



*The World's Largest Open Access Agricultural & Applied Economics Digital Library*

**This document is discoverable and free to researchers across the globe due to the work of AgEcon Search.**

**Help ensure our sustainability.**

Give to AgEcon Search

AgEcon Search

<http://ageconsearch.umn.edu>

[aesearch@umn.edu](mailto:aesearch@umn.edu)

*Papers downloaded from **AgEcon Search** may be used for non-commercial purposes and personal study only. No other use, including posting to another Internet site, is permitted without permission from the copyright owner (not AgEcon Search), or as allowed under the provisions of Fair Use, U.S. Copyright Act, Title 17 U.S.C.*

*No endorsement of AgEcon Search or its fundraising activities by the author(s) of the following work or their employer(s) is intended or implied.*

**Private Sector Promotion of Climate-Smart Technologies: Experimental Evidence from Nigeria**

**Lenis Saweda Liverpool-Tasie, Michigan State University, lliverp@msu.edu**  
**Andrew Dillon, Northwestern University, Andrew.dillon@kellogg.northwestern.edu**  
**Jeffrey R. Bloem, USDA Economic Research Service, Jeffrey.bloem@usda.gov**  
**Guigonan Serge Adjognon, Amazon, guigonan.adjognon@gmail.com**

***Selected Paper prepared for presentation at the 2022 Agricultural & Applied Economics Association  
Annual Meeting, Anaheim, CA; July 31-August 2***

*Copyright 2022 by [authors]. All rights reserved. Readers may make verbatim copies of this document for non-commercial purposes by any means, provided that this copyright notice appears on all such copies.*

# Private Sector Promotion of Climate-Smart Technologies: Experimental Evidence from Nigeria

Lenis Saweda Liverpool-Tasie<sup>a</sup>, Andrew Dillon<sup>b</sup>, Jeffrey R. Bloem<sup>c,\*</sup>,  
Guigonan Serge Adjognon<sup>d</sup>

<sup>a</sup>*Michigan State University*

<sup>b</sup>*Northwestern University*

<sup>c</sup>*USDA Economic Research Service*

<sup>d</sup>*Amazon*

---

## Abstract

Sustainable intensification and climate adaptation are predicated on climate-smart agricultural input adoption. We test strategies for promoting the adoption of climate-smart agricultural inputs in Nigeria with a private sector firm. We disentangle the effects of price discount promotions (25 percent discounts) relative to the firm’s standard “business as usual” marketing package. We find that the standard marketing package increases the adoption of climate-smart urea super granule (USG) fertilizer by 24 percentage points while reducing prilled urea utilization by 17 percentage points. Discounts increase adoption of USG by an additional eight percentage points, but are not profitable for the input supply firm as a scalable marketing strategy. The treatment did not lead to increased rice yields for farmers.

*Keywords:* Technology Adoption, Fertilizer, Climate-Smart, Nigeria, Rice

---

---

\*Authors are listed in reverse alphabetical order but share equal seniority. The authors thank David Spielman, Jacob Ricker-Gilbert, and other participants of the 2021 International Conference for Agricultural Economists (ICAE) and the 2021 Private Sector Development Research Network (PSDRN) conference for thoughtful comments and feedback on an initial draft of this paper. We gratefully acknowledge funding from the Bill and Melinda Gates Foundation under grant RC102253. This study was ethically reviewed by the Michigan State University Institutional Review Board application number x12-1237e. The findings and conclusions in this manuscript are ours and should not be construed to represent any official U.S. Department of Agriculture, or US Government determination or policy. This paper was supported in part by the U.S. Department of Agriculture, Economic Research Service. All errors are our own. Corresponding author: Jeffrey R. Bloem, jeffrey.bloem@usda.gov.

## 1. Introduction

The adoption of climate-smart agricultural technology represents an important mechanism for promoting sustainable intensification and climate adaptation in many low- and middle-income countries—especially in sub-Saharan Africa. Agricultural extension services can effectively transfer information about new technologies to smallholder farmers and promote adoption (Kondylis *et al.*, 2017; Emerick and Dar, 2021), but more evidence on the role of supply-side firms in promoting technology adoption is needed (Magruder, 2018). Private sector firms have the potential to solve a host of challenges that constrain the adoption of climate-smart technologies, especially as they increase climate-smart product development and manufacturing in low- and middle-income countries.

We study the role of the private sector in promoting the adoption of “climate-smart” agricultural inputs, reporting results from a randomized controlled trial with a private agricultural input company in Kwara State, Nigeria. In the experiment, we test the effectiveness of the standard “business as usual” marketing used by the company and the additional effect of providing a discounted price on the adoption of urea super granules (USG) with the urea deep placement application method. In the first treatment, we randomly assign rice farmers to a treatment group where the standard “business as usual” marketing is composed of two key features. The first feature is an information campaign and a demonstration plot showing how USG with urea deep placement can be a cost-efficient intensification technology that is environmentally sustainable. The second feature is the introduction within

the village of a local USG supplier. In the second treatment, we randomly assign a subset of farmers to receive a 25 percent discount on the price of USG from the local retailer in addition to the “business as usual” marketing. Rice farmers in control villages receive no treatment and are free to use any fertilizer they can purchase.

Our experiment leads to four core findings. First, we pool the treatment arms to find that the supply and marketing of USG led to increased USG adoption and the disadoption of prilled urea (a substitute technology). Rice farmers in treatment villages increase their use of USG from zero percent at baseline to 28 percent at endline and reduce their use of prilled urea from 50 percent at baseline to 30 percent at endline. Farmers in control villages do not systematically adopt USG or disadopt prilled urea. Second, we disaggregate our treatment to estimate the additional effect of the discount. We find that farmers in treatment villages who receive only the standard “business as usual” marketing (i.e., T1) increase their use of USG from zero percent at baseline to 24 percent at endline, while farmers in treatment villages who also receive the additional discount (i.e., T2) increase their use of USG to 32 percent at endline. Therefore, the price discount led to an additional eight percentage point increase in the adoption rate of USG. Third, estimated effects on the quantity of USG used by farmers in treatment villages show that the discount is only profitable for the fertilizer company if their production costs are roughly a quarter of the non-discounted selling price. Finally, although using USG is associated with higher rice yields in our data and the agronomy literature finds large gains in rice yields attributable to USG ([Lupin \*et al.\*, 1983](#); [Thomas and Prasad, 1987](#); [Ahmed \*et al.\*, 2000](#); [Jena](#)

*et al.*, 2003; Kabir *et al.*, 2009; Islam *et al.*, 2012), we are unable to reject a null effect of either treatment on rice yields. This may be due to the observation that some farmers substitute away from both prilled urea and NPK (a complementary technology including nitrogen, phosphorous, and potassium) and that farmers in treatment villages are not more likely than farmers in control villages to adopt recommended practices associated with the optimal use of USG.

Our paper is closely related to other randomized controlled trials that test various approaches to boost the adoption of agricultural technologies. These approaches include: providing access to credit (Karlan *et al.*, 2014), providing free and subsidized access to inputs (Beaman *et al.*, 2013), harnessing social learning (Beaman and Dillon, 2018; BenYishay and Mobarak, 2019), providing direct training to farmers (Kondylis *et al.*, 2017; Emerick and Dar, 2021), leveraging behavioral incentives (Duflo *et al.*, 2011), and improving local availability (Emerick *et al.*, 2016). Our experiment differs in that we directly examine private sector strategies allowing us to study both (i) the private feasibility of standard marketing and additional discounts and (ii) the effectiveness of these strategies in improving agricultural productivity for rice farmers. This is important as we find that while the standard marketing and the additional discount promote the adoption of USG, the discount is likely not privately profitable for the distributor. The treatment does not lead to increased rice yields for farmers, in part, because of farmer disadoption of less environmentally friendly fertilizers (i.e., prilled urea).

We make three contributions. First, we add to the literature on barriers to the adoption of improved agricultural technologies. Much of this litera-

ture considers the technology adoption choice as the result of a constrained optimization problem subject to a set of constraints. These constraints include: (i) the lack of knowledge about the technology or about how to use the technology, especially when the technology is new (Besley and Case, 1993; Foster and Rosenzweig, 1995; Conley and Udry, 2010), (ii) the lack of capital or access to financial services (Croppenstedt *et al.*, 2003), (iii) behavioral traits such as risk aversion, self-control, and time inconsistencies (Dercon and Christiaensen, 2011; Duflo *et al.*, 2011), (iv) transportation and other transaction costs related to imperfections in input and output markets (Goetz, 1992; Heltberg *et al.*, 2001; Key *et al.*, 2000; Suri, 2011; Liverpool-Tasie *et al.*, 2017). Our results show the standard “business as usual” marketing of a private sector agricultural input company successfully encourages farmers to adopt a new technology. In addition, farmers are relatively sensitive to the price of the new technology and providing a price discount leads to additional adoption.

Moreover, we document the *dis*adoption of agricultural technologies (Neill and Lee, 2001; Simtowe and Mausch, 2019; Razafimahatratra *et al.*, 2021). Although the adoption of a new technology often implies or requires the disadoption of an old substitute technology, few studies explicitly report rates of disadoption. Reporting disadoption is important, however, because the optimal use of new technology often requires the sustained use of complementary technologies. We find that although farmers in treatment villages disadopt prilled urea, a substitute technology to USG, we also find noisy estimates suggesting the disadoption of NPK, a complementary technology to USG. This latter finding may partially explain why rice yields did not increase in

treatment villages despite the observation that using USG is associated with higher rice yields in our data.

