Africa RISING

Africa Research in Sustainable Intensification for the Next Generation

Capstone Final Report

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The Africa Research in Sustainable Intensification for the Next Generation (Africa RISING) program comprises three research-for-development projects supported by the United States Agency for International Development as part of the U.S. government's Feed the Future initiative.

Through action research and development partnerships, Africa RISING will create opportunities for smallholder farm households to move out of hunger and poverty through sustainably intensified farming systems that improve food, nutrition, and income security, particularly for women and children, and conserve or enhance the natural resource base.

The three regional projects are led by the International Institute of Tropical Agriculture (in West Africa and East and Southern Africa) and the International Livestock Research Institute (in the Ethiopian Highlands). The International Food Policy Research Institute leads the program's monitoring, evaluation and impact assessment. http://africa-rising.net/

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Executive Summary

Motivation

Food security is a marked concern for the countries of Sub-Saharan Africa. The region's small farmers have proven unable to meet their households' nutritional needs due to several limitations, including: low productivity, limited access to finance, and the underutilization of agricultural technologies. Africa Research In Sustainable Intensification for the Next Generation (Africa RISING or AR) is a multi-country program that seeks to address these issues by creating opportunities for small farmers to use yield-increasing technologies. AR delivers these opportunities through various activities including: field days promoting the usage of improved seeds, advanced ploughing, intercropping, and leguminous trees and the provision of coupons subsidizing the purchase of seeds and fertilizer.

Background

The International Food Policy Research Institute (IFPRI) invited the Capstone Team to provide assistance in measuring the early effects of Africa RISING's technology-promoting activities in Tanzania. IFPRI informed the team that it was interested in identifying whether Africa RISING increased households' usage of technologies, the characteristics of households that did use program technologies, and if use improved crop yields affected participants' willingness to pay for technologies. The data available for this exercise included a household-level baseline collected in three Tanzanian districts, roughly two years after the start of the program, and a panel survey applied in a select group of households from the Babati district that participated in an AR lottery that raffled fertilizer coupons. Both surveys contain data on households that participated and did not participate in AR.

Objectives

This report uses the aforementioned data to answer three questions corresponding to IFPRI's research interests:

1. *What factors predict usage of improved maize seeds among beneficiary and comparison households included in the baseline survey?*
2. *Does exposure to AR affect the usage of improved seeds and other program technologies among the beneficiary households included in the baseline survey?*
3. *What is the impact of providing fertilizer coupons on fertilizer usage, maize yields, and willingness to pay for technologies among the participants of the Babati lottery?*

Methodology

Our report addresses these questions by employing a unique mix of evaluation methodologies. We explore Question 1 using logit regression and lasso, a machine learning technique that determines which variables, from the universe of covariates included in the baseline survey, are correlated with households' decision to adopt the program technologies. For Question 2, we use propensity score matching to estimate AR's effect on technology usage among households who participated in the program. We exploit the lottery underlying Question 3 by using experimental evaluation techniques to determine AR's impact on technology usage, crop yields, and willingness to pay for technologies.

Results

Our analyses of Africa RISING result in the following conclusions:

1. Providing free access to agricultural technology for one year can have a positive impact on the long-term behavior among farmer households. Farmers become aware of the benefits of using improved agricultural technology and therefore keep investing in

technology. In addition, free access to agricultural technology increases agricultural yield.

2. We find important information on the market price of fertilizers. Willingness-to-pay (WTP) for fertilizers increased among treated farmers, but fertilizer usage did not increase. Even after the increase in WTP, the amount was still much lower than the average market price of fertilizers.
3. Our predictive analyses find a number of important predictors of agricultural technology adoption that are more specific to the case of Africa RISING in Tanzania. As in the literature review, we find that soil characteristics and distance to markets are important predictors of agricultural usage.
4. Our efforts to study the predictors of adaption and relationship between AR and technology usage reveal that program beneficiaries are systematically different from non-beneficiaries. Households that participated in the program are wealthier, better educated, and demonstrate distinct patterns of land ownership and composition.

We hope these conclusions will advance IFPRI's understanding of the early effects of Africa RISING in Tanzania. We also consider our findings raise important questions for future research: How do bio-fiscal and geographic characteristics affect technology usage? Will AR succeed in increasing technology usage and productivity in the average population of high-need farmers? What factors contribute to sustained purchase of seeds? Finally, we believe our work has two important policy implications regarding AR's design and interventions:

1. Our analysis of the characteristics of technology users in beneficiary and comparison households highlights important household characteristics that seem to play a role in both groups' decision to use technology. Specifically, we find distance to markets and poor soil quality has an adverse effect on adoption, even among households who

participate in AR. We consider this finding calls for more in-depth analyses of barriers to adoption that may not be removed by AR. Identifying and using these barriers to set the program's targeting strategies will be important step towards potentially raising adoption rates and cost effectiveness.

2. Our research suggests that examining farmers' reported fertilizer prices are key to understanding their willingness to use and pay for this technology. Analyses of the Babati experiment reveal that while fertilizer coupons have a positive effect on farmers' usage and willingness to pay (WTP) for this technology, WTP is still below participant's reports of market prices for this technology. Fertilizer markets are highly variable within AR's work sites, yet the persistent gap between WTP and reported fertilizer prices could be an important explanation for low usage of fertilizer among beneficiary and comparison household. We consider that AR could benefit from conducting comparative assessments of actual market prices for fertilizer, reported prices, and WTP. In addition, looking at supply side characteristics of fertilizer market would help better understand the price variation observed in reported priced. This information could help the program have a better understand of how price may affect the immediate and sustained usage of this technology in program areas.

Limitations

Our findings on Africa RISING are generally positive. Yet, their validity is challenged by four important limitations. First, our baseline data was collected after the roll-out of AR. If the covariates included in our analysis for Questions 1 and 2 are affected by treatment, our results may be biased. Second, all of our analyses rely on very small samples, hence our findings my fail to materialize in larger samples. Third, because AR's beneficiary households were not randomly selected, the PSM methodology used for Questions 2 is sensitive to selection bias that may undermine our results if it remains uncorrected. Finally, our results have limited external validity because our sample of treatment and comparison households was selected according to their willingness to participate in AR. As the literature review suggests, willingness to engage technology promotion programs is not random, but driven by identifiable characteristics.

Acknowledgements

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1. Introduction

In the past decade, population growth, rising competition for resources, and climate change have made food security a priority for international policy agendas. The countries of Sub-Saharan Africa, including Tanzania, are a focus of concern. Statistics compiled by the World Food Organization reveal that 32.1% of Tanzanian households are chronically undernourished. This figure trumps the sub-regional average of 23% and is heavily concentrated in the country's rural, farming households.[1] Small farmer's inability to meet the nutritional needs of their households is linked to various limitations, including: low productivity, limited access to finance, and the underutilization of agricultural technologies. Improving Tanzania's food security will require addressing these challenges via interventions that increase food output, improve nutrition, and alleviate poverty.

Africa Research In Sustainable Intensification for the Next Generation (Africa RISING or AR)[2] is a direct response to low levels of agricultural productivity observed in Tanzania, Ghana, Mali, Zambia, Malawi, and Ethiopia. AR intends to raise agricultural output by creating opportunities for small farmers to use technologies suited to their unique bio-physical contexts.[3] The program's work in Tanzania has focused on providing small farmers in three districts-- Babati, Kiteto, and Kongwa-- with exposure and access to seeds, fertilizer, and planting and intercropping techniques aimed at increasing yields of maize and other regional staples. AR has dispensed these benefits through mother and baby trials, field days, and the provision of coupons for improved seeds and fertilizer. [4]

[1] FAO. (2015). Regional Overview of Food Insecurity: African food insecurity prospects brighter than ever. Accra: FAO. Available at: http://www.fao.org/3/a-i4635e.pdf
[2] The official name of this program is Africa Research in Sustainable Intensification for the Next Generation. AR is supported by USAID, as part of the US Government's "Feed the Future" initiative.
[3] AR focuses on increasing the adoption, or long-term usage, of agricultural technologies. Our project is focused on short-term technology usage which is technically not adoption, yet we use the terms "technology usage" and "adoption" interchangeably.
[4] Mother and baby trials feature a centrally-located mother trial that is set up with researchers' support. Baby trials, which contain subsets of the mother trial treatments, are grown, managed and evaluated by interested farmers. Field days are public events in which AR demonstrates the usage of specific technologies.

Are Africa RISING's interventions raising the well-being of farming households in Sub-Saharan Africa? Africa RISING's theory of change sustains that provision of opportunities to engage locally-appropriate technologies will encourage the adoption of such technologies.[5] The usage of AR technologies raises yields, and, eventually, reduces poverty and improves nutrition. This document uses survey data from Africa RISING's Tanzania program to assess if its interventions secure two outcomes, which according to the aforementioned theory, are required for the program to have a positive impact its beneficiary's well-being: (1) increased usage of agricultural technologies and (2) improved (maize) yields. By examining if the program secures these outcomes, our analysis intends to shed light on results of AR early interactions with program participants, provide information that will aid the interpretation of forthcoming studies of program impact, and highlight considerations for future research and program activities.

Our report will proceed in the following way. Section 3 presents a literature review covering research on the relationship between technology adoption, poverty, and nutrition; the determinants of technology adoption, and our study's contribution to these fields. Section 4 reviews the evaluation design and data available for our study and provides summary statistics recounting key aspects of our data. Section 5 presents the three research questions addressed by our study. Sections 6-8 address each research question independently while Section 9 discusses the overall implications of our study.

[5] Figure 3 in the Appendix presents Africa Rising's Theory of Change.

2. Literature Review

2.1 Technology Adoption, Poverty, and Nutrition

The adoption of agricultural technologies plays a critical role in improving the economic and nutritional status of poor households in developing countries. Kassie, Shiferaw and Muricho (2011) demonstrate this fact in rural Uganda by using matching methods to show that the adoption of improved groundnut varieties significantly increases household income and reduces poverty rates by 7-9 percentage points. Asfaw, Shiferaw, Simtowe and Lipper (2012) also examine the relationship of adoption and welfare, but do so in rural Ethiopia and Tanzania. They find that technology adoption reduces poverty, increases consumption expenditure, improves food security, and increases households’ overall ability to withstand risk. In Bangladesh, Mendola (2006) arrives at a similar conclusion validating that employing propensity score matching to show that agricultural technology adoption has a robust, positive effect of on household wellbeing, measured as the natural logarithm of gross income.

The strong link between agricultural technology adoption, nutritional status, and poverty reported in the previous studies and others has made identifying the determinants of technology adoption a strong priority for academics and development practitioners. However, while the past two decades have produced a wide body of research on this topic, there is still no simple answer to what factors drive or correlate with adoption behavior. The determinants of adoption have proven to be diverse, fluctuating across contexts, populations, crops, and technologies (Gebreselassie & Sanders, 2006). These variations make it difficult to make generalize findings on this subject. Nonetheless, it is possible to discuss five factors whose relation to adoption has been widely examined in the existing literature. These are: profitability, access to technology, education and information, quality of technology and risk aversion.

2.2 The Determinants of Technology Adoption

Profitability is the first factor widely regarded to have a strong relation to adoption. Suri (2011) studies how profitability affects the adoption of hybrid maize seeds amongst farmers in Kenya The findings suggest that, even when farmers get high gross returns from hybrid seeds, adoption is low, and further explains this outcome noting that the high costs of acquiring seed technology reduced overall profitability and diminish adoption. Duflo, Kremer, and Robinson (2008) find similar results. They use a randomized control trial (RCT) to study fertilizer adoption among farmers in Busia, Kenya. They find that even though fertilizers may raise crop yields in test settings, high yields may not materialize in "real-world" farms with less optimal conditions (i.e. poor soil quality, imperfect usage, and geographic constraints). The authors demonstrate that, indeed, less-than-optimal conditions diminish the profitability of fertilizers for most farms in Busia's "real world" farms and result low adoption.

Access to technologies is a second factor correlated with adoption. Ghimire, Wen-chi and Shrestha (2014) examine this issue studying the correlates of adoption among rice farmers in Nepal. Using a probit model, they find that having improved seeds available in local stores has a positive, significant impact on adoption. The author's estimate that local access to improved seed increases the probability of adoption by 4.9%. Kassie, Shiferaw and Muricho (2011) study the adoption of hybrid seeds by Ugandan farmers. In accordance with the previous study, they confirm distance to markets is a major barrier to adoption. Specifically, the authors find that a one unit increases in distance, decreases the log odds of adoption by 0.0714.

Third, education and information are among the most often studied determinants of adoption. Research on these topics, conducted in various contexts, crops, and technologies, widely concurs that both parameters have positive, statistically significant effects on households' adoption behaviors. Studies differ, however, in their assessment of which education/information channels influence adoption decisions. Abebaw and Haile (2013) use propensity score matching to find that, in Ethiopia, belonging to a smallholder farmer cooperative has a significant effect on farmers' decision to adopt fertilizer. This effect is heterogeneous, being concentrated on farmers living in remote areas. Cole and Fernando (2012) designed an RCT to test whether having access to on-demand information on technologies, via mobile phone, influences the adoption behaviors of Indian farmers with weak access to extension services. They find that providing access to this type of information generated a significant, 10% increase in the use of non-toxic pesticide and 20% significant decrease in the use of toxic inputs.

Fourth, counterfeit or low quality agricultural inputs are a new, but increasingly accepted explanation for low technology adoption in East Africa other contexts with inputs of variable quality. Bold, Kaizzi, Svensson and Yanagizawa-Drott (2015) find that 30% of nutrients were missing in fertilizers purchased in local markets in Uganda; hybrid maize seed contains less than 50 % authentic seed. The authors argue that, in this context, even farmers who know the benefits of using fertilizers will not do so due to their perceptions of fertilizer quality. The authors back this argument contrasting low take up rates to perceptions of quality. They find that that farmers in their study expect fertilizer bought in the market place to contain 38 % less nutrients than they should; the authors link these expectations to low fertilizer take-up.

Finally, research on the effect of risk perceptions on adoption patterns is a relatively recent addition to the adoption literature. Gine and Yang (2009) study this angle of adoption by using an RCT to assess if adoption changes in response to risky credit vs. safe credit offers in Malawi. They examine this question by randomly offering farmers "risky" credit (traditional credit) or "safe" credit (tradition credit bundled with insurance) for purchasing technologies.

They find that the type of credit offered does not seem to affect the take-up of credit or adoption- a surprising find that is typical of the largely mixed results of this field of study.

2.3 Contribution to the Literature

Our review suggests that the adoption of agricultural technologies is key to raising household productivity and nutrition. Nonetheless, the literature on the determinants of adoption is specific to geological areas, crops, and technologies. The lack of general findings in this field suggests there is a need for ongoing, rigorous research on what interventions and household characteristics increase the probability of adoption in different contexts. Our study responds to this gap by using a machine learning technique to identify household characteristics that affect adoption and quasi- experimental and experimental evaluation methods to examine if AR increases technology usage and raises agricultural yields in three districts in Tanzania that share similar bio-physical characteristics, and where the same technologies are being implemented.

