Transaction Costs, Input Subsidies, and Climate-Smart Agricultural Technology Adoption: Experimental Evidence from Rice Farmers in Nigeria

by Guigonan Serge Adjognon, Lenis Saweda Liverpool-Tasie, Andrew Dillon, and Jeffrey R. Bloem

Transaction Costs, Input Subsidies, and Climate-Smart Agricultural Technology Adoption: Experimental Evidence from Rice Farmers in Nigeria

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Abstract

In a randomized controlled trial with rice farmers in Kwara State, Nigeria, we test two approaches for promoting urea super granules (USG) and the associated urea deep placement technology as a sustainable intensification strategy. While farmers in control villages received no intervention, farmers in treatment villages received an information campaign involving a demonstration plot, as well as a guaranteed supply of USG through a local retailer. Within treatment villages, a random subset of farmers received a 25 percent subsidy voucher towards their purchase of USG. We find that farmers in treatment villages who did not receive the additional subsidy increased their use of USG from zero percent at baseline to 35 percent at endline, while farmers in treatment villages who did receive the additional subsidy increased their use of USG by only an additional eight percentage points. Heterogeneity analysis shows, however, that this result reverses among farmers who use prilled urea at baseline, the technology USG replaces. These results carry implications for both private and public strategies aiming to promote the adoption of sustainable agricultural technologies.

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

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*The findings and conclusions in this manuscript are ours and should not be construed to represent any official World Bank, USDA, or US Government determination or policy. All errors are our own. Corresponding author: Guigonan Serge Adjognon, gadjognon@worldbank.org.

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1. Introduction

Classic models suggest that structural transformation and economic development critically rely on agricultural productivity growth (Johnston and Mellor, 1961) and the adoption of innovative agricultural technologies (Hayami and Ruttan, 1970). Despite dramatic improvements in many dimensions of well-being around the world, agricultural workers in the richest 10 percent of countries produce on average 50 times more output per worker than those in the poorest 10 percent (Gollin *et al.*, 2014), and low levels of fertilizer use may partially explain this observed agricultural productivity gap (de Janvry *et al.*, 2016; Sheahan and Barrett, 2017). Moreover, the world now faces the triple challenge of (i) promoting agricultural productivity growth, (ii) producing a sufficient, nutritious, and safe food supply, and (iii) reducing greenhouse gas emissions. Understanding the barriers to the adoption of productive and climate-smart agricultural technologies may help close the global gap in agricultural productivity and address the triple challenge of sustainable economic development.

In this paper we report results from a randomized controlled trial with rice farmers in Kwara State, Nigeria to test two popular approaches for promoting the adoption of improved agricultural technologies. We conduct a two-stage experimental design. In the first stage, we randomly assign 757 rice farmers within 45 villages to treatment and control groups at the village level. The treatment villages receive information campaigns and a demonstration plot about urea deep placement as a sustainable and more cost efficient intensification technology. In addition, treatment villages receive a guaranteed supply of urea super granules (USG), the primary fertilizer input involved in the urea deep placement technology, via a village leader who served as local retailer. This treatment (i.e., T1) is similar to popular agricultural extension programs, with an additional supply guarantee, that aim to boost agricultural productivity and the adoption of new technologies. The control villages receive nothing. In the second stage, we randomly assign a subset of farmers within treatment villages to receive a 25 percent subsidy voucher toward the purchase of USG from the local retailer. This treatment (i.e., T2) is similar to popular agricultural input subsidy programs that also aim to boost agricultural productivity and the adoption of new technologies.

Our experiment leads to three core findings. First, pooling all farmers in treatment villages together, we find that farmers in treatment villages increase their use rate of USG by 39 percentage points and reduce their use rate of prilled urea by 25 percentage points. Second, estimating specific effects for farmers in treatment villages receiving an additional subsidy and not receiving an additional subsidy, we find that most of the effect of our treatment is attributable to the agricultural extension plus supply guarantee treatment (i.e., T1) and a relatively small share of the effect is attributable to the additional subsidy (i.e., T2). Third, heterogeneity analysis shows that the previous result reverses among farmers who use prilled urea at baseline, the technology USG replaces. We find that among farmers who use prilled urea at baseline, the additional subsidy is instrumental for increasing the use rate of USG. These findings can be explained with a model of transaction costs. For the average farmer, facilitating information and access to a technology is most helpful, and additional financial subsidies help but are not as meaningful as reducing non-financial transaction costs. For farmers who already use a substitute technology, however, non-financial transaction costs are not a binding constraint and the additional subsidy encourages adoption of the new technology.

