducing adoption of the DAP recommendations in the cross sectional estimates, these results are not validated by our first differences estimations. Visual features and in person-interactions, which differentiate the app and training treatments from the radio and IVR treatments, seem to play an important role in knowledge and adoption of new agricultural practices in the Nepalese context.

8.2. External validity considerations

Qualitative data reveals that the second most popular cited reason for adopting new technologies is trusting the information source. CIMMYT is a well-established and known organization that has been working in Nepal since 1985, so the possibility that the observed behavioral changes happened from farmers' trust in CIMMYT's advice, rather than actual learning from the treatments cannot be excluded. This can limit the external validity of the results in countries and regions where the extension service providers might not be as influential. Additionally, the study reveals that accessing the app through someone else's smartphone works equally well, but the app's success remains contingent on owning a smartphone or accessing one through one's social networks. This temporarily limits the reach of the app for farmers living in low smartphone penetration areas, but smartphone-based technologies are rapidly expanding, which opens the possibility to extend the benefits to wider sections of the population.

8.3. Policy recommendations

Although our study finds reassuring evidence of the effectiveness of extension trainings in inducing technology adoption, these services remain costly to deliver and of limited reach. Our smartphone app has important policy implications through its potential to add value to existing extension services, reducing the cost of communication in remote rural areas. Although the app still requires staff and/or marketing efforts to share the app with farmers, this is likely to be cheaper than hiring extension agents, since the present research proved that this technology does not require additional explanations for its successful implementation and can be self-sufficient on its own. The app could therefore be shared by any non-experts or farmers themselves. However, there is a need to extend the information provided by the app to also cover maize crop pesticide related advice and give more detailed information on the quantities of fertilizer to apply based on farmers' feedback from the study. The results suggest that female farmers are more likely to adopt urea recommendations through more traditional services (i.e., radio and training) compared to men.

Radio services could therefore be used to deliver agricultural advice for female dominated crops. However, no statistically significant differential effects on the app's success between male and female farmers are found. These results show promising potential of apps to effectively help close farmers' information gaps.

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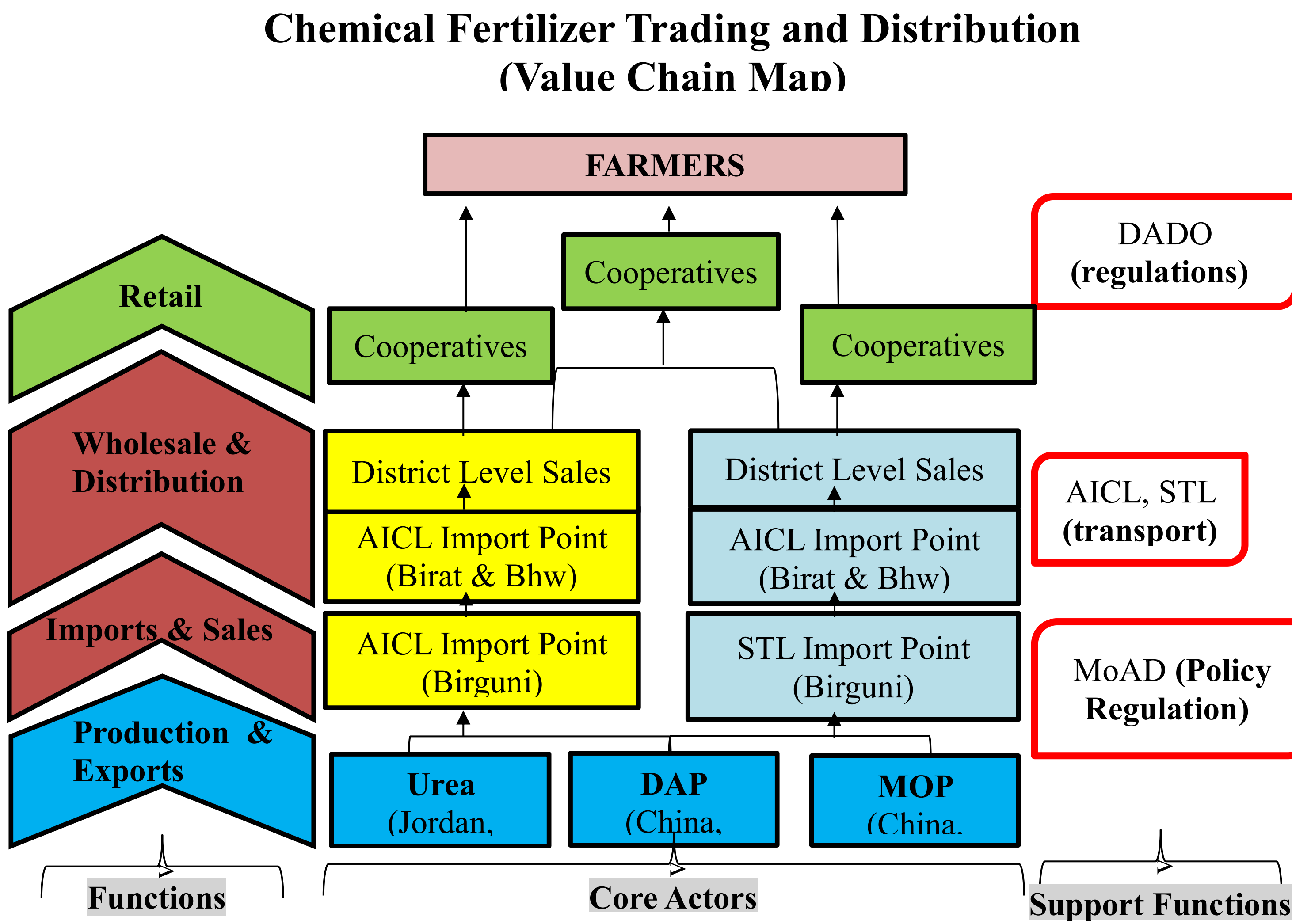
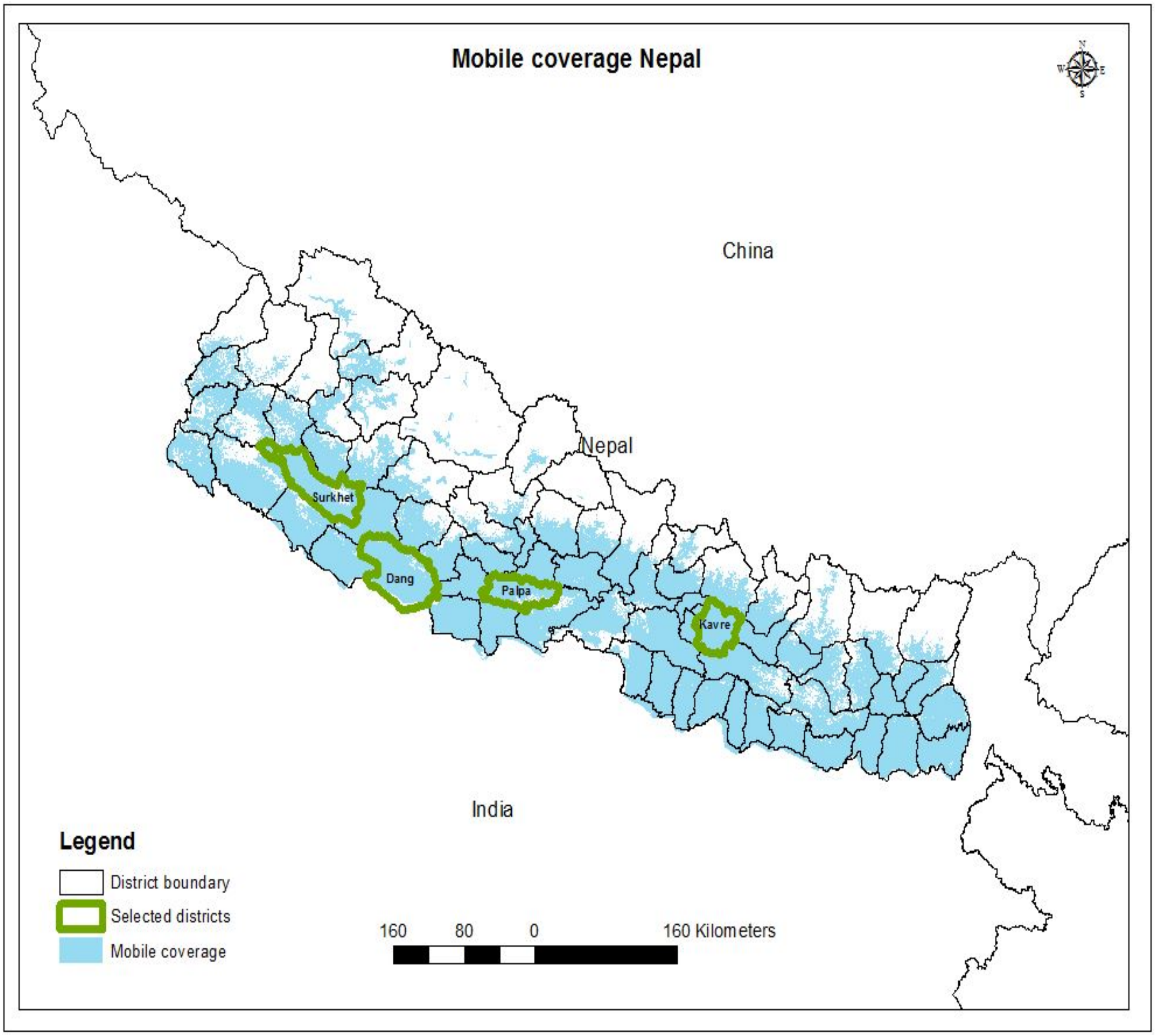
Figures