3 Intervention, Evaluation Design, and Data

3.1 Intervention

The Africa RISING program started in 2012 and was initially implemented in the Babati, Kiteto and Kongwa districts of northern and central Tanzania.[6] The rollout of AR program activities reached a total of 7 villages in these regions over several months. Program activities varied across villages and included field days exposing farmers to new technologies, mother and baby trials demonstrating planting techniques, and provision of coupons subsidizing the purchase of selected technologies. Table 1 presents the specific technologies and crops targeted by AR. The precise dates and activities used to promote these innovations available are not available, but are assumed to be within two agricultural seasons from 2012 to 2014.

[6] AR will be implemented in a total of 11 villages. However, the data used for this exercise was collected at a time when only 7 villages had been treated. Thereby, we consider the four villages that were not treated by the time data was collected as untreated or comparison villages.

Table 1. AR Technologies in Tanzania 2014-2016

Technology	
Improved Seeds on:	Maize Bean Pigeon Pea Irish Potato Sorghum
Fertilizer use, which includes:	Urea NPK D. Compound CAN A Combination
Soil Management as:	Stone terraces Fanya huu/chini Other terrace Grass strips/barriers (e.g. vetiver grass) Drainage/ditches Trash lines Planting trees Contour bands Marker ridges Box ridges
Tillage	
Ploughing	Tractor, moldboard plough Tractor, disc plough
Leguminous Trees	
Inter-cropping/Crop Rotation	

Source: Author's, based on Ainsley Charles, Tanzania Africa RISING Baseline Evaluation Survey 2014 Summary Report

1.2 Evaluation Design

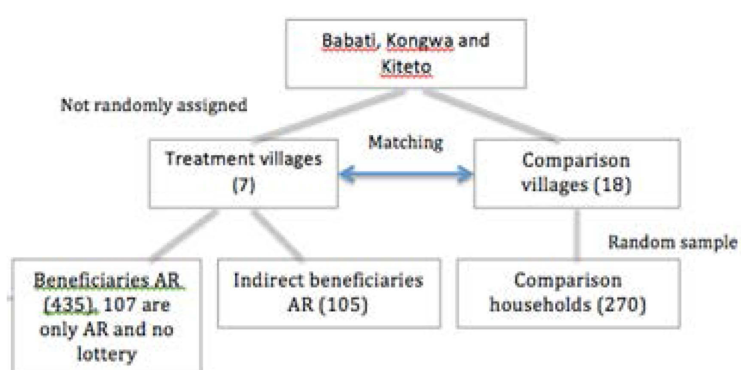
AR selected its 7 beneficiary (treatment) villages by: (1) dividing each district into strata defined by elevation and rainfall conditions and (2) requesting AR's implementing partners to propose beneficiary villages in each strata.[7] Partners did not select beneficiaries on strict criteria; rather, they proposed villages they considered willing to participate in the program. Once beneficiary villages were selected, AR's M&E team identified a group of comparable

[7] AR will be implemented in a total of 11 villages. However, the data used for this exercise was collected at a time when only 7 villages had been treated. Thereby, we consider the four villages that were not treated by the time data was collected as untreated or comparison villages.

villages that could serve as a counterfactual or comparison to the treatment villages. The team selected 18 comparison villages by using a "distant but comparable" matching strategy. This procedure sought to select strata-level comparisons that were distant enough from treated villages to rule-out potential contamination but still comparable on demographic features and bio-physical characteristics. The final sample of comparison villages consists of seven comparison villages in Kongwa, nine in Babati and two in Kiteto.

All beneficiary villages and households were featured in the survey alongside a random sample of households from comparison villages. The comparison households included in the survey were selected by a two-stage sampling method. First, one sub-village was randomly chosen from within each comparison village. Then, 20 households were randomly chosen from within each sub-village. It is important to note that among the survey's beneficiary households, not all households in beneficiary villages participated in AR. Participation at the village-level was limited to a subset of households chosen by AR's implementing partners.[8] Aside from the beneficiary and comparison households, the baseline survey also collected data from a random subset of 15 households in beneficiary villages that did *not* participate in AR ("non-beneficiary households"). This data is intended to measure spillover effects.

Figure 1. Experiment Design and Available Comparison Groups

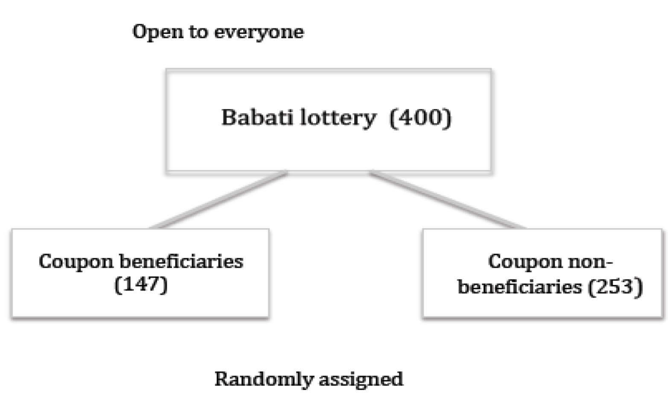


[8] Beneficiary households were those involved in one or more of AR's work packages dating from program onset or from membership in an input-provision experiment conducted by IFPRI in mid-2013.

In June 2013, IFPRI researchers initiated a study involving farmers who attended a field day organized by AR partners in Babati district (in the villages of Long, Sabilo and Seloto). On this occasion, 403 participants from Babati and other districts took part on in an information session on improved maize seed and inorganic fertilizer (Minjingu mazao). At the end of the session, IFPRI researchers conducted a lottery that randomly selected 147 farmers to receive coupons for the technology featured in the session. Specifically, the coupons awarded to the lottery winners facilitated the acquisition of 50 kg of minjingu mazao and 2 kg of improved maize seeds per half an acre of land at the start of the 2014 agricultural season.

The winners and losers of the Babati field day lottery are marked in the baseline survey. The latter is intended to be a valid control group for the former in efforts to measure the impact of AR's maize and fertilizer coupons. It is also worth noting that the households included in the Babati experiment were the subject of a second round of data collection drawn in the summer of 2015. The contents of this follow-up survey are similar to those of the baseline survey. This survey is critical to assessing the effects of the Babati experiment as, unlike the baseline survey, it covers more than one planting season since the experiment.

Figure 2. Babati Lottery Design



Source: Author's, based on Ainsley Charles, Tanzania Africa RISING Baseline Evaluation Survey 2014 Summary Report

AR's M&E team collected the first round of data in February – March 2014, using the "Tanzania Africa RISING Baseline Evaluation Survey".[9] Table 2 presents the final sample of households included in the baseline survey. This sample is comprised of a total of 435 beneficiary households in the treatment villages, 105 non-beneficiary households in the treatment villages, and 270 comparison households in comparison villages. Summing across these households, the baseline data has a total sample size of 810 households (5109 individuals) located in 18 villages.

Table 2. Number of Households and Villages

	Villages			Households			
	Treatment	**Comparison**	**Total**	**Africa RISING**	**Non-Beneficiaries**	**Comparison**	**Total**
Babati	3	9	12	418	45	135	598
Kiteto	1	2	3	3	15	30	48
Kongwa	3	7	10	14	45	105	164
Total	7	18	25	435	105	270	810

Source: Ainsley Charles, Tanzania Africa RISING Baseline Evaluation Survey 2014 Summary Report.

Notes: The 328 households that were part of the Babati experiment are included in the "Africa RISING" and "Babati Experiment" are treatment households in treatment villages. However only the 107 AR only households were used in the analysis of question 1 and 2.

3.3. Data

The baseline survey collected data on two levels –household and village. In the village survey, 124 informants[10] provided village-level information on demographics, access to basic services, advice extended to farmers, type of land, farmer organizations, major crops, economic shocks, and food prices. The information collected through the household survey includes demographic information (household size, education, and religion), socio economic measures (asset ownership, household consumption expenditure), health and anthropomorphic

[9] Baseline was conducted two years after the start of the program. Hence, it does not provide traditional "baseline" measures.

[10] These included senior village executives (25 chairpersons and 81 executive officers, counselors, and development committee members), 9 teachers, and 8 representatives of business and religion and, in one case, a "model farmer".

measures, and information on agricultural holdings and practices (agricultural inputs and technology, agricultural yields, sales, among others).

3.2 Descriptive Statistics and Balance Tests

3.2.1 Summary Characteristics

Africa RISING's Beneficiary and Comparison Households

Table 3 summarizes demographic and socioeconomic characteristics of our 107 program beneficiary and 270 comparison households. Beneficiary and comparison households are predominantly male-headed. Average households size is 6, with 3 children per household. Household heads have an average of 4.7 years of education. Based on self-reported consumption and asset data, the households in our sample are poor. Average household food consumption is 17,675 TZH per family per week, or $0.2 per person per day. Total food and non-food consumption is $0.3 per person per day. Asset data shows that a mere 19% of households have a stove (charcoal/wood, kerosene, or gas) and just over half (56%) own a bed (wooden or metal). The farmland available to our sample is predominantly flat sloped, with equal proportions of loam and sand-loam soil. Finally, our sample lacks easy access to markets, as interpreted with the survey results where households report, it takes them an average of 40 minutes to reach the nearest market.

Babati Lottery Beneficiaries and Non-Beneficiaries

Table 4 summarizes the demographic and socioeconomic characteristics of the 147 coupon beneficiary and 253 non-beneficiary who participated in the 1-day lottery in Babati. The households are predominantly male-headed. Average household size is 7, with 4 children per household. Household heads have an average of 6.1 years of education. Like the households in the previous sample, these are very poor. Average self-reported household food consumption is 20,838 TZH per family per week, or 0.2 dollars per person per day. Total food and non-food consumption is roughly 0.3 dollars per person per day. The farmland available to this sample is equal proportions of flat and gentle sloped (40% of land area per HH of each type); 70% of the land area per household has loam soil.

3.2.2 Balance Tests

We test the balance or comparability of program's beneficiary and comparison households and the Babati lottery's beneficiary and non-beneficiary households by running the following regression:

$$Baseline\ Variable = \beta_0 + \beta_1 * Beneficiary_i\ (1 = Beneficiary, 0 = Control) + \varepsilon_i \quad (1)$$

Our specification includes 84 control variables that measure demographic (i.e., age, gender, and number of family members), farmland (i.e., type, color, and slope of soil), bio-physical (elevation and distance to market), and community (i.e., access to agricultural extension services and property rights) characteristics at the household level

Africa RISING's Beneficiary and Comparison Households

Given the limitations of evaluation design, we expect to find significant differences in the characteristics of programs beneficiary and comparison households. Table 3 reports the results of our balance tests between program's 107 beneficiary and 270 comparison households. The beneficiary and comparison households differ significantly on several characteristics. First, AR beneficiaries are older, more educated, and richer. Their mean household consumption is twice, and total income thrice that of comparison households. Second, AR beneficiaries live closer to market and have better property rights. [11] Third, majority of beneficiary farms have loam soil. Comparison households have equal proportions of sand-loam and loam soil.

[11] 10% of the AR beneficiaries live in communities that provide certificates of land where over 60% of the comparison households are in such communities

Babati Lottery Beneficiaries and Non-Beneficiaries

The Babati coupon beneficiaries and non-beneficiaries were randomly selected by a lottery. Hence, ex-ante we expect no significant differences in their characteristics. Columns 5-7 of Table 4 show the results of our balance tests between the two groups. The coupon beneficiary and non-beneficiary households have similar characteristic in terms of their access to technology, demographic features, land characteristics, and access to extension services. They only differ in 3 variables - total family income per month, exposure to drought or flood, and water shortage in 2012-13 farming season. Furthermore, the differences in self-reported monthly income may be due to data quality – as only 30% of the coupon beneficiaries and 31% non-beneficiaries reported a non-zero monthly income. Given the number of variables considered, the difference in three variables is not more than what one would expect by chance. Hence, imbalance is not a problem.

Africa RISING Households and Babati Lottery Participants

Table 5 provides balance tests comparing the characteristics of program beneficiary and comparison households and Babati lottery participants. We find these households differ on several characteristics. First, Babati households are larger, more educated, and closer to market. Second, Babati households spend a higher proportion of income on food. Third, the use of agricultural technology like improved seeds and fertilizers is significantly higher among Babati households.

4 Research Questions

Studying if AR increases the usage of agricultural technologies and if it has positive effects on yields is key to understanding the early effects of the program. The Capstone Team will, thereby, address three research questions aimed at studying these effects:

1. *What factors predict usage of improved maize seeds among 107 beneficiary and 270 comparison households included in the baseline survey?*
2. *Does exposure to AR affect the usage of improved seeds and other program technologies among the 107 beneficiary households included in the baseline survey?*
3. *What is the impact of providing fertilizer coupons on fertilizer usage, maize yields, and willingness to pay for technologies among the participants of the Babati lottery*?

5 Question 1: Factors that predict usage of improved maize

5.1 Introduction

The purpose of this chapter is to 1) understand which variables best predict usage of technology once households receive treatment, and 2) understand the characteristics of non-beneficiary households that use technology. This information will help IFPRI improve how it targets beneficiary households and increase cost-effectiveness. Over time, IFPRI can save economic resources by tailoring their data collection instruments to collect information only on those variables that will best predict technology usage in their region of interest in Tanzania. It is of note that this chapter also does not analyze the impact of the program, but instead looks for the best accurate predication of what the usage of technology is once treatment is provided. Question 2 addresses the effect of treatment on technology usage.

We conduct our analysis on two samples –107 AR beneficiary households and 270 comparison households. From the analysis on the beneficiary samples we learn about the characteristics of those households that use technology once they receive treatment. From the comparison sample we learn about the characteristics of households that use technology in the absence of treatment.

In this question, technology adoption usage is defined as the use of improved seed in maize on the last farming season (y1)[12]. The methods used to analyze this question are adequate to the binomial distribution of the outcome.

[12] We also considered the use of improved seed on any of the crops promoted by AR as a second outcome. However, given AR's big push on the adoption of improved maize, there was an almost perfect correlation between use of improved maize seed and use of any improved maize seed (0.923 in the beneficiary sample and 0.994 in the comparison group).

5.2 Methodology

We apply two methodologies to answer the question, logistic model (logit) and least absolute shrinkage and selection operator (lasso) method through machine learning. In the logistic model we use the variables that were found to correlate with technology adoption in the literature review as predictors. Through the lasso we are identifying the set of variables that best predict usage of technology in the samples using as many of the variables provided by the baseline survey as possible. We will compare both models and find which one is more suited for the data provided.

5.2.1 Logistic model

The logistic regression model estimates the probability that the outcome belongs to a particular category, in this case improved maize seed or not improved maize seed. In logistic regression we use the logistic function (Tibshirani, 2013):

$$p(x) = \frac{e^{\beta_0 + X\beta_1}}{1 + e^{\beta_0 + X\beta_1}}$$

To fit this function we use the Maximum likelihood method. The likelihood gives the probability of observed zeros and ones. Coefficients are chosen to maximize the likelihood of the observed data:

$$\ell(\beta_0, \beta_1) = \prod_{i:y_i=1} p(x_i) \prod_{i:y_i=0} (1 - p(x_i))$$

To interpret the results it is necessary to choose levels of X and plug these values and the coefficients in the logistic function. The interpretation can be tricky, but it is important to remember that regardless of the values of x_1, if β_1 is positive then increasing x_1 will be associated with an increase in $p(x)$.