Our paper is closely related to other randomized control trials that test various approaches to boost the adoption of improved agricultural technologies. These approaches include: providing access to credit (Karlan *et al.*, 2014), harnessing social learning (Beaman and Dillon, 2018; BenYishay and Mobarak, 2019), providing direct training to farmers (Kondylis *et al.*, 2017), leveraging behavioral incentives (Duflo *et al.*, 2011), and improving local availability (Emerick *et al.*, 2016). In our experiment, we test the relative effects of providing either agricultural extension services with a supply guarantee or additional agricultural input subsidies in improving the adoption of a new agricultural technology.

We make three contributions to the literature on barriers to the adoption of improved agricultural technologies. First, much of this literature considers the technology adoption choice as the result of a constrained optimization problem by a rational economic agent 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 and time inconsistencies (Dercon and Christiaensen, 2011), (iv) and transaction costs related to imperfections in input and output markets (Goetz, 1992; Heltberg *et al.*, 2001; Key *et al.*, 2000; Suri, 2011). Our results show that the binding constraint on the adoption of an improved agricultural technology critically depends on time-variant farmer-level characteristics—in our case, whether or not the farmer used the "old" substitute technology at baseline. This heterogeneity carries implications for both public and private strategies aiming to promote the adoption of new improved agricultural technologies.

Second, we aim to focus on informing the effective design of agricultural input supply chains. As suggested by de Janvry *et al.* (2016), the development of agricultural input supply chains can influence other efforts to address the constraints to technology adoption. For example, a farmer who is trained about the benefits of a new improved agricultural input would likely not adopt if he has to incur large transaction costs to access the new technology. Our results show that providing both information and guaranteed supply of the fertilizer increase the adoption of USG and the associated urea deep placement application method.

Finally, we extend the base of knowledge to Nigeria. In the literature to date, there are relatively few experimental studies that aim to understand the barriers to agricultural technology adoption, and in particular improved fertilizer use, conducted in West Africa. This limits the ability of policy makers in the Economic Community of West African States (ECOWAS) to make evidence-based decisions about agricultural policies. Given existing concerns about the external validity of many randomized controlled trials (Deaton and Cartwright, 2018), we aim to rigorously test the effectiveness of various strategies commonly used in West Africa for boosting agricultural productivity.

The rest of this paper is organized as follows. In Section 2, we discuss the study setting in detail. In Section 3, we discuss our empirical framework and specify our strategy for estimating effects of our experimental treatments. In Section 4, we present and discuss the results of our study. Finally, Section 5 concludes.

2. Study Setting

2.1. The Technology

Fertilizer application as part of agricultural production aims to provide nutrients to plants to increase or sustain optimal crop yields. Although traditionally farmers broadcast the prilled urea on their plots, the urea deep placement technology 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 urea deep placement compared to prilled urea in countries such as India and Bangladesh (Lupin *et al.*, 1983). The nitrogen required to obtain an increase rice paddy yield by one ton is between 25 and 45 percent less with USG than with prilled urea (Lupin *et al.*, 1983). In Niger state, Nigeria, nitrogen use efficiency under irrigated rice increased by 40 percent while yields on trial plots increased by up to 50 percent when urea is deep placed compared to traditional broadcasting (IFDC, 2012). Other studies show that on average only about 50 percent of the nitrogen applied using broadcast methods reaches crops (Dobermann, 2005). This rate is even lower under certain management conditions and varies across crops. For example, Fan *et al.* (2009) estimates nitrogen recovery at between 30 to

35 percent for cereals in China. In addition, low nitrogen take up also leads to nitrogen immobilization in soil organic matter and its evaporation 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). Thus USG with urea deep placement may both have important productivity and environmental benefits.

Despite the likely 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 particular, the recommended practices for optimal benefit of USG and urea deep placement include planting on leveled fields, the consistent availability of water, and rigid application timing. Consequently, the potential for this technology to revolutionize rice production in Nigeria is not clear. And more specifically to the focus of this paper, the extent to which farmers adopt this technology—despite the expected yield and environmental benefits—is not yet well understood.

2.2. 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 is focused on researching USG and has piloted the use of the urea deep placement technology on across several locations. Despite encouraging results of these trials, constrains along the input supply chain for USG limit the widespread adoption of this improved technology. In particular, a briquetting machine is required for converting prilled urea to the super granules. This machine is relatively expensive and, thus, not widely available. In recent years, however, several private fertilizer companies in Nigeria have begun to develop a production line for briquetting, packaging, and shipping, USG to the market.

