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One Size Fits All?
Experimental Evidence on the Digital Delivery of Personalized Extension Advice in Nigeria*

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Abstract

Blanket advice on optimal fertilizer application rates has failed to achieve potential yield gains for crop production in much of Sub-Saharan Africa. However, digital technology now makes it possible to deliver personalized extension services to farmers at a much lower cost. In this paper, we present results from a randomized control trial designed to evaluate the effectiveness of a mobile app that provides personalized advice on rice nutrient management. The experiment induced variation in both access to the app and access to an input grant for fertilizer. We find that households with access to the app have 15 percent higher yields and 20 percent higher profits. We show that, on average, personalized advice increases yields without increasing the overall quantity of fertilizer used. Rather, some households increase their use of fertilizer while other households decrease their use of the input. We conclude that the scaling of personalized extension services could improve productivity and livelihoods in Sub-Saharan Africa without necessarily increasing the total amount of fertilizer in use.

JEL codes: C93, D24, O33, Q16
Keywords: mobile technology, information interventions, extension services, nutrient management, rice, Nigeria

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Throughout Sub-Saharan Africa, efforts by governments and development organizations to spur agricultural intensification have been meet with continued low levels of adoption of improved inputs. The economics literature has proposed numerous potential solutions to the persistent puzzle of limited adoption of apparently profitable technologies. Examples include access to credit constraints (Karlan et al., 2014), insecure property rights (Burchardi et al., 2019), limited access to insurance (Casaburi and Willis, 2018), missing input markets (Byerlee and Deininger, 2013), missing output markets (Michler et al., 2019), and learning externalities (Conley and Udry, 2010). Even in regions where adoption has occurred, households frequently fail to realize the potential yield gains and subsequently dis-adopt the technology.

One explanation for the empirical puzzle is that returns to improved inputs are highly heterogeneous. Suri (2011) ascribes the source of this heterogeneity to unobserved differences in farmer ability with the new technology, though Foster and Rosenzweig (2010) enumerate additional possibilities, including heterogeneity in soil quality. Historically, it was prohibitively expensive to account for heterogeneity in soil quality when producing recommendations on optimal input levels. This made blanket recommendations necessary, even if failure to formulate advice that was soil, crop, and climate specific resulted in inefficiencies, reducing yield and profit. In the past few years, however, mobile technology in the form of decision support tools (DSTs) have greatly reduced the cost of delivering personalized extension services (MacCarthy et al., 2017, Tjernström et al., 2019). Use of DSTs presumably reduces inefficiencies coming from overly general recommendations, thereby raising the productivity and profitability from adopting improved inputs, though there is little rigorous evidence to demonstrate this conjecture.

In this paper, we assess the impact of personalized extension services delivered using a specific DST: RiceAdvice. RiceAdvice is an Android-based app that was developed by AfricaRice to provide personalized recommendations on nutrient management (type, quantity, and timing of fertilizer) in rice production. The app utilizes information and communication technologies that enable extension agents to provide farming households with specific crop, field, and seasonal advice regarding fertilizer application and agro-management practices (Saito et al., 2015a).

To measure how households respond to personalized advice from the app compared to blanket advice from extension officers, we conduct a clustered randomized control trial (RCT) in Nigeria. We establish two simple treatment arms: rice production with personalized advice on nutrient management (T1) and rice production with personalized advice plus a grant to fully cover the cost of the recommended level of fertilizer (T2). T2 aims to assess the importance of liquidity constraints on adoption of improved inputs. In addition, a control group (C) received blanket advice provided by the official extension agency. We calculate impacts using OLS, along with Analysis of Covariance (ANCOVA) estimation, and ANCOVA with kernel weighted matching. Regardless of the estimation strategy, we find that households who were given personalized advice increase their yield by around 15 percent and increase their net income by around

20 percent. Interestingly, we find that RiceAdvice tends to have no effect on the average amount of fertilizer used by those in the treatment. Rather, in response to the recommendations provided by the app some households increase their use of fertilizer while other households decrease their use of the input. This suggests that scaling personalized extension services via DSTs could improve productivity and livelihoods in Sub-Saharan Africa without necessarily increasing the overall amount of chemical fertilizer used and the corresponding negative effects on the environment.

Our study contributes to the extensive literature on technology adoption in several ways. First, we provide evidence that failure to account for heterogeneity in soil quality may be a limiting factor in the adoption of improved technology, at least among rice farmers in Nigeria. Numerous studies have documented a variety of reasons for why households in developing countries fail to adopt apparently profitable technologies (Foster and Rosenzweig, 2010; Jack, 2011, Magruder, 2018). Some of these reasons, such a missing input or output markets (Byerlee and Deininger, 2013; Michler et al., 2019), have long been commented on in the literature. More recently, Suri (2011) has suggested that unobserved heterogeneity may make the returns to any individual farmer unprofitable, even if average returns to the technology are positive. While Suri (2011) focuses on heterogeneity in farmer ability, we focus on heterogeneity in soil quality. We find that providing personalized advice on optimal input use that accounts for differences in soil quality results in higher yields and greater net income, when compared to blanket extension advice. This suggests that how farmers are taught to use the technology plays an important role in whether that technology is profitable or not.

Second, we present new evidence regarding the effectiveness of information interventions. In general, information-only interventions have yielded null results. Bettinger et al. (2012) study the impact of providing aid eligibility information to low-income households, but find no effect. Ashraf et al. (2013) find that providing information about water purification fails to increase demand for pure water. Bryan et al. (2014) find no effect of information about migrant opportunities on the decision to migrate. One reason why studies of information-only interventions frequently find null results may be due to the overly broad nature of much of the information tested in these interventions. In the information-only arm of the RCT, we find positive and significant effects of personalized extension services on yield, net income, and technical efficiency. A study similar to ours, Tjernström et al. (2019), tests a mobile game designed to provide personalized information on input use for maize farmers in Kenya and finds similarly positive results.

Third, we present some of the first experimental evidence regarding the use of DSTs and other mobile technologies to address barriers to adoption. Innovations in information and communication technology have greatly reduced the cost of delivering information that is targeted to individual users. While personalization is increasingly used to provide advertising content to internet users, the innovations are rapidly being applied to a host of new purposes, including education (Walz and Detering, 2015). Recent studies have examined the use of DSTs in adapting to climate change (Watkiss et al., 2015), operationalizing ecosystem services (Grêt-Regamey et al., 2017), and improving agricultural production (Rose et al., 2016). However, most studies of DSTs are based on either observational data or on data collected from highly controlled laboratory-type settings. To our knowledge, this study, along with Tjernström et al. (2019), are the first RCTs to assess the economic impact of DSTs on agricultural production.

1. Rice in Nigeria and the RiceAdvice App

Rice now represents the staple food for more than 750 million people in Sub-Saharan Africa (USDA, 2018). Nigeria, a country with 170 million people, has a population growth rate of 2.5 percent per annum, while rice consumption has risen at approximately six percent per annum. This makes Nigeria the top consumer of rice in Sub-Saharan Africa.

Rice production in Nigeria is concentrated in seven states in the northwest of the country (Kano, Kaduna, Jigawa, Sokoto, Zamfara, Kebbi, and Niger) where 72 percent of rice is produced. Although rice production is increasing, local production represents only 55 percent of consumption (Saito et al., 2015b). As a result, Nigeria imported nearly 2.6 million tons of milled rice at a cost over one billion U.S. dollars in 2017 (USDA, 2018). The gap between production and consumption is partly due to yields that are well below their potential. Average yield is around two tons per hectare, while the potential yield for water-unlimited lowland rice is up to 12 tons per hectare (van Oort et al., 2017). With rice yield gaps that range from 10 to 70 percent in Sub-Saharan Africa, Nigeria is among the countries with the largest difference between potential and actual yields (Saito et al., 2015b).

To reduce its reliance on imported rice, the government of Nigeria has embarked on a program to increase production and productivity through intensifying rice cultivation. Among other actions, the government recently launched the Growth Enhancement Support Program, a major policy shift that transfers the supply system for farm inputs from the state to the private sector. However, the policy aims at increasing adoption of fertilizer by addressing only missing input or output markets. The effectiveness of such a policy may be limited unless it also seeks to address on-farm inefficiency in fertilizer use due to heterogeneity in soil quality. To help address this gap, AfricaRice, in conjunction with national partners, developed the RiceAdvice mobile app.

The RiceAdvice app is an Android-based DST that extension agents can use to provide farming households with pre-season, field-specific management guidelines for rice production. The extension advice includes a nutrient management plan, a suggested crop calendar, and information regarding best practices for rice cultivation. To generate this advice, users provide information on the geographic location of the plot, descriptive soil quality measures, local rice-growing conditions, seed variety, typical management practices, expected sowing date, availability of fertilizers, market prices for inputs, and expected production costs (Saito et al., 2015a). Figure 1.A provides examples of the data input screens for the app. As output, RiceAdvice gives farm-specific information on the chemical fertilizers required, a fertilizer application plan, fertilizer cost, and recommendations regarding cultivation practices, such as levelling, timely and uniform sowing, weeding, and anticipated harvest date. Figure 1.B provides examples of the personalized output from the app. RiceAdvice also offers the opportunity to provide post-harvest feedback on the advice received, allowing the app to assess the effectiveness of the recommendations and improve the calibration of the advice.

