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Private Sector Promotion of Climate-Smart Technologies

Experimental Evidence from Nigeria

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Abstract

Sustainable intensification is 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. Although treatment reduces nitrogen runoff damages valued between USD 43 and 113 per hectare, it did not lead to increased rice yields for farmers.

Keywords: Technology Adoption, Fertilizer, Climate-Smart, Micro-dosing, Nigeria, Rice

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1. Introduction

The adoption of climate-smart agricultural technology represents an important mechanism for achieving sustainable intensification and climate adaptation in many low- and middle-income countries—especially in sub-Saharan Africa (Lipper *et al.*, 2014; Campbell *et al.*, 2014; Clay and Zimmerer, 2020). Agricultural extension services can effectively transfer information about new technologies to smallholder farmers and promote adoption on the demand side (Kondylis *et al.*, 2017; Emerick and Dar, 2021); but there is little rigorous evidence on the productivity effects attributable to the adoption of climate-smart agricultural technologies for farmers (Andersson and D'Souza, 2014; Michler *et al.*, 2019). On the supply side, private sector firms have the potential to solve a host of challenges that constrain the adoption and effective use of climate-smart technologies, but more evidence on the profitability of different marketing strategies in promoting technology adoption on the supply side is needed (Magruder, 2018).

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.[1] In the first treatment (T1), we

[1] As we discuss in more detail in Section 2, USG is a substitute technology to prilled urea. While both provide nitrogen, when applied with the deep placement method USG carries the potential of both private productivity benefits for rice farmers and broader

randomly assign villages to a treatment group receiving the standard "business as usual" marketing which 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 an effective intensification technology that is environmentally sustainable. The second feature is the introduction, within the village, of a local USG supplier. In the second treatment (T2), we randomly assign a subset of treatment village 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 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 or 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, similar to the work of Dar *et al.* (2021), 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 and environmental outcomes for rice farmers.[2] This is important as we find that while the standard marketing

environmental benefits.

[2]The complementary work of Dar *et al.* (2021) considers an information treatment

and the additional discount promote the adoption of USG and is associated with substantial environmental benefits, the discount is likely not privately profitable for the distributor and the treatment does not lead to increased rice yields.

We make three contributions. First, we add to the literature on barriers to the adoption of improved agricultural technologies. Much of this literature considers the technology adoption choice as the result of an optimization problem subject to a set of constraints which often lead to market failures justifying government interventions in agricultural markets (Besley, 1994).[3] Our results highlight both the potential and challenge of the private sector's role in promoting the sustainable adoption of improved agricultural technologies. We find that the standard "business as usual" marketing of a private sector agricultural input company successfully encourages farmers to adopt a new technology from zero percent at baseline to 28 percent at endline. In addition, farmers are relatively sensitive to the price of the new technology and providing a price discount leads to an additional eight percentage points on the rate of USG adoption. Despite the increase in customers due to the price discount, we do not find evidence that this marketing strategy would be profitable for the firm.

provided to private agricultural input suppliers.

[3]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).

Farmer adoption of USG leads to a substitution from alternative fertilizers. The disadoption of alternative production techniques (Neill and Lee, 2001; Simtowe and Mausch, 2019; Razafimahatratra *et al.*, 2021) is important to document because the environmental benefits associated with the adoption of a new technology often require the disadoption of an "old" substitute technology. We find that farmers in treatment villages disadopt prilled urea, a substitute fertilizer to USG, from 50 percent at baseline to 30 percent at endline. We also find some (albeit noisy) estimates suggesting the disadoption of NPK, a complementary technology to USG (Rakotoson *et al.*, 2021).