We partner with Notore, one of the private fertilizer companies producing and distributing USG in Nigeria, and implement a randomized controlled trial with rice farmers, to test two complementary approaches for promoting the adoption USG and the associated urea deep placement application. The first approach mirrors agricultural extension programs that are popular in many countries, enhanced with a transaction costs reducing intervention. Villages randomly selected into this treatment receive an information campaign, with a demonstration plot, as well as guaranteed supply of USG through a local retailer. In all 30 treatment villages, information about urea deep placement was introduced and a guaranteed supply of the USG (as well as NPK and regular prilled urea fertilizer) was provided through field agents of the private sector input supplier Notore, our private sector partner.[1] The second approach mirrors agricultural input subsidy programs that are also popular in many countries. Within treatment villages, a subset of farmers randomly receive a voucher providing them with a 25 percent discount on their purchase of USG.

[1]Notore has developed a training system for farmers in Nigeria, to demonstrate how urea deep placement technology works. This includes Notore fertilizer promoter training, video testimonials of other farmers, and physical demonstrations. This approach was followed in our study villages.

2.3. Experimental Design

Our research sites consists of a random sample of 45 villages selected from two major rice producing Local Government Areas (LGAs) in Kwara State, north central Nigeria. Figure A.1 in the Appendix shows the geographical distribution of the study villages. The study design involves two levels of randomization. First, we randomly assigned 30 villages to the treatment and 15 villages to control groups. Second, within treatment villages we randomly selected a subset of farmers to receive a 25 percent subsidy voucher on their purchase of USG from a local retailer.

In January of 2014, and during the pre-planting season, we conducted a baseline survey of 757 households in all 45 villages (e.g., both treatment and control villages). After the completion of the baseline survey the treatment phase began during the later pre-planting and planting seasons of 2014. This treatment phase began with the selection and training of village promoters and senior village promoters,[2] via a participatory approach involving the whole community, and the establishment of demonstration plots prior to the planting season. One senior village promoters was selected from each local government to provide oversight over the village promoters in their local government and assist in coordinating the implementation of various project activities in the treatment villages with their local government.

The village promoter training included a video documentary of USG application procedure and its effects, role playing sessions on the establish-

[2] The concept of the village promoter is a mix of commerce and extension developed by Notore to sell fertilizer. 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.

ment of nursery and demonstration plots as well as on the method of applying USG in urea deep placement. At the end of the training, each village promoter received improved rice seed, NPK, and USG for the nursery and demonstration plot establishment. Following the training, with the support of the research team and Notore, village promoters set up demonstration plots in conjunction with local farmers. On these plots, village promoters demonstrated the use of USG and the associated urea deep placement with recommended best practices. These demonstration plots included plots using only traditional practices. This direct comparison between improved and traditional technology use allow farmers to clearly see the difference between the two plots in terms of plant development and yield. At the beginning of the normal rice growing season (e.g., between April and May 2014), Village promoters organized field days with representatives of Notore and members of the research team. All farmers from each treatment village was 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.

2.4. Data Sources

We use two rounds of household surveys (e.g., a baseline and endline). We collected the baseline data between April and May 2014 using a multimodule LSMS-style household survey instrument capturing households socio-economic and demographic characteristics, agricultural production (e.g., practices, inputs, and labor use, harvest yield, etc.), as well as well being indicators (e.g., income and food security). We collected endline data between April and May 2015. The endline survey uses a similar instrument as the baseline, but excludes several modules containing information that do not change over time. The endline survey also includes additional modules capturing intervention participation and USG adoption.

3. Empirical Framework

3.1. Estimation Strategy

Based on the experimental design described above, treatment status of each household is randomly assigned and we have both baseline and endline data. Therefore, we can estimate treatment effects in two ways. First, we estimate the following ordinary least squares (OLS) regression specification:

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

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 measured at endline and the treatment status of the household, $T1_{vh}$ and $T2_{vh}$, with the control group serving as the reference group. The coefficients, β and δ, represent intent-to-treat (ITT) 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, the error term is clustered at the village level.

Second, we estimate the following Analysis of Covariance (ANCOVA) regression specification:

$$Y_{vh,Endline} = \kappa + \gamma T1_{vh} + \lambda T2_{vh} + Y_{vh,Baseline} + \mathbf{X'_{vh,Baseline}}\psi + \mu_{vh} \quad (2)$$