Following the literature on technology usage and constrained by the fact that the baseline data was collected after the disbursement of AR, we hypothesize that usage rates in the treatment sample will be correlated to demographic characteristics and access to alternatives sources of information to AR in both samples. As specified in the pre-analysis plan, we propose our model to be:

$$y_i = \beta_0 + X_i\gamma + \beta_1 I_i + \beta_3 V_i + e_i$$

The outcome is the uptake of improved maize seed on any of the plots of a household. The vector X_i contained the number of members in the household, the head of the household's age, education level, literacy and gender. To account for access to information (I_i) we used the participation of farmers in farmers' cooperatives in their villages. To account for village fixed effects we included V_i in our model.

5.2.2 Lasso, out-of-sample prediction and K-fold cross validation

The method was developed by Robert Tibshirani in 1996 and has become one of the most widely used variable selection techniques in statistics (Tibshirani, 1996). It is a constrained generalized linear model (GLM) regression that penalizes coefficients that do not contribute to the prediction of the outcome. The method penalizes complexity by adding a penalty to the estimation error if the maximum likelihood coefficient predictors. Lasso minimizes:

$$max\left\{\sum_{I=1}^{N}\left[y_i(\beta_0 + \beta^T x_i) - \log(1 + e^{\beta_0+\beta^T x_i})\right] - \lambda\sum_{j=1}^{p}|\beta_j|\right\}$$

In a few words, lasso relies upon linear models but uses an alternative fitting procedure for estimating the coefficients. The new procedure is more restrictive in estimating the coefficients and sets a number of them exactly to zero. This property makes lasso well suited for machine learning technique and is widely used in situations where the datasets contain more variables than observations for variable selection (Tibshirani, 2013).

We run the lasso with all the variables transformed at the household level that would most likely not be affected by the treatment. Because of the restrictive component of the lasso

(λ), those variables that don't add any predictive power to the model are penalized to zero and taken out of the model. Therefore, choosing the right λ is very important for the accuracy of our prediction.

The data we have is a sample of the population, as such we want to fit a model that is accurate enough for the sample but it is not over-fitted, we are looking for a general model that can be applied to the population. In statistics out-of-sample prediction helps estimating the accuracy of a predictive model. The simplest way to do out-of-sample prediction is to split the sample in two, with one half you fit the model and with the other half you predict the outcomes as if you were missing the outcomes. The first half is conventionally called training data set. The second half is called test data set.

For the lasso we will use the K-fold cross validation method to estimate our out-of-sample prediction model. This means that we will split our data in K folds of the same size. For each fold we construct a new training set with one fold left out. The fold that is missing becomes the test set. We fit a model for each training set with different values of λ and estimate the mean classification performance for the test set. We choose the λ that gives us the best test mean classification performance and check how many variables were penalized to zero. By using cross-validation in our lasso we are avoiding the estimation of an over-fitting model that wouldn't best predict the population data (Crane-Droesch, 2016).

5.2.3 Classification and confusion matrix

To predict the binomial outcome given the results of our logistic model and lasso we need to assign the resulting probability as one or zero. In statistics, this is called classification. A general rule is to classify the variable as one if the probability to be one is estimated greater than 0.5(Crane-Droesch, 2016). We are using this rule to classify our estimated predictions in both the logistic model and lasso as one or zero.

Once we classify our predictions, we can estimate how many of those were accurately predicted and how many were not and tabulate in a matrix, this is called the confusion matrix. By estimating the proportion of accurate predictions over the total of predictions we can get an idea of how good our model predicts outcome:

$$\frac{Accurate\ predictions}{Total\ predictions}$$

This mean classification performance will be used to compare the predictive power of the logistic model and the lasso.

5.3 Analysis

5.3.1 *Logistic results*

We began by aggregating the data at the household level, as the raw survey data was at the plot, parcel, crop, individual and community level. We aggregate at the household level because of IFPRI's interest of identifying household predictors that can be more easily collected. Although less practical, we note that working at the parcel level would have increased the amount of observations, increasing statistical power and reducing risk of over-fitting of the logistic model.

Table 6 in the Appendix presents the results of our logistic model. In the sample of AR beneficiaries, only gender has a negative and significant relation with technology usage. In other words, holding total members, age and education level of the household at their mean, not belonging to a farmers cooperative and living in village is associated to a likelihood of improved maize seed usage of 0.47 if the household head is female and 0.92 if the household head is male. This is consistent with a large number of research findings in which women have much slower rates of adoption of a wide range of technologies than men (Ragasa, 2012).

No other variable has a significant relation with the uptake. Similarly, none of the variables selected have a significant relation in the comparison sample. When we use the model to classify the prediction, we get very high mean classification performance in both samples. In the AR beneficiaries sample 90 percent of the predictions are accurately classified. In the comparison sample, 80 percent of the predictions are accurately classified (Table 7 in the Appendix).

By only using the samples to fit the model, the prediction power of the model will be diminished when tested on new data. To reduce the risk of over-fitting our model we run the lasso model with K fold cross validation.

5.3.2 Lasso results

The sample of AR beneficiaries had 107 households, but some imprecision in the collection of the data resulted in seven missing values and a final sample of 100 observations. In the lasso we include all the variables available to us in the baseline survey that would most likely not change do to treatment[13]. Ultimately, the AR beneficiary dataset used in the model contains 100 observations and 236 variables. Similarly, the comparison dataset used was reduced from 270 households to 236 observations and 258 variables.

It is a standard procedure to divide the training data in 5 to 10 folds in the cross-validation method (Tibshirani, 2013). This increases the validity of the model in out-of-sample predictions. We use 8 folds for our estimation and get a similar mean classification performance than in the logistic model for the training data. In the AR beneficiaries sample 91 percent of the predictions are accurately classified. In the comparison sample, 84 percent of the predictions are accurately classified (Table 8 in the Appendix).

The lasso not only would predict more accurately with new data, it also has slightly better mean classification performance in the sample. All coefficients but nine are penalized to zero, as shown in Table 9 in the Appendix. None of the predictors chosen by lasso are in the

[13] Baseline data was collected one year after the implementation of the treatment.

logistic model, which means that including these variables as predictors increase the predictive power of the model. The results show that those nine variables best predict the usage of improved maize seed in the sample of AR beneficiaries.[14] By ranking the importance of the predictors given the magnitude of their coefficients, we find that being a widow head of household is the most important variable that predicts usage.

When we test our results with different seed numbers to generate the random numbers that define the sampling in the cross validation, we find that the predictors chosen by the lasso are sensitive to the number set on the seed. Only four of the nine predictors in Table 9 are stable in the different simulations (Widow as marital status, Travel Time 50K+ (hours), Temperature Seasonality (standard deviation *100) and having the majority of the parcels in the households as "sand" soil). This means that only these four variables can be considered as robust predictors for the AR beneficiary sample.

When we estimate the results in the comparison sample, with the same number of folds, the best lambda that penalized the coefficients is 0.038. Only 20 of the 236 variables are not penalized to zero, as shown in Table 10 in the Appendix. And, unlike the previous case, the predictors' estimations are stable to different seed numbers. In agreement with our literature review, both the household's head education level and literacy are chosen as predictors in the comparison sample.

The estimated predictors in the comparison samples are not only more, but also different from the estimated predictors in the AR beneficiary sample. The only variable that is both a predictor in the AR beneficiary sample and the comparison sample is the color of the parcel, the variable is ranked among the 6 most important predictors in both models. Gender of the household head is only a predictor in the comparison group.

[14] Results found when seed of R's random number generator is set to 1. To replicate the results done by the analysis in R, we established the seed for the generation of random numbers to be 1.

The results help us understand the characteristics of both samples. Given the analysis in the Descriptive Statistics section, we believe that the difference between the set of predictors is due to the differences between the household characteristics of both samples. However, we decided to pool the samples together to see if receiving treatment is selected as a predictive variable.

When we pool both samples together and run LASSO, shown in Table 11 of the Appendix, we find that receiving treatment is not only one of the 32 variables that predicts outcome, but also the most important predictor given its magnitude. As in the comparison sample, the results remain stable at different seed number simulations.

All models included village level variables transformed to the household level. Tables 11 to 13 in the Appendix contain the results of the lasso models when we exclude village level variables from the analysis. As expected, the household level predictors found in Tables 8, 9, and 10 are expanded in the household only analysis. Both widow status of the household head and the majority of the households having sand type in the majority of their parcels are still predictors at different seed numbers. The difference is that by excluding village level information our mean classification performance is reduced from 0.91 in the AR beneficiary sample to 0.89, from 0.84 in the comparison sample to 0.77, and from 0.86 to 0.81 in the pooled sample.

The different lasso models included all variables that would not change after the provision of the treatment[15]. At the suggestion of IFPRI, we include long-term assets in the analysis; the results are in tables 14.1 and 14.2. From the seven variables included only three are not completely reduced to zero in the beneficiary sample (Main source of drinking water is river, Main source of drinking water is public tap, Main material used for the house is mud/earth) and

[15] Because the baseline survey data was collected after treatment was provided.

two in the comparison group (Main type of toilet is KVIP, Main source of drinking water is river). Including these variables increases the mean classification performance to 0.94 in the beneficiary sample and to 0.87 in the comparison sample, both higher than when we exclude the assets variables. It is important to note that the variables included in the models with and without long-term asset variables are roughly the same. Only inheritance of the land gets dropped from the previous beneficiary sample model. All, slope of the area, if household members have roughly the same diet, and household head is female are dropped from the previous comparison sample model.

5.4 Findings

None of the predictors found in the lasso are even considered in the logistic model. The added value of conducting the lasso is 1) we find variables that are important for predicting usage that were not part of the literature review, and 2) we reduce the risk of over-fitting our sample. Through the lasso, we find that 1) the widow status of the household head and having sand type of land in the majority of the parcels are stable predictors in various simulations in the AR beneficiary sample. At the village level both 2) travel time to the closest market and temperature seasonality are stable predictors in various simulations in the AR beneficiary sample, and 3) both education and literacy status of the household head are predictors in the comparison sample but not in the AR sample.

The inclusion of long-term variables in the lasso analysis moves gender of the household out from the predictors list in the comparison group. Likewise, when we include the long-term assets variables in the logit analysis, gender of the household in the beneficiary group losses its significance. Wealth proxies of the household end up being better predictors than the gender of the household.

Not only does the lasso allows us to understand which variables predict technology usage in the case of Africa RISING, it also provided us findings that are consistent with the literature review. Similar to the results of Duflo, Kremer, and Robinson (2008), we find that farmers are less likely to use improved maize seeds when constrained by poor soil quality. Even when the beneficiary group has access to technology, having sand type of soil in the majority of the parcels is negatively associated with the use of improved maize seed. Like Kassie, Shiferaw and Muricho (2011), we find that distance to markets is also negatively associated with technology. Finally, in the absence of Africa RISING, education and literacy status of the household head becomes a positively associated predictor of improved maize seed usage.

Knowing which variables predict usage in AR beneficiaries allows the program to collect information at the household and or village level on the set of predictors and estimate which type of farmers would most likely use the technology once it is available to them. Similarly, knowing which types of households don't use technology in the comparison sample helps the program reach out to those households and encourage them to adopt technology. The analysis provided on this question sets the steps in the right direction towards increasing the cost-effectiveness of the program. We encourage more data collection and predictive analysis to refine our findings.

6 Question 2: Does exposure to Africa RISING affect the usage of improved seeds and other program technologies?

5.1 Introduction

Examining whether Africa RISING increases the adoption of agricultural technologies is key to assessing if it will achieve its desired impact. If AR beneficiaries do not take-up its technologies, the program is unlikely to improve household productivity and nutrition. Had Africa RISING selected its beneficiaries randomly, we could identify its causal impact on adoption by measuring differences in the take-up rates of beneficiary and comparison households. Unfortunately, Africa RISING's beneficiaries were chosen according to their willingness to participate in the program. Our literature review suggests that the willingness to participate in technology-promotion activities is not random, but driven by observable characteristics— education, wealth, and risk aversion— that correlate to adoption. If we assess Africa RISING's effect on adoption by comparing beneficiary and comparison households, we will obtain treatment estimates that measure program *and* selection effects.

In this chapter, we use a quasi-experimental technique—propensity score matching (PSM)—to produce unbiased estimates AR's effect on the adoption of three program technologies: improved maize seeds, any improved seed, and an index of non-seed technologies promoted by the program. Tables 15 and 16 describe of our outcome variables. We center our identification strategy on PSM considering it is the methodology that best fits Africa RISING's assignment rules and data. The former do not include strict rules for selecting beneficiaries and the latter includes ample baseline data on household characteristics.[16] This chapter presents our

[16] Gertler et al. (2011) establish that matching can be applied in the context of any program that has defined control group that has not participated in the program, has treatment and comparison groups that differ only on observable characteristics, and has sufficient data to account for observable differences between the treatment and comparison group.

findings on Africa RISING's effect on adoption by reviewing propensity score matching; demonstrating the data's fit to PSM's assumptions; and presenting our estimates of the effect of Africa RISING on technology adoption.

5.2 Methodology

5.2.1 PSM's Definition and Assumptions

We will employ propensity score matching to produce unbiased estimates of Africa RISING's effect on adoption. PSM does this by constructing an index of covariates that predict the probability of participating in AR (the propensity score) and using it to "match" beneficiary and comparison households with similar characteristics (Rosenbaum & Rubin, 1983). "Matched" beneficiary and comparison households provide an unbiased sample for estimating Africa RISING's effect on households that participated in the program (average treatment effect on the treated-ATT) when PSM satisfies three assumptions:[17]

1. **Conditional Mean Independence**: $E\left(Y_i^C \middle| Z, T=1\right) = E(Y_i^C | Z, T=0)$ Let Y_i^C represent household *i*'s adoption outcome if it did not participate in AR; T is an indicator variable marking if household *i* received AR (T=1); Z is the vector of covariates included in the propensity score. Conditional mean independence implies that, given Z, the expected outcomes of beneficiary and comparison households will be the same, on average, in the absence of AR (Imbens, 2004).[18]
2. **Common Support**: 0 <P(T = 1|Z)< 1 The common support assumption implies that conditional on Z (i) no observation has a perfect probability of being a beneficiary or

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[17] The average treatment effect on the treated (ATT) measures the effect of treatment on those households who chose to participate in the program. Formally, let Y_i^{AR} be household *i's* adoption outcome if it participated in AR and Y_i^C be household *i*'s adoption outcome if it did not participate in AR. T is an indicator variable marking if household *i* received AR (T=1) and Z is the vector of covariates (e.g., the variables included in the propensity score).

$$ATT = E(Y_i^{AR}|Z, T=1) - E(Y_i^C|Z, T=1).$$

ATT is equivalent to the average treatment effect (ATE) – the effect of Africa RISING on the population of households eligible for the program– if the households that participated in the program do not have characteristics that make them different from the population of eligible households. We do not believe ATT and ATE are equivalent in our study as we suspect that households who self-selected into Africa RISING had unique characteristics.