Second, we add to the literature studying the effects of micro-dosing fertilizer (Ibrahim *et al.*, 2015; Bielders and Gérard, 2015; Saidia *et al.*, 2019; Sebnie *et al.*, 2020; Tsujimoto *et al.*, 2021) by documenting the environmental benefits associated with the level of adoption in our field experiment. Urea fertilizer, in either prilled or granulated form, provides nitrogen to plots. Providing the optimal amount of nitrogen is important as too little nitrogen stunts plant growth and too much nitrogen can become toxic to plants. Additionally, in large part due to its use in agricultural production (Liu *et al.*, 2010), excess nitrogen can leach from rice plots into adjacent or underground water sources and lead to eutrophication (Ho *et al.*, 2019). Based on the rate of both the adoption of USG and the disadoption of prilled urea in our experiment, we can estimate plausible bounds on the environmental benefits within our sample. We find that receiving the standard "business as usual" marketing reduces nitrogen losses by between 1.95 to 3.89 kgs per hectare, an effect that translates to a reduction of between USD 43 and 86 per hectare in annual damage costs. The additional discount increases the reduction in nitrogen loss to between 2.55 and 5.11 kgs per hectare, which translates to a reduction of between USD 56 and 113 per hectare in annual damage costs. Therefore, every dollar spent subsidizing the the adoption of USG is associated with between USD 6 and 13 in environmental benefits.

Third, we add to the literature studying the productivity effects attributable to the adoption of climate-smart technology adoption (Mazvimavi and Twomlow, 2009; Michler *et al.*, 2019; Amadu *et al.*, 2020; Berkouwer and Dean, 2022). Although widely promoted by donor agencies, governments, and research centers around the world very little research rigorously estimates the effect of adopting climate-smart agricultural technologies on agricultural productivity (Andersson and D'Souza, 2014). Many of the studies that do exist use observational data and are unable to account for endogenous adoption by farmers (Pannell *et al.*, 2014). Similar to the results of Michler *et al.* (2019) who find limited yield effects attributable to the adoption of climate-smart agricultural technologies in Zimbabwe, we find that our experimental treatment did not lead to increased rice yields in treatment villages. The finding of limited yield effects contrasts with findings from the agronomic literature that USG used with the associated deep placement technology leads to between 15 to 25 percent increases in rice yield (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).[4] Additionally, the relative

[4]This finding is relevant 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).

price of USG does not lead to reduced input costs or increased farm profit. We also examine the profitability of the additional discount for the private fertilizer company and find that the discount is only profitable if their production costs are roughly a quarter of the non-discounted selling price. These findings are important because the success in promoting sustainable intensification and climate adaptation critically relies on both (i) farmers willingly adopting climate-smart technologies and (ii) private firms profitably promoting climate-smart technologies. Limited (or negative) yield effects, with relatively small cost reductions, may discourage widespread adoption of these technologies despite their environmental benefits.

The rest of this paper is organized as follows. In Section 2, we discuss the study setting, introduce the "climate-smart" technology, and explain the implementation of our randomized control trial. In Section 3, we explain our empirical framework. In Section 4, we discuss our main results on the use of fertilizer, the effect of our treatment on rice yields, and explore possible mechanisms that might explain the lack of positive yield effects. 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.*, 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 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 and yield benefits among rice farmers in Nigeria. In particular, the recommended practices for the 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. Our implementation partner, the private fertilizer company, notes that irrigation can be a high and prohibitive cost for rice farmers especially during the dry season and that sub-optimal crop management practices (e.g., soil preparation, seek quality, timely weeding, etc.) can limit the yield gains associated with the use of USG. Moreover, a meaningful delay in sowing or transplanting of the rice plants can lead to a reduction in rice yields. 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.[5]

[5] 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.

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 they can purchase on their own from existing agricultural input suppliers operating in their village.

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 60 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. The same number of farm households are selected in the control group, but do not receive a discount voucher.

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.[6]

[6]We provide more detail about our data collection effort in Section 3.1.

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, senior village promoters, and the establishment of demonstration plots prior to the planting season.[7] One senior village promoter from each local government provides 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 demonstrations 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

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

technology.

The information provided to farmers at the field day include the following two elements. First, village promoters provide a motivating statement about why USG is an important and effective input for rice production. USG provides nitrogen which rice needs for optimal yield. Importantly, relative to prilled urea, USG applied with the deep placement approach allows for a more efficient up take of nitrogen by rice plants and, in agronomic trials, increased rice yields. Second, village promoters demonstrate the urea deep placement application method. This involves placing a handful of USG 5-6 centimeters deep in the ground between four rice plants. The village promoters also emphasize a set of recommended practices to achieve the optimal benefits associated with the use of USG, including: the need to use the improved variety of rice seeds, to apply NPK at the time of transplanting the rice plant, to apply USG one week later, to release irrigation water 2-3 days after USG application, and the need for frequent irrigation. Despite this emphasis, however, some of these recommended practices (e.g., use of improved seed, consistent irrigation, etc.) may be financially or practically infeasible for some rice farmers in this study.