Source: CIMMYT

Note: The Agro Inputs Company Limited (AICL) and Salt Trading Corporation Limited (STCL) receive fertilizer imports at Birguni entry port and then transfer them to the other two regional points for distribution: Biratnagar (Birat) and Bhairahawa (Bhw). The AICL and STCL will then distribute fertilizers to local offices and district branches where they will be sold to registered cooperatives. The Ministry of Agriculture Development (MoAD) implements fertilizer policies and regulations and the District Agriculture Development Office (DADO) along with the "Fertilizer Supply and Distribution Management Committee" monitor the sale of fertilizers to legitimate cooperatives. Farmers can then purchase subsidized fertilizers from their cooperatives.

Figure 1: Cooperatives Role in the Chemical Fertilizer Trading and Distribution



Note: This map was taken from the polygon vector dataset from the Collins Bartholomew's Mobile Coverage Explorer, which represents the area covered by mobile communication networks around the world. The data is created from submission made directly to Collins Bartholomew or the GSMA from the mobile operators.

Figure 2: Mobile coverage Nepal

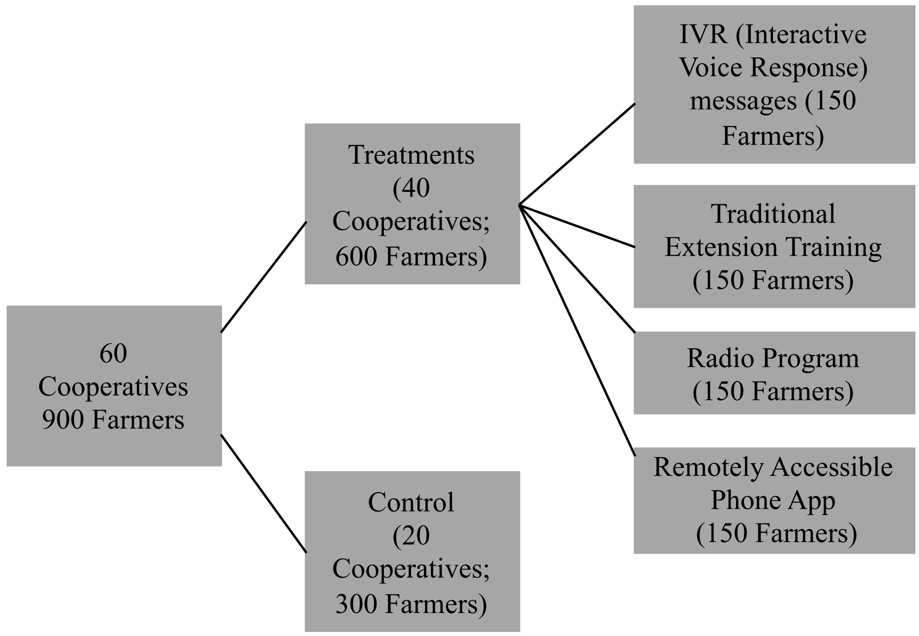
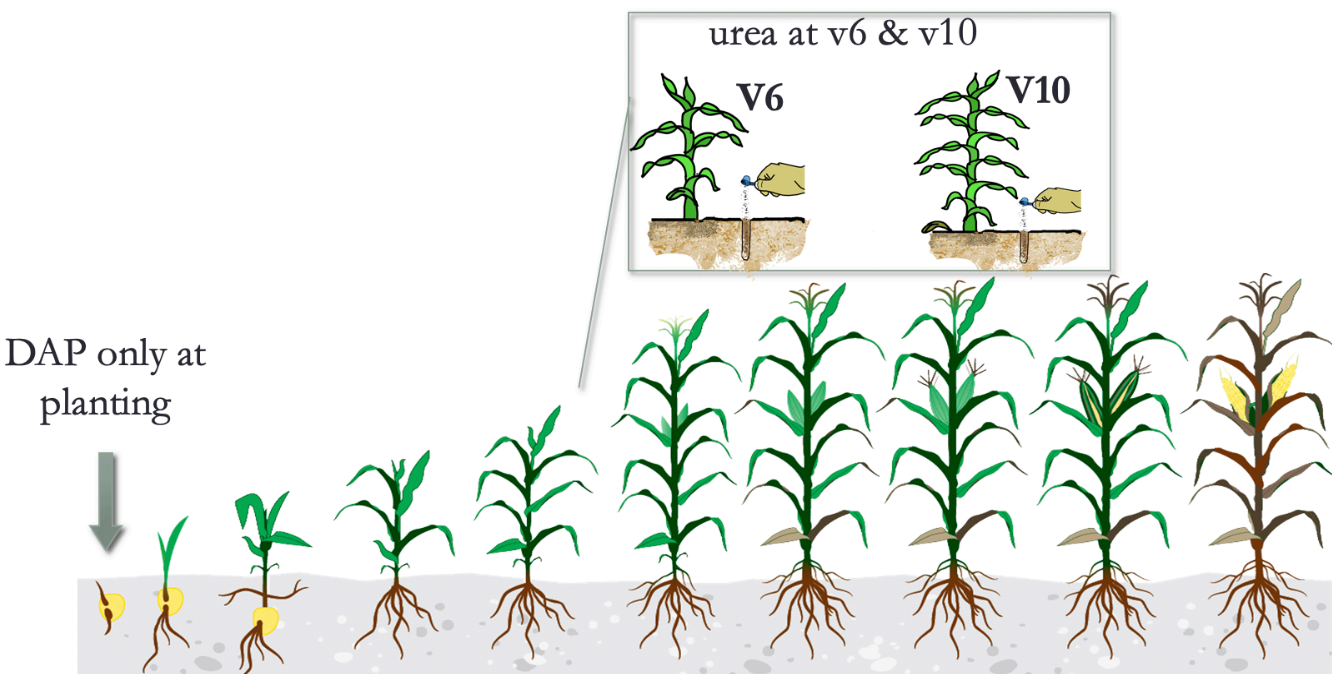


Figure 3: Treatment randomization



Source: CIMMYT

The infographics above summarize the agricultural recommendations that were provided by each treatment, consisting 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).

Figure 4: Fertilizer Recommendations

Tables

Table 1: Treatment Compliance Rates

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

[1]User data was estimated counting the number of farmers who attended the training and the app meetings, after receiving an invitation. The radio and IVR treatments usage were recovered from the data gathered by the company VIAMO, who recorded whether farmers picked up the calls for the IVR messages and the radio reminders.