Figure 1.A: Screenshot of RiceAdvice data inputs

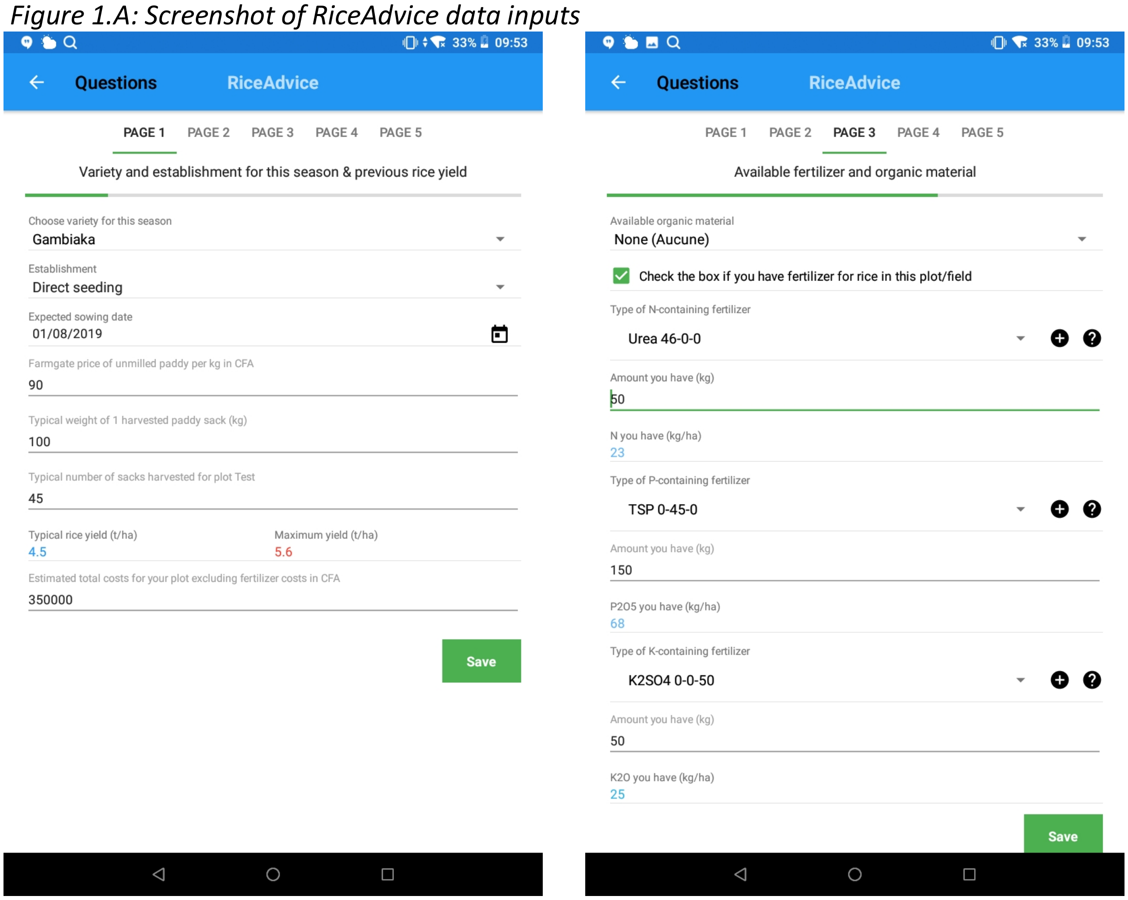
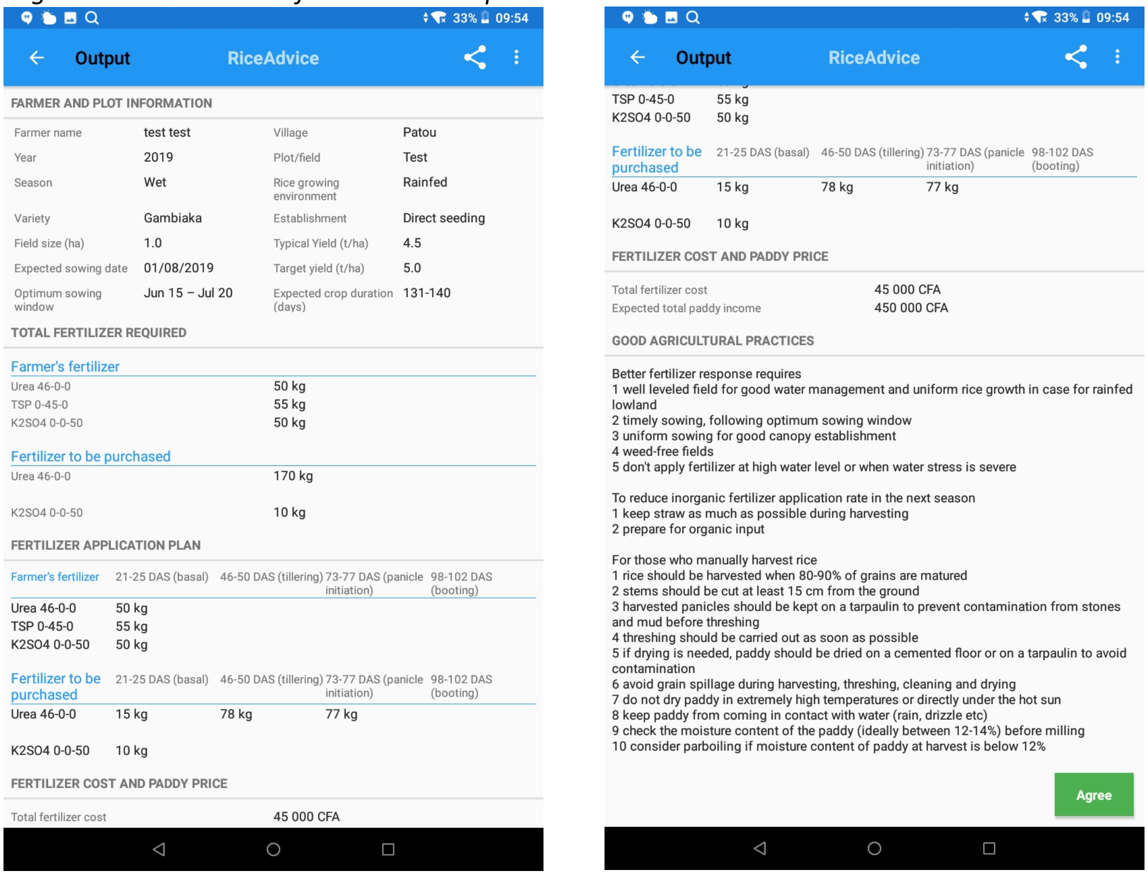


Figure 1.B: Screenshot of RiceAdvice outputs



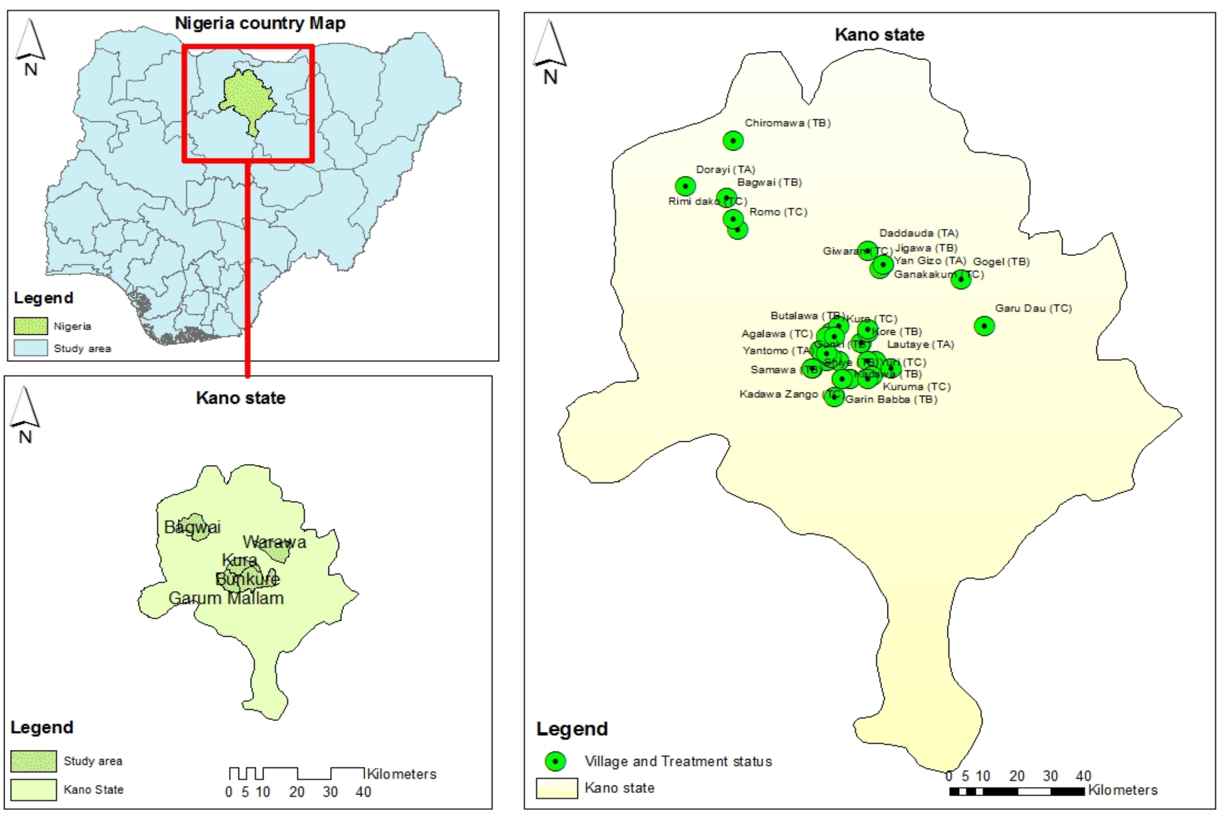
2. Experimental design, sampling, and data

To assess the impact of personalized advice provided by the DST on household decision making, we conducted a clustered RCT in the main rice producing state of Kano. In treatment one (T1), all households were offered personalized advice delivered by an extension agent using the RiceAdvice app. To remove the liquidity constraint that is commonly assumed to bind with smallholder farmers in developing countries, we established a second treatment arm (T2). The households in T2 were offered personalized advice as in treatment T1 but also received a 100 percent subsidy (grant) for the quantity of fertilizer recommended by the RiceAdvice app. The control group (C) received blanket advice provided by an extension agent. The blanket advice, which comes from the Federal Ministry of Agriculture and Rural Development, varies solely by crop and whether soil is classified by low, medium, or high fertility (Chude et al., 2012). Table A.1 in the appendix reproduces the government's recommendations for fertilizing rice.

2.1. Sampling, compliance, and attrition

To select the study area and farming households in the sample, we used a multi-level stratified sampling approach. First, we selected Kano state because it is the major rice producing region in Nigeria. In Kano, we identified the rice production Local Government Areas (LGAs), and randomly selected five from the eight major irrigated rice production LGAs (see Figure 2). Second, within each LGA, we randomly selected rice producing villages as the primary sampling units. The number of villages per LGA was proportional to the total number of rice-growing villages in the LGA. In total, 35 villages were selected and were randomly divided into two groups: 18 treated villages and 17 control (see Figure 3). In addition, the treated villages were divided into two treatment arms: treatment villages that received personalized information from RiceAdvice (T1) and villages that received personalized information from RiceAdvice plus a grant to purchase the recommended amount of fertilizer (T2). As secondary sampling units, 20 households in each village were selected from a census of all rice farming households. In total, 700 households were sampled in 35 villages, including 360 treated households and 340 control households. The treated households were divided into two groups: 260 treated households for T1 and 100 treated households for T2.

Figure 2: Map of study area

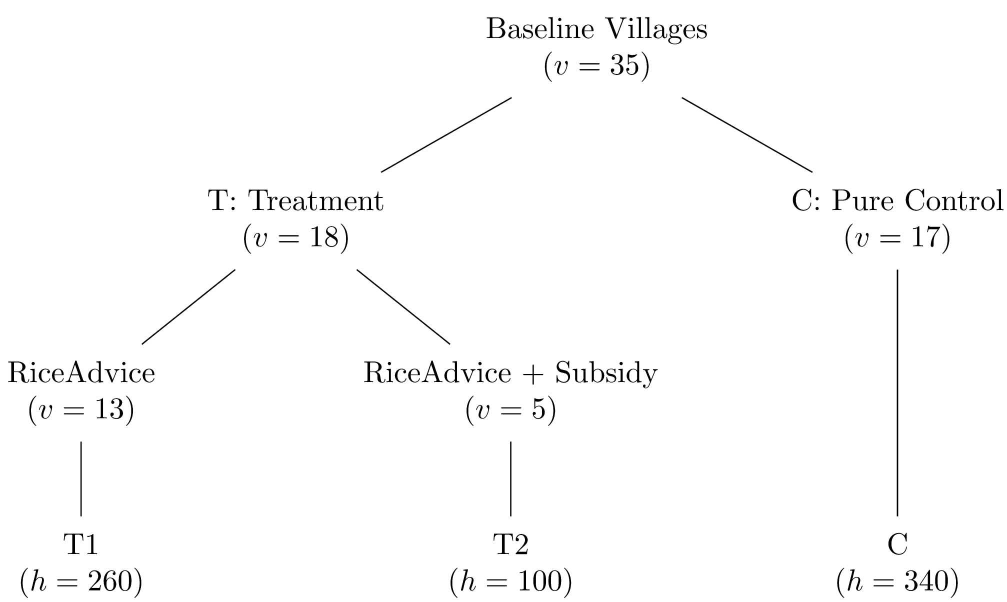


The sample size of each group was determined by our own power calculations and the administrative budget available to provide the fertilizer subsidy for household in T2.[1] To increase the power

[1] To calculate the sample size, we used rice production data from 200 households who participated in an on-farm trial in the survey area. With a minimum detectable effect size of 0.5t/ha (the yield control was estimated to be 4t/ha and

of the sampling, we selected treatment and control villages in each LGA using a matched pair randomization approach (Imai et al., 2009). However, implementation of our design was imperfect in that one control village was treated by an extension agent, which shifted the sample size to 380 and 320 for the treated and control groups, respectively. This represents a contamination rate of 2.8 percent but analysis shows that this has no effect on the impact of RiceAdvice on our outcomes.[2] The rate of non-compliance was also low. Only 12 households out of 700 did not use the personalized advice, which represents a rate of 1.7 percent. This non-compliance rate is much lower than those experienced in other information interventions. For instance, Fafchamps and Minten (2012) report a non-compliance rate of 27 percent in their SMS-based information intervention. The main reason given for non-compliance in our sample was uncertainty about the riskiness of applying fertilizer at a rate different from a household's historic application rate.