[18] Practically, this means that the propensity score eliminates bias by accounting for all significant factors that, in the absence of Africa RISING, make beneficiary households distinct from comparison households.

comparison household (ii) observations with the similar propensity scores have a positive probability of being a beneficiary or comparison household. If PSM meets these requirements there will be "common support" or a range of propensity score values over which beneficiary households will have "matches" among comparison households (Heckman, Ichimura, & Todd, 1997; Caliendo & Kopeinig, 2008).[19]

3. **Balance**: $T \quad Z$ The balance assumption implies that the variables included in Z must be independent of T, such that (i) only pre-treatment or treatment-invariant covariates should be included in Z and (ii) the mean values of the variables included in Z and the propensity score, P(Z), should be the same for treatment and comparison households at particular intervals of P(Z) (Lee, 2013).

5.2.2 PSM Effect Estimators

If PSM satisfies the conditional mean independence, common support, and balance assumptions it will generate unbiased estimates of Africa RISING's effect on adoption by finding the average difference in the outcomes of matched beneficiary and comparison households. PSM does using a variety of estimators (e.g., kernel, nearest neighbor, local linear) that differ in how they "match" and compare households. A generalized form of these estimators is:[20]

$$ATT = \frac{1}{n_1} \sum_{i \epsilon I_1 \cap S_p} \left[Y_i^{AR} - E\left(Y_i^C \middle| D = 1, P(X)_i \right) \right]$$

$$E(Y_i^C | D = 1, P(X)_i = \sum_{j \in I_0} W(i,j) Y_j^C$$

Where I_1 and I_o denote the set of Africa RISING beneficiaries and comparison households, Y_i^{AR} and Y_i^C represent the technology usage outcomes of beneficiary and comparison households, S_p marks the region of common support, and n_1 the number of households in set $I_1 \cap S_p$. The

[19] A "weaker" form of this condition is that P (T = 1|Z)< 1. We display the "strong" assumption, but acknowledge the weak assumption is sufficient for producing clean measures of Africa RISING's effect on adoption.
[20] This generalized equation is presented in Todd (2006).

matches for each beneficiary household within S_p are constructed as a weighted average of the outcomes of comparison households. Weights are defined according to the distance between the propensity scores of the beneficiary and comparison households ($P(X)_i$) and $P(X)_j$) being matched. PSM estimators vary in how they define this distance and thus the weights included in the aforementioned equation.

5.3 Analysis

5.3.1 *Propensity Score Model*

We use PSM to estimate Africa RISING's effect on technology adoption among beneficiary households by, first, using a probit regression to estimate a propensity score for the 107 beneficiary and 209 comparison households included in Africa RISING's baseline survey. Table 6 displays the results of this model. Tables 17 and 20 define the household-level covariates included in our propensity scores: gender, age, literacy and education of the household head; household size, a distance index, and a wealth index.[21] While the covariates included in the propensity score need not have a significant relationship the treatment variable, our probit regression (Table 20) finds that four variables included in our propensity score do have significant relationships to treatment (Gilligan & Hoddinott, 2007). These are: age and literacy of the household head, household size, and the wealth index.

5.3.2 *Balance and Common Support Assumptions*

Second, we verify if our model satisfies assumptions (2) and (3) by conducting a graphical assessment of the distribution propensity scores by treatment status and testing for balance and common support. We do not check for mean conditional independence, as this assumption is untestable. Figures 9-11 in the Appendix display kernel density plots of our

[21] While there are no strict rules for selecting the variables included in the propensity score, clear theoretical justification linking the propensity score's components variables to the probability of treatment or observed outcome is usually encouraged. Hence, we selected the variables included in our score using the findings of our literature review and previous work by IFPRI (Haile, B. et al., 2015).

propensity scores, by treatment status. The range of the propensity scores assigned to the sample of beneficiary and comparison households is .0185-.9161. As required by Common Support, no observation has a score greater than 1 or less than 0. The distribution of beneficiary households' scores angles to the right, indicating they have higher conditional probabilities of participating in Africa RISING. The distribution of comparison households' score is concentrated to the left, confirming they have a lower probability of participating in Africa RISING. These patterns meet expectations (beneficiary households should have a higher probability of being treated and comparison households should have a lower probability) and do not reveal any irregularities (e.g., bi-modal curves) that suggest our households are not comparable.

We formally verify whether we satisfy common support by identifying the values of P(Z) for which beneficiary households have "matches" among comparison households. STATA's "pscore" command confirms common support is found at: $.07682<P(Z)<.9161$. This range contains 46% of the observations in our sample.[22] Finally, we use STATA's "pscore" command to confirm if we meet the balance assumption. "pscore" tests for balance by using a series of t-tests to verify if the average values of Z and P(Z) are statistically indistinct for beneficiary and comparison households over five intervals of P(Z) within the region of common support.[23] Our t-tests confirm balance is satisfied.

5.3.3 Balance Tests within Common Support

Further testing is not needed to demonstrate that PSM can be used to estimate Africa RISING's effect on technology adoption. Nonetheless, in Tables 18-19 we examine the comparability of the beneficiary and comparison households in the area of common support by

[22] The sample of households located within the area of common support is greatly reduced by: (1) extreme propensity score values (10 observations) and (2) missing propensity score values (192 observations). A household's propensity score took a value of missing if that household had missing values for any of variable included in the propensity score. We choose not to impute missing values as we could not distinguish whether these values were missing due to low response rates or human error and found no patterns to suspect missing values were distributed systematically.

[23] The intervals or "blocks" used to test balance were optimally determined by STATA's "pscore command." They are P(Z)= .07682-.2, .2-.4., .4-.6, and .6-.9161.

running balance tests that verify if there are significant differences between these groups' average characteristics. We find that of the variables included in our propensity score, roughly 56% are not balanced between beneficiary and comparison households. While this figure seems high, it is an improvement over the number of differences found in the full sample of treatment and comparison households. As can be observed in Table 19, 84% of the variables in the propensity score are unbalanced for the full sample of beneficiary and comparison households. This suggests that, while the households within the area of common support are not perfectly comparable, they are more similar than the full sample of beneficiary and control households.

5.3.4 *PSM Effect Estimators*

Having confirmed that all assumptions are met, we use kernel matching with bootstrapped standard errors to estimate the effect of Africa RISING on improved maize seed, improved any seed, and the AR technology index. [24] Kernel matching estimates effects by comparing each beneficiary household to range of comparison households with similar propensity scores (bandwidth=.8). As a robustness check, we produce a second set of effect estimates using nearest neighbor matching (NN-matching) with Abadie-Imbens standard errors.[25] Nearest neighbor matching derives treatment effects by comparing each treatment household to its "nearest neighbor(s)." Due the small size of our sample, our NN-matching matching estimates will consider one nearest neighbor (one-to-one matching). Finally, to assess how our matching estimates compare to non-experimental estimators, we generate OLS

[24] We use STATA's psmatch2 command to calculate our standard errors. Psmatch2 calculates approximate standard errors, "assuming independent observations, fixed weights, and homoscedasticity of the outcome variable within the treated and within the control groups and that the variance of the outcome does not depend on the propensity score." See http://repec.org/bocode/p/psmatch2.html for more details.

[25] Abadie and Imbens (2008) claim that bootstrapping the standard errors of matching estimators is not justified for one to one nearest neighbor matching and recommend reporting robust Abadie-Imbens (AI) standard errors. Gilligan & Hoddinott (2007) note this critique may not apply to kernel matching and recommend reporting bootstrapped standard errors. Acknowledging both points revising Haile et al.'s (2015) choice of standard errors, we present bootstrapped standard errors for our kernel estimates and AI standard errors for our NN-matching estimates.

estimates of AR's relation to adoption by running a simple regression that includes our propensity score variables as controls.[26]

5.4 Results

Table 21 presents our kernel matching, NN-matching, and OLS estimates of Africa RISING's effect on the usage of improved maize seeds, usage of any improved seed, and AR technology index. Our kernel estimates suggest that Africa RISING has a significant effect the adoption rates of all technologies. Specifically, we find participating in Africa RISING raises the usage of improved maize seed by 25.1 percentage points; the usage of any seed by a proportion of 29.1 percentage points; and the AR technology index by 3.075 standardized units. These effects are economically large as the corresponding level of usage by the control group for each technology is .598, .563, and 1.581, respectively. All effects, moreover, have strong significance, displaying a p value of .01 or better. Our NN-matching effect estimates are very similar to our kernel estimates in magnitude and significance, suggesting our measures are robust. Finally, the size and significance of our OLS estimates are similar to that of our matching estimates, suggesting that our matching estimates offer little advantages over non-experimental OLS estimates. This outcome is not surprising, however, given our small sample, persisting imbalances in the characteristics of our matched sample, and further limitations of our model discussed in the following section.

5.5 Limitations

Our results suggest that Africa RISING succeeded in encouraging beneficiary households in to increase their usage of agricultural technologies. This conclusion is positive in the sense that it suggests AR is progressing towards generating the impacts specified in its theory of

[26]The estimating equation used to derive our OLS effect estimates is: $Y_i = \beta_0 + \beta_1 T + \beta_2 Z_i + \varepsilon_i$. For simplicity we run this equation as a simple linear probability model for our two binary outcome variables—uses improved maize seeds and uses any improved seeds—and as a regular OLS model for the AR Technology Index. We estimate normal standard errors.

change. Nonetheless, it is important to highlight five limitations that challenge validity and applicability of our findings.

First, our analysis is based on a small sample of 175 households, most of which are comparison households. Our sample is limited as of our full sample of 377 households, only 175 (46%) are in the region of common support. While large standard errors, the most harmful consequence of small samples, do not seem to impede our analysis, it is still worth noting that effects found in small samples may fail to materialize in different or larger samples. This possibility challenges the reliability of our results.

Second, matching estimates are sensitive to the choice of variables included in the propensity score (Dehejia, 2005). The covariates featured in our propensity score represent the choice of variables that are the most successful fit to theory and the assumptions of PSM. This does not assure, however, that our results would hold under different, successful specifications of the propensity score.

Third, a key assumption of the PSM model is that there are no unobservable differences that make beneficiary households different from comparison households (Gertler et al., 2011). This implies that the variables included in our PSM should account for all household characteristics that may bias our effect estimates. We assume the latter is true, but cannot prove that our model satisfies this assumption.

Fourth, the balancing assumption states that variables included in the propensity score must be pre-treatment or invariant to treatment. Our propensity score includes one variable that may vary with treatment: the wealth index. We include this variable assuming that large household assets are unlikely to change with treatment in the short 2-harvest period that transpired between the rollout of AR and the baseline. Still, we raise this point as, if household assets did increase unexpectedly between treatment and the baseline, our treatment estimates may be biased.

Finally, the most problematic aspect of our analysis is that it has limited external validity in two respects. First, because Africa RISING's beneficiaries are not a random subset of Tanzania's high-need farmer population, they are not representative of the general farmer population. Our results, thereby, cannot be extended to all farmers or future Africa RISING catchment areas. Second, our analysis measures ATT, or the effect of treatment on the treated, rather than ATE, the effect of the program on a household randomly drawn from the program population. Given to households' self-selection into Africa RISING, we do not expect our population of treated households to be the same the population of households in beneficiary villages. In other words, we do not expect ATT to equal ATE and advise against extending the findings of this chapter to the general population of Africa RISING villages.

6 Question 3: Babati lottery

6.1 Introduction

The Babati experiment is part of a wider M&E responsibility entrusted to IFPRI by the Africa RISING team. While, the program started in early 2012, IFPRI researchers were invited to monitor and evaluate only in late 2012. Field visits and participatory research indicated low take-up and a prevailing negative perception about effect of fertilizers on soil. With experimental evidence of a potential yield gain of 4.2T/ hec with the use of improved seeds and fertilizers, the team was interested to see if free-access could help improve take-up. To this end, the team designed a randomized experiment in Babati, hereafter referred as the "Babati experiment".

The Babati experiment, held in June 2013, comprised of a 1 day field experiment and a lottery. As part of the one day field trial, farmers were explained the usage and advantages of improved maize seeds (Pannar 691 and Seedco 627) and fertilizer (Minjingu mazao). At the end of the day, IFPRI researchers randomized the 400 participating farmers into 147 coupon beneficiaries and 253 non-beneficiaries based on a lottery. The coupon beneficiaries received free access to 2kgs of improved maize seeds and 50kgs of fertilizers per half acre of land. In this chapter, we evaluate the impact of free access to technology coupon on overall yield, propensity to take-up improved seeds and fertilizers, and willingness to pay.

6.2 Research Questions:

Our key research questions are:

a) *What's the impact of providing free access to technologies (coupons) on yield of maize?*

b) *What's the impact of providing free access to technologies (coupons) on take-up of technology?*

c) *Did free access to technology affect farmers' willingness to buy improved seeds and fertilizer?*

6.3 Methodology

6.3.1 Outcome Variable

For the proposed research questions, we use three outcome indicators:

Maize Yield

$$Maize\ Yield = \frac{Total\ production\ in\ kgs}{Total\ land\ area\ in\ hectares}$$

Maize yield, defined as total maize production per hectare of land area, had significant outliers. To compensate for any biases of mis-reporting and error in entry, the yield was capped at 99 percentile. The regressions, however, are run on both reported yield and capped yield. In addition, to adjust for normality, we consider both yield and log of yield. The results together will test for robustness of results.

Technology Take-up

Technology take-up is a binary variable with a value of 1 if a farmer uses the specific technology and 0 otherwise. In addition to reported use, we also consider purchase of technology as an outcome variable. In the latter case, technology take-up is 1 if farmer purchases the technology in 2014-15 and 0 otherwise. The take-up is considered for improved seeds, fertilizers, both seeds and fertilizers, and any of the two.

Willingness-to-pay

The WTP is the maximum self-reported price (point estimate) farmers are willing to pay for buying fertilizers and improved seeds.

6.3.2 Research Question 3.a

The correlation between the baseline and the endline yield is very low (≈ 0.10) for reported and treated yield. Since the ANCOVA model gives more power in these cases (McKenzie, 2012) we use the model as highlighted below[27].

$$Yield\ at\ endline_i = \beta_0 + \beta_1 * Yield\ at\ baseline_i + \beta_2 * coupon\ beneficiary_i + \beta_3 * sabilo_i + \beta_4 * seloto_i + \beta_5 * AR_i + \boldsymbol{X_i} * B_6 + \varepsilon \quad \text{--- (2)}$$

Sabilo and Seloto are village dummies; AR is a binary for program participation; coupon beneficiary is a binary for coupon winners; X is a vector of controls

The first set of regressions (for yield and log yield) are run without any controls. In the subsequent models, we include a vector of control variables X consisting of demographic information (including age, gender, partner status and education of household head, average years of education in the household), land characteristics (proportion of land with each variety of soil, proportion of land irrigated), total monthly income and total livestock ownership at baseline.