Table 2: Balanced Test for Controls

Controls	Radio	App	Training	IVR	Constant	N
	(1)	(2)	(3)	(4)	(5)	(6)
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)**	
Female_respondent (Yes=1)	-0.0333	**-0.225*****	**-0.287*****	**-0.231*****	**0.611*****	886
	(0.0491)	**(0.0493)**	**(0.0486)**	**(0.0491)**	**(0.0283)**	
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	1447.155	1095.414	193.85	-256.131	**3530.826****	898
	(1.93)	(1.46)	(0.26)	(0.34)	**(8.19)**	

from main maize plot 2017 (kg/ha)						
Area main maize plot 2017	-0.031 (0.77)	0.045 (1.09)	0.056 (1.36)	0.014 (0.34)	**0.565**** **(23.85)**	900
Land ownership (ha)	-0.0318 (0.0425)	0.0397 (0.0427)	0.0123 (0.0421)	-0.0541 (0.0425)	**0.5694***** **(0.0245)**	886
Wealth asset index	0.1401 (0.1005)	**-0.22**** **(0.1010)**	0.0023 (0.0996)	0.1538 (0.1005)	-0.0076 (0.0579)	886
Durables index	-0.0432 (0.0998)	**-0.352***** **(0.1002)**	-0.079 (0.0989)	0.1236 (0.0998)	0.0653 (0.0575)	886
Livestock index	**-0.218**** **(0.1008)**	-0.0641 (0.1012)	0.1175 (0.0999)	-0.0596 (0.1008)	0.0389 (0.0581)	886
Productiv e index	**-0.171*** **(0.1010)**	0.0038 (0.1015)	-0.1226 (0.1001)	-0.1434 (0.101)	0.0694 (0.0582)	886

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

This table reports the balanced tests between the treatment groups, columns (1)-(4) and the control group, column (5). The estimations come from an OLS linear regression model regressing each covariate at baseline against the treatment dummy variables. Standard errors are presented in brackets below the coefficients. The significance reported corresponds to statistically significant differences in the covariate means between the treatment groups and the control group at baseline.

Table 3: Anticipated Sign

Controls	**Outcome Variables**			
	Agronomic literacy (general)	**Agronomic literacy (relevant)**	**Urea at v6 and v10**	**DAP at planting**
	(1)	**(2)**	**(3)**	**(4)**
No educ (Yes=1)	-	-	-	-
High school and above (Yes=1)	+	+	+	+
Female head (Yes=1)	-	-	-	-
Political (Yes=1)	+	+	+	+
Fertilizer applied at planting 2017 (Yes=1)	+	+	+	+
Fertilizer applied after planting 2017 (Yes=1)	+	+	+	+
Dependency_ratio	-	-	-	-
Wealth asset index	+	+	+	+
Age_respondent	+	+	+	+
Irrigation (Yes=1)	Not included	Not included	+	+
Agro Machinery (Yes=1)	Not included	Not included	+	+
Hired labour (Yes=1)	Not included	Not included	+	+

This table reports the anticipated sign of the direction of the relationship between the covariates and the outcome variables of interest, prior to estimating the regressions.

Table 4: Balanced Test for Outcome Variables

Variables	Radio	App	Training	IVR	Constant	N
	(1)	(2)	(3)	(4)	(5)	(6)
Relevant	1.4877	1.881	-0.537	2.5081	**35.3604*** **	886
agronomic score (%)	2.0233	2.0326	2.0053	2.0233	**(1.1655)**	
General	1.5285	**3.3322** **	1.9477	1.7759	**24.6929*** **	886
agronomic score (%)	1.5407	**(1.5478)**	1.527	1.5407	**(0.8875)**	
UREA	**0.0273***	**0.0691*** **	-0.0068	0	0.0068	886
applied at v6 and v10	**(0.0144)**	**(0.0145)**	0.0143	0.0144	0.0083	
DAP	0.0179	-0.0009	**-0.0588***	**0.0587***	**0.125*** **	886
applied at planting	0.0336	0.0337	**(0.0333)**	**(0.0336)**	**(0.0193)**	

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

This table reports the balanced tests between the treatment groups, columns (1)-(4) and the control group, column (5). The estimations come from an OLS linear regression model regressing each outcome variable at baseline against the treatment dummies. Standard errors are presented in brackets below the coefficients. The significance reported corresponds to statistically significant differences in the outcome variable means between the treatments and control groups at baseline.

Table 5: Number of Farmers Applying 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[1]	5	11	0	1	2

[1] This table reports the number of farmers in each treatment who declared having applied urea at v6 and v10 in the 2017 maize planting season. These figures are taken among those who applied urea fertilizer in the 2017 maize planting season (baseline).

Table 6: Impact of Treatments on Agricultural Knowledge

Explanatory Variables	Dependent Variables (First Difference Estimates)			
	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)		1.043		-4.768
		(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.

This table reports first differences estimating the impact of the treatments on knowledge outcomes. Columns (1)-(2), contain the regressions for the general agronomic literacy test scores and columns (3)-(4) the estimations for the relevant agronomic literacy test scores. Standard errors are presented in brackets below the coefficients. The statistical significance reported corresponds to the statistically significant effects of the treatments in inducing percent changes in agronomic test scores (over 100%). All the regressions use clustered standard errors and include village fixed effects.

Table 7: Impact of Treatments on Adoption Rates

Explanatory Variables	Dependent Variables (First Difference Estimates)			
	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.

This table reports first-differences estimating the impact of the treatments on the adoption of the recommended practices. Columns (1)-(2), report the adoption of DAP fertilizer only at planting and columns (3)-(4) the adoption of the urea recommendations at v6 and v10. Standard errors are presented in brackets below the coefficients. The statistical significance reported corresponds to statistically significant effects of the treatments and controls in inducing one step change in the likelihood of adopting the recommended practices. All the regressions use clustered standard errors and include village fixed effects.

Table 8: Impact of Treatments by Gender (Female; Yes=1)

Explanatory Variables	**Dependent Variables (First Difference Estimates)**			
	General Agronomic Literacy	**Relevant Agronomic Literacy**	**Urea at v6 and v10**	**DAP at planting**
	(1)	**(2)**	**(3)**	**(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.

This table reports the impact of the treatments by gender, using first difference estimations and interacting a dummy variable capturing the respondent's gender with each one of the treatment dummies. The dummy variable capturing gender is called "Female" and takes the value of 1 if the respondent is female or 0 otherwise. Standard errors are presented in brackets below the coefficients. The significance reported has the standard interpretation and corresponds to statistically significant effects of the treatments on the outcome variables of interest, agronomic literacy test scores (columns (1)-(2)) and adoption rates (columns (3)-(4)). Statistically significant coefficients in the interaction terms denote the differential effects between female and male farmers (i.e., male is captured by the constant) on the outcomes of interest. All the regressions use clustered standard errors and include village fixed effects.

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

Explanatory Variables	Dependent Variables (First Difference Estimates)			
	General Agronomic Literacy	Relevant Agronomic Literacy	Urea at v6 and v10	DAP at planting
	(1)	(2)	(3)	(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

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

This table reports the impact of the treatments by poorest wealth income quartile, using first difference estimations and interacting a dummy variable capturing the respondent's wealth with each one of the treatment dummies. The dummy variable "Poorest" captures whether a farmer falls below the 25th income quartile (i.e., calculated using the wealth asset index), taking the value of 1 if yes and 0 otherwise. Standard errors are presented in brackets below the coefficients. The statistical significance reported has the standard interpretation and corresponds to the statistically significant effects of the treatments in inducing percentage changes in agronomic literacy tests scores (columns (1)-(2)) and one step changes in the likelihood of adopting the recommended practices (columns (3)-(4)). Statistically significant coefficients in the interaction terms denote the differential effects between poorest farmers and the rest of farmers, who lie above the 25th income quartile (i.e., captured by the constant), on the outcomes of interest. All the regressions use clustered standard errors and include village fixed effects.

Table 10: Impact of Treatments by Richest Income Quartile (Richest; Yes=1)

Explanatory Variables	**Dependent Variables (First Difference Estimates)**			
	General Agronomic Literacy	**Relevant Agronomic Literacy**	**Urea at v6 and v10**	**DAP at planting**
	(1)	**(2)**	**(3)**	**(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.

This table reports the impact of the treatments by richest wealth income quartile, using first difference estimations and interacting a dummy variable capturing the respondent's wealth with each one of the treatment dummies. The dummy variable "Richest" captures whether a farmer is above the 75th income quartile (i.e., calculated using the wealth asset index), taking the value of 1 if yes and 0 otherwise. Standard errors are presented in brackets below the coefficients. The statistical significance reported has the standard interpretation and corresponds to the statistically significant effects of the treatments in inducing percentage changes in agronomic literacy tests scores (columns (1)-(2)) and one step changes in the likelihood of adopting the recommended practices (columns (3)-(4)). Statistically significant coefficients in the interaction terms denote the differential effects between richest farmers and the rest of farmers, who lie below the 75th income quartile (i.e., captured by the constant), on the outcomes of interest. All the regressions use clustered standard errors and include village fixed effects.