Figure 3: Experiment design



We use three rounds of a household-level panel survey data in our analysis. First, a baseline survey was conducted in early 2016 in order to collect information on farm production before the treatment. We then conducted our intervention ahead of the rice growing season. A second survey was conducted immediately after the 2016 rice harvest was completed. Finally, we conducted a follow-up survey one year later, at the end of the 2017 rice season in order to analyze the behavior of rice farmers during the second

4.5t/ha for the treatment groups), a standard deviation of 1.64 t/ha and a power of 0.8, we required sample sizes of 340 (C) and 340 (T1+T2) to detect effects at standard levels of confidence.

[2] The impact on outcomes did not change when the contaminated households are dropped from the analysis. The results are not shown here but can be obtained from the authors.

year following the intervention. While we were able to follow-up with all households in every year, not every household chose to produce rice in every year. Thus, while there was no attrition between the baseline and the two follow-up surveys, sample size does vary slightly from year-to-year. Table A.2 in the Appendix reports these differences in sample size.

2.2. Measurement

In order to reduce both noise and bias in the measurement of our outcome variables, we relied as much as possible on objective instead of self-reported information. To determine yields, rice plots were traced using hand-held GPS devices. At harvest, we implemented one-meter squared crop cutting and took crop cuts from two locations in each plot. The quantity of fertilizer input was measured on a scale for those receiving the fertilizer grant but was self-reported for treatment 1 and control households. Rice income is calculated by multiplying the yield (in tons per hectare) by the unit price of paddy rice (in US$ per ton). Net income is simply the difference between rice income and the sum of all rice production costs, except labor and equipment, for which unit prices are notoriously difficult to calculate. Technical efficiency is estimated using a Cobb-Douglas frontier production function (see Table A.3 in the Appendix).

Socio-economic data was collected through interviews using CAPI software. Measurement of age and household size are straightforward. Education is recorded as a dummy variable equal to one if the farmer had received formal education for at least six years (completed primary school). The household's

Table 1: Baseline characteristics and balance between the treated and control groups

	Control group ($h = 320$) (1)	Difference with Treated ($h = 380$) (2)	Difference with T1 ($h = 280$) (3)	Difference with T2 ($h = 100$) (4)
Household characteristics				
Age of rice farmer (year)	37.36 (11.17)	-1.375	-2.081**	0.604
Household size (n)	11.71 (7.720)	-0.196	-0.346	0.224
Formal education (=1)	0.256 (0.437)	-0.006	0.008	-0.046
Farming is main activity (=1)	0.875 (0.331)	0.004	-0.004	0.025
Number of agricultural training days (n)	0.622 (2.449)	0.323	0.135	0.848**
Access to credit (=1)	0.138 (0.345)	0.026	0.030	0.012
Production values				
Quantity of NPK (kg/ha)	181.6 (87.40)	1.524	0.829	3.470
Quantity of urea (kg/ha)	159.7 (86.56)	18.06**	17.26**	20.32*
Rice area (ha)	0.773 (0.509)	0.186**	0.163**	0.250***
Rice yield (t/ha)	3.420 (1.777)	-0.043	0.030	-0.248
Rice income (US$/ha)	1,644 (854.4)	-20.69	14.48	-119.2
Profit (US$/ha)	1,330 (807.8)	-22.38	10.98	-115.8
Technical efficiency	0.671 (0.177)	0.000	0.010	-0.026

Note: Coefficients in columns (2) - (4) are calculated by implementing an OLS that controls for LGA with a sampling weight and clustering at the village level. (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

main activity is measured by a dummy variable equal to one if crop production is the main occupation of the household head. In cases where farming is not the main activity, the household head is typically engaged in trade or transportation, with other household members responsible for the farm. The number of agricultural training days is measured as the number of days the farmer participated in agricultural training over the previous twelve-month period. Access to credit is a dummy variable equal to one if the household received credit to cover the cost of any farm production practice, not just rice, over the last twelve months.

2.3. Baseline balance checks

Table 1 presents the pre-treatment balance of the baseline randomization.[3] Column (1) reports the mean value of each variable for the control group and its standard deviation, while columns (2) - (4) report the coefficients from OLS regressions comparing treated households with the control. We regress the variable of interest (row) on an indicator of treatment status (column) along with LGA fixed-effects and standard errors clustered at the village level. Column (2) shows the pre-treatment difference in the means between the treated (T, i.e., T1+T2) and control (C) groups. Column (3) shows the difference between the T1 treatment (those who received personalized extension advice) and the control. The pre-treatment difference between the T2 treatment (those who received personalized extensions advice and fertilizer) and the control is in column (4).

The coefficients suggest a good balance for most household characteristics. The two exceptions are age of household head, where those in the control are older by two years compared to those in treatment T1, and the number of days spent receiving agricultural training, where those in treatment T2 had one more day of training than those in the control. Among the variables related to farm production, there is balance on all the outcome variables but significant differences exist between the treatment and control for the quantity of urea fertilizer used and the area under rice cultivation. At baseline, households in each of the treatment groups used more urea fertilizer compared to those in the control group. On average, the difference is estimated to be 18 kg/ha, or about 10 percent more than the control. There is also a difference in the rice area, where treatment households cultivated 0.19 more hectares, or about 24 percent more area, than the control. We account for these differences in baseline characteristics in several of our econometric specifications.

[3] We also check for balance based on the original, pre-contaminated, random assignment (see Table A.4 in the Appendix). As is to be expected if the contamination occurred by chance, the balance between treatment and control in the two samples (pre- and post-contamination) is virtually identical.

3. Causal pathway and outcomes

Before outlining our empirical strategy, it is useful to formulate the assumptions underlying the causal pathway from the provision of personalized extension advice via DST to measured outcomes. First, we assume that households are aware that nutrient management (type of fertilizer, quantity of fertilizer, and application timing) has a direct effect on rice yield and profitability. Second, we assume that households believe that personalized advice from DSTs such as RiceAdvice will recommend levels of input use that differ from their current level of input use. Third, we assume that treated households believe that the use of personalized advice will increase the productivity of rice compared to blanket advice. Finally, we assume that the treated and non-treated households sell rice at the same price and that the value of the increase in yield will be greater than the change in the production cost related to the use of the personalized advice. These assumptions are supported by anecdotal evidence in both Saito et al. (2015a) and MacCarthy et al. (2017).

Based on these assumptions, the causal pathway is straightforward. RiceAdvice will generate personalized advice that differs from the household's current practice and thus will result in a change in the quantity, type, and timing of fertilizer. This change in nutrient management will affect land productivity, leading to changes in production. Ultimately, the changes in production will have a positive impact on income.

Given the causal pathway, our main outcomes of interest are yield, net income, and technical efficiency. However, we also report on secondary outcomes in order to elucidate the causal chain. In the results, we explicitly distinguish between the expected main outcomes and secondary outcomes (the quantity and type of fertilizer and application timing). All primary outcomes are estimated for two years (2016 and 2017) using a balanced panel.

4. Empirical strategy

We focus on the estimation of the impact of personalized advice regarding nutrient management on rice yield, net income, and technical efficiency. To estimate these impacts, we compare the outcomes of the treated households with the outcomes in the absence of the treatment. Because we have the benefit of observing each household in our sample before and after treatment, we employ three different methods to calculate the intent-to-treat (ITT) effects, which measure the effect of living in a village randomly assigned to T1 or T2, irrespective of actual treatment participation. These methods are i) a simple mean difference estimate via OLS that uses only the post-intervention data, ii) an ANCOVA estimate that uses the baseline and post-intervention data, and iii) a kernel propensity-score matching ANCOVA estimate that matches the treated and non-treated households.

4.1. Intent-to-treat (ITT) estimation

For the simple mean difference, we estimate the ITT effect (ρ^{OLS}) for household h in village v and LGA g as:

$$S_{hvg} = \alpha + \rho^{OLS}T_h + \sigma_g + \varepsilon_{hvg} \qquad (1)$$

where S_{hvg} is the observed outcome variable and T_h is a household-level indicator that equals one if the household was randomly offered the treatment (T1 or T2) and is zero otherwise (C). Additionally, σ_g is a region fixed-effect that accounts for variation across the LGAs and ε_{hvg} is an idiosyncratic error term that is orthogonal to the ITT effect because of the randomization. In order to account for the imbalance in some of the baseline characteristics, we specify a second OLS regression that adds a vector of household covariates. These covariates include age of the household head, household size, the number of days the farmer participated in agricultural training, and indicators if the household head has any formal education, if crop production is the main household occupation, and if the household had access to credit over the last twelve months.

Our second estimator is an Analysis of Covariance (ANCOVA) estimate of the treatment effect:

$$S_{hvg,t} = \alpha + \rho^{ANCOVA}T_{h,t} + \mu S_{hvg,PRE} + \delta_t + \sigma_g + \varepsilon_{hvg,t}. \qquad (2)$$

Here $S_{hvg,PRE}$ is the value of the outcome variable from the pre-treatment growing season and ρ^{ANCOVA} is the coefficient on the ANCOVA estimate of the ITT effect. The equation also includes time fixed effects (δ_t) in addition to the LGA fixed effects. The ANCOVA estimator has more power than the typical difference-in-difference estimator, especially when there are multiple rounds of post-treatment data (McKenzie, 2012), which we have in our sample. Similar to the OLS estimates, we also estimate ANCOVA with and without covariates.

Finally, since a comparison in the region of common support increases the efficiency in the ANCOVA estimator, we incorporate kernel propensity-score weights into the ITT estimates. We use the observed baseline characteristics to estimate the propensity score (the likelihood of being treated) and calculate the kernel weights following Heckman et al. (1998). After matching the treated and control households according to their propensity score, we estimate the kernel ANCOVA with and without covariates. Although randomization means that the OLS estimator provides unbiased estimates of the ITT, the ANCOVA and kernel-matched ANCOVA estimators are preferred because they take advantage of the pre-treatment data as well as our multiple follow-up rounds.

4.2. Sampling weights, clustering, and multiple hypothesis testing

Because we used a multi-level stratified sampling approach, different households have different probabilities of being sampled. As a result, assuming equal probability could lead to biased estimates of the population effects (Ksoll et al., 2016). Therefore, we use sampling weights calculated as the inverse probability of being selected in any given village for each observation. We use the weighted data in all the regression throughout the paper, though our results are robust to using the raw data.

Because the ultimate sampling units (households) are clustered within our unit of randomization (village), we cannot rule out serial correlation within a village. Although the intra-cluster correlation coefficient (ICC) is relatively low (see Table A.5 in the Appendix), ignoring the clustered design will lead to standard errors that are too small and t-values that are too large. Even when individual behaviour may generate homoscedastic regression functions within a cluster, there is heterogeneity between villages, and there will be heteroscedasticity in the overall regression (Cameron and Miller, 2015). Therefore, we use heteroscedasticity robust-standard errors clustered at the village level for all inference.

Because we are making inference on a large number of hypotheses, it is possible that significant results emerge from our analysis due to chance rather than actual treatment effects. While the problem of multiple inference is well known, there is as yet no consensus regarding the best way to correct for multiple hypothesis testing. We follow Arouna et al. (2019) and adjust the p-values in a number of different ways. We calculate sharpened q-values as in Anderson (2008) along with Bonferroni- and Holm-adjusted p-values as suggested by List et al. (2019). In the Appendix, Table A.6 through Table A.9 present the results of these corrections along with the unadjusted p-values from standard errors clustered at the village level. Our findings are generally robust to the correction for multiple hypothesis testing and we highlight were differences exist.

5. Results for primary outcomes

All our analysis is conducted in terms of ITT, that is, the treated households were offered personalized advice using the RiceAdvice app, whether or not they applied it. We first present the results of the primary outcomes (rice yield, net income, and technical efficiency) and in the next section examine whether the intervention also changed input management behaviors and practices.

For each outcome we begin by presenting ANCOVA results for the full sample. These regressions include the pretreatment outcome (2015) as an independent variable and data from both post-treatment rounds (2016 and 2017) as the dependent variable. As discussed, we calculate several ITT estimates for each outcome. For tables relying on the full set of data, columns (1) and (2) present the ANCOVA estimates while columns (3) and (4) present the kernel propensity-score matching ANCOVA estimates. The odd numbered columns are without covariates while the even numbered columns include covariates. Because they rely on the full sample of data, these are our preferred estimates. We then estimate effects for each year individually, using OLS and ANCOVA, in order to gain a better sense of how outcomes changed over time.