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 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.[8]

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:

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

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 for household h in village v 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, β and δ, represent intent-to-treat estimates of each treatment. Finally, ϵ_{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 rice production and yield:

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

[8] See Table A.1 in the Supplemental Appendix for more specific summary statistics about our sample.

Equation (2) uses 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, γ and λ, 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.

4. Results and Discussion

We present four sets of results. First, we report farmer adoption results, i.e., the intent-to-treat effect of our experimental treatment on the binary use of specific inorganic fertilizer (i.e., USG, prilled urea, and NPK) at endline. From this ITT effect, we estimate bounds of environmental benefits associated with USG adoption and prilled urea disadoption. Second, we use the experimental design to infer whether the USG price discount is profitable for the fertilizer company by estimating the intent-to-treat effect 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 (i.e., 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.

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

	(1) USG	(2) Urea	(3) NPK	(4) Inorganic
Panel A: Pooled Treatment				
Pooled Treatment	0.282***	-0.197*	-0.147	-0.0437
	(0.0545)	(0.0992)	(0.108)	(0.0835)
Observations	1,112	1,112	1,112	1,112
R-squared	0.088	0.033	0.017	0.002
Panel B: Disaggregated Treatment				
T1: No Discount	0.242***	-0.174*	-0.166	-0.0505
	(0.0476)	(0.101)	(0.109)	(0.0834)
T2: Discount	0.320***	-0.219**	-0.129	-0.0371
	(0.0654)	(0.100)	(0.110)	(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

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 fertilizer. 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 14 kg at end-

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***	-56.13	-69.32	-111.6
	(3.027)	(36.68)	(75.60)	(110.8)
T2: Discount	21.04***	-64.21*	-40.56	-83.73
	(5.859)	(36.16)	(77.52)	(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

line. 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 difference 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.

Environmental Benefits—Urea fertilizer, in either prilled or granulated form, provides nitrogen to plants. The right amount of nitrogen plays a key role in plant growth and represents an important part of the natural cycle of nitrogen moving through the atmosphere, soil, water, plants, and animals (Brady and Weil, 2010; Geisseler and Scow, 2014). Too little nitrogen and plants may become stunted, however, too much nitrogen can become toxic to plants (Britto and Kronzucker, 2002). Excess nitrogen can also leach from soil into adjacent or underground water sources and lead to eutrophication,

Table 3: The Intent-to-Treat (ITT) Effect on Environmental Benefits

	(1) N loss/ha upper	(2) N loss/ha lower	(3) Damage cost upper	(4) Damage cost lower
T1: No Discount	-3.890*	-1.945*	-85.88*	-42.94*
	(2.109)	(1.054)	(46.57)	(23.28)
T2: Discount	-5.106**	-2.553**	-112.7**	-56.37**
	(2.070)	(1.035)	(45.71)	(22.86)
T1 = T2	0.086	0.086	0.086	0.086
Observations	1,112	1,112	1,112	1,112
R-squared	0.023	0.023	0.023	0.023
Baseline mean	8.34	4.17	184.15	92.08

Notes: The outcome variables measure plausible bounds on indicators of nitrogen loss per hectare of rice cultivated and estimated damage costs associated with nitrogen leaching. 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

which causes the excessive growth of plants and algae in nearby bodies of water (Chislock *et al.*, 2013; Ho *et al.*, 2019). Crop production represents is the largest contributor to alterations in the global nitrogen cycle (Liu *et al.*, 2010).