Table 11: Village Structure and Potential Spillover Effects

Treatments per Village	**Number of villages**
Control Only	3
One Treatment Only	3
Two Treatments	1
Three Treatments	2
One Treatment+Control	3
Two Treatments+Control	7
Three Treatments+Control	1
Total Villages	20

This table denotes how many villages were pure control villages (i.e., “Control Only”) and how many of them had one or more treatment cooperatives (“One Treatment+Control”, “Two Treatments+Control”, “Three Treatments+Control”). Villages where only treatment cooperatives were in place are denoted by “One Treatment Only”, “Two Treatments” and “Three Treatments”.

Table 12: Results controlling for Village Spillover

Explanatory Variables	Dependent Variables (First Difference Estimates)			
	General Agronomic Literacy	**Relevant Agronomic Literacy**	**Urea at v6 and v10**	**DAP at planting**
	(1)	**(2)**	**(3)**	**(4)**
Phone App	**7.547****	**4.128***	0.036	0.00551
	(3.194)	**(2.304)**	(0.0279)	(0.0552)
Radio	1.839	1.64	0.0189	-0.00517
	-(3.122)	-(2.237)	-(0.0223)	-(0.041)
IVR	**-4.831***	-2.266	0.0139	-0.027
	(2.607)	-(1.722)	-(0.0312)	-(0.0435)
Training	**9.077****	4.728	**0.110*****	-0.00109
	(3.444)	-(3.001)	**(0.041)**	(0.0545)
Control_Only_Villages	-2.275	-1.096	0.00422	**-0.0785*****
	(4.295)	(2.143)	(0.025)	**(0.0237)**
No educ (Yes=1)	2.112	1.158	-0.0144	-0.0182
	(2.143)	(1.516)	(0.0222)	(0.0339)
High school and above (Yes=1)	1.149	0.897	-0.0364	-0.00782
	(1.924)	(1.263)	(0.0262)	(0.0325)
Female head (Yes=1)	-0.632	0.332	-0.022	-0.0317
	(2.142)	(1.632)	(0.018)	(0.025)
Political Participation (Yes=1)	-3.323	-1.195	-0.00987	0.0474
	(2.603)	(1.77)	(0.0223)	(0.0315)
Fertilizer was applied at planting 2017 (Yes=1)	0.354	-4.582	**0.120****	0.0415
	(4.415)	(3.266)	**(0.0516)**	(0.0793)
Fertilizer was applied after planting 2017 (Yes=1)	0.0518	0.226	**0.0648*****	-0.000655
	(2.045)	(1.557)	**(0.0242)**	(0.0243)
Dependency_ratio	**-9.200****	**-5.724***	-0.0508	-0.00727
	(4.367)	**(2.998)**	(0.0429)	(0.0388)
Comprehensive asset index	-0.536	-0.276	0.00158	0.00989
	(0.972)	(0.751)	(0.0105)	(0.015)
Age_respondent	0.0822	**0.0980****	-0.000343	-0.000956
	(0.0708)	**(0.048)**	(0.000601)	(0.000866)
Irrigation (Yes=1)			0.0539	**0.140*****
			(0.0343)	**(0.0485)**
Agro Machinery (Yes=1)			0.00541	0.0326
			(0.02)	(0.0337)
Hired labour (Yes=1)			0.0196	-0.0121
			(0.0152)	(0.0322)
Constant	-0.705	4.808	-0.0836	0.102
	(5.575)	(4.544)	(0.0601)	(0.0864)

	(1)	(2)	(3)	(4)
Clustered SE at Cooperative level	YES	YES	YES	YES
Village Fixed Effects	NO	NO	NO	NO
Observations	880	880	880	880
R-squared	0.052	0.034	0.055	0.037

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

This table reports the first difference estimates on the impact of the treatments on agronomic test scores in columns (1)-(2), and adoption rates in columns (3)-(4), without including village fixed effects. Instead, we include a dummy variable for pure control villages, "Control_Only_Villages", to control for potential spillover effects. The constant captures villages where other treatments are also in place. Standard errors are presented in brackets below the coefficients. The statistical significance reported has the standard interpretation and corresponds to the statistically significant effects of the treatments in increasing percentage scores in agronomic literacy tests scores (columns (1)-(2)) and in inducing one step change in the likelihood of adopting the recommended practices (columns (3)-(4)). Statistically significant coefficients in the dummy variable "Control_Only_Villages" denote any differences in the outcome variables in control only villages compared to controls with village spillover effects. All the regressions use clustered standard errors.

Table 13.a: Robustness Checks

Explanatory Variables	Dependent Variables (Cross Sectional Estimates)			
	General Agronomic Literacy		Relevant Agronomic Literacy	
	(1)	(2)	(3)	(4)
Phone App	**5.984***	**4.759***	**6.876***	**6.163***
	(2.457)	**(2.248)**	**(2.733)**	**(2.553)**
Radio	0.537	-1.14	0.041	-1.335
	(2.753)	(2.21)	(3.014)	(2.923)
IVR	1.884	-0.277	-0.445	-2.229
	(2.541)	(2.334)	(3.038)	(2.911)
Training	4.251	1.585	3.859	1.631
	(3.346)	(3.376)	(3.256)	(3.435)
No educ (Yes=1)		**-4.578****		-3.379
		(1.385)		(1.817)
High school and above (Yes=1)		**6.545****		**4.612****
		(1.048)		**(1.405)**
Female head (Yes=1)		-1.998		-2.844
		(1.44)		(1.718)
Political Participation (Yes=1)		0.401		0.03
		(1.308)		(1.415)
Fertilizer was applied at planting 2017 (Yes=1)		-6.048		-6.551
		(3.782)		(3.743)
Fertilizer was applied after planting 2017 (Yes=1)		1.339		3.148
		(1.591)		(1.824)
Dependency_ratio		**-6.895***		**-6.763***
		(2.613)		**(2.866)**
Comprehensive asset index		-0.795		0.317
		(0.871)		(1.039)
Age_respondent		**0.162****		**0.162***
		(0.053)		**(0.071)**
Constant	**28.389****	**29.169****	**36.696****	**37.364****
	(1.702)	**(5.205)**	**(1.812)**	**(5.582)**
Control	NO	YES	NO	YES
Clustered SE at Cooperative level	YES	YES	YES	YES
Village Fixed Effects	YES	YES	YES	YES
Pseudo R2	0.01	0.09	0.02	0.06
N	886	880	886	880

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

This table reports the cross-sectional estimates on the impact of the treatments on knowledge outcomes, as robustness checks. Columns (1)-(2), contain the regressions for the general agronomic knowledge test scores and columns (3)-(4) the estimations for the relevant agronomic knowledge test scores. Standard errors are presented in brackets below the coefficients. The statistical significance reported corresponds to statistically significant effects of the treatments in inducing percent changes in agronomic test scores (over 100%). All regressions include clustered standard errors and village fixed effects.

Table 13.b: Robustness Checks

Explanatory Variables	**Dependent Variables (Cross Sectional Estimates)**			
	Urea at v6 and v10		**DAP at planting**	
	(5)	**(6)**	**(7)**	**(8)**
Phone App	**0.098****	**0.102****	0.022	-0.012
	(0.03)	**(0.034)**	(0.051)	(0.048)
Radio	0.039	0.054	0.049	0.033
	(0.033)	(0.036)	(0.062)	(0.057)
IVR	0.048	0.044	**0.139***	**0.103***
	(0.04)	(0.04)	**(0.057)**	**(0.048)**
Training	**0.12****	**0.131***	0.078	0.05
	(0.045)	**(0.049)**	(0.055)	(0.045)
No educ (Yes=1)		-0.027		-0.034
		(0.025)		(0.029)
High school and above (Yes=1)		-0.042		0.019
		(0.026)		(0.033)
Female head (Yes=1)		-0.029		0.007
		(0.018)		(0.022)
Political Participation (Yes=1)		-0.003		0.012
		(0.024)		(0.031)
Fertilizer was applied at planting 2017 (Yes=1)		**0.16****		-0.038
		(0.046)		(0.068)
Fertilizer was applied after planting 2017 (Yes=1)		0.024		**0.134****
		(0.025)		(0.04)
Dependency_ratio		-0.037		-0.002
		(0.045)		(0.056)
Comprehensive asset index		0.024		-0.035
		(0.015)		(0.019)
Age_respondent		-0.001		0.001
		(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	0.013	-0.091	**0.115****	0.02
	(0.017)	(0.06)	**(0.036)**	(0.094)
Control	NO	YES	NO	YES
Clustered SE at Cooperative level	YES	YES	YES	YES
Village Fixed Effects	YES	YES	YES	YES

Pseudo R2	0.03	0.05	0.01	0.07
N	886	880	886	880

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

This table reports the cross-sectional estimates of the impact of the treatments on adoption of the recommended practices, as robustness checks, Columns (1)-(2), report the outcomes for DAP fertilizer application at planting and columns (3)-(4) those for urea application at v6 and v10. Standard errors are presented in brackets below the coefficients. The statistical significance reported corresponds to statistically significant effects of the treatments in inducing one step changes in the likelihoods of adopting the recommended practices. All the regressions use clustered standard errors and include village fixed effects.