Second, we add to the literature finding differences in estimated yield gains between agronomic trials and farmers using the same inputs under real-life conditions (Dar *et al.*, 2013; Abate *et al.*, 2018; Haile *et al.*, 2017; Laajaj *et al.*, 2020; Paul, 2021). The agronomic literature is clear that USG and the urea deep placement technology lead to increased rice yields (Lupin *et al.*, 1983; Thomas and Prasad, 1987; Ahmed *et al.*, 2000; Dobermann, 2005; Jena *et al.*, 2003; Kabir *et al.*, 2009; Islam *et al.*, 2012). In our study, despite the observation that the use of USG is associated with higher rice yields compared to the use of prilled urea, we find that rice farmers in treatment villages do not realize any increase in rice yields. Research by Laajaj *et al.* (2020) shows that differences in estimated yield gains between agronomic studies and randomized controlled trials observing farmers in real-life conditions are likely driven by the influence of agronomic researchers on the conditions and associated practices conducted along-side agronomic trials. Farmers operating in real-life conditions may not have the ability to replicate the “ideal” conditions used during the agronomic trial due to availability, knowledge, or resource constraints. Consistent with this explanation, we find that farmers in treatment villages are no more likely to adopt recommended practices associated with the optimal use of USG. Climate-smart agricultural inputs may improve environmental effects relative to broadcast fertilizer methods, but do not necessarily increase farmer yield or welfare if direct substitution between USG and prilled ureas result.

Third, we add to the literature on private sector supply side develop-



ment interventions (Schulpen and Gibbon, 2002; McKenzie, 2010; Giné and Karlan, 2014; Montgomery and Weiss, 2011; Magruder, 2018; Getahun and Villanger, 2019). Aside from studies that examine the effect of extending access to credit or insurance services to rural farmers (Giné and Yang, 2009; Cole *et al.*, 2013), there is a paucity of research that studies the effectiveness of private sector strategies in promoting agricultural technology adoption.<sup>1</sup> Our results highlight both the potential and challenge facing a private sector strategy. We find the standard “business as usual” marketing of a private agricultural input company led to the adoption of an improved agricultural input, but farmer’s had relatively inelastic demand. Increased adoption of USG due to the price discount was not profitable for the firm.

The rest of this paper is organized as follows. In Section 2, we discuss the study setting. In Section 3, we explain our empirical framework. In Section 4, we discuss our main results. Finally, Section 5 concludes.

## 2. The Technology and Study Setting

Farmers traditionally broadcast prilled urea on the surface of their plots. The urea deep placement technology, however, consists of applying USG in a targeted manner close to the root of the plant and beyond the roots of weeds. Agronomic research demonstrates the efficiency of using USG with urea deep placement compared to broadcasting prilled urea in India and Bangladesh (Lupin *et al.*, 1983; Thomas and Prasad, 1987; Ahmed *et al.*,

---

<sup>1</sup>More recent work aims to study the role of private sector agricultural value chain development (e.g., contracting arrangements, quality standards, and management practices) in promoting trade and economic development generally (Macchiavello, 2010; Macchiavello and Morjaria, 2015; Casaburi and Macchiavello, 2019; Macchiavello, 2010).

2000; Jena *et al.*, 2003; Kabir *et al.*, 2009; Islam *et al.*, 2012). In addition, using USG with urea deep placement requires 25 to 45 percent less nitrogen than with prilled urea to increase rice paddy yield by one ton (Lupin *et al.*, 1983). This increased efficiency is likely due to the fact that only about half of the nitrogen applied using broadcast methods reaches crops (Dobermann, 2005). Moreover, low nitrogen take up also leads to nitrogen immobilization in soil organic matter and the evaporation of nitrogen into the environment. Nitrogen immobilized in the soil can become a pollutant of ground or surface waters, while nitrogen evaporating into the air can contribute to the accumulation of greenhouse gasses and environmental damage (Chien *et al.*, 2009). Therefore, USG with urea deep placement may both have important productivity and environmental benefits.

Despite these productivity and environmental benefits, there are several challenges associated with USG and the urea deep placement application method that could limit its adoption among rice farmers in Nigeria. In particular, the recommended practices for optimal benefit of USG and urea deep placement include planting on leveled fields, the consistent availability of water, rigid application timing, and the deep placement requirement. Consequently, the potential for this technology to revolutionize rice production in Nigeria is unclear and limited by its adoption and appropriate use by rice farmers.

### *2.1. The Intervention*

The International Fertilizer Development Center (IFDC) is a global leader in promoting sustainable agricultural solutions aiming to improve soil health,

food security, and livelihoods around the world. In Nigeria, the IFDC has piloted the use of USG with the urea deep placement technology across several locations (Tarfa and Kiger, 2013). Despite encouraging results of these trials, constraints along the input supply chain for USG limit the widespread adoption of this technology. In particular, the production of USG requires a briquetting machine to convert prilled urea to super granules. Although this machine is relatively expensive and not widely available, in recent years several private fertilizer companies in Nigeria have developed a production line for briquetting, packaging, and shipping USG to the market.

In this experiment we partner with one of the private fertilizer companies producing and distributing USG in Nigeria, and implement a randomized controlled trial with rice farmers, to explore the role of the private sector in promoting the adoption USG and the associated urea deep placement application. First, villages randomly selected into treatment receive the standard “business as usual” marketing used by the private fertilizer company when they enter a new market. This includes an information campaign, a demonstration plot, and a guaranteed supply of USG through a local retailer.<sup>2</sup> Second, within treatment villages, a subset of farmers randomly receive a voucher providing them with a 25 percent discount on their purchase of USG. This subsidy was financed by grant-supported funds. The company, received the full selling price for USG during the experiment. All farmers living in control villages receive no treatment and are free to use any fertilizer

---

<sup>2</sup>The information treatment follows a training program developed by the company to demonstrate how urea deep placement technology works. This includes fertilizer promoter training, video testimonials of other farmers, and physical demonstrations.

they can purchase on their own.

## *2.2. Experimental Design*

Our study sites consists of a random sample of 45 villages selected from two major rice producing Local Government Areas (LGAs) in Kwara State in north central Nigeria. Using a listing of all the villages in all the LGAs across Kwara State, and an existing census of farmers across those villages, we identified two LGAs with the largest concentrations of rice producers. Then, within those two LGAs we created a list of 88 villages with at least 40 rice producers, and used that list as a sample frame for randomly selecting our 45 study villages. The study design employs two stages of randomization. First, we randomly assign 30 villages to the treatment and 15 villages to control groups. Second, within treatment villages we randomly select a subset of farmers to receive a 25 percent discount voucher on their purchase of USG from a local retailer.

In February of 2014, during the pre-planting season, we conducted a baseline survey of 1,170 households in all 45 treatment and control villages. After the completion of the baseline survey the treatment implementation phase began during the later pre-planting and planting seasons. This treatment phase began with the selection and training of village promoters and senior village promoters, via a participatory approach involving the whole community, and the establishment of demonstration plots prior to the planting season.<sup>3</sup> One senior village promoter from each local government provides

---

<sup>3</sup>The village promoter is a farmer based in the village who has sufficient social capital to be able to teach other farmers improved farming practices while simultaneously serving

oversight over the village promoters in their local government and assists in coordination the implementation of various project activities in the treatment villages.

The village promoter training includes a video introducing the urea deep placement application procedure and sessions establishing demonstration plots. At the end of the training, each village promoter received improved rice seed, NPK, and USG for use on the demonstration plot. Following the training, village promoters set up demonstration plots in conjunction with local farmers. These demonstration plots included plots using USG with urea deep placement and plots using traditional practices to allow for a direct comparison between improved and traditional technology use. At the beginning of the normal rice growing season (i.e., between April and May 2014), village promoters organized field days with representatives of the private fertilizer company and members of the research team. Farmers from each treatment village were invited to attend a presentation of the technology at the demonstration plot, followed by a video projection of the urea deep placement technology, to increase awareness and understanding of the technology.

### **3. Empirical Framework**

As discussed above, we implement a randomized controlled trial to study the effect of “business as usual” marketing and an additional price discount on the adoption of and yield response to USG with the associated urea deep

---

as the local supplier of the technology. Village promoters are identified by the company to conduct sales and extension work within the village.

placement application method. We specifically use household level data, which we collect with two rounds of surveys.

### *3.1. Data Collection*

Figure [A.1](#) summarizes the timeline of the intervention. Between October and December 2013, we implemented a full census of households in the study area. The census led to the enumeration of 3,266 households across the 45 villages in the study. We followed this census with baseline data collection, in February 2014, on a randomly selected representative sample of 1,200 households from the 45 villages. We collected baseline data with a multi-topic household survey instrument capturing household socio-economic and demographic characteristics, agricultural production (i.e., practices, inputs, and labor use, harvest yield), as well as economic well-being indicators (i.e., income, expenditures, and food security). We successfully interviewed 1,170 out of the 1,200 households sampled for the baseline data collection. These 1,170 serve as the sample frame for the random assignment of households to receive coupons within treatment villages.

We collected endline data a year later between April and May 2015. The endline survey uses a similar survey instrument as the baseline survey, but excludes several modules containing time invariant information. During endline data collection, we successfully interviewed 1,112 households. Our final sample, therefore, includes 1,112 rice producing households.

All households in our data farmed rice, almost exclusively had a male head of the household, and include about three children and three adults. At baseline none of the households use USG, half use prilled urea and about

70 percent use NPK. These rates do not differ across treatment status. In addition, about 80 percent of households use inorganic fertilizer, about 90 percent use herbicide, about 13 percent use some form of irrigation, and about 20 percent use pesticide. Again, these rates do not differ across treatment status.<sup>4</sup>

### 3.2. Estimation Strategies

We estimate intent-to-treat effects using two specifications. First, we estimate the following ordinary least squares (OLS) regression specification with outcomes measuring fertilizer use on both the extensive and intensive margins:

$$Y_{vh,Endline} = \alpha + \beta T1_{vh} + \delta T2_{vh} + \epsilon_{vh} \quad (1)$$

Equation (1) is a simple specification using information only from our endline survey that includes  $Y_{vh,Endline}$ , the value of a given outcome variable measured at endline and the treatment status of the household,  $T1_{vh}$  and  $T2_{vh}$ , with the control group serving as the reference. The coefficients,  $\beta$  and  $\delta$ , represent intent-to-treat estimates of each treatment. Finally,  $\epsilon_{vh}$  is an unobserved error term, which we assume is independent with treatment status. Since treatment varies at the village level, we cluster standard errors at the village level.