6.3.3 Research Question 3.b

We use probit model to analyze the role of free access to technology in driving take-up amongst the Babati farmers.

$$\Pr(Technology\ takeup\ at\ endline_i) = \phi\ (\beta_0 + \beta_1 * technology\ takeup\ at\ baseline_i + \beta_2 * coupon\ beneficiary_i + \beta_3 * sabilo_i + \beta_4 * seloto_i + \beta_5 * AR_i + \boldsymbol{X_i} * B_6) + \varepsilon \quad \text{--- (3)}$$

Sabilo and Seloto are village dummies; AR is a binary for program participation; coupon beneficiary is a binary for coupon winners; X is a vector of controls

[27] The model was also run using Difference-in-Difference methodology and please contact Georgetown team for these results, if need be.

Our team used two probit models, first with take-up in 2013-14 as the outcome and a second with take-up in 2014-15 as outcome.

6.3.4 Research Question 3.c

We use a multivariate regression model to analyze the impact of free technology on farmer's willingness-to-pay for improved seeds and fertilizer.

$$WTP_i = \beta_0 + \beta_1 * coupon\ beneficiary_i + \beta_2 * sabilo_i + \beta_3 * seloto_i + \beta_4 * AR_i + \boldsymbol{X_i} * B_5 + \varepsilon \qquad \text{--- (4)}$$

Sabilo and Seloto are village dummies; AR is a binary for program participation; coupon beneficiary is a binary for coupon winners; X is a vector of controls

6.4 Results

6.4.2 Maize Yield

Ex-ante, our assumption was that free access to technology would drive technology take-up, which in turn would improve productivity. In line with expectations, free access of technology has a large impact on the maize yield. Table 22 shows the results of impact of treatment on maize yield.

Column 5 shows the results of the regression without any controls. In column 6, we control for variables unbalanced at baseline namely income, exposure to drought or floods and water-shortage. In column 7, we add demographic and other control variables to the model. Lastly, to test if the impact is driven by observations lost due to missing controls or because of controls itself, we run another regression on the 385 observations in column 7 without any controls. These results are represented in column 8.[28] Our preferred specification is column 6

[28] Columns 1-4 present similar results but with reported yield as the outcome variable.

because it controls for the unbalanced baseline variables and we don't lose observations like in column 7 or 8.

Compared to the mean yield at baseline, the treatment has an impact of around 335.6 kgs/hec (column 6). With a mean yield of 3146kgs/ hec in 2012-13 (Table 27), this represents an impact of over 10% of mean yield. Furthermore, the non-beneficiary group has a high take-up and hence the effect of treatment is largely guided by the extra proportion of coupon beneficiaries who took-up technology compared to non-beneficiaries[29]. Although we lack non-beneficiaries' technology take-up rates for 2013-14 but assuming the take-up is between the 2014-15 take-up rate (76.3%) and 2012-13 take-up rate (87.7%) (Table 26), the minimum estimate of increase in yield is [335.6kgs/hec / {100% - 76.3%}] = 1.3T/hec. Considering the extremely low income and consumption levels in the sample group, the results signify a sizeable increase in production level.

It is important to note that the yield fell significantly between 2012-13 and 2013-14 farming season (p=0.0316). While the average yield at baseline was 3146 kgs/ hec, at endline it was 2902 kgs/hec (Table 27). This signifies a decrease of 7.7%. The endline survey was fairly limited in scope and didn't cover any questions on exposure to shocks or use of agricultural inputs other than fertilizers and seeds. Hence it's difficult to establish reasons. By looking separately at coupon beneficiary and non-beneficiary groups, we find that the maize yield for non-beneficiaries decreased by over 11%. The decrease, during the same time, for coupon beneficiaries was only 0.8% (Table 28).

6.4.3 Technology take-up:

Farming Season 2013-14

[29] Table 11 shows the summary of technology take-up in coupon beneficiary and non-beneficiary group.

The near universal take-up of improved seeds and fertilizers reflects program's success in improving use of technology. Out of 147 coupon beneficiaries, 146 used improved seeds in the 2013-14 farming season. In addition, in spite of a strong bias against fertilizers at baseline, of the 147 coupon beneficiaries, 133 used Minjingu mazao in 2013-14 agricultural season.

Farming Season 2014-15

The coupon beneficiaries have a significantly higher propensity to use technology in 2014-15. Based on the results from the probit model, free access to technology has a positive and significant impact on use of technology in 2014-15 (Table 23). Considering that only limited quantities of improved seeds and fertilizers were provided in 2013-14 and over 90% of the farmers report using these in the same year, how did farmers get access to new seeds and fertilizers for use in 2014-15?

The endline purchase data indicates that of the 124 coupon beneficiaries who used improved seeds in 2014-15, 122 bought at least some portion of seeds used. Similarly, of the 14 coupon beneficiaries who used fertilizers in 2014-15, 10 bought at least some portion of fertilizer used. In addition, free access to technology has a positive and significant impact on purchase of technology in 2014-15 (Table 24). The results imply long-term benefits of such interventions. It is interesting to note that the propensity to take-up improved seeds increases by much more than propensity to take-up fertilizers. This is in-line with the general bias against fertilizers found during participatory research.

6.4.4 Willingness-to-pay:

Table 25 shows the results for willingness to pay. The treatment has a significant and positive impact on willingness-to-pay for fertilizers. Owing to lack of willingness-to-pay data at baseline, it is difficult to establish if the coupon beneficiaries did or did not have an existing higher willingness-to-pay. The insignificant difference in use of improved seeds between coupon beneficiaries and non-beneficiaries at baseline, however, tends to imply that willingness-to-pay might have been similar. In light of this and the regression results shown in Table 25, we can infer that free access to fertilizers increases their valuation and hence, the money they are willing to spend on fertilizers. The free access to technology does not have a significant impact on willingness-to-pay for seeds. The high take-up of improved seeds at baseline seems to suggest that perhaps both coupon beneficiaries and non-beneficiaries understand the importance of improved seeds and already value it highly.

6.5 Findings and Discussion

Not only do we see a positive and large impact on yield for coupon beneficiaries, but also a higher likelihood to continue using improved seeds in 2014-15. This means that such interventions may have potential long-term effects. Farmers who are once exposed to improved seeds are more prone to get benefits and continue investing. Since promoted seeds have been tested and are suitable to local conditions, their use could improve the livelihood of these farming communities on the long term.

The results for fertilizers are mixed. While, the treatment had a significant and positive impact on both use of fertilizers and willingness-to-pay, the actual use of fertilizers dropped drastically in 2014-15. Over 90% of the coupon beneficiaries used fertilizers in 2013-14 compared to a mere 9.5% in 2014-15 farming season (Table 29)

The drop may be because of the following reasons –

a. Inherent bias against fertilizers: The participatory research found that farmers were fearful of potential side-effects of fertilizers on soil. The low take-up of fertilizers at baseline seems to corroborate this thinking. In 2013-14 farming season, however, over 90% of coupon beneficiaries used fertilizers. But they also saw an average drop in yield. Assuming the inherent bias, it's far more likely for farmers to attribute the drop in yield (from 2012-13 to 2013-14) to use of fertilizers and perhaps this is a reason for the sharp drop in usage rate of fertilizers.

b. Lack of a properly functioning fertilizer market: Only 18 farmers report purchasing fertilizers in 2014-15 season and hence, the average price is estimated using this sample. That said, the average price is still 30,000 TSH (more than a household's weekly food consumption). In addition, the reported price ranges from 5,000 TSH to 65,000 TSH (approximately 4times the weekly food consumption for a household of 6). In comparison, the farmers' willingness-to-pay increased by only 4,613 TSH (column 2, Table 25). Both the high mean and variation may indicate a lack of properly functioning market of fertilizers and possibly issues relating to quality of fertilizers. Moving forward, this could be one of the focus areas of program designers. Perhaps developing local markets for fertilizers and ensuring easy availability could help improve take-up.

To conclude, the program does have a significant impact on take-up of improved seeds both in the year of free provision and the succeeding year. Similarly, free access has a positive and significant impact on long term take-up of fertilizers. In addition, free access increases the farmers' willingness-to-pay for fertilizers. Considering the high and variables fertilizer cost, ensuring easy access and a stable market for fertilizers could be one area of focus for program designers in phase II.

7 Discussion

The study aims to understand if the intervention activities proposed by Africa RISING are an effective way to increase uptake of new agricultural technology[30] and improve agricultural productivity. It further explores the household characteristics that best predict the uptake of new agricultural technology. Africa RISING intervention consisted of two sets of activity. First set of activity consisted of information sessions that included field days exposing farmers to new technologies, mother and baby trials demonstrating planting techniques, and provision of access to selected technologies. Second set of activity consisted of a random lottery that included coupons designed to provide free access to new agricultural technology.

For our analysis, we work with two sets of samples. Our first sample consists of 107 treated households from 7 villages and 270 comparison households from 18 villages. Treatment in this sample refers to Africa RISING intervention that consisted of information sessions. According to our balance tests, we see that treatment and comparison groups in this sample are significantly different from each other. They differ significantly on several characteristics. To give you an idea, the treated households are not only older, more educated, and richer but their household consumption is twice that of the comparison group.

Our second sample consists of 147 treated households and 253 comparison households. Treatment in this sample refers to Africa RISING intervention that consisted of a random lottery therefore treated households are lottery winners and comparison households are lottery losers. According to our balance tests, the two groups are very similar on average. We expect this since the intervention in this sample was assigned randomly. The groups differ only in terms of household income, exposure to drought and water shortage. However, we believe imbalance in these variables is not a problem since income is self-reported while other factors are external

30 Agricultural technology refers to improved maize seeds and fertilizers.

for which one would expect the differences to occur due to chance. In any case, we control for these variables in our analysis.

Using our first sample, we first investigate the characteristics of rural households in both treatment and comparison group that are associated with the uptake of new agricultural technologies. Using a logit model, we find that gender of household is the only factor that determines uptake of new technology in the treatment group. While in the comparison group we find that none of the selected variables[31] had any significant association with uptake of new agricultural technology. In our treatment group, we find that gender of household head is negatively associated with technology adoption. That is if the household head is female, it decreases the likelihood of technology adoption. This is consistent with (Ragasa, 2012) who finds that men adopt new technology at higher rates than women.

Using a lasso model, we find that the factors that predict the usage of these new technologies differ significantly among the treatment and comparison group. In the treatment group, widow as marital status, travel time 50K+ and having majority of the parcels in the households with "sand" soil are the top three predictors that predict the farmer's adoption of new agricultural technology. All of these predictors in treatment group are negatively associated with technology adoption. In the comparison group, mean diurnal range, having majority of the parcels in the households with "loam" type of soil and having the majority of the parcels in the households with gentile slope were among the top three predictors that predict farmer's adoption of new agricultural technology. In this group (i.e. comparison group) predictors are positively associated with technology adoption. Therefore, according to our lasso results, a treated household is less likely to adopt new agricultural technology if household head is a widow or if majority of the parcels in the household have "sand" type of soil.

31 Selected variables include household head gender, household head age, household head education, household members, and household association with farmer cooperative.

On the other hand, a comparison household is more likely to adopt new agricultural technology the higher the mean diurnal range or if majority of the parcels in the household have "loam" type of soil. When we pool the samples together, we find that being a participant in the Africa RISING program serves as the number one factor that predicts the uptake of new agricultural technology. However, given the two groups are significantly different on many aspects; we cannot conclude that the predictors in the two samples are different due to the intervention. It is important to note that our lasso results found a lot of important predictors of agricultural technology adoption that have not been found by literature before.

Our findings suggest that in addition to household characteristics such as education and literacy, geographic constraints faced by households are also important predictors of agricultural technology adoption. Our results are consistent with Duflo, Kremer, and Robinson (2008), who find that farmers are less likely to use new agricultural technology when constrained by poor soil quality and with Kassie, Shiferaw and Muricho (2011), who find that distance to markets, is negatively associated with technology adoption. In general, our lasso results serve as an important targeting mechanism for the Africa RISING program. It provides the AR program with information on which farmers to target. This will increase the cost-effectiveness of the program. For example, technology uptake will be lower in villages where soil is not conducive to the technology while households in remote villages are less likely to have access to technology and adopt it. We highly encourage more data collection in order to refine the predictive analysis.

Second we attempt to evaluate the effect of these Africa RISING activities on agricultural technology adoption and agricultural yield. Using our first sample, we use a PSM model to measure the impact of AR information sessions on technology adoption. We find that AR activities that consisted of information sessions significantly increased the uptake of agricultural technology among the rural households in Tanzania. In other words, households that participated in the AR information sessions significantly increased the usage of new agricultural technology as compared to the households that did not participate. This suggests that the intervention was successful in increasing agricultural technology adoption. However, it is important to note that the large differences in the characteristics of treatment and comparison group in this sample make it difficult to conclude with any confidence that the difference in outcomes we observe is due to the Africa RISING intervention.

Using the second sample, we use ANCOVA and Probit model to measure the impact of AR lottery on agricultural yield and technology adoption. First, we find that AR activities that consisted of coupons that, provide free access to agricultural technology significantly, increased agricultural yield among coupon beneficiary households. As expected, we saw that providing free access to agricultural technology had a positive impact on yield.

Second, we find that similar AR activities not only increased uptake of agricultural technology but also increased the likelihood of continued use in the following year. This suggests that once the farmers are exposed the potential benefits of using improved agricultural technology; they are more likely to keep investing in new technology. Therefore, an intervention like this can potentially have long term benefits in terms of improving the livelihood of these farmers.

Third, we get some interesting results when we disaggregate the different kinds of agricultural technology. We find that AR activities drastically increased the uptake of fertilizers among treated households from 8.9 % to 90% in the year that the coupons were provided but decreased significantly in the following year to 9.5 %. While the treatment increased the uptake of fertilizers and continued use of fertilizers, we think there are several reasons for why we see a significant drop in the following year. First, we think that market for fertilizers is not functioning properly. This is because, while the intervention increased the willingness-to-pay among treated farmers, the average market price was still way above the willingness-to-pay for majority of the farmers. Hence, majority of the farmers did not have the ability to purchase fertilizers in the following year. We find that only 18 farmers reported purchasing fertilizers in the following year when there is no free access to fertilizers. Second, we think that there might be an inherent bias against fertilizers because according to participatory research, it was found that farmers are reluctant to use fertilizers due to its potential side effects to the soil. Given the decrease in average agricultural yield, we believe that farmers attribute the decrease to fertilizers. Therefore, we believe these are some of the reasons for why there is a significant drop in uptake of fertilizers in the following year.

8 Conclusion

Our predictive analyses provide important information on the determinants of technology adoption that has not been considered by literature in the past. It will allow the AR program to increase the cost-effectiveness of the program by better targeting of households. As far impact of AR intervention on technology adoption and agricultural yield is concerned, our estimates show strong evidence of the increase in uptake of technology and agricultural yield due to the AR program. Our results highlight that providing free access to agricultural technology for one year can have a positive impact on the long-term behavior among farmer households. Farmers become aware of the benefits of using improved agricultural technology and therefore keep investing in improved technology. In addition to that, our findings provide important information for AR program in regards to the market price of fertilizers. We observe that willingness-to-pay among treated farmers increased but it was still much lower than the average market price of fertilizers. Therefore, AR program should consider various policy tools that could help them in providing the fertilizers at a lower cost.