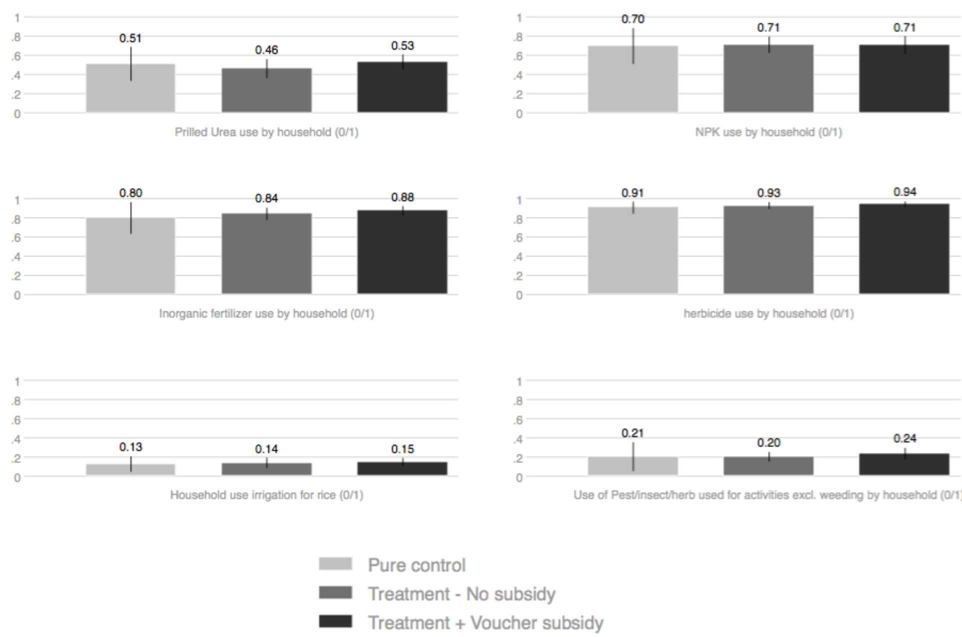
Equation (2) is an augmented specification using information from both our baseline and endline survey. Similar with equation (1), $Y_{vh,Endline}$ is the value of a given outcome variable measured at endline and $T1_{vh}$ and $T2_{vh}$ are the treatment status of the household with the control group serving as the reference group. Similarly, the coefficients, γ and λ, represent intent-to-treat (ITT) estimates of each treatment. Equation (2), however, also includes the baseline value of the outcome variable, $Y_{vh,Baseline}$ and baseline values of control variables, $\mathbf{X'_{vh,Baseline}}$. When autocorrelation is low, as it is with the main outcomes we use in our analysis, 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, the error term is clustered at the village level.

3.2. Descriptive Statistics

Our sample includes 757 rice farmers from Kwara State in Nigeria. We use household level data to study the effect of our experimental treatment on the adoption of USG and the associated urea deep placement application. The households all farmed rice, almost exclusively had a male head of the households, and included about three children and three adults. See Table A.1 in the Appendix for more specific summary statistics about our sample.

Figure 1 shows the share of households who used different types of agricultural inputs disaggregated by treatment status. At the time of our baseline survey about half of households used prilled urea fertilizer and about 70 percent used NPK fertilizer. These rates do not differ across treatment status. In addition, at the time of our baseline survey, about 80 percent of households used inorganic fertilizer, about 90 percent used herbicide, about 13 percent use some form of irrigation, and about 20 percent use pesticide. Again, these rates do not differ across treatment status. See Table A.1 in the Appendix for more formal balance test. This table shows strong evidence of balance in observable characteristics across treatment status and supports our assumption of the exogeneity of our randomized treatment assignment.

Figure 1: Summary Statistics by Treatment Status



Notes: Means associated with agricultural input use for rice farmers in Nigeria. Standard errors, shown with error bars, are clustered at the village level. See Table A.1 in the Appendix for T-tests showing balance across these and other baseline variables.

4. Results

We present three sets of results from a randomized control trial with rice farmers in Kwara State, Nigeria. First, we estimate the effect of living in a treatment village relative to living in a control village by pooling together all households living in treatment villages. This approach estimates the intent-to-treat effect of receiving extension services with guaranteed supply on fertilizer use. Second, we estimate the effect of each treatment separately relative to living in a control village. Comparing the coefficients on each treatment to each other estimates the relative effect of being offered the additional subsidy while to living in a treatment village. Finally, we estimate heterogenenous effects by examining the effect of each treatment relative to living in a control village based on baseline prilled urea use. USG is a direct substitute for prilled urea, so we expect that treatment effects may differ based on whether or not the household used prilled urea at baseline. Each set of results include treatment effects on binary outcomes variables that measure fertilizer use at the extensive margin.

Table 1 shows intent-to-treat effect of living in a treatment village relative to living in a control village on the binary use of USG, prilled urea, and NPK fertilizer. In columns (1) and (2) we find that living in a treatment village increases the use of USG from zero percent at baseline to 39 percent at endline. This finding demonstrates that our treatment encouraged the adoption of USG fertilizer among rice farmers in Kwara State, Nigeria. In columns (3) and (4) we find that living in a treatment village reduces the use of prilled urea by about 50 percent, from a use rate of 50 percent at