The results from Table 2 allow us to estimate plausible bounds on the environmental benefits associated with the adoption of USG and the dis-adoption of prilled urea. Agronomic research shows that nitrogen losses with prilled urea could be as high as 50 percent and the adoption of USG effectively reduces nitrogen losses to zero (De Datta *et al.*, 1990; Dobermann, 2005; Islam *et al.*, 2018; Sarma, 2021). This implies an upper bound on nitrogen losses associated with the use of prilled urea. We assume a lower bound of nitrogen losses associated with prilled urea of 25 percent. We convert nitrogen losses into a per hectare (ha) measures of rice area cultivated for each farmer in our data. To quantify the cost of environmental damage of nitrogen loss, due to leaching of nitrogen through the soil and into the local water system, we rely on Sobota *et al.* (2015) who estimate that each kilogram of excess nitrogen leads to roughly USD 22 (in 2022 dollars) in environmental damage due to eutrophication and toxic levels of nitrogen in surrounding soil and water.[9]

Table 3 presents estimates of plausible bounds of the environmental benefits associated with our experimental treatment, which inspired the adoption of USG and the disadoption of prilled urea. Columns (1) and (2) show the upper and lower bounds, respectively, of the intent-to-treat effect of our treatments on nitrogen loss/ha. Columns (3) and (4) show the upper and lower bounds of the damage costs associated with nitrogen loss. We find that receiving the standard "business as usual" marketing but not the additional discount reduced nitrogen losses/ha by between 1.95 to 3.89 kgs. This translates to a reduction of between USD 43 and 86 per ha in annual damage costs. The additional discount increases the reduction in nitrogen loss/ha by over an additional kg. The standard marketing with the additional discount reduced nitrogen losses/ha by between 2.55 and 5.11 kgs with a value of USD 56 and 113 per ha in annual damage costs. The value of the 25 percent discount voucher (in 2022 dollars), based on the reported amount purchased

[9]It is important to note that the environmental costs of excess nitrogen use can vary substantially across geographic areas (Keeler *et al.*, 2016). The lack of precise estimates of the environmental cost of excess nitrogen in Nigeria motivates our bounding approach where we estimate plausible lower and upper bounds on the true magnitude of environmental benefits associated with endline USG and prilled urea use within our study.

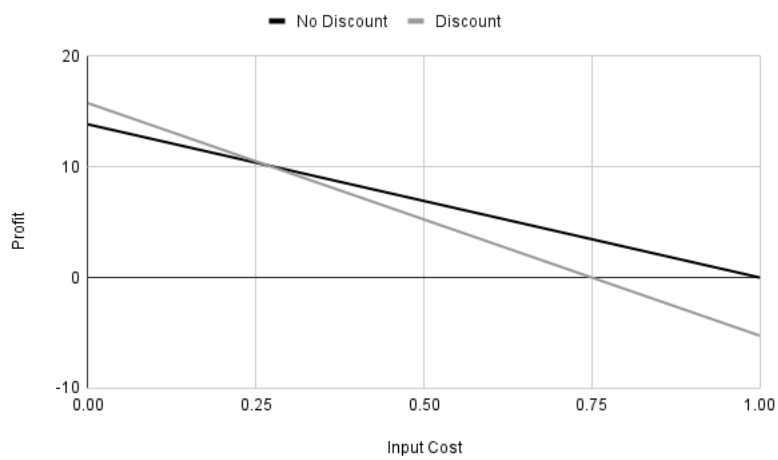
with the voucher is roughly \$10 at baseline. Therefore, in per hectare terms, the cost benefit ratio of environmental benefits associated with the additional discount relative to the environmental benefit is between 2.13 and 2.27. For every dollar spent subsidizing the the adoption of USG is associated with between USD 6 and 13 in environmental benefits.

Fertilizer Distributor Profitability—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. 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.[10] Finally, we use the estimated treatment 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 lower than 27 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.[11]

[10]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.

[11]If an increase in sales volume (Q) leads to a reduction in average input costs (c) due to any fixed costs associated with supplying USG to the agricultural input dealer, then the profit function incorporating the discount in Figure 1 will shift to the right and the discount may become profitable. However, even with a 10 percent reduction in input costs associated with the increase in sales volume due to the discount, input costs would still need to be nearly 50 percent of the un-discounted output price for the discount to be profitable for the agricultural input dealer.

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.

4.3. Effects on Rice Yield

We now turn to estimating the intent-to-treat effect of our treatment on rice yield. Table 2 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.[12] We then estimate the quantities of the given fertilizer used on average at endline for each treatment group.[13] In column (1) we see that the average quantity of USG used in each of the 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.