5.1. Treatment effect on yield

Table 2 presents the ITT effects of personalized advice from the RiceAdvice DST on rice yield. Panel 1 compares all treated (T) households with control households (C). Panel 2 compares households that only received advice (T1) with control households. Panel 3 compares households that received both advice and fertilizer (T2) with control households. Finally, panel 4 compares T2 households with T1 households.

We find consistent evidence that personalized advice increases rice yield subsequent to the treatment. For the unmatched sample, yields increase by about 450 kg/ha, which represents an increase of 12 percent compared to the control. When we use the matched sample, the magnitude of the impact increases slightly. Treatment households increase yields by 549 kg/ha compared to their matched control

Table 2: Treatment effects on rice yield

	(1)	(2)	(3)	(4)
Treatment effect (T-C)	0.458***	0.450***	0.549***	0.549***
	(0.127)	(0.119)	(0.116)	(0.110)
Mean dependent variable in control	3.672			
Household covariates	No	Yes	No	Yes
Observation	1,353	1,353	1,353	1,353
R-squared	0.204	0.210	0.176	0.182
Treatment effect (T1-C)	0.331**	0.341***	0.373***	0.367***
	(0.121)	(0.115)	(0.109)	(0.111)
Mean dependent variable in control	3.672			
Household covariates	No	Yes	No	Yes
Observation	1,154	1,154	1,154	1,154
R-squared	0.226	0.235	0.199	0.206
Treatment effect (T2-C)	0.857***	0.830***	0.882***	0.871***
	(0.100)	(0.109)	(0.110)	(0.093)
Mean dependent variable in control	3.672			
Household covariates	No	Yes	No	Yes
Observation	799	799	799	799
R-squared	0.212	0.215	0.140	0.148
Treatment effect (T2-T1)	0.467***	0.457***	0.354***	0.385***
	(0.111)	(0.097)	(0.070)	(0.094)
Mean dependent variable in T1	4.310			
Household covariates	No	Yes	No	Yes
Observation	753	753	753	753
R-squared	0.218	0.225	0.200	0.210

Note: Coefficient estimates are only reported for the treatment effect. All regressions include year and LGA fixed effects. Odd numbered columns are from regressions without covariates while even numbered columns include covariates. Household covariates include household size, age of household head, number of days in agricultural training, and indicators for if the household head has formal education, if farming is the household's main activity, and if they have access to credit. Columns (1) and (2) present ANCOVA estimates while columns (3) and (4) present the kernel matching ANCOVA estimates. Robust standard errors, clustered at the village level, are shown in parentheses. (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

Table 3: Treatment effects on rice yield in 2016

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment effect (T-C)	0.385***	0.369***	0.408***	0.391***	0.406***	0.379***
	(0.122)	(0.123)	(0.133)	(0.133)	(0.120)	(0.121)
Mean dependent variable in control	3.734					
Household covariates	No	Yes	No	Yes	No	Yes
Observation	694	694	686	686	686	686
R-squared	0.216	0.222	0.224	0.229	0.214	0.220
Treatment effect (T1-C)	0.303**	0.296**	0.316**	0.312**	0.345**	0.303**
	(0.120)	(0.120)	(0.127)	(0.129)	(0.131)	(0.128)
Mean dependent variable in control	3.734					
Household covariates	No	Yes	No	Yes	No	Yes
Observation	594	594	586	586	586	586
R-squared	0.259	0.268	0.257	0.267	0.250	0.260
Treatment effect (T2-C)	0.647***	0.616***	0.674***	0.641***	0.591***	0.531**
	(0.141)	(0.159)	(0.162)	(0.178)	(0.180)	(0.190)
Mean dependent variable in control	3.734					
Household covariates	No	Yes	No	Yes	No	Yes
Observation	414	414	406	406	406	406
R-squared	0.219	0.231	0.244	0.254	0.223	0.231
Treatment effect (T2-T1)	0.365***	0.380***	0.345***	0.358***	0.374***	0.401***
	(0.078)	(0.081)	(0.067)	(0.070)	(0.066)	(0.089)
Mean dependent variable in treated T1	4.193					
Household covariates	No	Yes	No	Yes	No	Yes
Observation	380	380	380	380	380	380
R-squared	0.206	0.220	0.220	0.232	0.216	0.235

Note: Coefficient estimates are only reported for the treatment effect. All regressions include year and LGA fixed effects. Odd numbered columns are from regressions without covariates while even numbered columns include covariates. Household covariates include household size, age of household head, number of days in agricultural training, and indicators for if the household head has formal education, if farming is the household's main activity, and if they have access to credit. Columns (1) and (2) present OLS estimates, columns (3) and (4) present ANCOVA estimates, while columns (5) and (6) present kernel matching ANCOVA estimates. Robust standard errors, clustered at the village level, are shown in parentheses. ($***\, p < 0.01$, $**\, p < 0.05$, $*\, p < 0.1$).

households, an increase of 15 percent. The similarity between estimates with and without controls suggests that the small differences in baseline characteristics are uncorrelated with treatment.

Focusing on the impact of the information-only intervention, we find that households in T1 increase yields by about 350 kg/ha, which is equivalent to a 10 percent gain. When households were given a grant of the recommended amount of fertilizer, yields increase by about 850 kg/ha, which represents a 24 percent gain over yields for control households. Not only is the effect size of T2 larger than T1, when we compare outcomes between these two treatment arms, we find that this difference is statistically significant. While there are some differences between estimates on the matched and unmatched samples, these tend to be small in magnitude. The largest difference, between columns (1) and (3) when comparing T2 to T1, is a difference of only three percentage points (an 11 percent increase instead of an eight percent increase).

While we give preference to the ANCOVA results using all three years of data, it is useful to understand how outcomes change over time. To do this, we present results that rely only on outcomes in 2016, the harvest immediately following the intervention. Table 3 presents results from simple OLS estimates of the mean difference between post-intervention treatment and control in columns (1) and (2).

Table 4: Treatment effects on rice yield in 2017

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment effect (T-C)	0.520***	0.515***	0.507***	0.506***	0.695***	0.730***
	(0.175)	(0.161)	(0.177)	(0.165)	(0.170)	(0.182)
Mean dependent variable in control	3.608					
Household covariates	No	Yes	No	Yes	No	Yes
Observation	674	674	667	667	667	667
R-squared	0.309	0.329	0.309	0.328	0.288	0.302
Treatment effect (T1-C)	0.350**	0.371**	0.343*	0.366**	0.556***	0.591***
	(0.171)	(0.163)	(0.172)	(0.167)	(0.175)	(0.184)
Mean dependent variable in control	3.608					
Household covariates	No	Yes	No	Yes	No	Yes
Observation	575	575	568	568	568	568
R-squared	0.342	0.363	0.343	0.363	0.316	0.328
Treatment effect (T2-C)	1.048***	1.017***	1.027***	1.002***	0.978***	0.956***
	(0.076)	(0.085)	(0.081)	(0.090)	(0.109)	(0.126)
Mean dependent variable in control	3.608					
Household covariates	No	Yes	No	Yes	No	Yes
Observation	400	400	393	393	393	393
R-squared	0.335	0.340	0.338	0.341	0.266	0.280
Treatment effect (T2-T1)	0.585**	0.549***	0.588**	0.552***	0.442***	0.424***
	(0.218)	(0.190)	(0.218)	(0.191)	(0.142)	(0.143)
Mean dependent variable in treated T1	4.431					
Household covariates	No	Yes	No	Yes	No	Yes
Observation	373	373	373	373	373	373
R-squared	0.322	0.343	0.322	0.343	0.274	0.304

Note: Coefficient estimates are only reported for the treatment effect. All regressions include year and LGA fixed effects. Odd numbered columns are from regressions without covariates while even numbered columns include covariates. Household covariates include household size, age of household head, number of days in agricultural training, and indicators for if the household head has formal education, if farming is the household's main activity, and if they have access to credit. Columns (1) and (2) present OLS estimates, columns (3) and (4) present ANCOVA estimates, while columns (5) and (6) present kernel matching ANCOVA estimates. Robust standard errors, clustered at the village level, are shown in parentheses. ($^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$).

Columns (3) – (6) are ANCOVA estimates similar to those in Table 2. Across all regressions we find effect sizes in 2016 that are smaller than the estimated effect sizes using all rounds of data. While the differences in magnitudes are not substantial, only being one or two percentage points different, it is informative that the estimates are always smaller. This suggests some element of learning-by-doing, as impacts in the initial year appear to be smaller than overall impacts.

To better assess this conjecture, we estimate the ITT using yield data from one year after the intervention (2017). Given that soil characteristics change very slowly over time, the advice provided as part of the study should still be valid a year later. Thus, if there are no learning effects, we would expect impacts to be of a similar size regardless of whether we use the 2016 or 2017 yield data. Instead, Table 4 shows that treatment effects not only remain positive but increase in magnitude. This is despite yields in the control group declining slightly between 2016 and 2017. Comparing T, T1, and T2 to the control group, percentage increases were roughly double in 2017 what they had been in 2016. Focusing just on column (6), in 2016 households in the treatment increase their yields by 10 percent compared to the control while in 2017 yields are 20 percent larger than the control. Similarly, in the information-only treatment arm, yields in 2016 are eight percent higher than the control while yields in 2017 are 16 percent higher than the control. For households that received the RiceAdvice plus fertilizer subsidy treatment, yields in 2016 are 14 percent higher than the control group while in 2017 yields are slightly less than double: 26 percent higher.

These results imply that knowledge, and not liquidity, is the binding constraint in the study area. If liquidity were the binding constraint, then the information-only treatment would have no discernable effect. This is not to say that credit markets operate perfectly in the region. If they did, then there would be no difference in outcomes between T2 and T1. Rather, our results demonstrate that while liquidity is an issue, households are still able to take advantage of extension advice if it has been adapted to their context. This result is surprising, because the agricultural development literature frequently argues for the importance of liquidity constraints and finds little evidence for the effectiveness of information-only interventions (Holden and Lunduka, 2013; Jones and Kondylis, 2018). Two important factors should be considered when comparing our results to those in the literature. First, Nigeria is among the countries in Africa with the

Table 5: Treatment effects on net income

	(1)	(2)	(3)	(4)
Treatment effect (T-C)	195.7***	199.3***	231.8***	226.9***
	(49.14)	(45.29)	(45.97)	(45.21)
Mean dependent variable in control	1,147			
Household covariates	No	Yes	No	Yes
Observation	1,353	1,353	1,353	1,353
R-squared	0.322	0.325	0.281	0.283
Treatment effect (T1-C)	150.2***	161.3***	179.5***	182.8***
	(47.74)	(44.94)	(43.59)	(45.60)
Mean dependent variable in control	1,147			
Household covariates	No	Yes	No	Yes
Observation	1,154	1,154	1,154	1,154
R-squared	0.354	0.361	0.304	0.310
Treatment effect (T2-C)	332.0***	316.8***	345.7***	345.1***
	(37.68)	(44.60)	(47.14)	(43.99)
Mean dependent variable in control	1,147			
Household covariates	No	Yes	No	Yes
Observation	799	799	799	799
R-squared	0.307	0.313	0.253	0.260
Treatment effect (T2-T1)	156.7***	160.2***	123.7***	138.3***
	(42.75)	(42.86)	(27.44)	(38.30)
Mean dependent variable in T1	1,407			
Household covariates	No	Yes	No	Yes
Observation	753	753	753	753
R-squared	0.321	0.325	0.287	0.293

Note: Coefficient estimates are only reported for the treatment effect. All regressions include year and LGA fixed effects. Odd numbered columns are from regressions without covariates while even numbered columns include covariates. Household covariates include household size, age of household head, number of days in agricultural training, and indicators for if the household head has formal education, if farming is the household's main activity, and if they have access to credit. Columns (1) and (2) present ANCOVA estimates while columns (3) and (4) present the kernel matching ANCOVA estimates. Robust standard errors, clustered at the village level, are shown in parentheses. (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

highest levels of fertilizer use and fertilizer use is relatively common in Kano (Liverpool-Tasie, 2014). Second, previous studies of information-only interventions focus on the delivery of broad or general advice. The information provided by the DST in our study is tailored to each treated household. Thus, while the absence of evidence regarding a binding credit constraint may lack external validity, the impact of digitally delivered personalized extension advice is likely to be generalizable to other settings.