Table 14: 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.

This table reports the logit estimates for the binary outcome variables measuring adoption rates, as robustness checks. Standard errors are presented in brackets below the coefficients. The significance reported has the standard interpretation and corresponds to statistically significant effects of the treatments in inducing on step changes in the likelihood of adopting the urea recommendations at v6 and v10 (1)-(2), and DAP only at planting in columns (3)-(4). All the regressions use clustered standard errors.

Table 15.a: 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**	
	(1)	**(2)**	**(3)**	**(4)**
Phone App	**8.131****	5.499	**8.251****	**6.04***
	(2.717)	(2.778)	**(2.975)**	**(2.929)**
Radio	3.768	-0.438	2.231	-1.552
	(2.742)	(2.433)	(3.035)	(3.128)
IVR	**5.419***	1.27	2.849	-0.801
	(2.582)	(2.533)	(3.384)	(3.349)
Training	5.907	2.384	4.436	1.451
	(3.623)	(3.674)	(3.355)	(3.599)
App*Female	**-5.277***	-1.556	-3.056	0.751
	(2.595)	(3.256)	(2.774)	(3.446)
Radio*Female	**-5.37***	-0.999	-3.226	0.835
	(2.114)	(2.622)	(2.573)	(2.876)
IVR*Female	**-9.347****	-3.65	**-8.499****	-3.459
	(2.146)	(2.329)	**(2.961)**	(3.204)
Training*Female	-5.247	-2.241	-1.307	1.174
	(3.063)	(3.237)	(2.84)	(3.01)
No educ (Yes=1)		**-4.074****		-3.268
		(1.525)		(1.955)
High school and above (Yes=1)		**6.208****		**4.506****
		(1.058)		**(1.421)**
Female head (Yes=1)		-1.538		-2.828
		(1.536)		(1.86)
Political Participation (Yes=1)		0.359		0.009
		(1.29)		(1.401)
Fertilizer was applied at planting 2017 (Yes=1)		-6.647		-6.273
		(3.902)		(4.039)
Fertilizer was applied after planting 2017 (Yes=1)		1.353		3.045
		(1.568)		(1.829)
Dependency_ratio		**-6.827***		**-6.786***
		(2.665)		**(2.935)**
Comprehensive asset index		-0.797		0.338
		(0.867)		(1.048)
Age_respondent		**0.14***		**0.16***
		(0.062)		**(0.079)**
Constant	**28.363****	**30.575****	**36.575****	**37.124****

	(1.661)	**(5.532)**	**(1.806)**	**(6.004)**
Controls	NO	YES	NO	YES
Clustered SE at Cooperative level	YES	YES	YES	YES
Village Fixed Effects	YES	YES	YES	YES
Pseudo R2	0.04	0.09	0.02	0.06
N	886	880	886	880

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

This table reports the impact of the treatments by gender, using cross sectional estimates, as robustness checks, and interacting a dummy variable capturing respondent's gender with each one of the treatment dummies. The dummy variable capturing gender is called "Female" and takes the value of 1 if the respondent is female or 0 otherwise. Standard errors are presented in brackets below the coefficients. The significance reported has the standard interpretation and corresponds to statistically significant effects of the treatments on the outcome variables of interest, agronomic literacy test scores, general test scores in columns (1)-(2), and relevant test scores in columns (3)-(4). Statistically significant coefficients in the interaction terms denote the differential effects between female and male farmers (i.e., male is captured by the constant) on the outcomes of interest. All the regressions use clustered standard errors and include village fixed effects.

Table 15.b.: Robustness Checks on the Impact of Treatments by Gender (Female; Yes=1)

Explanatory Variables	**Dependent Variables (Cross Sectional Estimates)**			
	Urea at v6 and v10		**DAP at planting**	
	(5)	**(6)**	**(7)**	**(8)**
Phone App	**0.126****	**0.124****	0.053	0.015
	(0.032)	**(0.035)**	(0.06)	(0.058)
Radio	0.003	0.013	0.092	0.062
	(0.034)	(0.037)	(0.08)	(0.079)
IVR	0.068	0.063	**0.147***	0.1
	(0.048)	(0.047)	**(0.06)**	(0.057)
Training	**0.1***	**0.108***	0.083	0.056
	(0.039)	**(0.044)**	(0.059)	(0.051)
App*Female	-0.057	-0.041	-0.079	-0.068
	(0.039)	(0.042)	(0.051)	(0.054)
Radio*Female	**0.08***	**0.092***	-0.074	-0.052
	(0.035)	**(0.038)**	(0.062)	(0.061)
IVR*Female	-0.04	-0.04	-0.023	0.01
	(0.037)	(0.039)	(0.078)	(0.075)
Training*Female	**0.082***	**0.094***	-0.012	-0.016
	(0.033)	**(0.036)**	(0.041)	(0.055)
No educ (Yes=1)		-0.031		-0.028
		(0.026)		(0.029)
High school and above (Yes=1)		-0.039		0.015
		(0.026)		(0.033)
Female head (Yes=1)		-0.035		0.016
		(0.019)		(0.022)
Political Participation (Yes=1)		-0.005		0.01
		(0.024)		(0.031)
Fertilizer was applied at planting 2017 (Yes=1)		**0.184****		-0.045
		(0.051)		(0.075)
Fertilizer was applied after planting 2017 (Yes=1)		0.02		**0.136****
		(0.025)		**(0.04)**
Dependency_ratio		-0.035		0
		(0.045)		(0.055)
Comprehensive asset index		0.023		-0.036
		(0.015)		(0.019)
Age_respondent		0		0
		(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	0.009	-0.126	**0.115****	0.038
	(0.017)	(0.066)	**(0.036)**	(0.101)
Controls	NO	YES	NO	YES
Clustered SE at Cooperative level	YES	YES	YES	YES
Village Fixed Effects	YES	YES	YES	YES
Pseudo R2	0.04	0.07	0.02	0.07
N	886	880	886	880

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

This table reports the impact of the treatments by gender, using cross sectional estimates, as robustness checks, and interacting a dummy variable capturing respondent's gender with each one of the treatment dummies. The dummy variable capturing gender is called "Female" and takes the value of 1 if the respondent is female or 0 otherwise. Standard errors are presented in brackets below the coefficients. The significance reported has the standard interpretation and corresponds to statistically significant effects of the treatments on the outcome variables of interest, adoption rates, urea at v5 and v10 is reported in columns (5)-(6), and DAP only at planting in columns (7)-(8). Statistically significant coefficients in the interaction terms denote the differential effects between female and male farmers (i.e., male is captured by the constant) on the outcomes of interest. All the regressions use clustered standard errors and include village fixed effects.