[12] 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.

[13] 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 4 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 relatively to baseline levels. In addition, the additional discount does not make any statistical difference in rice yield.[14]

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

[14] 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 yeilds at the low end of the rice yield distribution.

Table 4: The Intent-to-Treat (ITT) Effect on Rice Yield (kg/ha)

	(1) Yield	(2) Yield	(3) Yield	(4) Yield
Pooled Treatment	-66.70	-70.15		
	(71.27)	(65.84)		
T1: No Discount			-60.14	-62.45
			(73.73)	(68.64)
T2: Discount			-72.94	-77.49
			(72.12)	(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

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 that finds yield effects ranging between 15 and 25 percent (Kabir *et al.*, 2009; Islam *et al.*, 2012; Sikder and Xiaoying, 2014; Rahman *et al.*, 2016; Bhuyan *et al.*, 2016). 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 expected rice yields that are larger than expected rice yields of farmers in the control group.

4.4. What Explains Null Yield 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, investigate participation in our intervention and estimate treatment-on-the-treated effects to explore whether farmers who participated in the intervention (i.e., 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.

Intervention Participation—We first examine the effect of our experimental intervention on those who participated in the intervention. Table 5 shows that not every farmer in our sample within each treatment group participated in our intervention. In particular, between 50 to 60 percent of

Table 5: Intervention Participation

	(1) Attended Field Day	(2) Visit Demonstration	(3) Increased Understanding	(4) Received Voucher	(5) Used Voucher
T1: No Discount	0.519***	0.579***	0.394***	0.130***	0.102***
	(0.0429)	(0.0556)	(0.0398)	(0.0269)	(0.0274)
T2: Discount	0.570***	0.653***	0.458***	0.473***	0.297***
	(0.0442)	(0.0461)	(0.0427)	(0.0491)	(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

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

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 A.8 in the Supplemental Appendix 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.[15]

Farmer Input Costs—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 aim to reduce their input costs rather than increase their revenue. Although we do not have complete information on all relevant farmer input costs, we do have some information about value and quantity of important inputs such as labor, pesticide, herbicide, and seeds. Table 6 reports these results. Column (1) shows that the purchase value of USG for farmers in treatment villages is greater than for farmers in control villages. In addition, the purchase value of USG for farmers within treatment villages who were offered a discount voucher is greater than for farmers in treatment villages who were not offered a discount voucher. Columns (2) and (3) show that, although the differences are not statistically significant, the purchase value of prilled urea for is about 50 percent less and the purchase value of NPK is about 30 percent less for farmers in treatment villages relative to farmers in control villages. Considering the purchase value of all inorganic

[15]We also show estimates of the treatment-on-the-treated effect on fertilizer adoption, rice production (kg), and rice area (ha) in Tables A.6, A.7, 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.

fertilizer (e.g., USG, prilled urea, and NPK), although the difference is not statistically significant, column (4) shows that farmers in treatment villages report about 30 percent less purchase value of all inorganic fertilizer than farmers in control villages. Noting that these average effects are sufficiently noisy such that we cannot rule-out a null effect, these average effects represent a possibly meaningful reduction in inorganic fertilizer costs for farmers in treatment villages.

Table 6 also reports treatment effects on other variables representing important input costs. Columns (5) through (8) report effects of each treatment on the number of days spent on rice production activities. In each of these columns we are not able to rule out a null effect. Considering each type of production activity together, in column (8), we find that farmers in treatment villages report between two and 15 fewer production days depending on whether the farmer was offered a discount voucher. In addition, we examine treatment effects on the value and quantity of other inputs. In column (9) we find that the purchase value of chemicals for farmers in treatment villages is less than for farmers in control villages. Although this effect is only statistically significant at the 10 percent level, it represents roughly a 23 percent reduction in the purchase value of chemicals. In column (10), although not statistically significant at conventional levels, we find that the purchase value of pesticide is roughly 50 percent larger in treatment villages than in control villages. To the contrary, in column (11), although we cannot rule out a null effect, we find that the purchase value of herbicide is roughly 14 percent smaller in treatment villages than in control villages. Finally, in column (12), although the difference is not statistically significant at con-