Second, we estimate the following analysis of covariance (ANCOVA) regression specification to supplement our analysis with outcomes measuring

---

<sup>4</sup>See Table A.1 in the Supplemental Appendix for more specific summary statistics about our sample.

rice production and yield:

$$Y_{vh,Endline} = \kappa + \gamma T1_{vh} + \lambda T2_{vh} + \pi Y_{vh,Baseline} + \mu_{vh} \quad (2)$$

Equation (2) is an augmented specification using information from both our baseline and endline survey. Similar with equation (1),  $Y_{vh,Endline}$  is the value of a given outcome variable measured at endline and  $T1_{vh}$  and  $T2_{vh}$  are the treatment status of the household with the control group serving as the reference. The coefficients,  $\gamma$  and  $\lambda$ , represent intent-to-treat estimates of each treatment. Equation (2), however, also includes the baseline value of the outcome variable,  $Y_{vh,Baseline}$ . When autocorrelation is relatively low, as it is with the outcomes measuring rice production and yield, the ANCOVA regression specification has more statistical power than the standard difference-in-difference regression specification (McKenzie, 2012). Again, since treatment varies at the village level, standard errors are clustered at the village level.

In addition to estimates of intent-to-treat, we can also estimate treatment-on-the-treated effects using our village-level randomized treatment assignment within an instrumental variables framework. We specifically estimate the following two-stage least squares regression:

$$X_{vh} = \iota + \phi PT_v + \zeta_{vh} \quad (3)$$

$$Y_{vh,Endline} = \psi + \rho \widehat{X}_{vh} + \xi_{vh} \quad (4)$$

Equation (3) represents the first-stage regression of our pooled treatment



indicator  $PT_v$  on a variable indicating participation in our intervention  $X_{vh}$ . We use five indicators of intervention participation: (i) field day attendance, (ii) demonstration plot visit, (iii) discount voucher receipt, (iv) field day attendance and demonstration plot visit, and (v) field day attendance, demonstration plot visit, and discount voucher receipt. Equation (4) represents the second-stage regression with the predicted value of the dependent variable from equation (3) regressed on  $Y_{vh,Endline}$ , the value of a given outcome variable measured at endline. The coefficient  $\rho$  represents the treatment-on-the-treated effect estimate of the pooled treatment. Again, since treatment varies at the village level, the error terms in equations (3) and (4) are clustered at the village level.

#### 4. Results and Discussion

We present four sets of results. First, we report adoption results, i.e., the intent-to-treat effect of our experimental treatment on the binary use of specific inorganic fertilizer (e.g., USG, prilled urea, and NPK) at endline. Second, we investigate whether the additional discount is profitable for the fertilizer company by estimating the intent-to-treat effect of our experimental treatment on the quantity used of specific inorganic fertilizer at endline. Third, we estimate the intent-to-treat effects of our experimental treatment on rice yields. Finally, we investigate possible explanations for null effects we estimated on rice yields in our previous regressions. This leads us to report treatment-on-the-treated effects, investigate farmer profits, and test whether farmers in the treatment groups adopted the recommended practices associated with the optimal use of USG.

#### *4.1. Adoption Results*

We first estimate the effect of our pooled treatment, i.e., comparing fertilizer use between rice farmers in treatment villages and control villages. Panel A in Table 1 shows the estimated intent-to-treat effect of the pooled treatment on the binary use of USG, prilled urea, NPK, and any inorganic (e.g., USG, prilled urea, or NPK) fertilizer. In column (1) we find that the pooled treatment increases the use of USG from zero percent at baseline to 28 percent at endline. In column (2) we find that the pooled treatment reduces the use of prilled urea by about 20 percentage points, from a use rate of 50 percent at baseline to about 30 percent at endline. This disadoption of prilled urea in treatment villages is expected because USG is a direct substitute for prilled urea. In column (3), we find that the pooled treatment reduces the use of NPK by about 15 percentage points, from a use rate of 70 percent at baseline to about 55 percent at endline. Although the estimated effect is relatively noisy and not statistically significant at conventional levels, NPK disadoption, a complementary fertilizer to USG, is substantial in magnitude and does not align with the recommended use of USG. Finally, in column (4) we find no statistically significant change in the use of any inorganic fertilizer attributable to the pooled treatment. This finding highlights that although our treatment did increase use of USG it also reduced the use of both urea and NPK so that there is essentially no noticeable change in the use of inorganic fertilizer.

Next we estimate the effect of the additional 25 percent discount offered to a random subset of farmers in treatment villages. Panel B in Table 1 reports the intent-to-treat effect of each treatment on the binary use of fer-

Table 1: The Intent-to-Treat (ITT) Effect on Binary Fertilizer Use

	(1)	(2)	(3)	(4)
	USG	Urea	NPK	Inorganic
<b>Panel A: Pooled Treatment</b>				
Pooled Treatment	0.282*** (0.0545)	-0.197* (0.0992)	-0.147 (0.108)	-0.0437 (0.0835)
Observations	1,112	1,112	1,112	1,112
R-squared	0.088	0.033	0.017	0.002
<b>Panel B: Disaggregated Treatment</b>				
T1: No Discount	0.242*** (0.0476)	-0.174* (0.101)	-0.166 (0.109)	-0.0505 (0.0834)
T2: Discount	0.320*** (0.0654)	-0.219** (0.100)	-0.129 (0.110)	-0.0371 (0.0862)
T1 = T2	0.038	0.139	0.146	0.653
Observations	1,112	1,112	1,112	1,112
R-squared	0.094	0.035	0.018	0.002
Baseline mean	0.000	0.50	0.705	0.843

*Notes:* The outcome variable measures the binary use of fertilizer at endline. In Panel A the coefficients estimate the ITT effect of the pooled treatment. In Panel B the coefficients estimate the ITT effect of each treatment. Tests for equality of treatment reports the associated p-value. Standard errors clustered at the village level are in parentheses. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

tilizer. Comparing the coefficients between T1 without the discount and T2 with the additional discount shows the effect of receiving the additional discount. In column (1) we find that receiving the standard “business as usual” marketing but not an additional discount increases USG use from zero percent at baseline to 24 percent at endline. Receiving the standard marketing and the additional discount increases the use rate of USG by eight more percentage points to 32 percent at endline. The difference between these two effect estimates—i.e., the effect of the additional discount—is statistically significant. In column (2) we find that although the effect of the additional discount leads to a slightly larger disadoption rate of prilled urea, the difference between the two treatments is not statistically significant at conventional levels. In column (3) although neither treatment leads to a statistically significant decline in NPK, the estimated effect remains economically meaningful. Finally, in column (4) we find no statistically significant effect in the use of any inorganic fertilizer due to our treatment with or without the additional discount.

The adoption results reported in Table 1 lead to three notable findings. First, both the standard “business as usual” marketing and the additional discount inspire the adoption of USG. The objective of marketing by a private firm is to promote adoption by providing information, demonstrating effectiveness, and supplying new technology to potential consumers. We find that this standard marketing is effective in encouraging the adoption of climate smart inputs. We also find that an additional discount, provided with standard marketing, encourages even more adoption. Second, when consumers adopt climate smart inputs, they also disadopt an “old” substitute

technology. This is an expected result as using USG essentially eliminates the need to use prilled urea. In our data, only seven percent of farmers in treatment villages use both USG and prilled urea at endline. Third, although the estimated effects are not statistically significant at conventional levels, we also observe some disadoption of NPK. In our data, only 15 percent of farmers in treatment villages use both USG and NPK at endline. This is an unexpected result as using NPK complements the effectiveness of USG. This finding highlights a key lesson for the marketing of climate smart inputs. To inspire the sustainable adoption, marketing must strike a balance between selling the potential effectiveness of a new technology while also clearly explaining the requirements for its optimal use. Without this balance, potential consumers may either not adopt the new technology or adopt the technology and not realize the potential benefits and eventually disadopt.

#### *4.2. Effects on Fertilizer Quantity*

We now turn to estimating the intent-to-treat effect of our treatment on the quantity of fertilizer used by rice farmers. Table 2 reports these results where comparing the coefficients between T1 and T2 shows the effect of receiving the additional discount. In column (1) we find that receiving the standard “business as usual” marketing but not an additional discount increases the quantity of USG used from zero at baseline to 13 kg at endline. Receiving the standard marketing and an additional discount increases the quantity of USG used from zero at baseline to 21 kg at endline. Thus, the additional discount leads to eight kg more USG used and this differ-

ence is statistically significant. In column (2) we continue to find results indicating the disadoption of prilled urea. Although the estimated effect is only statistically significant at conventional levels for farmers receiving the additional discount, the difference between these two effects is not itself statistically significant. In column (3) we also continue to find results indicating the disadoption of NPK. Although the estimated effect on both treatments is not statistically significant at conventional levels, the difference between these two effects is statistically significant. Farmers receiving the additional discount reduce NPK less than farmers who do not receive the additional discount. Finally, in column (4) although we find no statistically significant change in the quantity used of any inorganic fertilizer for either treatment, the difference between each treatment is statistically significant. Farmers receiving the additional discount reduce the quantity used of any inorganic fertilizer less than farmers not receiving the additional discount.

Table 2 also reports the marginal effect of the fertilizer quantity used on expected rice yield for each treatment group. To calculate these marginal effects we first estimate a simple production function including fertilizer quantities as inputs and rice yield as the output.<sup>5</sup> We then estimate the quantities of the given fertilizer used on average at endline for each treatment group.<sup>6</sup> In column (1) we see that the average quantity of USG used in each of the

---

<sup>5</sup>This simple production function includes: the quantity of USG, the quantity of prilled urea, the quantity of NPK, the quantity of  $USG \times NPK$ , the quantity of prilled urea  $\times$  NPK, and the quantity of  $USG \times$  urea. More sophisticated production functions that include squared and cubed terms, and the use of LASSO as an estimation approach, provide qualitatively similar results.