Table 16.a.: 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	
	(1)	(2)	(3)	(4)
Phone App	**6.217***	**5.569***	**8.934****	**8.184****
	(2.581)	**(2.476)**	**(2.921)**	**(2.773)**
Radio	-1.293	-1.699	-2.12	-2.797
	(3.031)	(2.6)	(3.114)	(3.024)
IVR	0.03	-1.193	-2.549	-3.798
	(2.521)	(2.475)	(3.092)	(3.077)
Training	2.502	1.033	3.33	1.735
	(3.967)	(4.146)	(4.079)	(4.45)
App*Poorest	-0.486	-2.234	**-6.625****	**-6.331***
	(3.217)	(3.549)	**(2.404)**	**(2.767)**
Radio*Poorest	6.884	2.253	**8.353****	5.899
	(3.537)	(3.76)	**(3.031)**	(3.279)
IVR*Poorest	**6.863***	3.532	7.403	5.764
	(3.408)	(3.174)	(5.293)	(5.263)
Training*Poorest	5.777	2.151	1.349	-0.431
	(4.278)	(4.613)	(4.728)	(5.404)
No educ (Yes=1)		**-4.443****		-3.051
		(1.376)		(1.822)
High school and above (Yes=1)		**6.465****		**4.55****
		(1.118)		**(1.444)**
Female head (Yes=1)		-2.015		-2.796
		(1.459)		(1.727)
Political Participation (Yes=1)		0.447		0.194
		(1.307)		(1.379)
Fertilizer was applied at planting 2017 (Yes=1)		-6.248		-7.081
		(3.777)		(3.798)
Fertilizer was applied after planting 2017 (Yes=1)		1.28		3
		(1.578)		(1.825)
Dependency_ratio		**-6.761***		**-6.454***
		(2.599)		**(2.895)**
Comprehensive asset index		-0.51		0.48
		(1.03)		(1.288)
Age_respondent		**0.158****		**0.157***

		(0.053)		**(0.07)**
Constant	**28.471****	**29.513****	**36.825****	**38.049****
	(1.635)	**(5.261)**	**(1.792)**	**(5.678)**
Controls	NO	YES	NO	YES
Clustered SE at Cooperative level	YES	YES	YES	YES
Village Fixed Effects	YES	YES	YES	YES
Pseudo R2	0.02	0.09	0.03	0.07
N	886	880	886	880

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

This table reports the impact of the treatments among the poorest farmers, using cross sectional estimates, as robustness checks, and interacting a dummy variable capturing whether a farmer falls below the 25th income quartile (i.e., calculated from the wealth asset index) with each one of the treatment dummies. The dummy variable is called "Poorest" and takes the value of 1 if yes and 0 otherwise. Standard errors are presented in brackets below the coefficients. The statistical significance reported has the standard interpretation and corresponds to the statistically significant effects of the treatments in inducing percentage changes in agronomic literacy tests scores for general test scores in columns (1)-(2) and for relevant test scores in columns (3)-(4). Statistically significant coefficients in the interaction terms denote the differential effects between poorest farmers and the rest of farmers, who lie above the 25th income quartile (i.e., captured by the constant), on the outcomes of interest. All the regressions use clustered standard errors and include village fixed effects.

Table 16.b.: Robustness Checks on the Impact of Treatments by Poorest Income Quartile (Poorest; Yes=1)

Explanatory Variables	**Dependent Variables (Cross Sectional Estimates)**			
	Urea at v6 and v10		**DAP at planting**	
	(5)	**(6)**	**(7)**	**(8)**
Phone App	**0.1****	**0.09***	0.035	0.011
	(0.03)	**(0.034)**	(0.058)	(0.052)
Radio	0.054	0.058	0.006	0.01
	(0.037)	(0.039)	(0.058)	(0.054)
IVR	0.066	0.058	**0.154***	**0.14***
	(0.04)	(0.04)	**(0.073)**	**(0.061)**
Training	**0.141***	**0.141***	0.058	0.06
	(0.058)	**(0.058)**	(0.057)	(0.048)
App*Poorest	-0.01	0.035	-0.058	-0.118
	(0.055)	(0.063)	(0.06)	(0.065)
Radio*Poorest	-0.052	-0.014	**0.134***	0.039
	(0.049)	(0.054)	**(0.067)**	(0.076)
IVR*Poorest	**-0.065***	-0.053	-0.063	-0.163
	(0.025)	(0.03)	(0.1)	(0.109)
Training*Poorest	-0.074	-0.041	0.05	-0.063
	(0.056)	(0.047)	(0.044)	(0.053)
No educ (Yes=1)		-0.029		-0.034
		(0.025)		(0.029)
High school and above (Yes=1)		-0.041		0.021
		(0.027)		(0.032)
Female head (Yes=1)		-0.029		0.01
		(0.018)		(0.022)
Political Participation (Yes=1)		-0.004		0.017
		(0.025)		(0.031)
Fertilizer was applied at planting 2017 (Yes=1)		**0.164****		-0.033
		(0.046)		(0.071)
Fertilizer was applied after planting 2017 (Yes=1)		0.025		**0.133****
		(0.025)		**(0.04)**
Dependency_ratio		-0.039		-0.001
		(0.045)		(0.054)
Comprehensive asset index		0.02		**-0.052***
		(0.016)		**(0.025)**
Age_respondent		-0.001		0.001
		(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	0.013	-0.096	**0.12****	0.015
	(0.018)	(0.06)	**(0.036)**	(0.092)
Controls	NO	YES	NO	YES
Clustered SE at Cooperative level	YES	YES	YES	YES
Village Fixed Effects	YES	YES	YES	YES
Pseudo R2	0.03	0.06	0.02	0.08
N	886	880	886	880

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

This table reports the impact of the treatments among the poorest farmers, using cross sectional estimates, as robustness checks, and interacting a dummy variable capturing whether a farmer falls below the 25th income quartile (i.e., calculated from the wealth asset index) with each one of the treatment dummies. The dummy variable is called "Poorest" and takes the value of 1 if yes and 0 otherwise. Standard errors are presented in brackets below the coefficients. The statistical significance reported has the standard interpretation and corresponds to the statistically significant effects of the treatments in inducing one step changes in the likelihood of adoption the urea recommendations at v6 and v10 in columns (5)-(6) and DAP only at planting in columns (7)-(8). Statistically significant coefficients in the interaction terms denote the differential effects between poorest farmers and the rest of farmers, who lie above the 25th income quartile (i.e., captured by the constant), on the outcomes of interest. All the regressions use clustered standard errors and include village fixed effects.

Table 17.a.: 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	
	(1)	**(2)**	**(3)**	**(4)**
Phone App	**6.966***	**5.391***	**7.782***	**7.208***
	(2.722)	**(2.522)**	**(3.11)**	**(2.943)**
Radio	1.487	0.394	1.834	0.714
	-(2.659)	-(2.327)	(2.904)	(2.786)
IVR	3.218	0.129	0.837	-1.237
	-(2.433)	(2.374)	(2.99)	(3.039)
Training	6.386	2.691	5.116	2.86
	-(3.789)	(4.048)	(3.719)	(4.162)
App*Richest	-7.031	-3.94	-6.922	-6.27
	-(5.425)	(4.554)	(8.436)	(7.602)
Radio*Richest	-6.204	-3.993	-9.317	-9.44
	-(3.983)	(3.891)	(5.387)	(5.28)
IVR*Richest	-5.087	-1.394	-4.802	-3.296
	-(3.329)	(3.511)	(4.26)	(4.606)
Training*Richest	-7.975	-3.633	-5.391	-4.29
	-(4.262)	(3.989)	(3.978)	(4.385)
No educ (Yes=1)		**-4.602****		-3.424
		(1.398)		(1.825)
High school and above (Yes=1)		**6.372****		**4.352****
		(1.024)		**(1.361)**
Female head (Yes=1)		-1.964		-2.692
		(1.463)		(1.711)
Political Participation (Yes=1)		0.49		0.227
		(1.314)		(1.36)
Fertilizer was applied at planting 2017 (Yes=1)		-5.9		-6.413
		(3.836)		(3.739)
Fertilizer was applied after planting 2017 (Yes=1)		1.471		3.329
		(1.565)		(1.772)
Dependency_ratio		**-6.717***		**-6.558***
		(2.602)		**(2.888)**
Comprehensive asset index		-0.154		1.455
		(0.975)		(1.161)
Age_respondent		**0.16****		**0.158***
		(0.054)		**(0.071)**
Constant	**28.662****	**29.138****	**37.017****	**37.396****
	(1.572)	**(5.281)**	**(1.73)**	**(5.59)**

Controls	NO	YES	NO	YES
Clustered SE at Cooperative level	YES	YES	YES	YES
Village Fixed Effects	YES	YES	YES	YES
Pseudo R2	0.03	0.09	0.03	0.07
N	886	880	886	880

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

This table reports the impact of the treatments among the richest farmers, using cross sectional estimates, as robustness checks, and interacting a dummy variable capturing whether a farmer falls above the 75th income quartile (i.e., calculated from the wealth asset index) with each one of the treatment dummies. The dummy variable is called "Richest" and takes the value of 1 if yes and 0 otherwise. Standard errors are presented in brackets below the coefficients. The statistical significance reported has the standard interpretation and corresponds to the statistically significant effects of the treatments in inducing percentage changes in agronomic literacy tests scores for general test scores in columns (1)-(2) and for relevant test scores in columns (3)-(4). Statistically significant coefficients in the interaction terms denote the differential effects between the richest farmers and the rest of farmers, who lie below the 75th income quartile (i.e., captured by the constant), on the outcomes of interest. All the regressions use clustered standard errors and include village fixed effects.