5.2. Treatment effect on net income

From an economic point of view, the positive impact of personalized advice from the app on yield cannot alone justify its promotion for scaling. Accordingly, in this section we focus on the income effect of the treatment. Table 5 presents the ITT effects of RiceAdvice on net income per hectare in the full set of data (both 2016 and 2017 outcomes). Table 6 presents results from the initial year while Table 7 presents results from the follow-up year.

Table 6: Treatment effects on net income in 2016

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment effect (T-C)	212.7***	211.3***	224.5***	222.6***	218.1***	206.1***
	(57.59)	(59.48)	(62.40)	(63.76)	(57.5)	(56.28)
Mean dependent variable in control	1,397					
Household covariates	No	Yes	No	Yes	No	Yes
Observation	694	694	686	686	686	686
R-squared	0.180	0.192	0.183	0.195	0.179	0.188
Treatment effect (T1-C)	187.8***	189.1***	193.9***	198.4***	215.2***	204.8***
	(57.53)	(60.05)	(61.54)	(63.78)	(59.87)	(58.49)
Mean dependent variable in control	1,397					
Household covariates	No	Yes	No	Yes	No	Yes
Observation	594	594	586	586	586	586
R-squared	0.212	0.212	0.212	0.212	0.212	0.212
Treatment effect (T2-C)	284.8***	284.8***	284.8***	284.8***	284.8***	284.8***
	(66.38)	(66.38)	(66.38)	(66.38)	(66.38)	(66.38)
Mean dependent variable in control	1,397					
Household covariates	No	Yes	No	Yes	No	Yes
Observation	414	414	406	406	406	406
R-squared	0.180	0.196	0.207	0.219	0.190	0.201
Treatment effect (T2-T1)	103.7**	120.3**	98.31**	114.2**	87.61**	104.2**
	(47.94)	(49.67)	(44.80)	(45.80)	(37.90)	(44.63)
Mean dependent variable in treated T1	1,669					
Household covariates	No	Yes	No	Yes	No	Yes
Observation	380	380	380	380	380	380
R-squared	0.156	0.178	0.163	0.184	0.174	0.199

Note: Coefficient estimates are only reported for the treatment effect. All regressions include year and LGA fixed effects. Odd numbered columns are from regressions without covariates while even numbered columns include covariates. Household covariates include household size, age of household head, number of days in agricultural training, and indicators for if the household head has formal education, if farming is the household's main activity, and if they have access to credit. Columns (1) and (2) present OLS estimates, columns (3) and (4) present ANCOVA estimates, while columns (5) and (6) present kernel matching ANCOVA estimates. Robust standard errors, clustered at the village level, are shown in parentheses. (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

Table 7: Treatment effects on net income in 2017

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment effect (T-C)	173.2***	180.9***	167.6***	175.7***	228.4***	244.7***
	(59.46)	(52.46)	(60.52)	(54.22)	(58.29)	(63.50)
Mean dependent variable in control	887.4					
Household covariates	No	Yes	No	Yes	No	Yes
Observation	674	674	667	667	667	667
R-squared	0.262	0.282	0.261	0.281	0.230	0.241
Treatment effect (T1-C)	110.9*	127.9**	106.4*	123.3**	166.9**	188.4***
	(54.46)	(50.56)	(55.17)	(52.53)	(60.87)	(63.50)
Mean dependent variable in control	887.4					
Household covariates	No	Yes	No	Yes	No	Yes
Observation	575	575	568	568	568	568
R-squared	0.310	0.333	0.310	0.332	0.272	0.282
Treatment effect (T2-C)	368.4***	355.1***	361.5***	348.6***	329.2***	333.8***
	(26.24)	(29.35)	(28.15)	(30.48)	(35.57)	(44.12)
Mean dependent variable in control	887.4					
Household covariates	No	Yes	No	Yes	No	Yes
Observation	400	400	393	393	393	393
R-squared	0.288	0.295	0.289	0.297	0.196	0.215
Treatment effect (T2-T1)	213.4***	202.9***	214.7***	204.9***	207.9***	199.1***
	(73.38)	(67.60)	(74.44)	(69.05)	(51.65)	(55.52)
Mean dependent variable in treated T1	1,138					
Household covariates	No	Yes	No	Yes	No	Yes
Observation	373	373	373	373	373	373
R-squared	0.274	0.296	0.275	0.297	0.229	0.258

Note: Coefficient estimates are only reported for the treatment effect. All regressions include year and LGA fixed effects. Odd numbered columns are from regressions without covariates while even numbered columns include covariates. Household covariates include household size, age of household head, number of days in agricultural training, and indicators for if the household head has formal education, if farming is the household's main activity, and if they have access to credit. Columns (1) and (2) present OLS estimates, columns (3) and (4) present ANCOVA estimates, while columns (5) and (6) present kernel matching ANCOVA estimates. Robust standard errors, clustered at the village level, are shown in parentheses. ($^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$).

We find clear evidence that personalized advice on nutrient management increase net income for rice producers. As with yields, the differences between matched and unmatched samples, as well as the differences with and without covariates are minor, so we focus on the results in column (4) of Table 5, which uses the matched data and includes covariates. Households randomly given personalized advice via the RiceAdvice app increase their income by about $227, or 20 percent over control households. Again, we find that this increase is not due solely to the provisioning of fully subsidized fertilizer to households in T2. The information-only treatment increases net income by about $183, a 16 percent gain over the control. Gains were substantially larger for households that received the fertilizer grant, as they were likely able to reallocate funds to other productive activities. Households in T2 saw income rise by $345 or 30 percent compared to control households. As with the results for yields, there are significant differences between outcomes for those in T2 compared to T1. What is interesting, though, is that the fertilizer subsidy is not a necessary condition for households to make use of the recommendations from RiceAdvice.

To understand the effects of the intervention over time, we again estimate the ITT for each year separately. Net income for treated households is significantly higher than the control in each year. Unlike our comparison of yields from year-to-year, we do not find consistent evidence that net income in 2017 is higher than in 2016. While the overall effect (T-C) is larger in 2017 than in 2016, this is partly driven by a large increase in 2017 net income for households in the second treatment arm. The relative size of the income gains for T2 is also driven by a decline in net income for control and T1 households. On average, households who received the information-only treatment increased their net income by 15 percent in 2016 and 21 percent in 2017. By comparison, households who received the fertilizer grant in addition to RiceAdvice increased their net income by 20 percent in 2016 and 38 percent in 2017. Thus, while yields doubled for nearly everyone in the treated from 2016 to 2017, changes in net income were not uniform.

These findings imply that additional production costs related to the personalized advice is less than the gain in yield. While the size of the gains is subject to year-to-year variation in input and output prices, the gains are always positive. Again, our results contrast with much of the existing literature on the impact

Table 8: Treatment effects on technical efficiency

	(1)	(2)	(3)	(4)
Treatment effect (T-C)	0.044***	0.042***	0.051***	0.050***
	(0.014)	(0.013)	(0.013)	(0.012)
Mean dependent variable in control	0.701			
Household covariates	No	Yes	No	Yes
Observation	1,353	1,353	1,353	1,353
R-squared	0.222	0.228	0.196	0.202
Treatment effect (T1-C)	0.033**	0.033**	0.036***	0.036***
	(0.014)	(0.013)	(0.013)	(0.012)
Mean dependent variable in control	0.701			
Household covariates	No	Yes	No	Yes
Observation	1,154	1,154	1,154	1,154
R-squared	0.245	0.253	0.213	0.221
Treatment effect (T2-C)	0.076***	0.074***	0.079***	0.081***
	(0.010)	(0.011)	(0.012)	(0.010)
Mean dependent variable in control	0.701			
Household covariates	No	Yes	No	Yes
Observation	799	799	799	799
R-squared	0.214	0.220	0.168	0.175
Treatment effect (T2-T1)	0.036**	0.035***	0.027***	0.029***
	(0.014)	(0.012)	(0.008)	(0.010)
Mean dependent variable in T1	0.763			
Household covariates	No	Yes	No	Yes
Observation	753	753	753	753
R-squared	0.227	0.233	0.211	0.222

Note: Coefficient estimates are only reported for the treatment effect. All regressions include year and LGA fixed effects. Odd numbered columns are from regressions without covariates while even numbered columns include covariates. Household covariates include household size, age of household head, number of days in agricultural training, and indicators for if the household head has formal education, if farming is the household's main activity, and if they have access to credit. Columns (1) and (2) present ANCOVA estimates while columns (3) and (4) present the kernel matching ANCOVA estimates. Robust standard errors, clustered at the village level, are shown in parentheses. (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

of information treatments. Indicative of this literature is Duflo et al. (2008), who find that blanket fertilizer advice from an official extension agency in Kenya has no effect on farm profits. We believe that such information-only interventions are ineffective because the information provided is too general and fails to account for heterogeneity at the farm-level. By contrast, our intervention relies on a mobile DST that provides nutrient management advice adapted to the needs of the specific household.

5.3. Treatment effect on technical efficiency

We also assess the impact of personalized advice on the technical efficiency of the households. As discussed in Section 3, we hypothesize that personalized advice will change the input use not only of fertilizer but of other inputs, such as labor. To test this, we first estimate technical efficiency using a Cobb-Douglas frontier production function (see Table A.3 in the Appendix). We then use the estimated efficiency score to assess the effects of personalized advice on technical efficiency for the full sample (Table 8). Table 9 presents results from the initial year while Table 10 presents results from the follow-up year.

Table 9: Treatment effects on technical efficiency in 2016

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment effect (T-C)	0.040*** (0.014)	0.037** (0.014)	0.042*** (0.014)	0.039** (0.015)	0.039*** (0.014)	0.035** (0.014)
Mean dependent variable in control	0.739					
Household covariates	No	Yes	No	Yes	No	Yes
Observation	694	694	686	686	686	686
R-squared	0.233	0.239	0.236	0.242	0.236	0.243
Treatment effect (T1-C)	0.032** (0.014)	0.030** (0.014)	0.034** (0.014)	0.032** (0.015)	0.038** (0.015)	0.033** (0.014)
Mean dependent variable in control	0.739					
Household covariates	No	Yes	No	Yes	No	Yes
Observation	594	594	586	586	586	586
R-squared	0.267	0.276	0.265	0.274	0.267	0.278
Treatment effect (T2-C)	0.060*** (0.015)	0.057*** (0.016)	0.062*** (0.017)	0.059*** (0.017)	0.056** (0.020)	0.051** (0.020)
Mean dependent variable in control	0.739					
Household covariates	No	Yes	No	Yes	No	Yes
Observation	414	414	406	406	406	406
R-squared	0.239	0.249	0.248	0.256	0.262	0.272
Treatment effect (T2-T1)	0.029** (0.011)	0.029** (0.011)	0.027** (0.010)	0.028*** (0.009)	0.025*** (0.007)	0.027*** (0.009)
Mean dependent variable in treated T1	0.788					
Household covariates	No	Yes	No	Yes	No	Yes
Observation	380	380	380	380	380	380
R-squared	0.211	0.227	0.222	0.236	0.233	0.255

Note: Coefficient estimates are only reported for the treatment effect. All regressions include year and LGA fixed effects. Odd numbered columns are from regressions without covariates while even numbered columns include covariates. Household covariates include household size, age of household head, number of days in agricultural training, and indicators for if the household head has formal education, if farming is the household's main activity, and if they have access to credit. Columns (1) and (2) present OLS estimates, columns (3) and (4) present ANCOVA estimates, while columns (5) and (6) present kernel matching ANCOVA estimates. Robust standard errors, clustered at the village level, are shown in parentheses. ($***\,p < 0.01$, $**\,p < 0.05$, $*\,p < 0.1$).