<sup>6</sup>At endline the control group, on average, uses 0.41 kg of USG, 119.22 kg of prilled urea, and 170 kg of NPK. The average use of a given fertilizer for each treatment group adds the coefficients from Table 2 to these endline quantities for the control group.

Table 2: The Intent-to-Treat (ITT) Effect on Fertilizer Use Quantity (kg)

	(1) USG	(2) Urea	(3) NPK	(4) Inorganic
T1: No Discount	13.86*** (3.027)	-56.13 (36.68)	-69.32 (75.60)	-111.6 (110.8)
T2: Discount	21.04*** (5.859)	-64.21* (36.16)	-40.56 (77.52)	-83.73 (112.3)
T1 = T2	0.059	0.278	0.047	0.099
Marginal effects (kg):				
E[Yield] for T1	542.23	534.25	527.61	n/a
E[Yield] for T2	567.10	530.84	539.06	n/a
E[Yield] for C	494.24	557.95	555.21	n/a
T1 - C	47.99***	-23.69***	-27.61	n/a
T2 - C	72.86***	-27.10***	-16.16	n/a
Observations	1,112	1,112	1,112	1,112
R-squared	0.059	0.027	0.010	0.013
Baseline mean	00.00	95.09	151.91	247.00

*Notes:* The outcome variable measures fertilizer use quantity (kg) at endline. The coefficients estimate the ITT effect of each treatment. Tests for equality of treatment reports the associated p-value. Marginal effects estimate the expected rice yield given the fertilizer quantities estimated for each treatment group. Tests for differences in expected yield report the expected yield difference with the level of statistical significance. Standard errors clustered at the village level are in parentheses. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

treatment groups is associated with a larger expected rice yield than that expected from the control group, and these differences are statistically significant at conventional levels. In columns (2) and (3), however, we see that the average quantity of urea and NPK used in each of the treatment groups is associated with a smaller expected rice yield than that expected from the control group. In column (2) the differences in expected yield are statistically significant at conventional levels, but in column (3) the differences are not statistically significant. Taken together, these marginal effects provide an ambiguous prediction of the effect of our experimental treatment on rice yields. In particular, the substitution away from prilled urea (a substitute fertilizer) and NPK (a complementary fertilizer) complicate any expected positive yield effect driven by the adoption of USG.

The finding that the additional discount increased the quantity of USG used motivates the question: Is the discount privately profitable for the fertilizer distributor? We can approximate an answer to this question with the estimated treatment effects from column (1) of Table 2.<sup>7</sup> Assuming a simple linear profit function of the form  $\Pi = (P - c) \times Q$ , we need three pieces of information. First, we normalize the un-discounted price of USG ( $P$ ) to one. Next, we allow the input cost of producing USG ( $c$ ) to vary on an interval from zero to one.<sup>8</sup> Finally, we use the estimated treatment

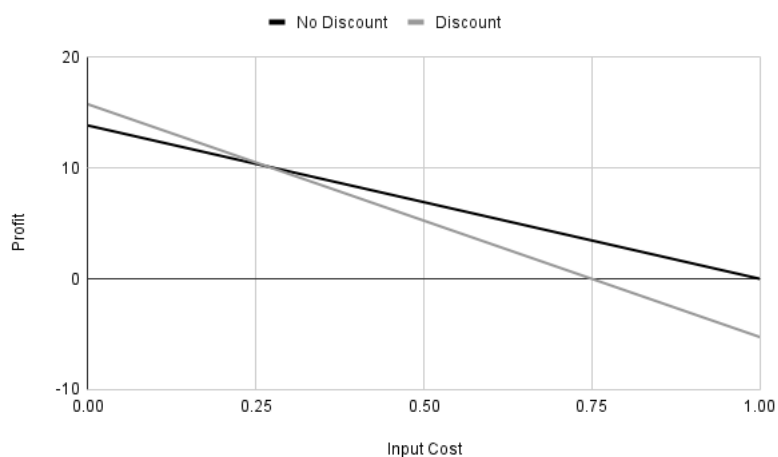
---

<sup>7</sup>This is only an approximate answer because we only consider if the discount on the price of USG is privately profitable for a firm that only sells USG. Given that most agricultural input distribution companies sell many products, a discount on one product may change the quantity sold from other products. Without more detailed data from the private fertilizer company, we cannot completely answer this question.

<sup>8</sup>This represents the relevant range of input costs for a profit maximizing firm, as input costs are almost certainly greater than zero and input costs greater than one would be unprofitable.



Figure 1: Is the Discount Privately Profitable for the Fertilizer Distributor?



*Notes:* This graph illustrates profit as a function of input costs with output price normalized to one. The dark line represents the relationship with no discount. The gray line represents the relationship with a 25 percent discount. The 25 percent discount is only privately profitable when input costs are roughly 25 percent of the un-discounted output price.

effects on the quantity of USG used ( $Q$ ) to estimate profit with and without the additional discount. As shown in Figure 1, selling USG is only more profitable with the discount when input costs are roughly 25 percent of the un-discounted output price. This represents a relatively large markup, and seems unlikely in the case of USG which has high input costs relative to alternative fertilizers.

#### 4.3. *Effects on Rice Productivity*

We now turn to estimating the intent-to-treat effect of our treatment on rice productivity. Table 3 reports the main productivity results using rice yields as the outcome variable. Each column represents a different specification with the same outcome variable. In columns (1) and (2) we estimate the effect of the pooled treatment on rice yields, with an ANCOVA specification in column (2). In both columns we are unable to reject a null effect despite an average effect estimate representing roughly a 15 percent decline in rice yields. In columns (3) and (4) we estimate the effect of each treatment on rice yields, with an ANCOVA specification in column (4). Again, in both columns we are unable to reject a null effect despite average effect estimates on each treatment representing relative meaningful declines in rice yields relative to baseline levels. In addition, the additional discount does not make any statistical difference in rice yield.<sup>9</sup>

---

<sup>9</sup>In the Supplemental Appendix, Figures A.2 and A.3 illustrate the endline distribution of rice yields between treatment and control villages. Figure A.2 plots histograms of the distribution of endline rice yield between treatment and control villages. The histograms are largely overlapping. Figure A.3 tests if there are specific regions within the distribution of endline rice yields that are statistically different, using the methodology of Goldman and Kaplan (2018). There is only a relatively narrow range of statistical difference in endline rice yields at the low end of the rice yield distribution.

Given that yield is measured as a ratio of farm production (kg) over area cultivated (ha), it may be that estimated effects on rice yields are obscured by measurement error in either the production or land variable. Tables A.2 and A.3 in the Supplemental Appendix demonstrate, however, that this is not the case. When disaggregating yield into separate measures of farm production and area cultivated, we are unable to reject a null effect on both outcomes. However, in both cases the additional discount reduces production and area cultivated less and this difference is statistically significant. Finally, in Table A.4 in the Supplemental Appendix we show results that instrument for the binary use of USG with an indicator of our pooled experimental treatment. This instrument is relevant, as shown in column (1) of Panel A in Table 1, and is exogenous given the random assignment of our pooled treatment. Again, despite estimating results with a relatively meaningful magnitude, we fail to reject a null effect.

These results contrast with the productivity gains associated with USG and the urea deep placement technology previously reported in the agronomy literature (Lupin *et al.*, 1983; Thomas and Prasad, 1987; Ahmed *et al.*, 2000; Dobermann, 2005; Jena *et al.*, 2003; Kabir *et al.*, 2009; Islam *et al.*, 2012). In addition, these results contrast with the observation that the use of USG is associated with higher rice yields than the use of prilled urea or NPK in our data. Table A.5 in the Supplemental Appendix shows these associations, which persist even when controlling for our experimental treatment and baseline measures of rice yield and fertilizer use. Moreover, as previously discussed and reported in Table 2, the marginal effect of the average quantity of USG used by farmers in each treatment group is associated with

Table 3: The Intent-to-Treat (ITT) Effect on Rice Yield (kg/ha)

	(1) Yield	(2) Yield	(3) Yield	(4) Yield
Pooled Treatment	-66.70 (71.27)	-70.15 (65.84)		
T1: No Discount			-60.14 (73.73)	-62.45 (68.64)
T2: Discount			-72.94 (72.12)	-77.49 (66.67)
T1 = T2	n/a	n/a	0.676	0.628
Observations	1,112	1,112	1,112	1,112
R-squared	0.004	0.023	0.004	0.024
Baseline mean	427.06	427.06	427.06	427.06
ANCOVA?	No	Yes	No	Yes

*Notes:* The outcome variable measures rice yield (kg/ha) at endline. The coefficients estimate the ITT effect of each treatment. Tests for equality of treatment reports the associated p-value. Standard errors clustered at the village level are in parentheses. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

expected rice yields that are larger than expected rice yields of farmers in the control group.

#### 4.4. *What Explains Null Productivity Effects?*

Null yield results raise the question: Why did our experimental treatment lead to adoption of USG but no increase in rice yields? In this sub-section we explore three possible explanations. First, we estimate treatment-on-the-treated effects to investigate whether farmers who participated in the intervention (e.g., attended the field day, visited the demonstration plot, and received the discount voucher) realized any increase in their rice yields. Second, we investigate whether profit maximizing behavior of farmers, which may run counter to behavior that maximizes yields, explains the lack of productivity effects. Third, we explore whether farmers in the treatment groups also adopt any of the recommended practices associated with the optimal use of USG.