Table 6: The Intent-to-Treat (ITT) Effect on Input Costs

	(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***	-4576.6	-6721.9	-9572.3	-3.095	-4.749	-7.797	-15.64	-1267.5*	446.8	-2172.3	7.804
	(387.7)	(3263.1)	(6760.6)	(9973.4)	(5.133)	(5.833)	(7.733)	(18.31)	(748.6)	(319.8)	(2256.4)	(12.43)
T2: Discount	2576.0***	-5156.9	-4356.1	-6937.0	-0.225	3.357	-6.028	-2.896	-872.4	287.5	-977.8	11.45
	(703.1)	(3215.4)	(6821.6)	(9984.9)	(5.522)	(6.178)	(7.486)	(18.61)	(730.1)	(298.5)	(2246.1)	(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

ventional levels, farmers in treatment villages use about 40 percent more improved seed than farmers in control villages.

Taken together the results reported in Table 6 provide an ambiguous answer to whether farmers in treatment villages are able to reduce their input costs. Although we cannot rule out a null effect of each treatment on the purchase value of inorganic fertilizer, the number of production days, or the purchase value of other key input variables, the average effects represent meaningful effects. The evidence suggests that the average farmer in a treatment village experienced a reduction in input costs relative to the average farmer in a control village, although we are not able to statistically distinguish this possibly large effect from zero.

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 7 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. In addition, as shown in Table A.10 in the Supplemental Appendix, based on responses to questions asked only to farmers in treatment villages who reported using USG at endline, less than one out of every five of these farmers report applying USG 7-10 days after transplanting, placing USG between four rice plants, applying USG on wet soil, and keeping the plot wet after transplanting. Each of these practices are specific recommended practices for the optimal use of USG. 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.

Table 7: 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	0.00308	-0.0304	-0.0786	-0.0156	0.00455	0.01342	0.000800
	(0.0197)	(0.00998)	(0.0579)	(0.0776)	(0.0296)	(0.0727)	(0.0060)	(0.0188)
T2: Discount	-0.00575	0.00736	0.00458	-0.0501	-0.0367	-0.00492	0.01563	-0.000385
	(0.0207)	(0.0114)	(0.0587)	(0.0765)	(0.0275)	(0.0766)	(0.0072)	(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

5. Conclusion

We conduct a 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 (Kabir *et al.*, 2009; Islam *et al.*, 2012; Sikder and Xiaoying, 2014; Rahman *et al.*, 2016; Bhuyan *et al.*, 2016), 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. Farmers are less likely to adopt and increase USG use if high profitability does not result from intial adoption. Firms will scale climate-smart agricultural technologies, such as USG, when they find it profitable, but the tested price discount, though increasing customers, does not lead to higher profits per customer for the firm. While the intervention led to a net environmental impact due to the adoption of USG and the disadoption of NPK, neither the demand or supply side of the market has incentive to scale without government or donor intervention.

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 limited yield effects. This finding of limited yield effects attributable to the adoption of climate-smart agricultural technologies aligns with emerging evidence from other contexts in sub-Saharan Africa (Michler *et al.*, 2019), and suggests that the improved adoption of complementary agronomic practices along with climate-smart inputs may lead to productivity gains and improved food supply.

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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.
- Tables A.6, A.7, and A.9 report treatment-on-the-treated effects on fertilizer adoption, rice production (kg), and rice area cultivated (ha).
- Table A.10 reports responses from a set of survey questions asked only to respondents in treatment villages who reported using USG at endline.