Table 10: Treatment effects on technical efficiency in 2017

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment effect (T-C)	0.045**	0.045**	0.045**	0.045**	0.064***	0.069***
	(0.020)	(0.018)	(0.020)	(0.018)	(0.019)	(0.020)
Mean dependent variable in control	0.662					
Household covariates	No	Yes	No	Yes	No	Yes
Observation	674	674	667	667	667	667
R-squared	0.304	0.325	0.309	0.329	0.294	0.306
Treatment effect (T1-C)	0.031	0.034*	0.031	0.034*	0.049**	0.054**
	(0.021)	(0.019)	(0.020)	(0.019)	(0.021)	(0.021)
Mean dependent variable in control	0.662					
Household covariates	No	Yes	No	Yes	No	Yes
Observation	575	575	568	568	568	568
R-squared	0.334	0.357	0.340	0.362	0.320	0.332
Treatment effect (T2-C)	0.089***	0.087***	0.087***	0.086***	0.081***	0.080***
	(0.009)	(0.011)	(0.010)	(0.011)	(0.012)	(0.014)
Mean dependent variable in control	0.662					
Household covariates	No	Yes	No	Yes	No	Yes
Observation	400	400	393	393	393	393
R-squared	0.308	0.314	0.312	0.317	0.284	0.294
Treatment effect (T2-T1)	0.045*	0.043*	0.044*	0.042*	0.036**	0.035**
	(0.025)	(0.022)	(0.023)	(0.021)	(0.015)	(0.015)
Mean dependent variable in treated T1	0.739					
Household covariates	No	Yes	No	Yes	No	Yes
Observation	373	373	373	373	373	373
R-squared	0.320	0.344	0.325	0.348	0.284	0.319

Note: Coefficient estimates are only reported for the treatment effect. All regressions include year and LGA fixed effects. Odd numbered columns are from regressions without covariates while even numbered columns include covariates. Household covariates include household size, age of household head, number of days in agricultural training, and indicators for if the household head has formal education, if farming is the household's main activity, and if they have access to credit. Columns (1) and (2) present OLS estimates, columns (3) and (4) present ANCOVA estimates, while columns (5) and (6) present kernel matching ANCOVA estimates. Robust standard errors, clustered at the village level, are shown in parentheses. (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

We find that technical efficiency is significantly higher for treatment households compared to control households. On average, the technical efficiency of households in the treatment is 0.05 higher than the control group, an increase of seven percent. The effect sizes are similar when we consider the impact of the information-only intervention.[4] The treatment effect with the grant is larger, resulting in an increase of 12 percent relative to the control. Differences between the information-only and information-plus-grant treatments are significant, though the magnitude is small – a four percent difference between T2 and T1.

When examining results from the year immediately following the intervention, we find a positive and significant increase in technical efficiency across all treatment groups and all specifications. Focusing on the kernel matched ANCOVA results with covariates in column (6), treated households increase their technical efficiency by between three and seven percent over the relevant comparison group. As with yields, there is a consistent increase in technical efficiency over time. In 2016 households in the treatment are five

[4] The OLS estimate without covariates for the treatment effect of T1 compared to the control becomes insignificant only when we use the Bonferroni adjustment to correct for multiple hypothesis test. See Table A.7 in the Appendix.

percent more efficient compared to the control while in 2017 they are 10 percent more efficient than the control. Similarly, in the information-only treatment arm, efficiency in 2016 is four percent higher than the control while efficiency in 2017 is eight percent higher than the control. For households that received the RiceAdvice plus fertilizer subsidy treatment, efficiency in 2016 is seven percent higher than the control group while in 2017 efficiency is 12 percent higher. As with yields, households in the treatment groups roughly doubled their gains in technical efficiency over the comparison groups.

Our results provide encouraging evidence regarding household behavior and on-farm decision-making. Similar to Tjernström et al. (2019), we find that households learn and adapt when provided with extension advice customized to their circumstances and setting. Households increase yields and net income not simply by adding more fertilizer and getting more rice. Rather, they are more efficient in the overall production process. This is despite the fact that the DST app focuses on fertilizer requirements and general best practices, with no advice for the application and allocation of other inputs. A future version of the RiceAdvice app that produces personalized advice for the timing and spacing of seed, the application of

Table 11: Treatment effects on total fertilizer used

	(1)	(2)	(3)	(4)
Treatment effect (T-C)	-14.09 (10.76)	-15.32 (9.642)	-8.497 (9.843)	-8.664 (9.272)
Mean dependent variable in control	367.4			
Household covariates	No	Yes	No	Yes
Observation	1,353	1,353	1,353	1,353
R-squared	0.099	0.109	0.118	0.123
Treatment effect (T1-C)	-9.481 (11.87)	-12.27 (10.43)	-5.971 (10.38)	-7.683 (11.41)
Mean dependent variable in control	367.4			
Household covariates	No	Yes	No	Yes
Observation	1,154	1,154	1,154	1,154
R-squared	0.099	0.110	0.121	0.125
Treatment effect (T2-C)	-25.41*** (8.575)	-18.11* (9.968)	-22.25 (16.74)	-23.72 (19.48)
Mean dependent variable in control	367.4			
Household covariates	No	Yes	No	Yes
Observation	799	799	799	799
R-squared	0.151	0.171	0.159	0.166
Treatment effect (T2-T1)	-22.44* (11.03)	-23.59** (9.823)	-11.71 (10.02)	-8.866 (12.53)
Mean dependent variable in T1	359.1			
Household covariates	No	Yes	No	Yes
Observation	753	753	753	753
R-squared	0.082	0.094	0.068	0.079

Note: Coefficient estimates are only reported for the treatment effect. All regressions include year and LGA fixed effects. Odd numbered columns are from regressions without covariates while even numbered columns include covariates. Household covariates include household size, age of household head, number of days in agricultural training, and indicators for if the household head has formal education, if farming is the household's main activity, and if they have access to credit. Columns (1) and (2) present ANCOVA estimates while columns (3) and (4) present the kernel matching ANCOVA estimates. Robust standard errors, clustered at the village level, are shown in parentheses. (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

herbicides and pesticides, and the allocation of labor time, could result in larger improvements to farm efficiency.

6. Results for secondary outcomes

To investigate possible causal channels through which the adoption of personalized advice may influence yield, we test the treatment effect on two intermediate outcomes: the quantity of fertilizer and the timing of fertilizer application. We focus the analysis on the full sample, restricting our results to just the ANCOVA estimates of post-treatment outcomes.

6.1. Treatment effect on fertilizer quantity

The provision of personalized advice to farming households may increase or decrease the quantity of fertilizer depending on the initial distance of production to the efficiency frontier. Table 11 presents results from estimations of the ITT effect on the quantity of fertilizer used. Contrary to our priors, we find no

Table 12: Treatment effect on the quantity of NPK fertilizer

	(1)	(2)	(3)	(4)
Treatment effect (T-C)	-18.58*** (6.001)	-18.34*** (5.660)	-16.31** (6.596)	-13.28** (6.272)
Mean dependent variable in control	176.7			
Household covariates	No	Yes	No	Yes
Observation	1,353	1,353	1,353	1,353
R-squared	0.086	0.099	0.107	0.116
Treatment effect (T1-C)	-17.22*** (6.241)	-18.03*** (5.961)	-15.21** (5.952)	-14.79** (6.274)
Mean dependent variable in control	176.7			
Household covariates	No	Yes	No	Yes
Observation	1,154	1,154	1,154	1,154
R-squared	0.125	0.130	0.117	0.122
Treatment effect (T2-C)	-20.45*** (5.594)	-15.37** (5.880)	-21.39* (11.29)	-20.27* (10.97)
Mean dependent variable in control	176.7			
Household covariates	No	Yes	No	Yes
Observation	799	799	799	799
R-squared	0.164	0.184	0.135	0.146
Treatment effect (T2-T1)	-7.211 (5.745)	-7.558 (5.519)	-4.383 (4.604)	-2.992 (6.301)
Mean dependent variable in T1	169.0			
Household covariates	No	Yes	No	Yes
Observation	753	753	753	753
R-squared	0.127	0.133	0.134	0.139

Note: Coefficient estimates are only reported for the treatment effect. All regressions include year and LGA fixed effects. Odd numbered columns are from regressions without covariates while even numbered columns include covariates. Household covariates include household size, age of household head, number of days in agricultural training, and indicators for if the household head has formal education, if farming is the household's main activity, and if they have access to credit. Columns (1) and (2) present ANCOVA estimates while columns (3) and (4) present the kernel matching ANCOVA estimates. Robust standard errors, clustered at the village level, are shown in parentheses. (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

Table 13: Treatment effect on the quantity of urea fertilizer

	(1)	(2)	(3)	(4)
Treatment effect (T-C)	11.42**	10.17**	12.93**	10.84*
	(5.099)	(4.833)	(5.124)	(5.436)
Mean dependent variable in control	137.5			
Household covariates	No	Yes	No	Yes
Observation	1,353	1,353	1,353	1,353
R-squared	0.086	0.099	0.107	0.116
Treatment effect (T1-C)	15.05***	13.57***	15.32***	13.08*
	(5.197)	(4.779)	(5.526)	(6.759)
Mean dependent variable in control	137.5			
Household covariates	No	Yes	No	Yes
Observation	1,154	1,154	1,154	1,154
R-squared	0.087	0.103	0.110	0.120
Treatment effect (T2-C)	-0.064	1.703	1.890	0.642
	(5.361)	(5.720)	(8.311)	(10.55)
Mean dependent variable in control	137.5			
Household covariates	No	Yes	No	Yes
Observation	799	799	799	799
R-squared	0.144	0.175	0.159	0.179
Treatment effect (T2-T1)	-16.23***	-17.40***	-11.35**	-10.56*
	(4.794)	(3.472)	(5.082)	(5.893)
Mean dependent variable in T1	165.6			
Household covariates	No	Yes	No	Yes
Observation	753	753	753	753
R-squared	0.080	0.096	0.066	0.079

Note: Coefficient estimates are only reported for the treatment effect. All regressions include year and LGA fixed effects. Odd numbered columns are from regressions without covariates while even numbered columns include covariates. Household covariates include household size, age of household head, number of days in agricultural training, and indicators for if the household head has formal education, if farming is the household's main activity, and if they have access to credit. Columns (1) and (2) present ANCOVA estimates while columns (3) and (4) present the kernel matching ANCOVA estimates. Robust standard errors, clustered at the village level, are shown in parentheses. (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

evidence that personalized advice on nutrient management has any effect on the quantity of fertilizer. Only the unmatched ANCOVA estimates of the difference between T2 and C and T2 and T1 are significant. These marginally significant results become statistically insignificant once we account for multiple hypotheses testing (See Table A.8 and Table A.9 in the Appendix). None of the matched ANCOVA estimates are significant.

There are two possible explanations for the null results. First, it may be that some households increase their fertilizer quantity while other households decrease it, which would lead to a null effect on average. To investigate this explanation, we use a quantile regression, similar to Hossain et al. (2019), in order to estimate the slope and shape of the conditional distribution. We estimate the ITT effect of personalized extension advice on fertilizer quantity for three quartiles: the lower quartile (25th percentile), the median quartile (50th percentile), and the upper quartile (75th percentile). We do not find substantial variation between quartiles in any of the treatment groups (see Table A.10 in the Appendix).

Second, rice farmers in the survey areas primarily use two types of fertilizer: NPK 15-15-15 and urea 46-0-0. The blanket extension advice provided by the Ministry of Agriculture and Rural Development breaks down fertilizer by deficiency in either nitrogen (N), phosphorous (P), and potassium (K). So, for both blanket advice and RiceAdvice, recommendations are for a specific compound fertilizer. Thus, the adoption of personalized extension advice may increase the quantity of one type of fertilizer while decreasing the quantity of the other type of fertilizer, which would result in a null effect on average. To investigate this second possible explanation, we model the treatment effect on NPK and urea quantities separately (see Table 12 and Table 13).[5]

Our results show that personalized advice does have an effect on both the type and quantity of fertilizer in use – a result masked by a focus on average effects. Households who received personalized advice tend to reduce the amount of NPK and increase the amount of urea, though the decrease in NPK (13-20 kg/ha) are larger than the increase in urea (10-13 kg/ha). We also find differences in NPK and urea use based on treatment arm. For NPK, the decrease in the amount of fertilizer used is similar for those in both the information-only and information-plus-grant treatments. When we directly compare T2 to T1, we find the differences in NPK use are not significant. For urea, the increase in quantity is completely driven by households in the information-only treatment. Households who received personalized advice plus the fertilizer subsidy apply the same amount of urea as households in the control.[6]

The NPK and ure regressions demonstrate that while the average amount of fertilizer used by the treatment group was unaffected by the treatment, households did change their amount of fertilizer, just in offsetting ways. These results support Suri's (2011) conjecture that a focus on average effects masks highly heterogeneous returns to agricultural technologies. The blanket advice offered by extension agents may be correct for the average household, but no single household is exactly average. Relying on blanket recommendations, some households end up over-using one type of fertilizer while other households under-use a different type of fertilizer. Households provided with personalized extension advice adjust their application rates up or down, as needed. The result is a null effect on average, though households in each quartile make adjustments to the quantity of each type of fertilizer they use.