Table 1: The Effect of Extension Services on Fertilizer Use

VARIABLES	(1) USG	(2) USG	(3) Urea	(4) Urea	(5) NPK	(6) NPK	(7) Inorganic	(8) Inorganic
Treatment	0.396***	0.397***	-0.250**	-0.260***	-0.147	-0.163**	-0.00822	-0.0190
	(0.0623)	(0.0602)	(0.100)	(0.0776)	(0.109)	(0.0732)	(0.0573)	(0.0414)
Observations	757	757	757	757	757	757	757	757
R-squared	0.146	0.173	0.050	0.111	0.017	0.144	0.000	0.103
Baseline mean	0.00	0.00	0.500	0.500	0.705	0.705	0.843	0.843
Controls	No	Yes	No	Yes	No	Yes	No	Yes

Notes: The coefficients estimate the effect of living in a treatment village relative to living in a control village. Standard errors clustered at the village level are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

baseline to about 25 percent at endline. This dis-adoption of prilled urea in treatment villages is expected because USG is a direct substitute for prilled urea. In columns (5) and (6) we find that living in a treatment village reduces the use of NPK by about 20 percent, from a use rate of 70 percent at baseline to about 50 percent at endline. This result is surprising, given that NPK is a complement to USG and therefore adoption of USG should not necessarily lead to a dis-adoption of NPK. Although this result is much less statistically precise and is smaller in magnitude than the estimates in columns (1) through (4), we further investigate this surprising result later in this paper. Finally, in columns (7) and (8) we find no statistically significant change in the use of any inorganic fertilizer (e.g., USG, prilled urea, or NPK). 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 rate of inorganic fertilizer.

So far, we have discussed the effect of living in a treatment village relative to living in a control village. As discussed above, however, a random subset of households in treatment villages received a 25 percent subsidy to reduce the cost of purchasing USG fertilizer from a local vendor. Table 2

Table 2: The Effect of an Additional Subsidy on Fertilizer Use

VARIABLES	(1) USG	(2) USG	(3) Urea	(4) Urea	(5) NPK	(6) NPK	(7) Inorganic	(8) Inorganic
T1: No Subsidy	0.351***	0.356***	-0.207**	-0.214***	-0.159	-0.179**	0.00327	-0.00568
	(0.0557)	(0.0550)	(0.101)	(0.0792)	(0.111)	(0.0774)	(0.0571)	(0.0412)
T2: Subsidy	0.437***	0.433***	-0.289***	-0.301***	-0.135	-0.148**	-0.0188	-0.0307
	(0.0751)	(0.0717)	(0.102)	(0.0800)	(0.109)	(0.0732)	(0.0605)	(0.0445)
T1 = T2	0.079	0.115	0.024	0.034	0.433	0.363	0.415	0.301
Observations	757	757	757	757	757	757	757	757
R-squared	0.152	0.178	0.055	0.117	0.018	0.145	0.001	0.104
Baseline mean	0.00	0.00	0.500	0.500	0.705	0.705	0.843	0.843
Controls	No	Yes	No	Yes	No	Yes	No	Yes

Notes: The Coefficients estimate the effect of each treatment (e.g., living in a treatment village without an additional subsidy, T1, and with the the additional subsidy, T2). Test for equality of treatments reports the associated p-value. Standard errors clustered at the village level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

dis-aggregates the effect of each treatment on the use of fertilizer relative to living in a control village. Comparing the coefficients between T1 without the subsidy to T2 with the subsidy shows the effect of receiving the additional subsidy for households who live in a treatment village. In columns (1) and (2) we find that living in a treatment village but not receiving an additional subsidy increases USG use from zero percent at baseline to 35 percent at endline. Living in a treatment village and receiving an additional subsidy increases the use rate of USG by eight additional percentage points to 43 percent at endline. Taken together these results suggest that both financial and non-financial transaction costs constrain the adoption of USG among rice farmers in Nigeria. However, the relative effect of extension services without an additional subsidy is larger than the relative effect of being offered an additional subsidy. This highlights the role of non-financial transaction costs in constraining the adoption of new agricultural technology.

We also continue to find that both treatments reduce the use of prilled urea (a close substitute to USG) and NPK (a complement to urea or USG). In columns (3) and (4) we find that living in a treatment village but not receiving an additional subsidy reduces prilled urea use by about 40 percent, from a use rate of 50 percent at baseline to about 30 percent at endline. Living in a treatment village and receiving an additional subsidy reduces prilled urea use by about 60 percent, from a use rate of 50 percent at baseline to about 20 percent at endline. The relative effect of the additional subsidy among households living in treatment villages is statistically significant at conventional levels. In columns (5) and (6) we find similar results, although the relative effect of the additional subsidy is not statistically significant. Living in a treatment village, whether or not the household was offered an additional subsidy, reduces NPK use by about 20-23 percent, from a use rate of 70 percent at baseline to about 50 percent at endline. While the substitution of traditional fertilizer and especially prilled urea for the more environmentally friendly USG is an expected result, the reduction in NPK, a complementary fertilizer, is less expected. It implies that the treatment in some way discouraged the use of a complementary technology and may limit the effectiveness of the improved technology in improving agricultural productivity. Finally, neither treatment changes the use of any inorganic fertilizer (e.g., USG, prilled urea, or NPK).