Figure A.1: Intervention and Data Collection Timeline

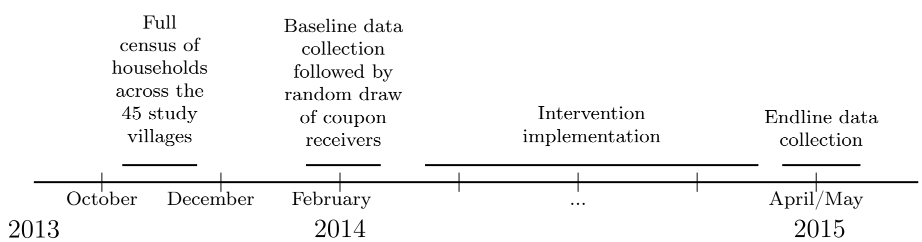
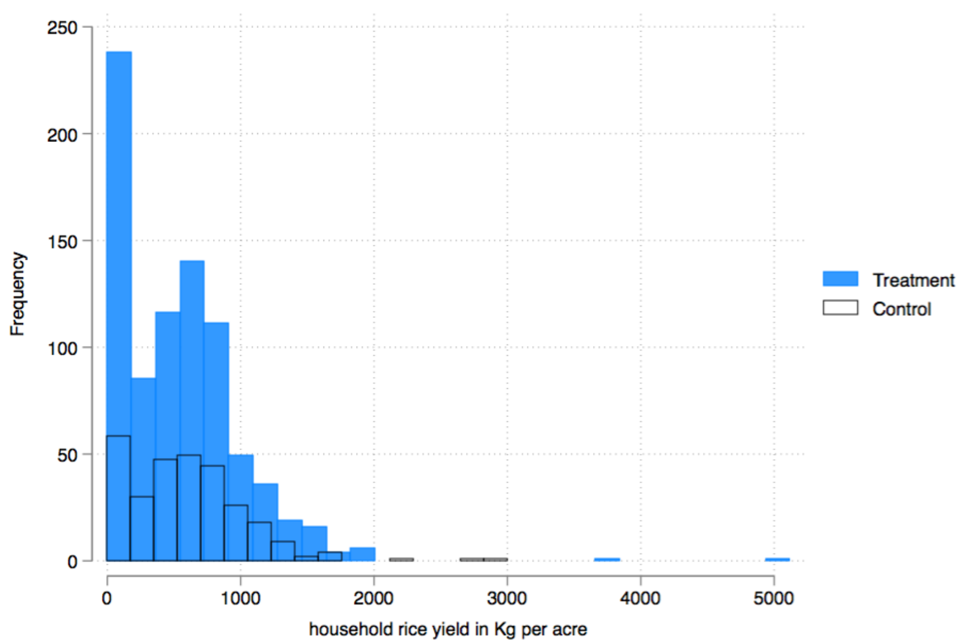


Table A.1: Balance Table

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

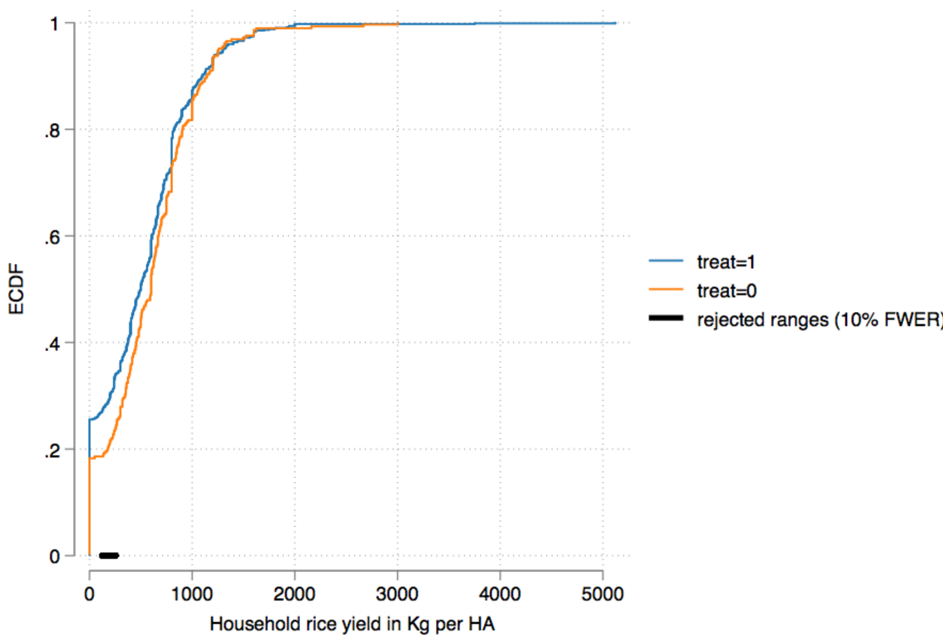
Notes: The value displayed for t-tests are the differences in the means across the groups. Standard errors are clustered at the village level. ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.