*Treatment-on-the-Treated Effects*—We first examine the effect of our experimental intervention on those who participated in the intervention. Table [A.6](#) shows that not every farmer in our sample within each treatment group participated in our intervention. In particular, between 50 to 60 percent of the farmers in our sample in treatment villages attended a field day, between 60 and 70 percent visited the demonstration plot, less than half reported an increased understanding of USG, less than half of farmers who were offered the discount voucher report receiving the voucher, and less than 30 percent report using the discount voucher. Although these estimates show that our experimental treatment did lead some farmers to participate in the inter-

vention, one-sided non-compliance persists. Therefore, the intent-to-treat effects estimated above may not equal the treatment-on-the-treated effects.

As described above, we estimate treatment-on-the-treated effects using an instrumental variables framework. Our instrument is relevant because farmers in our treatment group did participate in our intervention and excludable because no farmers in our control group participated in our intervention. Table 4 reports the treatment-on-the-treated effects on rice yield. Each column represents a different definition of intervention participation (e.g., attending a field day, visiting a demonstration plot, receiving a discount voucher, or a combination of these three indicators). We again find estimates that are relatively large in magnitude—representing roughly a 25 percent reduction in rice yield—but are not statistically significant at conventional levels. Therefore, similar to the intent-to-treat estimates reported above, we cannot rule-out a null treatment-on-the-treated effect on of our experimental treatment on rice yields.

We also show estimates of the treatment-on-the-treated effect on fertilizer adoption, rice production (kg), and rice area (ha) in Tables A.7, A.8, and A.9 respectively in the Supplemental Appendix. Again, similar to the intent-to-treat effects, although we find that the treatment-on-the-treated effect on USG adoption is substantial, we are unable to rule-out a null treatment-on-the-treated effect on rice production or rice area.

*Farmer Profits*—Next we examine the possibility that farmers behave to maximize profits and this may lead to behavior that does not necessarily maximize rice yields. In particular, it may be that farmers in the treatment groups increase their profits by reducing their costs rather than increasing

Table 4: The Treatment-on-the-Treated (TOT) Effect on Rice Yield (kg/ha)

	(1) Yield	(2) Yield	(3) Yield	(4) Yield	(5) Yield
Field Day Attendance	-122.4 (133.5)				
Demonstration Visit		-108.1 (118.0)			
Received Voucher			-218.4 (242.9)		
Field Day Attendance + Demonstration Visit				-98.78 (107.3)	
Field Day Attendance + Demonstration Visit + Received Voucher					-96.69 (105.1)
Observations	1,112	1,112	1,112	1,112	1,112
R-squared	0.542	0.546	0.529	0.549	0.549
First-stage F-stat	174.00	162.18	73.48	226.22	225.06
Baseline mean	427.06	427.06	427.06	427.06	427.06

*Notes:* The outcome variable measures rice yield (kg/ha) at endline. The coefficients estimate the treatment-on-the-treated (TOT) effect by instrumenting for various indicators of treatment take-up with the village-level randomized treatment assignment. The first-stage F-stat represents the Sanderson-Windmeijer first-stage F-statistic of instrument relevance. Standard errors clustered at the village level are in parentheses. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

their revenue. Although we do not have perfect information on farmer profits, we do have some information about value and quantity of key inputs such as labor, pesticide, herbicide, and seeds. Table A.10 in the Supplemental Appendix shows that we cannot rule out a null effect of each treatment on the number of production days or the value of other key input variables such as pesticide, herbicide, or seeds. Although these findings are not sufficient to rule-out the possibility the intervention helped treatment farmers increase their profits, we also do not find any systematic evidence supporting this explanation.

*Recommended Practices*—Finally, it is also possible that farmers in treatment villages who adopted USG did not adopt all of the recommended practices associated with the optimal use of USG. We have already discussed the observation that farmers in treatment villages disadopt and use less NPK, a complementary fertilizer that aids in the effectiveness of USG. This is potentially due to the fact that prilled urea and NPK are typically purchased as a bundle and so the disadoption of prilled urea led to the disadoption of NPK for some farmers. In addition, Table A.11 in the Supplemental Appendix shows estimated effects of each treatment on recommended practices such as irrigation, levelled and harrowed plots, and the use of herbicide, pesticide, improved seed, and organic fertilizer. We fail to reject a null effect for each treatment on each of these outcomes. Taken together, these results demonstrate that although the standard “business as usual” marketing and the additional discount inspired the adoption of USG, this treatment did not effectively communicate or emphasize the recommended practices necessary for the optimal productivity effects of using USG and urea deep placement.



This explanation is consistent with previous research on the real-world productivity effects of USG adoption among rice farmers in Niger State, Nigeria (Liverpool-Tasie *et al.*, 2015), where the authors find that adherence to several recommended practices, i.e., the establishment of a nursery, leveled fields, the consistent availability of water, and a rigid application timing is associated with higher rice yields among farmers using USG. In the present study, in Kwara State, Nigeria, despite finding relatively large adoption rates of USG, we find no evidence that the experimental treatment led to the adoption of any of these recommended practices.

## 5. Conclusion

We conduct a two-staged randomized controlled trial with a private agricultural input company and rice farmers in Kwara State, Nigeria to test strategies for promoting the adoption of USG with the associated urea deep placement application method. In the first stage of our experiment, we randomly assign 45 villages to treatment and control groups. The treatment villages receive the standard “business as usual” marketing of the private agricultural input distributor. This standard marketing includes an information campaign, a demonstration plot about urea deep placement, and a guaranteed supply of USG via a local retailer. In the second stage of our experiment, we randomly assign a subset of farmers within treatment villages to receive a 25 percent discount on the price of the USG from the local retailer. The control villages receive no treatment.

Our experiment leads to four core findings. First, comparing farmers in treatment villages to farmers in control villages, we find that the pooled

treatment led to the adoption of USG (the improved technology) and the disadoption prilled urea (a substitute technology). Second, dis-aggregating the pooled treatment we find that the additional price discount led to an additional eight percentage points on the adoption rate of USG. Third, based on estimates of the effect on the quantity of USG use we find that the discount is only profitable for the company if their production cost are roughly a quarter of the non-discounted selling price. Finally, although using USG is associated with higher rice yields in our data, we are unable to reject a null effect of either treatment on rice yields.

The lack of effects on rice yield contrasts with the agronomy literature which finds that USG increases rice yields ([Lupin \*et al.\*, 1983](#); [Thomas and Prasad, 1987](#); [Ahmed \*et al.\*, 2000](#); [Jena \*et al.\*, 2003](#); [Kabir \*et al.\*, 2009](#); [Islam \*et al.\*, 2012](#)), and may be due to the observation that farmers who adopted USG did not also adopt the recommended practices associated with the optimal use of USG. These results carry implications for both public and private strategies aiming to promote the adoption of agricultural technologies. More generally, our work contributes to a better understanding of the barriers to the adoption of productive and climate-smart agricultural technologies that can help address the triple challenge of sustainable economic development to (i) promote agricultural productivity, (ii) produce sufficient food supply, and (iii) reduce greenhouse gas emissions. We find that though there are benefits of adopting climate smart inputs on environmental outcomes, climate smart inputs substitute for more harmful inputs, leading to null yield effects. Improved adoption of complementary agronomic practices with climate smart inputs may lead to productivity gains and improved food supply.

## References

- ABATE, G. T., BERNARD, T., DE BRAUW, A. and MINOT, N. (2018). The impact of the use of new technologies on farmers' wheat yield in ethiopia: evidence from a randomized control trial. *Agricultural Economics*, **49** (4), 409–421.
- AHMED, M., ISLAM, M., KADER, M. and ANWAR, M. (2000). Evaluation of urea super granule as a source of nitrogen in transplant aman rice. *Pakistan Journal of Biological Sciences (Pakistan)*.
- BEAMAN, L. and DILLON, A. (2018). Diffusion of agricultural information within social networks: Evidence on gender inequalities from mali. *Journal of Development Economics*, **133**, 147–161.
- , KARLAN, D., THUYSBAERT, B. and UDRY, C. (2013). Profitability of fertilizer: Experimental evidence from female rice farmers in mali. *American Economic Review*, **103** (3), 381–86.
- BENYISHAY, A. and MOBARAK, A. M. (2019). Social learning and incentives for experimentation and communication. *The Review of Economic Studies*, **86** (3), 976–1009.
- BESLEY, T. and CASE, A. (1993). Modeling technology adoption in developing countries. *The American economic review*, **83** (2), 396–402.
- CASABURI, L. and MACCHIAVELLO, R. (2019). Demand and supply of infrequent payments as a commitment device: evidence from kenya. *American Economic Review*, **109** (2), 523–55.

- CHIEN, S., PROCHNOW, L. and CANTARELLA, A. H. (2009). Recent developments of fertilizer production and use to improve nutrient efficiency and minimize environmental impacts. *Advances in agronomy*, **102**, 267–322.
- COLE, S., GINÉ, X., TOBACMAN, J., TOPALOVA, P., TOWNSEND, R. and VICKERY, J. (2013). Barriers to household risk management: Evidence from india. *American Economic Journal: Applied Economics*, **5** (1), 104–35.
- CONLEY, T. G. and UDRY, C. R. (2010). Learning about a new technology: Pineapple in ghana. *American economic review*, **100** (1), 35–69.
- CROPPENSTEDT, A., DEMEKE, M. and MESCHI, M. M. (2003). Technology adoption in the presence of constraints: the case of fertilizer demand in ethiopia. *Review of Development Economics*, **7** (1), 58–70.
- DAR, M. H., DE JANVRY, A., EMERICK, K., RAITZER, D. and SADOULET, E. (2013). Flood-tolerant rice reduces yield variability, differentially benefiting socially disadvantaged groups in india. *Scientific Reports*, **3** (3315).
- DERCON, S. and CHRISTIAENSEN, L. (2011). Consumption risk, technology adoption and poverty traps: Evidence from ethiopia. *Journal of development economics*, **96** (2), 159–173.
- DOBERMANN, A. R. (2005). Nitrogen use efficiency-state of the art. *Agronomy–Faculty Publications*, p. 316.
- DUFLO, E., KREMER, M. and ROBINSON, J. (2011). Nudging farmers to

use fertilizer: Theory and experimental evidence from kenya. *American economic review*, **101** (6), 2350–90.