Table 3 disaggregates the intent-to-treat effects discussed above, by each households baseline prilled urea use status. We expect that farmers who use prilled urea at baseline and live in a treatment village will be more likely to adopt USG because they've already integrated the costs of prilled urea into their production function. In columns (1) and (2) the additional subsidy makes no difference among baseline prilled urea non-users, but does make a difference among baseline prilled urea users. In fact, among baseline prilled urea users living in a treatment village but not receiving an additional subsidy does not increase adoption of USG. Instead, among baseline prilled urea users, the additional subsidy is instrumental in increasing USG adoption. Meanwhile, among baseline prilled urea non-users, the additional subsidy has no effect on the adoption of USG. Taken together these findings can be explained with a model of transaction costs. For the average farmer, facilitating information and access to a technology is most helpful, and additional financial subsidies help but are not as meaningful. But for farmers who already understand how to procure and use an "old" substitute technology, the subsidy seems to encourage further adoption. These findings are relevant to ongoing policy debates about the relative benefits of alternative approaches—such as agricultural extension programs, supply guarantees, or agricultural input subsidy programs—for boosting technology adoption and agricultural productivity in low- and middle-income.

The additional subsidy also seems to lead to the dis-adoption of urea and NPK among baseline prilled urea users. In columns (3) and (4), we find no difference in the relative effect of the additional subsidy among baseline prilled urea non-users, but a statistically significant relative effect of the additional subsidy among baseline prilled urea users. Specifically, among baseline prilled urea users, living in a treatment village with the additional subsidy reduced the use of urea by over 30 percent, from 100 percent at baseline to about 70 percent at endline. Meanwhile, baseline prilled urea

Table 3: Heterogeneity by Baseline Urea Use

VARIABLES	(1) USG	(2) USG	(3) Urea	(4) Urea	(5) NPK	(6) NPK	(7) Inorganic	(8) Inorganic
T1: No Subsidy	0.354***	0.351***	-0.144	-0.182**	-0.0515	-0.105	0.0712	0.0470
	(0.0601)	(0.0591)	(0.0969)	(0.0845)	(0.108)	(0.0860)	(0.0655)	(0.0537)
T2: Subsidy	0.316***	0.312***	-0.102	-0.140	0.0430	-0.00854	0.0748	0.0501
	(0.0582)	(0.0558)	(0.106)	(0.0931)	(0.101)	(0.0797)	(0.0661)	(0.0532)
T1 × baseline urea user	-0.00401	0.000394	-0.107	-0.0519	-0.202**	-0.141*	-0.127*	-0.103
	(0.0567)	(0.0600)	(0.0877)	(0.0742)	(0.0935)	(0.0701)	(0.0663)	(0.0615)
T2 × baseline urea user	0.227***	0.230***	-0.363***	-0.306***	-0.347***	-0.267***	-0.184**	-0.155***
	(0.0597)	(0.0654)	(0.0846)	(0.0727)	(0.0868)	(0.0665)	(0.0684)	(0.0572)
T1 = T2 for baseline urea non-users	0.398	0.371	0.373	0.360	0.047	0.027	0.947	0.949
T1 = T2 for baseline urea users	0.001	0.002	0.000	0.000	0.022	0.043	0.471	0.487
Observations	757	757	757	757	757	757	757	757
R-squared	0.177	0.192	0.089	0.135	0.048	0.156	0.021	0.110
Baseline mean	0.00	0.00	0.500	0.500	0.705	0.705	0.843	0.843
Controls	No	Yes	No	Yes	No	Yes	No	Yes

Notes: The Coefficients estimate the effect of each treatment (e.g., living in a treatment village without an additional subsidy, T1, and with the the additional subsidy, T2), dis-aggregated by baseline urea use. Test for equality of treatments reports the associated p-value. Standard errors clustered at the village level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

users living in a treatment village but with no additional subsidy did not reduce their use of prilled urea. Similarly, in columns (5) and (6) essentially all of the reduction in the use of NPK in treatment villages is driven by baseline prilled urea users, and the additional subsidy lead to an increased reduction in NPK. Finally, in columns (7) and (8) we find that baseline prilled urea users who live in treatment villages actually reduce their use of any inorganic fertilizer (e.g., USG, urea, or NPK) at the extensive margin.