9 Appendix

Figure 3. Theory of Change

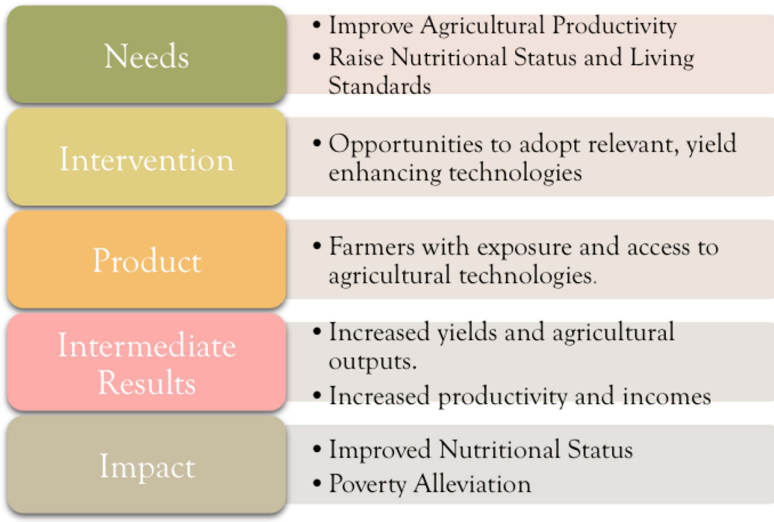


Table 3. Summary Statistics for Africa RISING Beneficiary and Comparison Households

					Regression Result*		
Variables	N	AR Mean (sd)	N	Comparison Mean (sd)	AR	se	R2
Baseline Measure of Outcome Variable							
Use of Improved maize at baseline	101	0.9 (0.3)	244	0.4 (0.5)	0.484***	(0.053)	0.195
Use of Fertilizers at baseline	105	0 (0.2)	266	0 (0.2)	0.004	(0.021)	0.000
Demographics							
Number of Family Members	107	7.5 (2.6)	270	5.6 (2.5)	1.864***	(0.291)	0.099
HH head is Male	107	0.9 (0.3)	270	0.8 (0.4)	0.071*	(0.041)	0.008
Age of HH head	107	51.5 (13.2)	270	47.3 (18.6)	4.229**	(1.969)	0.012
Years of education of HH head	105	6 (3.1)	264	4.2 (3.8)	1.769***	(0.417)	0.047
Partner status HH head	105	0.9 (0.3)	265	0.8 (0.4)	0.093**	(0.044)	0.012
Number of children	107	4.1 (2.1)	270	3 (2.1)	1.040***	(0.242)	0.047
Number of males	107	3.9 (1.7)	270	2.8 (1.7)	1.120***	(0.193)	0.082
Distance to market	98	28.7 (26.3)	186	47.1 (60.6)	-18.403***	(6.419)	0.028
Soil and land characteristics							
Propotion of land with loam soil	103	0.6 (0.5)	248	0.3 (0.5)	0.260***	(0.054)	0.062
Propotion of land with sand loam soil	103	0.2 (0.4)	248	0.4 (0.5)	-0.157***	(0.054)	0.023
Propotion of land with black soil	103	0.1 (0.3)	248	0.2 (0.4)	-0.089**	(0.044)	0.012
Propotion of land with flat slope	103	0.6 (0.4)	248	0.7 (0.4)	-0.139***	(0.051)	0.021
Propotion of land with gentle slope	103	0.3 (0.4)	248	0.2 (0.4)	0.113**	(0.047)	0.016
Shocks							
Drought or Flood	107	0.2 (0.4)	270	0.4 (0.5)	-0.193***	(0.053)	0.034
Water shortage	107	0 (0.2)	270	0.1 (0.3)	-0.037	(0.028)	0.005
Consumption							
Total Non food consumption per month	107	831422 (1224462)	270	413688 (1176273)	417,734.097***	(135,949.462)	0.025
Total food consumption per week	107	23543 (17342)	270	15349 (12267)	8,194.539***	(1,586.780)	0.066
Total income per month	107	101187 (334142)	270	27419 (103692)	73,768.027***	(22,638.227)	0.028
Community Level - Access to extention services							
Ploughing	107	0.3 (0.5)	270	0.4 (0.5)	-0.145***	(0.056)	0.018
Fertilizers	107	0.7 (0.5)	270	0.6 (0.5)	0.164***	(0.055)	0.023
Irrigation	107	0.1 (0.2)	270	0.2 (0.4)	-0.111***	(0.039)	0.021
Land Titles maintained by community	107	0.1 (0.3)	270	0.6 (0.5)	-0.481***	(0.051)	0.193

* Results of regression of the form: baseline variable= β_0+β_1*AR (1=AR,0=Control)+ ε

The first 4 columns represent the program and comparison groups' sample size (N) and mean. The last three columns on the right show result from the regression as below:

$$baseline\ variable_i = \beta_0 + \beta_1 * program\ beneficiairy\ (1 = beneficiary; 0 = comparison)_i + \varepsilon$$

Table 4. Summary Statistics for Babati Lottery Beneficiary and Non-beneficiary Households

					Regression Result*		
Variables	N	CB Mean (sd)	N	NB Mean (sd)	Coupon Beneficiary	se	R2
Baseline Measure of Outcome Variable							
Use of Improved maize at baseline	145	0.8 (0.4)	246	0.9 (0.3)	-0.054	(0.034)	0.007
Use of Fertilizers at baseline	146	0.09 (0.3)	252	0.05 (0.2)	0.037	-0.026	0.005
Demographics							
Number of Family Members	147	6.8 (2.6)	253	7 (3)	-0.171	(0.295)	0.001
Age of HH head	147	48.5 (13.7)	253	46.8 (13.6)	1.769	(1.413)	0.004
Gender of HH head	147	0.9 (0.3)	253	0.9 (0.3)	-0.017	(0.032)	0.001
Years of education of HH head	146	6 (3)	249	6.1 (3.1)	-0.230	(0.218)	0.003
Partner status HH head	146	0.8 (0.4)	249	0.8 (0.4)	0.018	(0.038)	0.001
Number of children	147	3.6 (2.2)	253	3.7 (2.3)	-0.072	(0.233)	0.000
Number of males	147	3.6 (1.7)	253	3.6 (1.8)	0.042	(0.187)	0.000
Distance to market	133	33.1 (29.5)	229	31.1 (25)	1.955	(2.914)	0.001
Soil and land characteristics							
Propotion of land with loam soil	146	0.7 (0.4)	250	0.7 (0.4)	0.031	(0.046)	0.001
Propotion of land with sand loam soil	146	0.2 (0.3)	250	0.2 (0.4)	-0.041	(0.039)	0.003
Propotion of land with black soil	146	0.2 (0.3)	250	0.2 (0.3)	0.041	(0.035)	0.004
Propotion of land with flat slope	146	0.6 (0.4)	250	0.6 (0.4)	0.011	(0.046)	0.000
Propotion of land with gentle slope	146	0.3 (0.4)	250	0.3 (0.4)	-0.025	(0.044)	0.001
Shocks							
Drought	147	0.3 (0.4)	253	0.2 (0.4)	0.098**	(0.042)	0.014
Water shortage	147	0.1 (0.3)	253	0 (0.2)	0.060**	(0.024)	0.015
Consumption							
Total Non food consumption per month	147	498810 (729819)	253	544623 (802119)	-45,813.259	(80,516.527)	0.001
Total food consumption per week	147	20549 (17027)	253	21006 (17687)	-457.368	(1,809.469)	0.000
Total income per month	147	30483 (78617)	253	76644 (284329)	-46,161.276*	(23,977.397)	0.009
Community Level - Access to extention services							
Ploughing	147	0.2 (0.4)	253	0.2 (0.4)	-0.038	(0.044)	0.002
Fertilizers	147	0.7 (0.5)	253	0.7 (0.5)	0.002	(0.049)	0.000
Irrigation	147	0	253	0	0	0	
Land Titles maintained by community	147	0	253	0	0	0	

* Results of regression of the form: baseline variable= β_0+β_1*Coupon Beneficiary (1=CB,0=NB)+ ε

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

The first 4 columns represent the babati coupon beneficiary and non-beneficiary groups' sample size (N) and mean. The last three columns on the right show result from the regression as below:

$$baseline\ variable_i = \beta_0 + \beta_1 * babati\ coupon\ beneficiary\ (1 = coupon\ beneficiary; 0 = non - beneficiary)_i + \varepsilon$$

Table 5. Summary Statistics for Babati sample and AR sample

					Regression Result*		
Variables	N	Babati Mean (sd)	N	AR Mean (sd)	Babati	se	R2
Baseline Measure of Outcome Variable							
Use of Improved maize at baseline	391	0.9 (0.3)	345	0.5 (0.5)	0.343***	(0.031)	0.146
Use of Fertilizers at baseline	398	0.1 (0.2)	371	0 (0.2)	0.030*	(0.016)	0.005
Demographics							
Number of Family Members	400	6.9 (2.8)	377	6.2 (2.7)	0.728***	(0.198)	0.017
HH head is Male	400	0.9 (0.3)	377	0.8 (0.4)	0.049**	(0.024)	0.005
Age of HH head	400	47.4 (13.6)	377	48.5 (17.3)	-1.080	(1.115)	0.001
Years of education of HH head	395	6.1 (3.1)	369	4.7 (3.7)	1.372***	(0.245)	0.039
Partner status HH head	395	0.8 (0.4)	370	0.8 (0.4)	0.019	(0.027)	0.001
Number of children	400	3.6 (2.2)	377	3.3 (2.2)	0.298*	(0.159)	0.005
Number of males	400	3.6 (1.8)	377	3.1 (1.8)	0.460***	(0.128)	0.016
Distance to market	362	31.9 (26.7)	284	40.8 (52.1)	-8.903***	(3.162)	0.012
Soil and land characteristics							
Propotion of land with loam soil	396	0.7 (0.4)	351	0.4 (0.5)	0.269***	(0.034)	0.080
Propotion of land with sand loam soil	396	0.2 (0.4)	351	0.4 (0.5)	-0.164***	(0.031)	0.037
Propotion of land with black soil	396	0.2 (0.3)	351	0.2 (0.4)	-0.036	(0.026)	0.003
Propotion of land with flat slope	396	0.6 (0.4)	351	0.7 (0.4)	-0.095***	(0.032)	0.011
Propotion of land with gentle slope	396	0.3 (0.4)	351	0.2 (0.4)	0.060**	(0.030)	0.005
Shocks							
Drought	400	0.2 (0.4)	377	0.3 (0.5)	-0.124***	(0.032)	0.020
Water shortage	400	0.1 (0.2)	377	0.1 (0.2)	-0.006	(0.017)	0.000
Consumption							
Total Non food consumption per month	400	527786.8 (775721)	377	532249.5 (1203377)	-4,462.719	(72,223.696)	0.000
Total food consumption per week	400	20837.9 (17427)	377	17674.5 (14357)	3,163.489***	(1,149.312)	0.010
Total income per month	400	59680 (231985)	377	48355.7 (200692)	11,324.297	(15,602.759)	0.001
Community Level - Access to extention services							
Ploughing	400	0.2 (0.4)	377	0.4 (0.5)	-0.168***	(0.033)	0.033
Fertilizers	400	0.7 (0.5)	377	0.6 (0.5)	0.070**	(0.034)	0.005
Irrigation	400	0 (0)	377	0.1 (0.3)	-0.135***	(0.017)	0.075
Land Titles maintained by community	400	0 (0)	377	0.4 (0.5)	-0.419***	(0.025)	0.271

* Results of regression of the form: baseline variable= β_0+β_1*Babati (1=Babati,0=AR)+ ε

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

The first 4 columns represent the program and Babati field day groups' sample size (N) and mean. The last three columns on the right show result from the regression as below:

$$baseline\ variable_i = \beta_0 + \beta_1 * babati\ coupon\ beneficiary\ (1 = coupon\ beneficiary; 0 = non - beneficiary)_i + \epsilon$$

Table 6. Logistic Model

VARIABLES	Maize AR	Maize comparison
Head's gender	-2.615*	-0.542
se	-1.529	-0.572
Total members	0.307	0.073
se	-0.208	-0.078
Head's age	-0.291	0.029
se	-0.443	-0.076
Head's age squared	0.004	-0.0003
se	-0.005	-0.001
Head's education level	0.033	0.025
se	-0.593	-0.139
Head's education level squared	0.027	0.008
se	-0.074	-0.015
Belongs to farmer cooperative	-0.19	-0.401
se	-0.002	-0.864
N	100	258
McFadden Pseudo R2	0.473	0.432
Village fixed effects	Yes	Yes

Table 7. Confusion Table: Logistic Regression

AR beneficiaries			Comparison		
	No usage	Usage		No usage	Usage
No usage	7	4	No usage	138	31
Usage	6	83	Usage	19	65

Table 8. Confusion Table: Lasso Regression

AR beneficiaries			Comparison		
	No usage	Usage		No usage	Usage
No usage	4	0	No usage	140	23
Usage	9	87	Usage	17	73

Table 9. Lasso results in AR only sample

AR Only	Rank	Coefficients
If the marital status of the household head is widow	**1**	**-1.29E+00**
Travel Time 50K+ (hours)	**2**	**-1.25E+00**
If the majority of the parcels in the household has "sand" type of soil	**3**	**-4.15E-01**
If the majority of the parcels in the household have "gray/brown" soil	4	-1.51E-01
Temperature Seasonality (standard deviation *100)	**5**	**-2.33E-02**
If the majority of the parcels in the household have "red" soil	6	9.29E-03
What percentage of this community consume finger millet	7	-5.77E-03
The main activity of the farmer cooperatives in the community are to share knowledge	8	-9.38E-04
Land own by the family was inherited	9	4.01E-16

Table 10. Lasso results in Comparison sample

Comparison	Rank	Coefficients
Mean diurnal range (mean of monthly (max temp-min temp)	1	2.047
If the majority of the parcels in the household has "loam" type of soil	2	0.578
The majority of the parcels in the household have gentile slope	3	0.549
The second most important activity in the household is livestock	4	0.393
If the majority of the parcels in the household have "red" soil	5	0.293
Annual rainfall in percent	6	0.258
If the principal activity of the head of the household is self employment	7	0.206
The household head is literate	8	0.166
Tropic - warm / semiarid	9	-0.107
Average number of plots per parcel	10	0.086
Isothermality (bio2/bio7)*100	11	0.067
If households member roughly have the same diet	12	0.048
Percentage of cultivated land devoted to soybeans	13	0.03
Household education	14	0.02
Slope of the area	15	-0.007
Rain is water source of the community	16	0.007
If the head of the household is female	17	-0.006
What percentage of this community consume other pulses, nuts	18	0.005
What percentage of this community consume finger bean	19	0.005
What percentage of this community consume pigeon pea	20	0.005