Table 17.b.: Robustness Checks on the Impact of Treatments by Richest Income Quartile (Richest; Yes=1)

Explanatory Variables	**Dependent Variables (Cross Sectional Estimates)**			
	Urea at v6 and v10		**DAP at planting**	
	(5)	**(6)**	**(7)**	**(8)**
Phone App	**0.109****	**0.125****	0.034	-0.007
	(0.032)	**(0.036)**	(0.05)	(0.049)
Radio	0.02	0.047	0.073	0.051
	(0.032)	(0.035)	(0.066)	(0.059)
IVR	0.049	0.058	**0.163****	**0.106****
	(0.05)	(0.05)	**(0.044)**	**(0.04)**
Training	**0.145****	**0.182****	0.098	0.056
	(0.051)	**(0.056)**	(0.055)	(0.046)
App*Richest	**-0.073***	**-0.133****	**-0.079****	-0.031
	(0.03)	**(0.039)**	**(0.029)**	(0.044)
Radio*Richest	0.055	0	-0.117	-0.084
	(0.033)	(0.033)	(0.08)	(0.071)
IVR*Richest	-0.007	-0.046	-0.088	-0.011
	(0.04)	(0.045)	(0.107)	(0.12)
Training*Richest	-0.076	**-0.157***	-0.082	-0.025
	(0.051)	**(0.06)**	(0.062)	(0.068)
No educ (Yes=1)		-0.026		-0.035
		(0.024)		(0.03)
High school and above (Yes=1)		-0.047		0.017
		(0.025)		(0.033)
Female head (Yes=1)		-0.032		0.009
		(0.018)		(0.022)
Political Participation (Yes=1)		-0.003		0.014
		(0.025)		(0.031)
Fertilizer was applied at planting 2017 (Yes=1)		**0.165O****		-0.036
		(0.045)		(0.069)
Fertilizer was applied after planting 2017 (Yes=1)		0.027		**0.136****
		(0.024)		**(0.04)**
Dependency_ratio		-0.029		0
		(0.046)		(0.055)
Comprehensive asset index		**0.04***		-0.027
		(0.018)		(0.022)
Age_respondent		-0.001		0.001
		(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	0.013	-0.09	**0.119****	0.018
	(0.015)	(0.058)	**(0.035)**	(0.093)
Controls	NO	YES	NO	YES
Clustered SE at Cooperative level	YES	YES	YES	YES
Village Fixed Effects	YES	YES	YES	YES
Pseudo R2	0.03	0.07	0.02	0.07
N	886	880	886	880

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

This table reports the impact of the treatments among the richest farmers, using cross sectional estimates, as robustness checks, and interacting a dummy variable capturing whether a farmer falls above the 75^{th} income quartile (i.e., calculated from the wealth asset index) with each one of the treatment dummies. The dummy variable is called "Richest" and takes the value of 1 if yes and 0 otherwise. Standard errors are presented in brackets below the coefficients. The statistical significance reported has the standard interpretation and corresponds to the statistically significant effects of the treatments in inducing one step changes in the likelihood of adoption the urea recommendations at v6 and v10 in columns (5)-(6) and DAP only at planting in columns (7)-(8). Statistically significant coefficients in the interaction terms denote the differential effects between the richest farmers and the rest of farmers, who lie below the 75^{th} income quartile (i.e., captured by the constant), on the outcomes of interest. All the regressions use clustered standard errors and include village fixed effects.

Table 18: Treatment Attributes

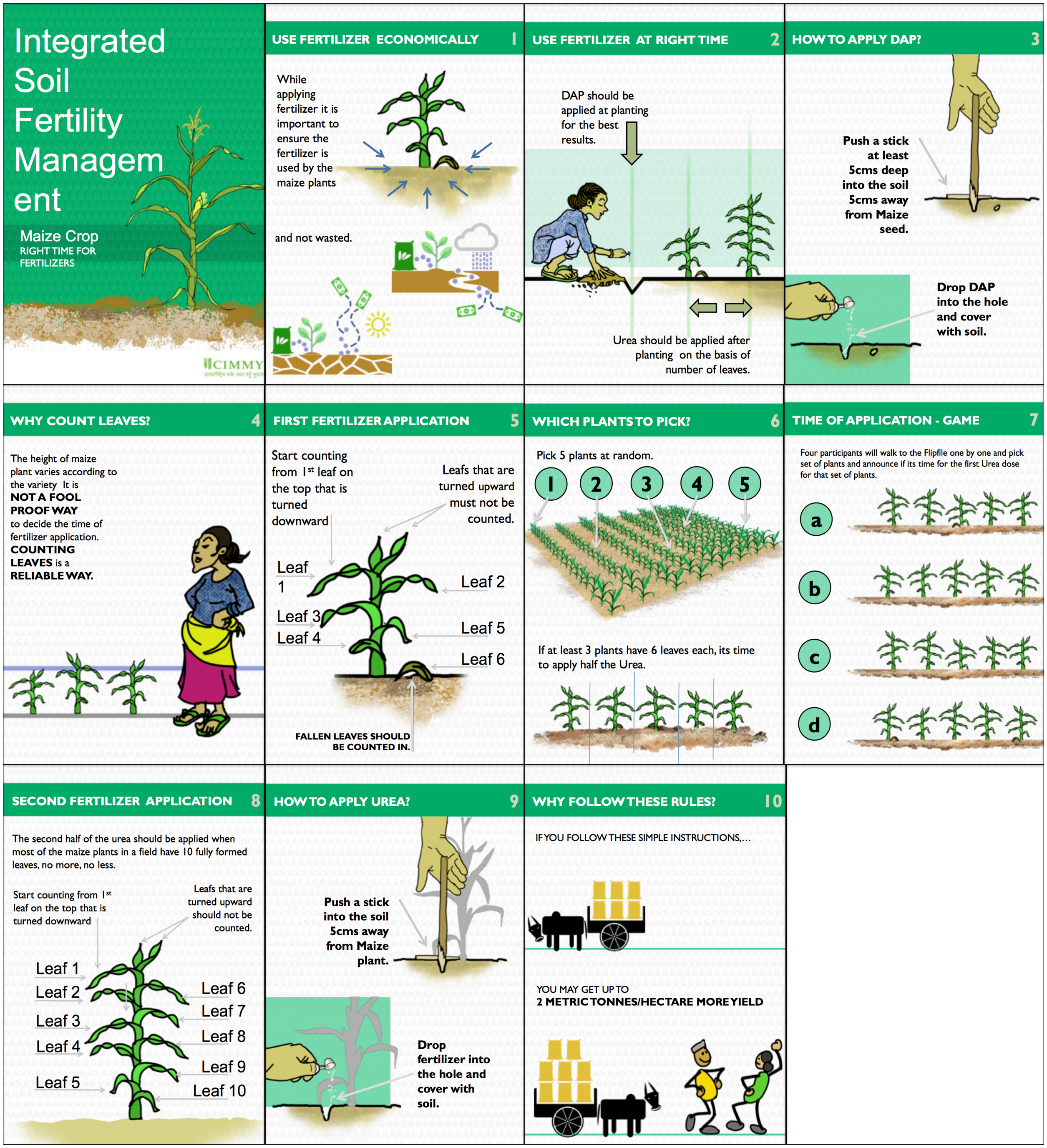
Controls	Outcome Variables			
	App	Training	IVR	Radio
Visual feature	X	X		
Auditive feature	X	X	X	X
Field demonstration		X		
In person delivery	X	X		
Timely exposure[1]	X		X	X
Frequent access[2]	X		X	X
Accessible to illiterate people[3]	X	X	X	X