6.2. Treatment effect on the application timing of fertilizer

In addition to the size of the fertilizer dose, application timing is vital to productive crop growth. In general, it is recommended to apply fertilizer four times during the rice growing season: basal (at transplanting or 16-20 days after sowing for direct seeding), tilling (36-40 days after sowing), panicle initiation (53-57 days

[5] As with total fertilizer, we also estimate quantiles for each type of fertilizer (NPK and urea). We fail to find any substantial evidence of heterogeneity across the quantiles. See Table A.11 and Table A.12 in the Appendix.

[6] Estimates of treatment effects on NPK and urea use are generally robust to our adjustment for multiple hypothesis testing. The exception is when the Bonferroni adjustment is used, which effects 10 estimates. But even then, 22 of 32 Bonferroni-adjusted p-values remain significant. See Table A.6 through Table A.9 in the Appendix.

Table 14: Treatment effects on the first application of NPK fertilizer

	(1)	(2)	(3)	(4)
Treatment effect (T-C)	-1.891***	-1.892***	-2.199***	-2.135***
	(0.407)	(0.415)	(0.439)	(0.441)
Mean dependent variable in control	15.72			
Household covariates	No	Yes	No	Yes
Observation	1,353	1,353	1,353	1,353
R-squared	0.214	0.224	0.178	0.187
Treatment effect (T1-C)	-2.088***	-2.079***	-2.273***	-2.105***
	(0.426)	(0.450)	(0.477)	(0.493)
Mean dependent variable in control	15.72			
Household covariates	No	Yes	No	Yes
Observation	1,154	1,154	1,154	1,154
R-squared	0.231	0.248	0.181	0.195
Treatment effect (T2-C)	-1.393***	-1.436***	-1.229**	-1.201***
	(0.433)	(0.333)	(0.500)	(0.403)
Mean dependent variable in control	15.72			
Household covariates	No	Yes	No	Yes
Observation	799	799	799	799
R-squared	0.192	0.193	0.171	0.175
Treatment effect (T2-T1)	0.369	0.326	0.212	0.003
	(0.599)	(0.559)	(0.470)	(0.474)
Mean dependent variable in T1	15.95			
Household covariates	No	Yes	No	Yes
Observation	753	753	753	753
R-squared	0.205	0.218	0.189	0.204

Note: Coefficient estimates are only reported for the treatment effect. All regressions include year and LGA fixed effects. Odd numbered columns are from regressions without covariates while even numbered columns include covariates. Household covariates include household size, age of household head, number of days in agricultural training, and indicators for if the household head has formal education, if farming is the household's main activity, and if they have access to credit. Columns (1) and (2) present ANCOVA estimates while columns (3) and (4) present the kernel matching ANCOVA estimates. Robust standard errors, clustered at the village level, are shown in parentheses. (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

after sowing), and booting (78-82 days after sowing). In Table 14 and Table 15, we assess the effect of personalized advice from RiceAdvice on the application timing of NPK and urea, respectively.

We find evidence of a negative effect on the application period (number of days after sowing) of NPK. [7] Treated households applied NPK about two days earlier than control households. As one would expect, there is no difference in application timing between the two treatment arms, since the only difference between T1 and T2 is the fertilizer grant. We find no evidence that the treatment had any effect on the application period of urea fertilizer, meaning that the treated and control households applied urea at approximately the same time after the sowing date.[8] The differences between the treatment's effect on NPK and urea timing may be due to differences in familiarity with the type of fertilizer. Alternatively, it could be due to the different application period of each fertilizer, with NPK typically being applied at

[7] Only one application of each type of fertilizer is common among farmers. So the application time used is the number of days after sowing for the first application of fertilizer.

[8] The only treatment effects on first application of urea that are significant become insignificant when we apply any of the three adjustments for multiple hypothesis testing. See Table A.8 and Table A.9 in the Appendix.

Table 15: Treatment effects on the first application of urea fertilizer

	(1)	(2)	(3)	(4)
Treatment effect (T-C)	-0.872 (0.708)	-0.956 (0.762)	-1.443 (1.029)	-1.503 (1.045)
Mean dependent variable in control	33.32			
Household covariates	No	Yes	No	Yes
Observation	1,353	1,353	1,353	1,353
R-squared	0.114	0.124	0.105	0.115
Treatment effect (T1-C)	-0.715 (0.743)	-1.093 (0.806)	-1.137 (1.238)	-0.782 (1.218)
Mean dependent variable in control	33.32			
Household covariates	No	Yes	No	Yes
Observation	1,154	1,154	1,154	1,154
R-squared	0.108	0.126	0.110	0.122
Treatment effect (T2-C)	-0.932 (0.759)	-0.753 (0.894)	-1.614** (0.685)	-1.167 (0.868)
Mean dependent variable in control	33.32			
Household covariates	No	Yes	No	Yes
Observation	799	799	799	799
R-squared	0.105	0.131	0.100	0.125
Treatment effect (T2-T1)	0.403 (0.481)	0.382 (0.551)	1.057* (0.568)	0.842 (0.626)
Mean dependent variable in T1	31.27			
Household covariates	No	Yes	No	Yes
Observation	753	753	753	753
R-squared	0.125	0.134	0.114	0.121

Note: Coefficient estimates are only reported for the treatment effect. All regressions include year and LGA fixed effects. Odd numbered columns are from regressions without covariates while even numbered columns include covariates. Household covariates include household size, age of household head, number of days in agricultural training, and indicators for if the household head has formal education, if farming is the household's main activity, and if they have access to credit. Columns (1) and (2) present ANCOVA estimates while columns (3) and (4) present the kernel matching ANCOVA estimates. Robust standard errors, clustered at the village level, are shown in parentheses. (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

transplanting and urea typically being applied at tilling. However, even where differences are significant, the size of the effect is only one to two days, which may not be meaningful in an agronomic sense, since the application windows are five days in length.

7. Conclusion

A persistent empirical puzzle in developing country agriculture is the low adoption rates of improved inputs. One potential solution to the puzzle is that high returns on average mask a great deal of heterogeneity at the individual level. Thus, while on average the recommended amount of fertilizer may substantially increase yields, for any given household the recommended amount may be too much or too little for a particular plot. Until recently, the cost of adapting extension advice to heterogeneity in soil quality was prohibitively expensive. But, with advances in mobile technology, decision support tools (DSTs) can be developed and disseminated at greatly reduced cost. By using DSTs, farmers and extension agents can fine-tune their management practices by taking into account variations in local environmental and economic conditions, reduce their inefficiencies, and shorten the learning process.

In this paper, we explore the potential for an Android-based DST called RiceAdvice. The mobile app allows households to provide information to extension agents about their local growing conditions, production costs, and market information. The extension agent can then use the app to provide recommendations for a nutrient management plan designed to increase both yields and profits. Using a randomized control trial, we find that households with access to RiceAdvice increase their yields and profits, while also increasing their technical efficiency. We also find that households are able to take advantage of the personalized extension information within their current credit constraints. Households in the information-only treatment arm are still able to significantly improve their outcomes, though not by as much as households who receive a grant to covers the full cost of the recommended fertilizer amount.

These outcomes are not driven by an overall increase in the use of fertilizer. On average there is no significant difference between fertilizer application rates for treatment and control households. Rather, the personalized extension advice allows households that previously over-used fertilizer to reduce their application rate and households who previously under-used fertilizer to increase their application rate. The study resulted in households increasing their yields and income while have a net zero effect on the amount of fertilizer. This suggests that improvements to productivity and livelihoods need not come at the cost of increased overall chemical fertilizer use and the corresponding negative effects on the environment.

While our results are specific to a particular DST, they add to a nascent body of literature suggesting that the null results typical of information-only interventions may be due to the overly broad information provided in the studies. In the case of technology adoption, how individuals are taught to use the technology plays an important role in whether that technology is beneficial or not. For farming households looking to take advantage of new seeds and other improved inputs, the revolution in mobile technology allows for a move away from the old one-size-fits-all advice and towards the delivery of personalized and profitable recommendations.

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Online Appendix

Table A.1: Fertility recommendations for rice in Nigeria

Nutrient	Fertility Class	Upland Rice	Lowland Rice
	Low	80kg N	100kg N
N	Medium	60kg N	80kg N
	High	40kg N	40kg N
	Low	30 - 40kg P_20_5	40 - 50kg P_20_5
P	Medium	30kg P_20_5	40kg P_20_5
	High	NIL	NIL
	Low	30 - 40kg K_20	30 - 40kg K_20
K	Medium	30kg K_20	30kg K_20
	High	NIL	NIL

Note: The table reproduces Table 2.9 in Chude et al. (2019). It is the official recommendations for fertilizer application for rice made by the Federal Ministry of Agriculture and Rural Development. This is the information provided as blanket advice to the control group.

Table A.2: Non-rice producing households in each year

Treatment	2015	2016	2017
C	9	6	19
T1	0	0	6
T2	0	0	1
Total	9	6	26

Table presents the number of households in the sample that did not produce rice in each year.

Table A.3: Stochastic frontier models for the production function

Log of production	**Coefficient**	**Standard Error**
log of area	-0.151***	0.028
log of total labor	0.005	0.015
log of total fertilizer	0.026***	0.008
Technical inefficiency		
Age of rice farmer (year)	0.008	0.007
Gender (=1 if rice farmer is man)	0.689	0.874
Married (=1)	0.755***	0.212
Household size (n)	-0.042**	0.019
Household members working age (n)	0.081**	0.033
Formal education (=1)	0.356**	0.139
Crop production is main activity (=1)	-0.589***	0.177
Member of a farmer group (=1)	-0.397***	0.125
Constance	-2.994***	0.903
Observation	694	
Log likelihood	8.832	

Note: Table presents results from a stochastic frontier model in which the technology is Cobb-Douglas. ($***p < 0.01$, $**p < 0.05$, $*p < 0.1$).

Table A.4: Baseline characteristics and balance pre-contamination

	Control group ($h = 340$) (1)	Difference with Treated ($h = 360$) (2)	Difference with T1 ($h = 260$) (3)	Difference with T2 ($h = 100$) (4)
Household characteristics				
Age of household head (year)	37.47 (11.27)	-1.662*	-2.492***	0.495
Household size (n)	11.52 (7.670)	0.166	0.070	0.415
Formal education (=1)	0.256 (0.437)	-0.006	0.010	-0.046
Farming is main activity (=1)	0.879 (0.326)	-0.004	-0.014	0.021
Number of agricultural training days (n)	0.653 (2.404)	0.280	0.074	0.817**
Access to credit (=1)	0.144 (0.352)	0.014	0.017	0.006
Production values				
Quantity of NPK (kg/ha)	184.0 (87.71)	-2.970	-4.529	1.084
Quantity of urea (kg/ha)	164.0 (88.91)	10.804	8.800	16.02
Rice area (ha)	0.760 (0.500)	0.221***	0.205***	0.263***
Rice yield (t/ha)	3.484 (1.759)	-0.168	-0.113	-0.312
Rice income (US$/ha)	1,675 (845.9)	-80.83	-54.27	-149.9
Profit (US$/ha)	1,357 (797.6)	-75.36	-49.44	-142.7
Technical efficiency	0.677 (0.174)	-0.011	-0.003	-0.032

Note: Coefficients in columns (2) - (4) are calculated by implementing an OLS that controls for LGA with a sampling weight and clustering at the village level. (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

Table A.5: Intra-cluster correlation coefficients for the outcomes variables

	ICC	**SE**
Yield (t/ha)	0.216	0.049
Net income (US$/ha)	0.202	0.048
Technical efficiency	0.228	0.051
Total quantity of fertilizer (kg/ha)	0.111	0.034
Quantity of NPK (kg/ha)	0.053	0.023
Quantity of urea (kg/ha)	0.131	0.037
First application of NPK (days)	0.105	0.034
First application of urea (days)	0.128	0.038

Notes: An ICC value of zero means that there is no difference between the variation within clusters (village) and the variation between clusters. When the ICC is closer to 1, the observations (20 households) within each village lack more variation (which implies no power gain or efficiency from having a larger sample). However, an ICC value closer to zero indicates a larger variation in the within sample, which is beneficial in terms of efficiency or power gain.