Table 11. Lasso Results in Pooled sample

Pooled sample	Rank	Coefficients
Received treatment	1	0.742
Type of soil of most of parcels is Slit	2	0.686
Access to a veterinary clinic in community	3	0.637
The main activity of the farmer cooperatives in the community are to share knowledge	4	-0.556
The majority of the parcels in the household have gentile slope	5	0.55
If the majority of the parcels in the household have "red" soil	6	0.536
Community settles disputes in Formal court	7	-0.493
If the majority of the parcels in the household has "loam" type of soil	8	0.487
Tropic - warm / semiarid	9	-0.485
Mean diurnal range (mean of monthly (max temp-min temp)	10	0.415
If the marital status of the household head is widow	11	-0.395
The second most important activity in the household is self employment	12	-0.35
Average number of plots per parcel	13	0.252
The second most important activity in the household is livestock	14	0.248
Too little rain in the last season	15	-0.227
Main source of finance for treatment when sick is Health insurance	16	0.198
Access to slaughter in community	17	0.148
Isothermality (bio2/bio7)*100	18	0.124
Main source of finance for treatment when sick is Own cash	19	-0.122
The household head is literate	20	0.099
If the head of the household is female	21	-0.093
Annual rainfall in percent	22	0.055
Household education	23	0.051
What percentage of this community consume finger millet	24	-0.028
What percentage of this community consume bean	25	0.01
What percentage of this community consume Sugar cane	26	0.009
What percentage of this community consume sorghum	27	-0.007
Rain is water source of the community	28	0.004
Amount of people that belong to a SACCO in the community	29	0.002
Portion of the parcel that has crusted soil	30	0.001
Amount of farmers in cooperatives	31	-0.001

Table 12. Lasso results in AR beneficiary sample with only household variables

Sample: Beneficiaries analysis only household variables	Rank	Coefficients
If the majority of the parcels in the household has "sand" type of soil	1	-1.941
If the marital status of the household head is widow	2	-1.638
Being self employed is the second most important activity	3	-1.234
If the majority of the parcels in the household have "gray/brown" soil	4	-0.983
Performing unpaid housework is the second most important activity	5	-0.615
If the majority of the parcels in the household has "loam" type of soil	6	0.313
If the main source of finance of the sick members of the households was own cash	7	-0.119
If the majority of the parcels in the household have "red" soil	8	0.084
Household education	9	0.074
Household education squared	10	0.003

Table 13. Lasso results in comparison sample with only household variables

Sample: Comparison analysis only household variables	Rank	Coefficients
If the majority of the parcels in the household has "loam" type of soil	1	0.823
The majority of the parcels in the household have gentile slope	2	0.739
The second most important activity in the household is livestock	3	0.612
The household head is literate	4	0.54
If the majority of the parcels in the household has "sand" type of soil	5	-0.444
If households member roughly have the same diet	6	0.358
If the majority of the parcels in the household have "red" soil	7	0.325
If the majority of the parcels in the household are rented	8	-0.223
The household head's principal activity is self employment	9	0.207
If the majority of the parcels in the household are own by the household	10	0.093
If the head of the household is female	11	-0.054
Household education	12	0.01
Total acres in the household	13	-0.007

Table 14. Lasso results in pooled sample with only household variables

Sample: Pooled analysis only household variables	**Rank**	**Coefficients**
Received treatment	1	1.505
If the majority of the parcels in the household has "sand" type of soil	2	-0.93
If the majority of the parcels in the household has "loam" type of soil	3	0.781
The second most important activity in the household is livestock	4	0.627
The majority of the parcels in the household have gentile slope	5	0.594
The household head is literate	6	0.506
If the majority of the parcels in the household have "red" soil	7	0.433
If the head of the household is female	8	-0.369
The household head's principal activity is self employment	9	0.18
Being self employed is the second most important activity	10	-0.149
If the majority of the parcels in the household are rented	11	-0.131
Average number of plots per parcel	12	0.09
Practiced crop rotation	13	0.053
Household education	14	0.038
If the majority of the parcels in the household are own by the household	15	-0.015
Total acres in the household	16	-0.007
Proportion of the household that has crusted soils	17	0.001

Table 14.1 Lasso results in AR only sample with long-term assets variables

AR Only	Rank	Coefficients
Main source of drinking water is river	1	-2.490
If the marital status of the household head is widow	2	-2.154
If the majority of the parcels in the household has "sand" type of soil	3	-1.527
Travel Time 50K+ (hours)	4	-0.932
Main source of drinking water is public tap	5	0.706
The main material used for the roof od the house is mud/earth	6	0.680
If the majority of the parcels in the household have "gray/brown" soil	7	-0.222
Main source of finance for treatment when sick is own cash	8	-0.191
The primary activity of the household head is farm employee	9	0.143
Temperature Seasonality (standard deviation *100)	10	-0.040
What percentage of this community consume finger millet	11	-0.031
Household education squared	12	0.005
The main activity of the farmer cooperatives in the community are to share knowledge	13	-3.00E-16

Table 14.2 Lasso results in Comparison sample with long-term assets variables

Comparison	Rank	Coefficients
Mean diurnal range (mean of monthly (max temp-min temp)	1	2.360
Main type of toilet is private KVIP	2	2.031
Main source of drinking water is river	3	-0.666
If the majority of the parcels in the household has "loam" type of soil	4	0.616
The majority of the parcels in the household have gentile slope	5	0.453
The second most important activity in the household is livestock	6	0.333
If the majority of the parcels in the household have "red" soil	7	0.297
The primary activity of the household head is self employed	8	0.239
Annual rainfall in percent	9	0.204
Average number of plots per parcel	10	0.162
Tropic - warm / semiarid	11	-0.161
The household head is literate	12	0.113
The main source of lightin is oil or kerosene lamp	13	0.039
Main source of drinking water is well without pump	14	-0.038
Percentage of cultivated land devoted to soybeans	15	0.030
Isothermality (bio2/bio7)*100	16	0.028
What percentage of this community consume finger bean	17	0.013
Household education	18	0.013
Rain is water source of the community	19	0.009
What percentage of this community consume other pulses, nuts	20	0.006
What percentage of this community consume pigeon pea	21	0.003

Table 15. Outcome Indicators

Adoption Indicators	Description
Improved Maize Seeds	Binary variable taking a value of "1" if a household reports using improved maize seeds on any household plot and "0" if the household does not report using improved maize seeds on any household plot. This variable was created by, first, identifying plots that reported using improved maize seeds and, second, assigning this "uses improved maize seed" a value of "1", at the household level, for all households with plots using improved maize seeds.
Any Improved Seed	Binary variable taking a value of "1" if a household reports using improved maize, sorghum, bean, pigeon pea, or Irish potato seeds on any household plot and "0" if the household does not report using improved seeds for any crop on any household plot. This variable was created by, first, identifying plots that reported using improved seeds for any of the aforementioned crops and, second, assigning this "uses any improved seed" a value of "1", at the household level, for all households with plots using improved seeds for any crop.
Index of AR Technologies	Kling index denoting usage of four AR technologies: fertilizer (NPK, urea, D-Compound, CAN, other, any combination), plough (tractor, mouldboard, or disc plough), leguminous trees, or intercropping (plots hosting a legume and any other crop). This variable was created by: (i) identifying plots that report using the aforementioned technologies, (ii) creating household–level indicators for each technology, (iii) assigning each indicator a value of 1 if the household has a plot reporting the use of that technology, (iv) standardizing all indicators using the mean and standard deviation of the control group for each indicator, (v) adding all normalized indicator values. Prior to creating the index, we imputed the values of missing variables with the mean value of the variable, by treatment status.

Table 16. Summary Statistics: Outcome Variables

	All		Beneficiary		Comparision		Ben. vs Comp.
	N	Mean	N	Mean	N	Mean	P-Value
Improved Maize Seed	351	0.538	103	0.874	248	0.399	0.000 ***
se		0.499		0.334		0.491	
Any Improved Seed	366	0.522	104	0.875	262	0.382	0.000 ***
se		0.500		0.332		0.487	
Improved Seed Bean	18	0.111	11	0.000	7	0.286	0.065 *
se		0.323		0.000		0.488	
Improved Seed Potato	5	0.000	4	0.000	1	0.000	.
se		0.000		0.000			
Improved Seed Pigeon Pea	7	0.000	2	0.000	5	0.000	.
se		0.000		0.000		0.000	
Improved Seed Sorghum	27	0.074	1	1.000	26	0.038	.
se		0.267				0.196	
AR Technology Index	377	1.731	107	4.159	270	0.769	0.000 ***
se		4.208		6.525		2.168	
Plough Technologies	377	0.805	107	0.971	270	0.740	0.000 ***
se		0.393		0.166		0.436	
Leguminous Trees	377	7.058	107	16.750	270	3.217	0.000 ***
se		26.121		46.481		7.085	
Intercropping	377	0.535	107	0.876	270	0.400	0.000 ***
se		0.499		0.328		0.491	
Fertilizer	377	0.022	107	0.019	270	0.023	0.836
se		0.144		0.136		0.148	

Notes: (1) We list the variables included in “Any Improved Seed” and the “ AR Technology Index” below each of these indicators. (2) We calculate normal standard errors.

Table 17. Propensity Score Covariates

Adoption Indicators	Description
Gender	Binary variable taking a value of "1" if the gender of the household head is male and "0." The gender variable was recoded from its original format in the Baseline survey to take 1, 0 values.
Age	Numerical variable capturing the self-reported age of the household head in years. We did not trim this variable, but did adjust its original missing category from "-99" to ".".
Education	Numerical variable reporting the years of education received by the household head. We created this variable granting the head an additional unit of education for each course or grade completed. We also recoded the missing values in this variable from "-99" to ".".
Literacy	Binary variable taking a value of "1" if the household head can read and right in at least one language and "0" otherwise. The literacy variable was recoded from its original format in the Baseline survey to take 1, 0 values.
Total Members	Numerical variable capturing the total number of members in the household. This variable was created by counting the number members reported in the Baseline survey.
Distance Index	Principle component analysis index measuring households' distance from key services or sites, including: market places, district capital, asphalt road, primary school, health care facility etc.
Wealth Index	Principle component analysis index measuring households' asset or material wealth. Indicators of wealth included in the index are: floor, wall, and room material; toilet and lighting type, number of distinct rooms, source of drinking water, and rental value of home.

Table 18. Summary Statistics: Propensity Score Covariates, Full Sample

	All		Beneficiary		Comparison		Ben. vs Comp.	
	N	Mean	N	Mean	N	Mean	P Value	
Gender	377	0.846	107	0.897	270	0.826	0.084	*
se		0.361		0.305		0.380		
Age	376	48.782	107	51.178	269	47.829	0.058	*
se		15.489		12.908		16.328		
Education	369	4.696	105	5.962	264	4.193	0.000	***
se		3.695		3.107		3.794		
Literacy	370	0.686	105	0.848	265	0.623	0.000	***
se		0.465		0.361		0.486		
Total Members	377	6.170	107	7.505	270	5.641	0.000	***
se		2.677		2.597		2.524		
Distance Index	236	0.336	84	-0.386	152	0.734	0.001	***
se		2.565		1.525		2.918		
Distance Nearest Motorable Road	375	12.392	107	13.150	268	12.090	0.721	
se		25.892		14.326		29.279		
Distance Nearest All Season Road	373	13.879	107	14.860	266	13.485	0.606	
se		23.270		15.610		25.732		
Distance Nearest Asphalt Road	317	100.186	104	76.394	213	111.803	0.001	***
se		92.157		46.808		105.743		
Distance Nearest Weekly Market	296	59.334	90	38.856	206	68.282	0.000	***
se		61.889		39.355		67.638		
Distance Nearest Daily Market	284	40.757	98	28.704	186	47.108	0.004	***
se		52.076		26.293		60.568		
Distance District Capital	348	145.273	106	125.283	242	154.029	0.009	***
se		95.124		72.683		102.343		
Distance Nearest Daily Bus	362	57.917	107	37.084	255	66.659	0.000	***
se		65.850		31.377		74.111		
Distance Nearest Health Facility	371	46.075	107	42.682	264	47.451	0.299	
se		39.981		35.143		41.767		
Distance Nearest Primary School	376	26.335	107	19.047	269	29.234	0.000	***
se		25.393		13.872		28.222		
Distance Nearest Secondary School	361	69.950	107	45.701	254	80.165	0.000	***
se		63.596		29.885		70.903		
Wealth Index	283	0.012	93	0.714	190	-0.332	0.000	***
se		1.457		1.661		1.209		
Outer Wall Material	371	1.515	106	1.830	265	1.389	0.000	***
se		0.904		1.073		0.795		
Floor Material	365	1.441	107	1.907	258	1.248	0.000	***
SE		1.064		1.398		0.818		
Roof Material	375	2.552	107	2.636	268	2.519	0.376	
se		1.152		0.862		1.250		
Rooms	376	2.880	107	3.523	269	2.625	0.000	***
se		1.250		1.348		1.111		
Rental Value	298	20406.040	94	27340.426	204	17210.784	0.000	***
se		21573.449		25635.389		18636.784		
Drinking Water	376	3.279	107	2.682	269	3.517	0.000	***
se		1.733		1.315		1.821		
Toilet Type	375	3.584	107	3.477	268	3.627	0.052	*
se		0.676		0.555		0.715		
Lighting	370	3.584	106	4.292	264	3.299	0.000	***
se		1.307		1.042		1.295		

Notes: (1) We list the variables included "Distance Index" and "Wealth Index" below each of these indicators. (2) We calculate normal standard errors. (4) Distance is measured in time for the variables included in the distance index. (5) The variables included in the wealth index are categorical variables, where higher values of these variables represent higher quality materials, water, and facilities.

Table 19. Summary Statistics: Propensity Score Covariates, Common Support

		All		Beneficiary		Comparison		Ben. vs Comp.	
		N	Mean	N	Mean	N	Mean	P Value	
Gender		175	0.863	71	0.887	104	0.846	0.440	
	se		0.345		0.318		0.363		
Age		175	49.023	71	51.296	104	47.471	0.105	
	se		15.313		13.189		16.489		
Education		175	5.297	71	5.789	104	4.962	0.138	
	se		3.622		3.004		3.968		
Literacy		175	0.771	71	0.845	104	0.721	0.056	*
	se		0.421		0.364		0.451		
Total Members		175	6.680	71	7.380	104	6.202	0.005	***
	se		2.761		2.810		2.634		
Distance Index		175	-0.142	71	-0.351	104	0.000	0.214	
	se		1.829		1.520		2.008		
Distance Nearest Motorable Road		175	11.646	71	11.789	104	11.548	0.957	
	se		28.623		13.649		35.460		
Distance Nearest All Season Road		175	10.411	71	12.507	104	8.981	0.083	*
	se		13.234		13.873		12.648		
Distance Nearest Asphalt Road		175	80.994	71	71.690	104	87.346	0.183	
	se		76.222		46.606		90.763		
Distance Nearest Weekly Market		175	50.646	71	41.423	104	56.942	0.034	**
	se		47.683		40.545		51.236		
Distance Nearest Daily Market		175	33.251	71	30.718	104	34.981	0.406	
	se		33.241		28.485		36.163		
Distance District Capital		175	136.686	71	129.789	104	141.394	0.420	
	se		93.207		79.774		101.468		
Distance Nearest Daily Bus		175	43.326	71	35.831	104	48.442	0.085	*
	se		47.621		28.822		56.579		
Distance Nearest Health Facility		175	39.766	71	45.408	104	35.913	0.065	*
	se		33.430		38.428		29.111		
Distance Nearest Primary School		175	20.069	71	19.577	104	20.404	0.751	
	se		16.817		14.885		18.080		
Distance Nearest Secondary School		175	53.526	71	45.845	104	58.769	0.041	**
	se		41.250		29.773		46.943		
Wealth Index		175	0.088	71	0.637	104	-0.286	0.000	***
	se		1.492		1.670		1.231		
Outer Wall Material		175	1.549	71	1.789	104	1.385	0.005	***
	se		0.939		1.068		0.804		
Floor Material		175	1.549	71	1.901	104	1.308	0.001	***
	SE		1.168		1.406		0.904		
Roof Material		175	2.526	71	2.704	104	2.404	0.049	**
	se		0.993		0.852		1.066		
Rooms		175	3.074	71	3.437	104	2.827	0.001	***
	se		1.194		1.204		1.127		
Rental Value		175	22491.429	71	26774.648	104	19567.308	0.040	**
	se		22831.182		26786.029		19279.127		
Drinking Water		175	2.914	71	2.775	104	3.010	0.318	
	se		1.523		1.375		1.616		
Toilet Type		175	3.389	71	3.408	104	3.375	0.732	
	se		0.632		0.575		0.671		
Lighting		175	3.903	71	4.310	104	3.625	0.000	***
	se		1.192		1.008		1.232		

Notes: (1) We list the variables included “Distance Index” and “Wealth Index” below each of these indicators. (2) We calculate normal standard errors. (3) Distance is measured in time for the variables included in the distance index. (4) The variables included in the wealth index are categorical variables, where higher values of these variables represent higher quality materials, water, and facilities.