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

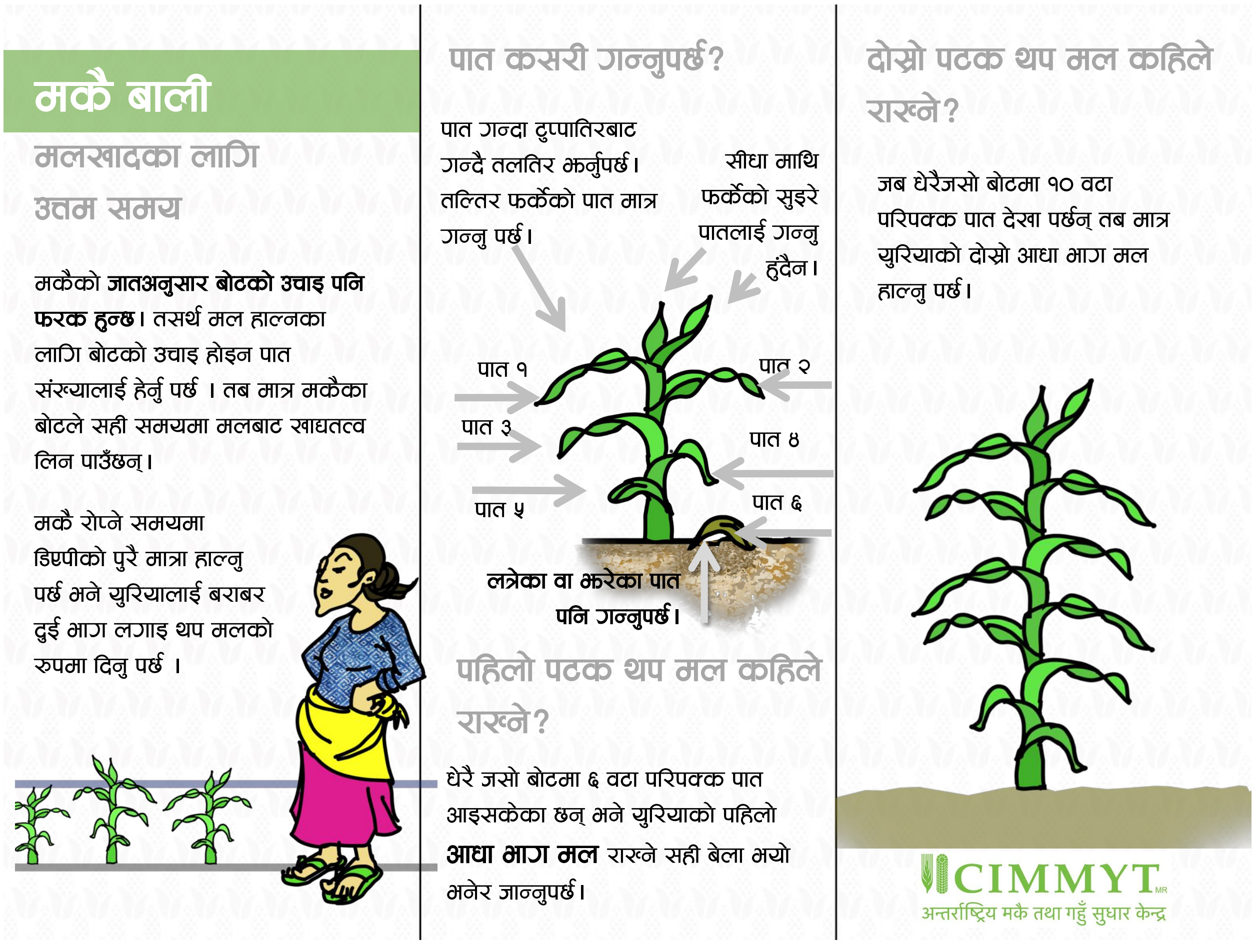
[2] Frequent access refers to weekly exposure to the information in the most relevant months.

[3] Literacy rates in our sample were 66.22%, calculated 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 A: App and Extension Training Slides



Appendix B: Extension Training Printed Poster Material



Appendix C: 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 D: IVR calls

Call 1	Namaste, we are calling to give you information on methods for increasing your maize crop production in partnership with USAID's Feed the Future Nepal Seed and Fertilizer project that focuses on national crop productivity improvement in Nepal. The series of messages will not take more that 5 minutes of your time. Please use the keypad to respond. This call is free and your responses are anonymous and confidential. Thank you for your time!

Call 1	Is now.a convenient time to talk? To listen to the agricultural advice now, Press 1 To listen to the agricultural advice tomorrow, Press 2
Call 1	A: Hello Bhim. Where are you rushing off to so early in the morning? B: I am going to X agrovet to buy UREA and DAP for my maize field. A: That's good. Do you know, I was able to increase maize production last season compared to what I could earlier by applying fertilizers the correct way.
Call 1	B: And how did you do that? A: First start off with applying and apply DAP at planting. The distance between plants should be 25 cm. After planting, apply half of the urea when your maize plants have six fully formed leaves. Also, remember to apply the urea 5cm from each plant, 5cm deep in the soil and cover it with more soil.
Call 1	B: What about the other remaining half of the urea? remaining? A: When you see your maize plants have ten fully formed leaves, apply the remaining half of urea in the same way. By doing so, there was a significant increase of up to 66 kg per Kattha* gain yield last season. You can achieve that too!
Call 1	A: Alright, I will apply the same practice too. Thank you for the information, Maila dai.
Call 1	Thank you for listening to the first message. You will receive 2 further calls over the next few weeks with more information. Happy Planting!

Call 2	Namaste! Your Maili Didi here. Do you remember when to apply the first half of urea to your maize plants? Press 1 if you think it's at planting. Press 3 if you think it's when six leaves have fully formed.
Call 2	Sorry that's incorrect. To get increased yields, you should apply DAP at planting and urea only after planting. It is also important to remember that there should be 25cm gap between each maize plant. The first half of urea that you have available or bought is applied when your maize plants have six fully formed leaves. 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. Pick 5 plants at random. If at least 3 plants have 6 leaves each, it's time to apply half the urea. It is important to also remember to apply the urea 5cm from each maize plant, 5 – 9 cm deep in the soil and cover with soil and watch your yields increase!
Call 2	Correct! To get increased yields, you should apply DAP at planting and urea after planting. The first half of urea that you have available or bought is applied when your maize plants have six fully formed leaves. 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. Pick 5 plants at random. If at least 3 plants have 6 leaves each, it's time to apply half the urea. Remember to apply the urea 5cm from each maize plant, 5-9 cm deep in the soil and cover with soil. Follow these steps and watch your yields increase!

Call 2	Thank you for listening to the second message. You should have completed the first half of your planting. You will receive 1 more call over the next few weeks with more information.

Call 3	Namaste! It is your Maili Didi again. Do you remember which fertilizer you should apply when your maize has ten fully formed leaves? Press 1 if you think it's Urea. Press 3 if you think it's DAP.
Call 3	Yes, that is the right answer! To get increased yields from fertilizer, you should apply DAP at planting and urea only after planting. It is also important to remember that there should be 25cm gap between each maize plant. The first half of urea that you have available or bought is applied when your maize plants have six fully formed leaves. The second half of urea is applied when the maize plants have ten fully formed leaves. 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. Pick 5 plants at random. If at least 3 plants have 10 leaves each, it's time to apply half the urea. Remember to apply the urea 5cm from each maize plant, 5-9 cm deep in the soil and cover with soil and that there is 25 cm space between plants. Follow these steps and watch your yields increase!

Call 3	Sorry that's incorrect. To see the most benefits from fertilizer you should apply DAP at planting and urea after planting. It is also important to remember that there should be 25cm gap between each maize plant. The first half of urea that you have available or bought is applied when your maize plants have six fully formed leaves. The second half of urea is applied when the maize plants have ten fully formed leaves. 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. Pick 5 plants at random. If at least 3 plants have 10 leaves each, it's time to apply half the urea. Remember to apply the urea 5cm from each maize plant, 5-9 cm deep in the soil and cover with soil. Follow these steps and watch your yields increase!
Call 3	Thank you for listening to the last message of this series. You should have completed the planting of your maize crops.

* Changed to 100kg/ropani for the hilly language version.

Appendix E: General and Relevant Agronomic Literacy Test Questionnaire

Agronomic Literacy Test[11]:

[11] 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.

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, whn 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

   [ ] 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 F: Factor Analysis for the Wealth Asset Indices

Table F.1. 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

Table F.2. 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

Table F.3. Asset Index Summary Statistics, by Percentile (Baseline)

	Quartiles	mean	std dev.	median	min	max
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