EMERICK, K. and DAR, M. H. (2021). Farmer field days and demonstrator selection for increasing technology adoption. *Review of Economics and Statistics*, **103** (4), 680–693.

—, DE JANVRY, A., SADOULET, E. and DAR, M. H. (2016). Technological innovations, downside risk, and the modernization of agriculture. *American Economic Review*, **106** (6), 1537–61.

FOSTER, A. D. and ROSENZWEIG, M. R. (1995). Learning by doing and learning from others: Human capital and technical change in agriculture. *Journal of political Economy*, **103** (6), 1176–1209.

GETAHUN, T. D. and VILLANGER, E. (2019). Active private sector development policies revisited: Impacts of the ethiopian industrial cluster policy. *The Journal of Development Studies*, **55** (7), 1548–1564.

GINÉ, X. and KARLAN, D. S. (2014). Group versus individual liability: Short and long term evidence from philippine microcredit lending groups. *Journal of development Economics*, **107**, 65–83.

— and YANG, D. (2009). Insurance, credit, and technology adoption: Field experimental evidence from malawi. *Journal of development Economics*, **89** (1), 1–11.

GOETZ, S. J. (1992). A selectivity model of household food marketing be-

havior in sub-saharan africa. *American Journal of Agricultural Economics*, **74** (2), 444–452.

GOLDMAN, M. and KAPLAN, D. M. (2018). Comparing distributions by multiple testing across quantiles or cdf values. *Journal of Econometrics*, **206** (1), 143–166.

HAILE, B., AZZARRI, C., ROBERTS, C. and SPIELMAN, D. J. (2017). Targeting, bias, and expected impact of complex innovations on developing-country agriculture: evidence from malawi. *Agricultural economics*, **48** (3), 317–326.

HELTBERG, R., TARP, F. *et al.* (2001). Agricultural supply response and poverty in mozambique. helsinki, united nations university. *World Institute for Development Economics Research*.

ISLAM, M., SARKAR, M., UDDIN, S. and PARVIN, S. (2012). Yield of fine rice varieties as influenced by integrated management of poultry manure urea super granules and prilled urea. *Journal of Environmental Science and Natural Resources*, **5** (1), 129–132.

JENA, D., MISRA, C. and BANDYOPADHYAY, K. (2003). Effect of prilled urea and urea super granules on dynamics of ammonia volatilisation and nitrogen use efficiency of rice. *Journal of the Indian Society of Soil Science*, **51** (3), 257–261.

KABIR, M., SARKAR, M. and CHOWDHURY, A. (2009). Effect of urea super granules, prilled urea and poultry manure on the yield of transplant aman

rice varieties. *Journal of the Bangladesh Agricultural University*, **7** (2), 259–263.

KARLAN, D., OSEI, R., OSEI-AKOTO, I. and UDRY, C. (2014). Agricultural decisions after relaxing credit and risk constraints. *The Quarterly Journal of Economics*, **129** (2), 597–652.

KEY, N., SADOULET, E. and JANVRY, A. D. (2000). Transactions costs and agricultural household supply response. *American journal of agricultural economics*, **82** (2), 245–259.

KONDYLIS, F., MUELLER, V. and ZHU, J. (2017). Seeing is believing? evidence from an extension network experiment. *Journal of Development Economics*, **125**, 1–20.

LAAJAJ, R., MACOURS, K., MASSO, C., THUITA, M. and VANLAUWE, B. (2020). Reconciling yield gains in agronomic trials with returns under african smallholder conditions. *Scientific Reports*, **10** (1), 1–15.

LIVERPOOL-TASIE, L., ADJOGNON, G. and KUKU-SHITTU, O. (2015). Productivity effects of sustainable intensification: The case of urea deep placement for rice production in niger state, nigeria. *African Journal of Agricultural and Resource Economics*, **10** (1), 51–63.

LIVERPOOL-TASIE, L. S. O., OMONONA, B. T., SANOU, A., OGUNLEYE, W. and OGUNLEYE (2017). Is increasing inorganic fertilizer use in sub-saharan africa a profitable proposition? evidence from nigeria. *Food Policy*, (67), 41–51.

- LUPIN, M., LAZO, J., LE, N. and LITTLE, A. (1983). Briquetting: Alternative process for urea supergranules. *International Fertilizer Development Center*, **T-26**.
- MACCHIAVELLO, R. (2010). Vertical integration and investor protection in developing countries. *Journal of Development Economics*, **93** (2), 162–172.
- and MORJARIA, A. (2015). The value of relationships: evidence from a supply shock to kenyan rose exports. *American Economic Review*, **105** (9), 2911–45.
- MAGRUDER, J. R. (2018). An assessment of experimental evidence on agricultural technology adoption in developing countries. *Annual Review of Resource Economics*, **10**, 299–316.
- MCKENZIE, D. (2010). Impact assessments in finance and private sector development: What have we learned and what should we learn? *The World Bank Research Observer*, **25** (2), 209–233.
- (2012). Beyond baseline and follow-up: The case for more t in experiments. *Journal of development Economics*, **99** (2), 210–221.
- MONTGOMERY, H. and WEISS, J. (2011). Can commercially-oriented microfinance help meet the millennium development goals? evidence from pakistan. *World Development*, **39** (1), 87–109.
- NEILL, S. P. and LEE, D. R. (2001). Explaining the adoption and disadoption of sustainable agriculture: the case of cover crops in northern honduras. *Economic development and cultural change*, **49** (4), 793–820.



- PAUL, L. (2021). Heterogeneous and conditional returns from dt maize for farmers in southern africa. *European Review of Agricultural Economics*, **forthcoming**.
- RAZAFIMAHATRATRA, H. M., BIGNEBAT, C., DAVID-BENZ, H., BÉLIÈRES, J.-F. and PENOT, E. (2021). Tryout and (dis) adoption of conservation agriculture. evidence from western madagascar. *Land Use Policy*, **100**, 104929.
- SCHULPEN, L. and GIBBON, P. (2002). Private sector development: policies, practices and problems. *World Development*, **30** (1), 1–15.
- SIMTOWE, F. and MAUSCH, K. (2019). Who is quitting? an analysis of the dis-adoption of climate smart sorghum varieties in tanzania. *International Journal of Climate Change Strategies and Management*.
- SURI, T. (2011). Selection and comparative advantage in technology adoption. *Econometrica*, **79** (1), 159–209.
- TARFA, B. and KIGER, B. (2013). Urea deep placement and rice production in nigeria: The experience so far. *IFDC, Guiding Investments in Sustainable Intensification in Africa*.
- THOMAS, J. and PRASAD, R. (1987). Relative efficiency of prilled urea, urea super granules, sulphur coated urea and nitrification inhibitor n-serve blended urea for direct seeded rice. *Journal of Agronomy and Crop Science*, **159** (5), 302–307.

## 6. Supplemental Appendix

This supplemental Appendix provides additional tables and figures referenced in the main manuscript. A list of these additional tables and figures are as follows:

- Figure [A.1](#) summarizes the timeline of the intervention and data collection associated with this project.
- Table [A.1](#) reports balance of observable baseline variables between treatment status.
- Figures [A.2](#) and [A.3](#) illustrate the endline distribution of rice yeilds.
- Table [A.2](#) reports estimates of each treatment on rice production (kg) and Table [A.3](#) reports estimates of each treatment on rice area cultivated (ha).
- Table [A.4](#) reports instrumental variable estimates on rice yield (kg/ha), production (kg), and area cultivated (ha).
- Table [A.5](#) reports the rice yield associated with the use of USG, prilled urea, and NPK conditional on several observable variables.
- Table [A.6](#) reports the effect of our experimental treatment on various indicators of intervention participation.
- Tables [A.7](#), [A.8](#), and [A.9](#) report treatment-on-the-treated effects on fertilizer adoption, rice production (kg), and rice area cultivated (ha).

- Table [A.10](#) reports intent-to-treat effect estimates on the value and quantity of key inputs for rice production.
- Table [A.11](#) report estimates of each treatment on several recommended practices for the optimal use of USG.

Figure A.1: Intervention and Data Collection Timeline

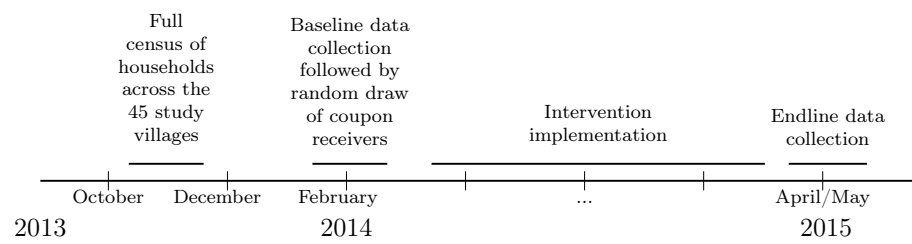
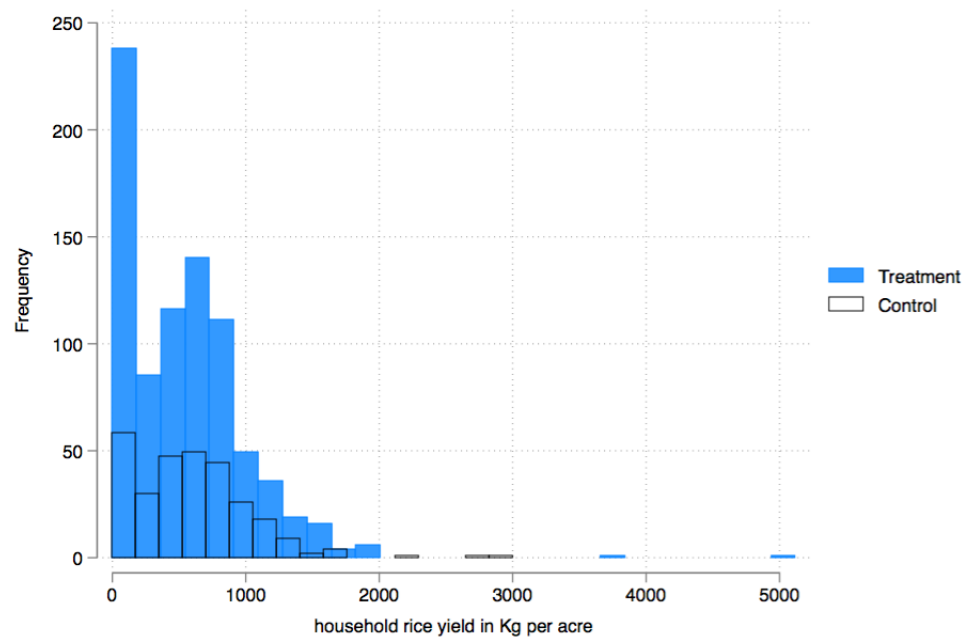