Table 20. Propensity Score Estimations

	dF/dx
Gender	0.082
se	-0.1
Age	0.009***
se	0
Education	0.005
se	-0.01
Literacy	0.232**
se	-0.1
Household Size	0.027*
se	-0.01
Distance Index	-0.017
se	-0.02
Wealth Index	0.085***
se	-0.03
N	185
Chi2	40.688***

Notes: (1) We report robust standard errors. (2) The p values corresponding to age, literacy, household size, and the wealth index are 0, .038, .072, and .001 respectably.

Table 21. Kernel and NN-Matching ATT Estimates

Kernel Matching Estimators					
	N	**Beneficiary**	**Comparison**	**Difference**	
Improved Maize Seed	157	0.849	0.598	0.251	***
se				0.08	
Any Improved Seed	165	0.854	0.563	0.291	***
se				0.073	
AR Technology Index	172	4.656	1.581	3.075	***
se				1.023	
Nearest Neighbor Matching Estimator (NN=1)					
	N	**Beneficiary**	**Comparison**	**Difference**	
Improved Maize Seed	157	0.849	0.585	0.264	***
se				0.115	
Any Improved Seed	165	0.855	0.564	0.291	***
se				0.115	
AR Technology Index	172	4.656	1.573	3.083	***
se				1.09	
OLS Regression					
	N	**Beneficiary**	**Comparison**	**Difference**	
Improved Maize Seed	157	0.849	0.585	0.263	***
se				.115	
Any Improved Seed	165	0.855	0.564	0.291	***
se				.115	
AR Technology Index	172	4.656	1.573	3.083	***
se				1.088	

Notes: (1) The distribution of beneficiary and comparison households for each outcome is: (a) Improved maize seed: 53 beneficiary and 53 comparison households, (b) any improved seed: 55 beneficiary and 110 comparison households, and (c) AR technology Index: 58 beneficiary and 114 comparison households. (2) Our kernel estimates have bootstrapped standard errors, nearest neighbor estimates have AI standard errors, and OLS estimates have normal standard errors.

**Figure 9. Kernel Density of Propensity Scores by Treatment Status
All Observations**

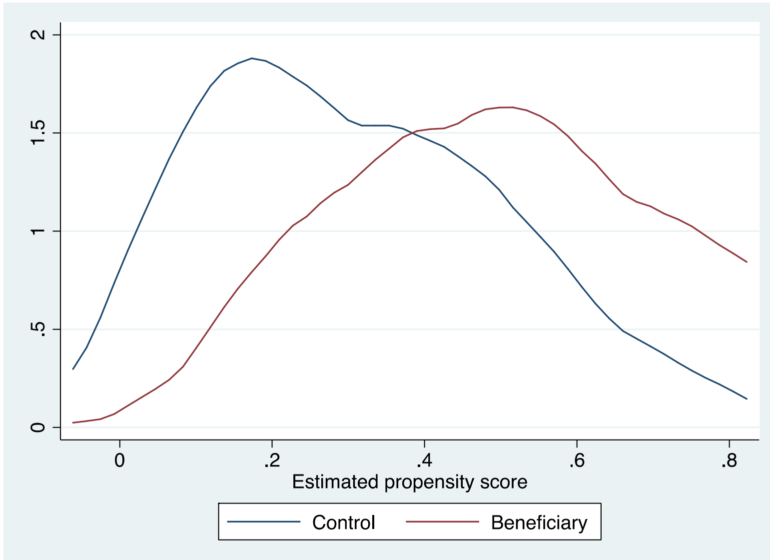
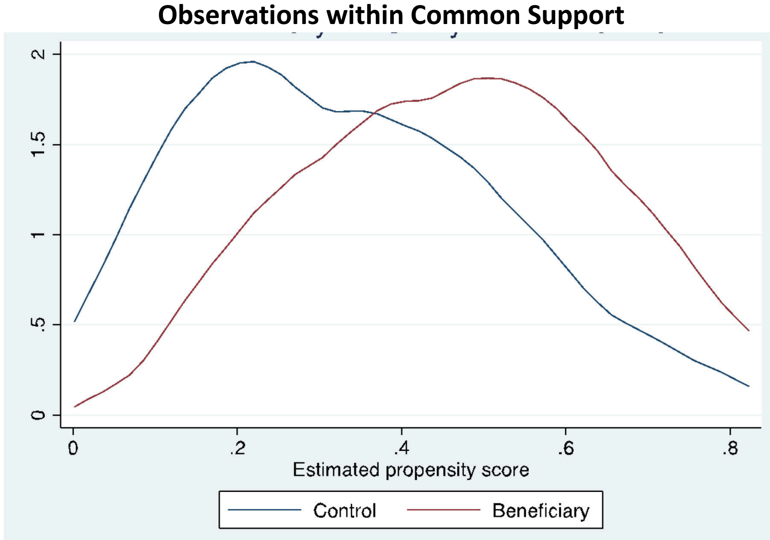


**Figure 10. Kernel Density of Propensity Scores by Treatment Status
Observations within Common Support**



Figures 11. Histogram of Propensity Scores by Treatment Status

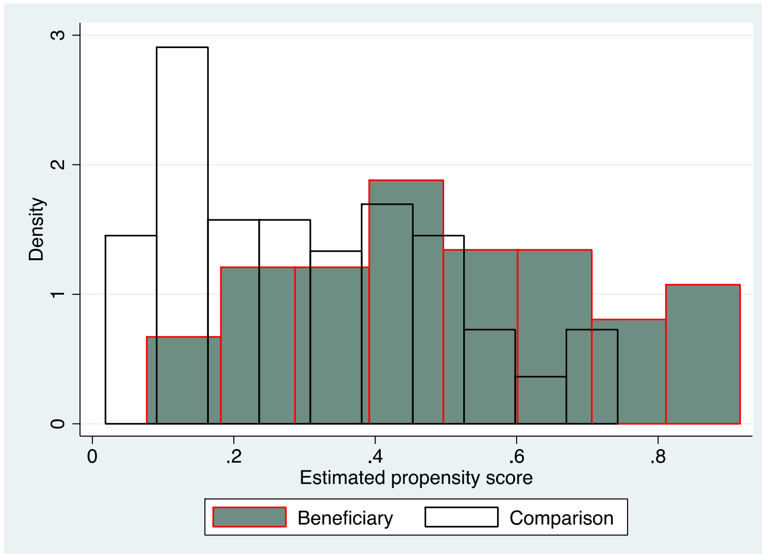


Table 22. Impact of coupon on maize yield

VARIABLES	(1) Yield	(2) Yield	(3) Yield	(4) Yield	(5) Yield (capped) ^*	(6) Yield (capped) ^*	(7) Yield (capped) ^*	(8) Yield (capped) ^*
Coupon Beneficiary	420.552**	418.814**	324.862	423.895**	338.053**	335.572**	181.762	341.195**
	(174.525)	(174.569)	(297.697)	(175.273)	(151.999)	(151.339)	(248.221)	(152.888)
Baseline Measure	0.076**	0.073**	0.077**	0.074**	0.093**	0.089**	0.095**	0.090**
	(0.034)	(0.034)	(0.034)	(0.034)	(0.036)	(0.037)	(0.038)	(0.036)
Is participant a AR beneficiary	174.497	162.464	223.342	182.690	109.610	98.521	162.156	116.642
	(195.866)	(198.979)	(206.986)	(197.884)	(163.459)	(166.142)	(174.221)	(164.918)
sabilo	-352.221*	-372.740*	-365.195*	-375.159*	-277.801	-300.556	-287.057	-299.459
	(205.736)	(207.951)	(220.427)	(207.738)	(190.669)	(193.590)	(202.833)	(192.304)
seloto	-598.375***	-631.908***	-678.024***	-617.874***	-503.808***	-536.932***	-584.767***	-521.435***
	(212.410)	(213.703)	(233.958)	(215.280)	(188.102)	(190.841)	(219.680)	(190.535)
Controlling for unbalanced baseline variables	No	Yes	Yes	No	No	Yes	Yes	No
Additional Controls	No	No	Yes	No	No	No	Yes	No
N	391	391	386	386	390	390	385	385
R2	0.054	0.058	0.083	0.056	0.048	0.052	0.085	0.049

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
^ Yield capped at 99 percentile
* 1 farmer who reported 0 yield was dropped

Column (1): without controls;
Column (2): controls only for variables unbalanced at baseline;
Column (3): controls for household demographics and unbalanced variables;
Column (4): retains the same observations as column 3 but without any controls;
Columns (5)-(8) are equivalent results with capped yield as outcome variable

Table 23. Impact of coupon on propensity to take-up technology (based on reported technology use in 2014-15)

	Reported use of technology in 2014-15 farming season			
VARIABLES	Improved Crop	Fertilizer	Any	Both
Coupon Beneficiary	0.097**	0.039**	0.118***	0.033*
	(0.041)	(0.019)	(0.039)	(0.017)
Baseline Measure	0.314***	0.057	0.334***	0.067
	(0.083)	(0.050)	(0.078)	(0.054)
AR	0.010	0.024	0.029	0.018
	(0.050)	(0.022)	(0.047)	(0.020)
sabilo	0.109**	-0.006	0.103**	0.001
	(0.051)	(0.017)	(0.051)	(0.017)
seloto	0.015	0.002	0.011	0.005
	(0.049)	(0.016)	(0.048)	(0.015)
Additional Controls	Yes	Yes	Yes	Yes
Pseudo R2	0.1	0.119	0.118	0.134
N	386	391	391	386

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 24. Impact of coupon on propensity to take-up technology (based on purchase of technology in 2014-15)

	Purchase of technology in 2014-15 farming season			
VARIABLES	Improved Crop	Fertilizers	Any	Both
Coupon Beneficiary	0.087**	0.044**	0.112***	0.019
	(0.042)	(0.021)	(0.040)	(0.013)
Baseline Measure	0.326***	0.049	0.340***	0.044
	(0.083)	(0.051)	(0.079)	(0.043)
AR	0.017	0.036	0.040	0.013
	(0.051)	(0.029)	(0.048)	(0.015)
sabilo	0.111**	0.014	0.115**	0.005
	(0.052)	(0.025)	(0.051)	(0.014)
seloto	-0.000	0.016	0.006	0.005
	(0.050)	(0.021)	(0.050)	(0.013)
Additional Controls	Yes	Yes	Yes	Yes
Pseudo R2	0.098	0.147	0.116	0.14
N	386	391	391	386

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 25. Impact of coupon on willingness-to-pay (farmer's self-reported willingness to pay for technology in TZH)

VARIABLES	(1) WTP Fertilizer	(2) WTP Fertilizer	(3) WTP Fertilizer	(4) WTP seed	(5) WTP seed	(6) WTP seed
Coupon Beneficiary	4,474.213**	4,612.980**	4,546.586**	773.457*	778.196*	788.845*
	(1,965.274)	(1,946.963)	(1,971.182)	(434.261)	(435.474)	(432.482)
AR	1,708.229	135.708	784.958	410.753	90.260	216.619
	(2,252.067)	(2,244.060)	(2,232.633)	(507.015)	(510.861)	(498.965)
sabilo	-434.555	267.734	-83.027	-480.385	-192.470	-167.854
	(2,468.853)	(2,483.713)	(2,446.428)	(587.706)	(575.318)	(574.431)
seloto	-4,177.192*	-3,507.421	-3,296.783	-185.060	35.229	82.236
	(2,268.642)	(2,206.568)	(2,269.178)	(568.969)	(553.096)	(551.302)
Additional Controls	No	Yes	No	No	Yes	No
N	400	391	391	400	391	391
R-squared	0.022	0.080	0.020	0.010	0.029	0.009

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 26. Use of technology by beneficiary group for 2012-13 and 2014-14

		Use of Any technology	
		N	Mean
Coupon Beneficiary	2012-13	147	83.7%
	2013-14	147	100.0%
	2014-15	147	85.7%
Non-beneficiary	2012-13	253	87.7%
	2013-14	n/a	n/a
	2014-15	253	76.3%

Table 27. Summary of reported yield by Babati farmers

	Self-Reported			Capped '*~		
	N	Mean	sd	N	Mean	sd
Yield 2012-13	391	3188.4	2301.9	390	3146.6	2301.9
Yield 2013-14	400	2898.4	1417	390	2902.6	1349

' 9 farmers didn't report yield at baseline
~ Yield capped at 99 percentile
* 1 farmer who reported 0 yield dropped

Table 28. Summary of reported yield of Babati farmers by beneficiary group

		Self-Reported			Capped '*~		
		N	Mean	sd	N	Mean	sd
Non- Beneficiary	Yield 2012-13	246	3235.6	2571.8	245	3169.2	2106.3
	Yield 2013-14	253	2775.8	1303.5	245	2796.6	1304.6
Coupon Beneficiary	Yield 2012-13	145	3108.3	1757.2	145	3108.3	1757.2
	Yield 2013-14	147	3109.4	1576.1	145	3081.7	1407.5

' 9 farmers didn't report yield at baseline
~ Yield capped at 99 percentile
* 1 farmer who reported 0 yield dropped

Table 29. Summary of fertilizer use of Babati farmers by beneficiary group

		Use of Fertilizers		
		N	Mean	sd
Coupon beneficiary	2012-13	146	0.089	0.286
	2013-14	147	0.905	0.295
	2014-15	147	0.095	0.295
Nonbeneficiary	2012-13	252	0.052	0.222
	2013-14	n/a	n/a	n/a
	2014-15	253	0.04	0.195

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