To investigate these dynamics further—and because all of our variables are binary—we can classify households based on their baseline prilled urea use, their treatment status, and their endline fertilizer use. Our sample include 757 households, with 204 living in a control village, 265 living in a treatment village but not receiving an additional subsidy, and 288 living in a treatment village and receiving an additional subsidy. Among the 288 households living in a treatment village and receiving the additional subsidy, 130 (45 percent) used adopted USG at endline. Within this 288 households living a treatment village and receiving the additional subsidy, 153 households used prilled urea at baseline and 86 (56 precent) used USG at endline. This leaves 67 households who lived in a treatment village, received the additional subsidy, and who used prilled urea at baseline. Among these 67 households, 27 (40 percent) are dis-adopters who did not use either urea or NPK at endline after receiving the treatment with the additional subsidy, 16 (23 percent) are switchers who used NPK but did not use urea at endline, 7 (10 percent) are non-USG-adopters who used urea but did not use NPK at endline, and 17 (23 percent) are non-USG-adopters who used both urea and NPK at endline.

5. Conclusion

We conduct a randomized controlled trial with rice farmers in Kwara State, Nigeria to test popular approaches for promoting the adoption of improved agricultural technologies. In the first stage of our experiment, we randomly assign 45 villages to treatment and control groups. The treatment villages receive information campaigns, a demonstration plot about urea deep placement, and a guaranteed supply of USG via a village leader who served as local retailer. The control villages receive nothing. In the second stage of our experiment, we randomly assign a subset of farmers within treatment villages to receive a 25 percent subsidy voucher toward the purchase of the USG from the local retailer.

Our experiment leads to three core findings. First, farmers in treatment villages increase their use rate of USG by 39 percentage points and reduce their use rate of prilled urea by 25 percentage points. Second, most of the effect of our treatment is attributable to the agricultural extension with guaranteed supply treatment and a relatively small share of the effect is attributable to the additional subsidy. Third, among farmers who use prilled urea at baseline, the additional subsidy is instrumental for increasing the use rate of USG.

These findings can be explained with a model of transaction costs. For the average farmer, facilitating information and access to a technology is most helpful, and additional financial subsidies help but are not as meaningful as reducing non-financial transaction costs. For farmers who already use a substitute technology, however, non-financial transaction costs are not a binding constraint and the additional subsidy encourages adoption of the new technology. These results carry implications for both public and private strategies aiming to promote the adoption of new improved 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.

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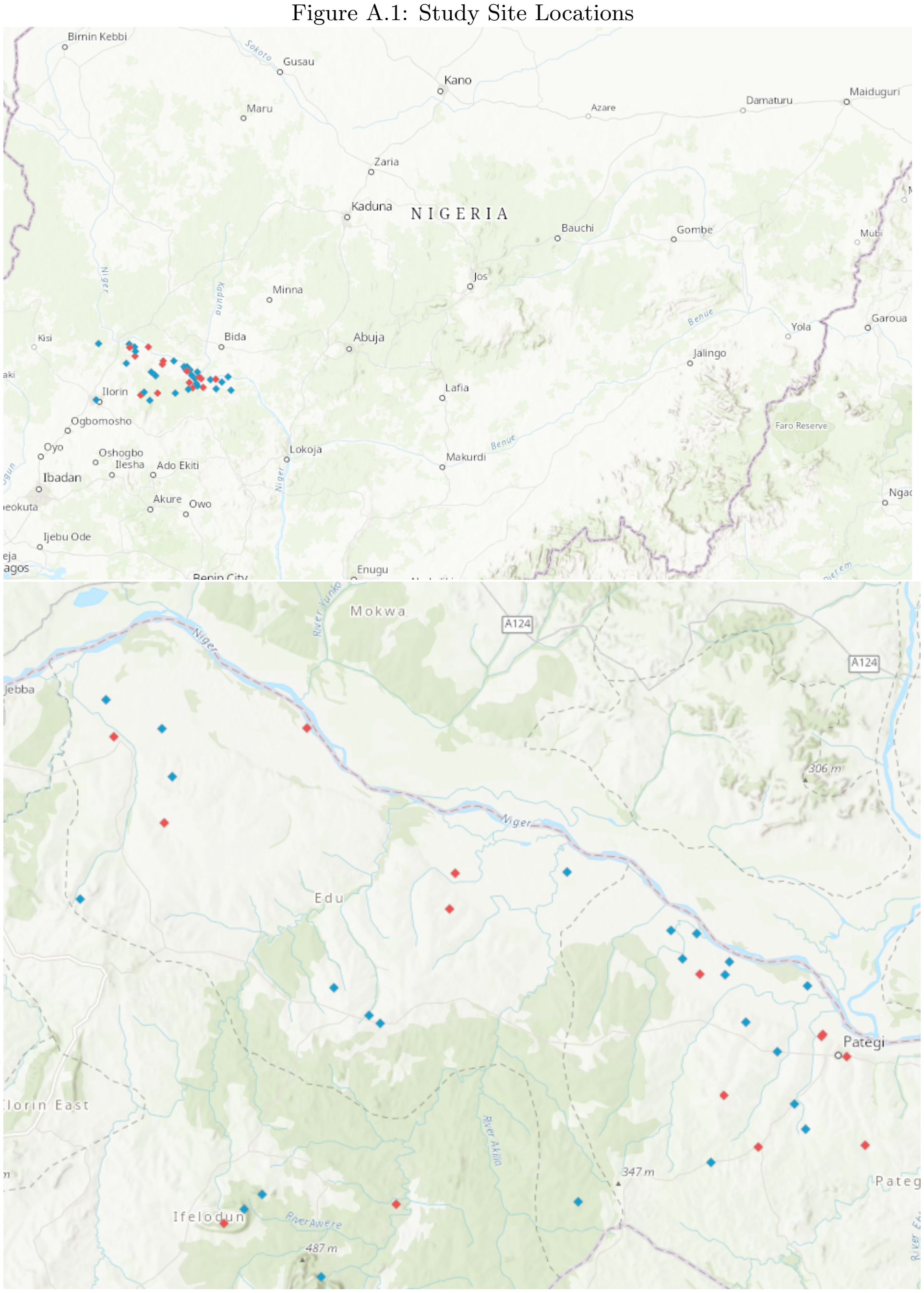
6. Appendix