Table A.1: Balance Table

Variable	(1) Pure control		(2) Treatment - No subsidy		(3) Treatment + Voucher subsidy		T-test Difference		
	N/[Clusters]	Mean/SE	N/[Clusters]	Mean/SE	N/[Clusters]	Mean/SE	(1)-(2)	(1)-(3)	(2)-(3)
Dependency ratio	290 [15]	1.103 (0.063)	401 [30]	1.139 (0.051)	421 [30]	1.123 (0.045)	-0.036	-0.019	0.016
Number of adults	290 [15]	3.648 (0.135)	401 [30]	3.529 (0.116)	421 [30]	3.736 (0.072)	0.120	-0.088	-0.208
Number of elderly	290 [15]	0.217 (0.034)	401 [30]	0.207 (0.024)	421 [30]	0.162 (0.026)	0.010	0.056	0.045
Number of children	290 [15]	3.366 (0.204)	401 [30]	3.441 (0.170)	421 [30]	3.544 (0.171)	-0.076	-0.178	-0.103
HH size	290 [15]	7.231 (0.269)	401 [30]	7.180 (0.212)	421 [30]	7.442 (0.185)	0.051	-0.211	-0.262
Male (0/1) HH head	290 [15]	0.990 (0.008)	401 [30]	1.000 (0.000)	421 [30]	0.995 (0.005)	-0.010	-0.006	0.005
Formal education (0/1) HH head	290 [15]	0.600 (0.034)	401 [30]	0.551 (0.029)	421 [30]	0.584 (0.039)	0.049	0.016	-0.033
Improved rice variety (0/1)	290 [15]	0.269 (0.062)	401 [30]	0.319 (0.035)	421 [30]	0.335 (0.044)	-0.050	-0.066	-0.016
Total land size	290 [15]	10.132 (1.089)	401 [30]	12.191 (1.019)	421 [30]	11.031 (0.578)	-2.059	-0.899	1.160
Rice yield	290 [15]	409.019 (60.225)	401 [30]	425.326 (36.413)	421 [30]	441.140 (36.647)	-16.307	-32.120	-15.814
Urea (0/1)	290 [15]	0.403 (0.080)	401 [30]	0.384 (0.044)	421 [30]	0.437 (0.039)	0.019	-0.034	-0.053*
NPK (0/1)	290 [15]	0.555 (0.090)	401 [30]	0.561 (0.048)	421 [30]	0.565 (0.048)	-0.006	-0.010	-0.004
Inorganic fertilizer (0/1)	290 [15]	0.641 (0.078)	401 [30]	0.691 (0.042)	421 [30]	0.717 (0.039)	-0.049	-0.076	-0.027
Organic fertilizer (0/1)	290 [15]	0.010 (0.007)	401 [30]	0.012 (0.006)	421 [30]	0.024 (0.007)	-0.002	-0.013	-0.011
Herbicide (0/1)	290 [15]	0.707 (0.059)	401 [30]	0.758 (0.042)	421 [30]	0.772 (0.042)	-0.051	-0.065	-0.014
Chemicals (0/1)	290 [15]	0.159 (0.060)	401 [30]	0.160 (0.022)	421 [30]	0.185 (0.028)	-0.001	-0.027	-0.026
Weeding (0/1)	290 [15]	0.641 (0.058)	401 [30]	0.668 (0.039)	421 [30]	0.691 (0.036)	-0.027	-0.050	-0.023

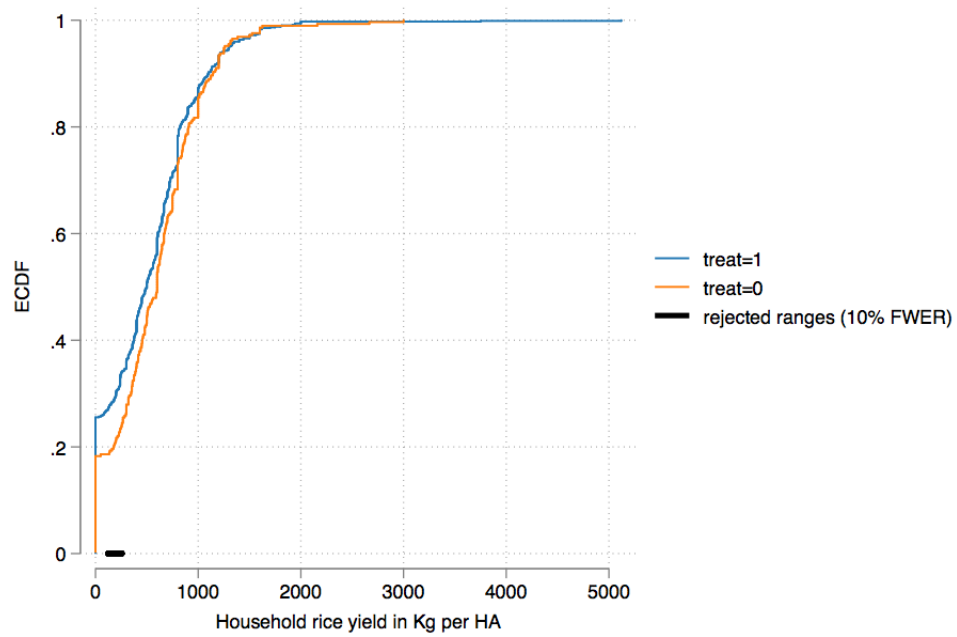
*Notes:* The value displayed for t-tests are the differences in the means across the groups. Standard errors are clustered at the village level. \*\*\*, \*\*, and \* indicate significance at the 1, 5, and 10 percent critical level.

Figure A.2: Endline Rice Yield Distributions



*Notes:* This figure plots a histogram of endline rice yields between treatment villages and control villages. The histogram shows the frequency of rice yield values and shows a skewed distribution for both groups.

Figure A.3: Empirical CDF of Endline Rice Yield



*Notes:* This figure plots the empirical CDF of endline rice yield between treatment and control villages. The figure also shows the range at which these two distributions are statistically different from each other, using the methodology of [Goldman and Kaplan \(2018\)](#). These results show a relatively narrow range of statistical difference in endline rice yields at a 10 percent family-wise error rate (FWER) between treatment and control villages.

Table A.2: The Intent-to-Treat (ITT) Effect on Rice Production (kg)

	(1)	(2)	(3)	(4)
	Production	Production	Production	Production
Pooled Treatment	-731.1 (912.9)	-714.3 (903.7)		
T1: No Discount			-925.5 (906.6)	-918.2 (899.4)
T2: Discount			-546.0 (931.1)	-519.6 (920.3)
T1 = T2	n/a	n/a	0.074	0.063
Observations	1,112	1,112	1,112	1,112
R-squared	0.006	0.013	0.008	0.015
Baseline mean	2,277	2,277	2,277	2,277
ANCOVA?	No	Yes	No	Yes

*Notes:* The outcome variable measures rice production (kg) at endline. The coefficients estimate the ITT effect of each treatment. Tests for equality of treatment reports the associated p-value. Standard errors clustered at the village level are in parentheses. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1



Table A.3: The Intent-to-Treat (ITT) Effect on Rice Area (ha)

	(1) Area	(2) Area	(3) Area	(4) Area
Pooled Treatment	-0.644 (1.157)	-0.747 (1.085)		
T1: No Discount			-1.186 (1.101)	-1.327 (1.032)
T2: Discount			-0.128 (1.262)	-0.197 (1.192)
T1 = T2	n/a	n/a	0.047	0.040
Observations	1,112	1,112	1,112	1,112
R-squared	0.001	0.030	0.005	0.035
Baseline mean	5.27	5.27	5.27	5.27
ANCOVA?	No	Yes	No	Yes

*Notes:* The outcome variable measures rice area cultivated (ha) at endline. The coefficients estimate the ITT effect of each treatment. Tests for equality of treatment reports the associated p-value. Standard errors clustered at the village level are in parentheses. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Table A.4: Instrumental Variable Estimates on Rice Productivity

	(1)	(2)	(3)	(4)
	USG (0/1)	Yield (kg/ha)	Production (kg)	Area (ha)
Pooled Treatment	0.282*** (0.0545)			
USG (0/1)		-236.5 (272.9)	-2,592 (3,350)	-2.285 (4.147)
Observations	1,112	1,112	1,112	1,112
Baseline mean	0.000	427.06	2,277	5.27
F-Stat		26.74	26.74	26.74

*Notes:* The outcome variables are noted in each column. Column (1) reports the first-stage regression. The coefficients in columns (2) through (4) report the IV estimates using our experimental treatment as an instrument for the binary use of USG. Standard errors clustered at the village level are in parentheses. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Table A.5: Fertilizer Use with Associated Rice Yields