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) Production	(2) Production	(3) Production	(4) Production
Pooled Treatment	-731.1	-714.3		
	(912.9)	(903.7)		
T1: No Discount			-925.5	-918.2
			(906.6)	(899.4)
T2: Discount			-546.0	-519.6
			(931.1)	(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	-0.747		
	(1.157)	(1.085)		
T1: No Discount			-1.186	-1.327
			(1.101)	(1.032)
T2: Discount			-0.128	-0.197
			(1.262)	(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) USG (0/1)	(2) Yield (kg/ha)	(3) Production (kg)	(4) Area (ha)
Pooled Treatment	0.282***			
	(0.0545)			
USG (0/1)		-236.5	-2,592	-2.285
		(272.9)	(3,350)	(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***	343.7***	336.9***	334.9***
	(50.86)	(52.16)	(50.87)	(51.98)
Urea (0/1)	196.3***	185.3***	179.1***	178.4***
	(37.31)	(39.55)	(39.46)	(39.35)
NPK (0/1)	223.6***	214.9***	209.8***	210.1***
	(47.05)	(43.85)	(42.62)	(47.21)
T1: No Discount		-75.45	-76.92*	-76.04
		(46.98)	(45.61)	(45.32)
T2: Discount		-114.5**	-116.7**	-116.8**
		(49.66)	(48.44)	(48.45)
Baseline Yield			0.0735**	0.0724**
			(0.0307)	(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 endline. 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: The Treatment-on-the-Treated (TOT) Effect on Binary Fertilizer Use

	(1) USG	(2) Urea	(3) NPK	(4) Inorganic
	Panel A			
Field Day Attendance	0.517***	-0.361*	-0.270	-0.0801
	(0.0780)	(0.185)	(0.203)	(0.154)
First-stage F-stat	174.00	174.00	174.00	174.00
R-squared	0.626	0.266	0.368	0.623
	Panel B			
Demonstration Visit	0.457***	-0.319*	-0.239	-0.0708
	(0.0725)	(0.164)	(0.179)	(0.136)
First-stage F-stat	162.18	162.18	162.18	162.18
R-squared	0.293	0.276	0.384	0.625
	Panel C			
Received Voucher	0.924***	-0.645*	-0.483	-0.143
	(0.108)	(0.336)	(0.370)	(0.276)
First-stage F-stat	73.48	73.48	73.48	73.48
R-squared	0.090	0.176	0.311	0.621
	Panel D			
Field Day Attendance	0.418***	-0.292*	-0.218	-0.0647
+ Demonstration Visit	(0.0677)	(0.149)	(0.163)	(0.124)
First-stage F-stat	226.22	226.22	226.22	226.22
R-squared	0.308	0.292	0.393	0.627
	Panel E			
Field Day Attendance	0.409***	-0.285*	-0.214	-0.0633
+ Demonstration Visit	(0.0656)	(0.146)	(0.160)	(0.121)
+ Received Voucher				
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.7: 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				-1,083	
+ Demonstration Visit				(1,359)	
Field Day Attendance					-1,060
+ Demonstration Visit					(1,332)
+ Received Voucher					
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	182,130	182,130	182,130	182,130	182,130

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.8: 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				-98.78	
+ Demonstration Visit				(107.3)	
Field Day Attendance					-96.69
+ Demonstration Visit					(105.1)
+ Received Voucher					
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. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

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				-0.954	
+ Demonstration Visit				(1.714)	
Field Day Attendance					-0.934
+ Demonstration Visit					(1.678)
+ Received Voucher					
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	5.27	5.27	5.27	5.27	5.27

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.10: Responses to Survey Questions for Adopting Rice Farmers

	(1) Mean	(2) Std. Dev.	(3) Obs.
USG applied 7-10 days after transplanting	0.155	0.363	258
One USG granule between four rice hills	0.174	0.380	258
USG applied on wet soil	0.171	0.377	258
Kept field wet after transplanting	0.171	0.377	258

Notes: This table reports responses to a set of survey questions asked only to respondents in treatment villages who reported using USG at endline.

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