Table A.1: Balance Table

Variable	(1) Pure control N/[Clusters]	Mean/SE	(2) Treatment - No subsidy N/[Clusters]	Mean/SE	(3) Treatment + Voucher subsidy N/[Clusters]	Mean/SE	T-test Difference (1)-(2)	(1)-(3)	(2)-(3)
Dependency ratio	204	1.172	265	1.154	288	1.127	0.018	0.045	0.027
	[15]	(0.070)	[29]	(0.062)	[30]	(0.058)			
Number of adults	204	3.775	265	3.536	288	3.733	0.239	0.042	-0.197
	[15]	(0.150)	[29]	(0.128)	[30]	(0.086)			
Number of elderly	204	0.191	265	0.189	288	0.156	0.002	0.035	0.032
	[15]	(0.038)	[29]	(0.027)	[30]	(0.037)			
Number of children	204	3.642	265	3.592	288	3.580	0.050	0.062	0.013
	[15]	(0.192)	[29]	(0.196)	[30]	(0.201)			
Household size	204	7.608	265	7.321	288	7.469	0.287	0.139	-0.148
	[15]	(0.250)	[29]	(0.222)	[30]	(0.221)			
Male (0/1)	204	1.000	265	1.000	288	0.997	N/A	0.003	0.003
	[15]	(0.000)	[29]	(0.000)	[30]	(0.003)			
Household head has formal education (0/1)	204	0.598	265	0.555	288	0.580	0.043	0.018	-0.025
	[15]	(0.041)	[29]	(0.041)	[30]	(0.046)			
Uses improved seed (0/1)	204	0.343	265	0.423	288	0.420	-0.080	-0.077	0.003
	[15]	(0.078)	[29]	(0.040)	[30]	(0.047)			
Total land owned (in acres)	204	12.341	265	14.866	288	12.832	-2.525*	-0.491	2.033*
	[15]	(0.921)	[29]	(1.154)	[30]	(0.397)			
Rice yield (KG per acre)	204	519.134	265	528.757	288	549.257	-9.623	-30.122	-20.499
	[15]	(58.302)	[29]	(37.593)	[30]	(34.167)			
Uses urea fertilizer (0/1)	204	0.510	265	0.460	288	0.531	0.049	-0.021	-0.071
	[15]	(0.090)	[29]	(0.050)	[30]	(0.038)			
Uses NPK fertilizer (0/1)	204	0.696	265	0.709	288	0.708	-0.013	-0.012	0.001
	[15]	(0.095)	[29]	(0.043)	[30]	(0.046)			
Uses organic fertilizer (0/1)	204	0.015	265	0.015	288	0.024	-0.000	-0.010	-0.009
	[15]	(0.012)	[29]	(0.008)	[30]	(0.007)			
Uses herbicide (0/1)	204	0.907	265	0.928	288	0.941	-0.021	-0.034	-0.013
	[15]	(0.032)	[29]	(0.018)	[30]	(0.015)			
Uses insecticide chemicals (0/1)	204	0.206	265	0.204	288	0.236	0.002	-0.030	-0.032
	[15]	(0.076)	[29]	(0.025)	[30]	(0.030)			
Uses weed chemicals (0/1)	204	0.804	265	0.804	288	0.840	0.000	-0.036	-0.037
	[15]	(0.049)	[29]	(0.034)	[30]	(0.022)			

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.1: Study Site Locations



Notes: .