	(1) Yield	(2) Yield	(3) Yield	(4) Yield
USG (0/1)	311.3*** (50.86)	343.7*** (52.16)	336.9*** (50.87)	334.9*** (51.98)
Urea (0/1)	196.3*** (37.31)	185.3*** (39.55)	179.1*** (39.46)	178.4*** (39.35)
NPK (0/1)	223.6*** (47.05)	214.9*** (43.85)	209.8*** (42.62)	210.1*** (47.21)
T1: No Discount		-75.45 (46.98)	-76.92* (45.61)	-76.04 (45.32)
T2: Discount		-114.5** (49.66)	-116.7** (48.44)	-116.8** (48.45)
Baseline Yield			0.0735** (0.0307)	0.0724** (0.0304)
Baseline Urea (0/1)				20.28 (29.38)
Baseline NPK (0/1)				-9.776 (29.58)
USG = Urea	0.026	0.008	0.007	0.008
USG = NPK	0.253	0.084	0.083	0.100
Observations	1,112	1,112	1,112	1,112
R-squared	0.203	0.211	0.216	0.216

*Notes:* The outcome variable measures rice yield (kg/ha) at end-line. The coefficients estimate the associated rice yield and should not be interpreted as causal estimates. Tests for equality of treatment reports the associated p-value. Standard errors clustered at the village level are in parentheses. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Table A.6: Intervention Participation

	(1)	(2)	(3)	(4)	(5)
	Attended Field Day (0/1)	Visit Demonstration (0/1)	Increased Understanding (0/1)	Received Voucher (0/1)	Used Voucher (0/1)
T1: No Discount	0.519*** (0.0429)	0.579*** (0.0556)	0.394*** (0.0398)	0.130*** (0.0269)	0.102*** (0.0274)
T2: Discount	0.570*** (0.0442)	0.653*** (0.0461)	0.458*** (0.0427)	0.473*** (0.0491)	0.297*** (0.0557)
Observations	1112	1112	1112	1112	1112
T1 = T2	0.070	0.0211	0.029	0.00	0.00
Baseline Mean	0.00	0.00	0.00	0.00	0.00

*Notes:* The outcome variable measures various aspects of our intervention. The coefficients estimate the intent to treat (ITT) effect of our randomized treatment on each of these measures and assesses intervention take-up. Test for equality of treatment reports the associated p-value. Standard errors clustered at the village level are in parentheses. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Table A.7: The Treatment-on-the-Treated (TOT) Effect on Binary Fertilizer Use

	(1) USG	(2) Urea	(3) NPK	(4) Inorganic
<b>Panel A</b>				
Field Day Attendance	0.517*** (0.0780)	-0.361* (0.185)	-0.270 (0.203)	-0.0801 (0.154)
First-stage F-stat	174.00	174.00	174.00	174.00
R-squared	0.626	0.266	0.368	0.623
<b>Panel B</b>				
Demonstration Visit	0.457*** (0.0725)	-0.319* (0.164)	-0.239 (0.179)	-0.0708 (0.136)
First-stage F-stat	162.18	162.18	162.18	162.18
R-squared	0.293	0.276	0.384	0.625
<b>Panel C</b>				
Received Voucher	0.924*** (0.108)	-0.645* (0.336)	-0.483 (0.370)	-0.143 (0.276)
First-stage F-stat	73.48	73.48	73.48	73.48
R-squared	0.090	0.176	0.311	0.621
<b>Panel D</b>				
Field Day Attendance + Demonstration Visit	0.418*** (0.0677)	-0.292* (0.149)	-0.218 (0.163)	-0.0647 (0.124)
First-stage F-stat	226.22	226.22	226.22	226.22
R-squared	0.308	0.292	0.393	0.627
<b>Panel E</b>				
Field Day Attendance + Demonstration Visit + Received Voucher	0.409*** (0.0656)	-0.285* (0.146)	-0.214 (0.160)	-0.0633 (0.121)
First-stage F-stat	225.06	225.06	225.06	225.06
R-squared	0.311	0.289	0.390	0.626
Observations	1,112	1,112	1,112	1,112
Baseline mean	0.000	0.50	0.705	0.843

*Notes:* The outcome variable measures the binary use of fertilizer at endline. The coefficients estimate the treatment-on-the-treated (TOT) effect by instrumenting for various indicators of treatment take-up with the village-level randomized treatment assignment. The first-stage F-stat represents the Sanderson-Windmeijer first-stage F-statistic of instrument relevance. Standard errors clustered at the village level are in parentheses. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Table A.8: The Treatment-on-the-Treated (TOT) Effect on Rice Production (kg)

	(1) Production	(2) Production	(3) Production	(4) Production	(5) Production
Field Day Attendance	-1,341 (1,686)				
Demonstration Visit		-1,185 (1,494)			
Received Voucher			-2,394 (3,042)		
Field Day Attendance + Demonstration Visit				-1,083 (1,359)	
Field Day Attendance + Demonstration Visit + Received Voucher					-1,060 (1,332)
Observations	1,112	1,112	1,112	1,112	1,112
R-squared	0.344	0.348	0.315	0.356	0.356
First-stage F-stat	274.00	162.18	74.48	226.22	225.06
Baseline mean	2,277	2,277	2,277	2,277	2,277

*Notes:* The outcome variable measures rice production (kg) at endline. The coefficients estimate the treatment-on-the-treated (TOT) effect by instrumenting for various indicators of treatment take-up with the village-level randomized treatment assignment. The first-stage F-stat represents the Sanderson-Windmeijer first-stage F-statistic of instrument relevance. Standard errors clustered at the village level are in parentheses. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Table A.9: The Treatment-on-the-Treated (TOT) Effect on Rice Area (ha)

	(1) Area	(2) Area	(3) Area	(4) Area	(5) Area
Field Day Attendance	-1.182 (2.122)				
Demonstration Visit		-1.045 (1.881)			
Received Voucher			-2.110 (3.797)		
Field Day Attendance + Demonstration Visit				-0.954 (1.714)	
Field Day Attendance + Demonstration Visit + Received Voucher					-0.934 (1.678)
Observations	1,112	1,112	1,112	1,112	1,112
R-squared	0.303	0.305	0.294	0.307	0.307
First-stage F-stat	274.00	162.18	74.48	226.22	225.06
Baseline mean	26.74	26.74	26.74	26.74	26.74

*Notes:* The outcome variable measures rice production (kg) at end-line. The coefficients estimate the treatment-on-the-treated (TOT) effect by instrumenting for various indicators of treatment take-up with the village-level randomized treatment assignment. The first-stage F-stat represents the Sanderson-Windmeijer first-stage F-statistic of instrument relevance. Standard errors clustered at the village level are in parentheses. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Table A.10: The Intent-to-Treat (ITT) Effect on Input Value and Quantity

	(1) USG (Naira)	(2) Urea (Naira)	(3) NPK (Naira)	(4) Inorganic (Naira)	(5) Sowing (Days)	(6) Weeding (Days)	(7) Harvest (Days)	(8) Production (Days)	(9) Chemicals (Naira)	(10) Pesticide (Naira)	(11) Herbicide (Naira)	(12) Imp. Seed (kg)
T1: No Discount	1726.2*** (387.7)	-4576.6 (3263.1)	-6721.9 (6760.6)	-9572.3 (9973.4)	-3.095 (5.133)	-4.749 (5.833)	-7.797 (7.733)	-15.64 (18.31)	-1267.5* (748.6)	446.8 (319.8)	-2172.3 (2256.4)	7.804 (12.43)
T2: Discount	2576.0*** (703.1)	-5156.9 (3215.4)	-4356.1 (6821.6)	-6937.0 (9984.9)	-0.225 (5.522)	3.357 (6.178)	-6.028 (7.486)	-2.896 (18.61)	-872.4 (730.1)	287.5 (298.5)	-977.8 (2246.1)	11.45 (12.88)
Observations	1112	1112	1112	1112	1112	1112	1112	1112	1112	1112	1112	1112
T1 = T2	0.06	0.38	0.08	0.10	0.35	0.03	0.44	0.11	0.21	0.47	0.16	0.46
Baseline Mean	72.41	9926.90	15032.59	25031.90	30.79	31.12	43.49	105.41	4338.36	656.90	10107.84	23.78

*Notes:* The outcome variable measures various measures of inputs. The coefficients estimate the intent to treat (ITT) effect of our randomized treatment on a variety of input cost values or quantities. Test for equality of treatment reports the associated p-value. Standard errors clustered at the village level are in parentheses. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1



Table A.11: Effect of Each Treatment on Recommended Practices

VARIABLES	(1) Irrigation	(2) Leveling	(3) Harrowing	(4) Herbicide	(5) Pesticide	(6) Improved Seed	(7) Nursery	(8) Organic Fertilizer
T1: No Discount	-0.0264 (0.0197)	0.00308 (0.00998)	-0.0304 (0.0579)	-0.0786 (0.0776)	-0.0156 (0.0296)	0.00455 (0.0727)	0.01342 (0.0060)	0.000800 (0.0188)
T2: Discount	-0.00575 (0.0207)	0.00736 (0.0114)	0.00458 (0.0587)	-0.0501 (0.0765)	-0.0367 (0.0275)	-0.00492 (0.0766)	0.01563 (0.0072)	-0.000385 (0.0187)
T1 = T2	0.044	0.740	0.360	0.345	0.191	0.783	0.880	0.920
Observations	1,112	1,112	1,112	1,112	1,112	1,112	1,112	1,112
R-squared	0.004	0.001	0.001	0.005	0.003	0.000	0.004	0.000
Baseline mean	0.109	0.028	0.127	0.750	0.169	0.312	0.001	0.0162

*Notes:* Each outcome variable represents a binary variable indicating use of a particular recommended practice measured at endline. Tests for equality of treatment reports the associated p-value. Standard errors clustered at the village level are in parentheses. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1