Table A.6: Multiple hypothesis testing (T-C)

	(1)	(2)	(3)	(4)
Panel A: Rice yield (t/ha)				
Unadjusted *p*-value	0.001	0.001	0.000	0.000
Bonferroni adjusted p-value	0.004	0.002	0.000	0.000
Holm adjusted p-value	0.001	0.002	0.000	0.000
Sharpened *q*-value	0.001	0.001	0.001	0.001
Panel B: Net income (USD/ha)				
Unadjusted *p*-value	0.000	0.000	0.000	0.000
Bonferroni adjusted p-value	0.001	0.000	0.000	0.000
Holm adjusted p-value	0.000	0.000	0.000	0.000
Sharpened q-value	0.001	0.001	0.001	0.001
Panel C: Technical efficiency (%)				
Unadjusted *p*-value	0.003	0.003	0.000	0.000
Bonferroni adjusted p-value	0.014	0.011	0.002	0.001
Holm adjusted p-value	0.003	0.006	0.000	0.000
Sharpened *q*-value	0.002	0.002	0.001	0.001
Panel D: Total quantity of fertilizer (kg/ha)				
Unadjusted *p*-value	0.199	0.121	0.394	0.357
Bonferroni adjusted p-value	0.797	0.485	1.000	1.000
Holm adjusted p-value	0.796	0.484	1.000	1.000
Sharpened *q*-value	0.651	0.651	0.651	0.651
Panel E: Quantity of NPK (kg/ha)				
Unadjusted *p*-value	0.004	0.003	0.019	0.042
Bonferroni adjusted p-value	0.016	0.011	0.074	0.166
Holm adjusted p-value	0.012	0.012	0.038	0.042
Sharpened *q*-value	0.008	0.008	0.013	0.022
Panel F: Quantity of urea (kg/ha)				
Unadjusted *p*-value	0.032	0.043	0.016	0.054
Bonferroni adjusted p-value	0.127	0.171	0.066	0.217
Holm adjusted p-value	0.096	0.086	0.064	0.054
Sharpened *q*-value	0.058	0.058	0.058	0.058
Panel G: First application of NPK (days)				
Unadjusted *p*-value	0.000	0.000	0.000	0.000
Bonferroni adjusted p-value	0.000	0.000	0.000	0.000
Holm adjusted p-value	0.000	0.000	0.000	0.000
Sharpened *q*-value	0.001	0.001	0.001	0.001
Panel H: First application of urea (days)				
Unadjusted *p*-value	0.227	0.218	0.173	0.159
Bonferroni adjusted p-value	0.906	0.873	0.691	0.638
Holm adjusted p-value	0.908	0.872	0.692	0.636
Sharpened *q*-value	0.293	0.293	0.293	0.293

Note: Each cell contains *p*- or *q*-values for the multiple regressions presented in the paper. Columns (1) and (2) present ANCOVA estimates, while columns (3) and (4) present kernel matching ANCOVA estimates. Bonferroni and Holm adjusted *p*-values are calculated following List et al. (2019). The sharpened *q*-values are calcualted using the Stata code from Anderson (2008).

Table A.7: Multiple hypothesis testing (T1-C)

	(1)	(2)	(3)	(4)
Panel A: Rice yield (t/ha)				
Unadjusted *p*-value	0.011	0.006	0.002	0.003
Bonferroni adjusted p-value	0.042	0.024	0.007	0.010
Holm adjusted p-value	0.011	0.012	0.008	0.009
Sharpened *q*-value	0.006	0.006	0.006	0.006
Panel B: Net income (USD/ha)				
Unadjusted *p*-value	0.004	0.001	0.000	0.000
Bonferroni adjusted p-value	0.015	0.005	0.001	0.002
Holm adjusted p-value	0.004	0.002	0.000	0.000
Sharpened q-value	0.002	0.001	0.001	0.001
Panel C: Technical efficiency (%)				
Unadjusted *p*-value	0.025	0.017	0.010	0.005
Bonferroni adjusted p-value	0.100	0.067	0.039	0.022
Holm adjusted p-value	0.025	0.034	0.030	0.020
Sharpened *q*-value	0.020	0.020	0.020	0.020
Panel D: Total quantity of fertilizer (kg/ha)				
Unadjusted *p*-value	0.431	0.249	0.570	0.506
Bonferroni adjusted p-value	1.000	0.996	1.000	1.000
Holm adjusted p-value	1.000	0.996	1.000	1.000
Sharpened *q*-value	1.000	1.000	1.000	1.000
Panel E: Quantity of NPK (kg/ha)				
Unadjusted *p*-value	0.010	0.005	0.016	0.025
Bonferroni adjusted p-value	0.040	0.021	0.064	0.101
Holm adjusted p-value	0.030	0.020	0.032	0.025
Sharpened *q*-value	0.021	0.021	0.021	0.021
Panel F: Quantity of urea (kg/ha)				
Unadjusted *p*-value	0.007	0.008	0.010	0.063
Bonferroni adjusted p-value	0.028	0.033	0.038	0.251
Holm adjusted p-value	0.028	0.024	0.020	0.063
Sharpened *q*-value	0.013	0.013	0.013	0.016
Panel G: First application of NPK (days)				
Unadjusted *p*-value	0.000	0.000	0.000	0.000
Bonferroni adjusted p-value	0.000	0.000	0.000	0.001
Holm adjusted p-value	0.000	0.000	0.000	0.000
Sharpened *q*-value	0.001	0.001	0.001	0.001
Panel H: First application of urea (days)				
Unadjusted *p*-value	0.344	0.186	0.366	0.526
Bonferroni adjusted p-value	1.000	0.742	1.000	1.000
Holm adjusted p-value	1.000	0.744	1.000	1.000
Sharpened *q*-value	0.954	0.954	0.954	0.954

Note: Each cell contains *p*- or *q*-values for the multiple regressions presented in the paper. Columns (1) and (2) present ANCOVA estimates, while columns (3) and (4) present kernel matching ANCOVA estimates. Bonferroni and Holm adjusted *p*-values are calculated following List et al. (2019). The sharpened *q*-values are calcualted using the Stata code from Anderson (2008).

Table A.8: Multiple hypothesis testing (T2-C)

	(1)	(2)	(3)	(4)
Panel A: Rice yield (t/ha)				
Unadjusted *p*-value	0.000	0.000	0.000	0.000
Bonferroni adjusted p-value	0.000	0.000	0.000	0.000
Holm adjusted p-value	0.000	0.000	0.000	0.000
Sharpened *q*-value	0.001	0.001	0.001	0.001
Panel B: Net income (USD/ha)				
Unadjusted *p*-value	0.000	0.000	0.000	0.000
Bonferroni adjusted p-value	0.000	0.000	0.000	0.000
Holm adjusted p-value	0.000	0.000	0.000	0.000
Sharpened q-value	0.001	0.001	0.001	0.001
Panel C: Technical efficiency (%)				
Unadjusted *p*-value	0.000	0.000	0.000	0.000
Bonferroni adjusted p-value	0.000	0.000	0.000	0.000
Holm adjusted p-value	0.000	0.000	0.000	0.000
Sharpened *q*-value	0.001	0.001	0.001	0.001
Panel D: Total quantity of fertilizer (kg/ha)				
Unadjusted *p*-value	0.007	0.084	0.198	0.237
Bonferroni adjusted p-value	0.030	0.334	0.792	0.947
Holm adjusted p-value	0.028	0.252	0.594	0.711
Sharpened *q*-value	0.031	0.144	0.201	0.201
Panel E: Quantity of NPK (kg/ha)				
Unadjusted *p*-value	0.001	0.016	0.072	0.079
Bonferroni adjusted p-value	0.006	0.065	0.288	0.315
Holm adjusted p-value	0.004	0.048	0.144	0.158
Sharpened *q*-value	0.006	0.025	0.042	0.042
Panel F: Quantity of urea (kg/ha)				
Unadjusted *p*-value	0.991	0.769	0.822	0.952
Bonferroni adjusted p-value	1.000	1.000	1.000	1.000
Holm adjusted p-value	1.000	1.000	1.000	1.000
Sharpened *q*-value	1.000	1.000	1.000	1.000
Panel G: First application of NPK (days)				
Unadjusted *p*-value	0.004	0.000	0.023	0.007
Bonferroni adjusted p-value	0.017	0.001	0.091	0.029
Holm adjusted p-value	0.012	0.000	0.023	0.014
Sharpened *q*-value	0.007	0.002	0.010	0.008
Panel H: First application of urea (days)				
Unadjusted *p*-value	0.233	0.409	0.028	0.193
Bonferroni adjusted p-value	0.932	1.000	0.113	0.773
Holm adjusted p-value	0.932	1.000	0.112	0.772
Sharpened *q*-value	0.304	0.443	0.128	0.304

Note: Each cell contains *p*- or *q*-values for the multiple regressions presented in the paper. Columns (1) and (2) present ANCOVA estimates, while columns (3) and (4) present kernel matching ANCOVA estimates. Bonferroni and Holm adjusted *p*-values are calculated following List et al. (2019). The sharpened *q*-values are calcualted using the Stata code from Anderson (2008).

Table A.9: Multiple hypothesis testing (T2-T1)

	(1)	(2)	(3)	(4)
Panel A: Rice yield (t/ha)				
Unadjusted *p*-value	0.001	0.000	0.000	0.001
Bonferroni adjusted p-value	0.002	0.001	0.000	0.003
Holm adjusted p-value	0.002	0.000	0.000	0.001
Sharpened *q*-value	0.001	0.001	0.001	0.001
Panel B: Net income (USD/ha)				
Unadjusted *p*-value	0.002	0.002	0.000	0.002
Bonferroni adjusted p-value	0.008	0.007	0.001	0.009
Holm adjusted p-value	0.004	0.006	0.000	0.002
Sharpened q-value	0.002	0.002	0.002	0.002
Panel C: Technical efficiency (%)				
Unadjusted *p*-value	0.020	0.010	0.004	0.010
Bonferroni adjusted p-value	0.079	0.038	0.014	0.040
Holm adjusted p-value	0.020	0.030	0.016	0.020
Sharpened *q*-value	0.057	0.057	0.057	0.057
Panel D: Total quantity of fertilizer (kg/ha)				
Unadjusted *p*-value	0.058	0.028	0.259	0.489
Bonferroni adjusted p-value	0.231	0.112	1.000	1.000
Holm adjusted p-value	0.232	0.112	1.000	1.000
Sharpened *q*-value	0.127	0.127	0.209	0.324
Panel E: Quantity of NPK (kg/ha)				
Unadjusted *p*-value	0.226	0.189	0.354	0.641
Bonferroni adjusted p-value	0.906	0.755	1.000	1.000
Holm adjusted p-value	0.904	0.756	1.000	1.000
Sharpened *q*-value	0.828	0.828	0.828	0.828
Panel F: Quantity of urea (kg/ha)				
Unadjusted *p*-value	0.004	0.000	0.039	0.091
Bonferroni adjusted p-value	0.014	0.000	0.157	0.363
Holm adjusted p-value	0.012	0.000	0.078	0.091
Sharpened *q*-value	0.006	0.001	0.027	0.048
Panel G: First application of NPK (days)				
Unadjusted *p*-value	0.546	0.567	0.658	0.995
Bonferroni adjusted p-value	1.000	1.000	1.000	1.000
Holm adjusted p-value	1.000	1.000	1.000	1.000
Sharpened *q*-value	1.000	1.000	1.000	1.000
Panel H: First application of urea (days)				
Unadjusted *p*-value	0.414	0.497	0.080	0.331
Bonferroni adjusted p-value	1.000	1.000	0.321	1.000
Holm adjusted p-value	1.000	1.000	0.320	1.000
Sharpened *q*-value	0.596	0.596	0.472	0.596

Note: Each cell contains *p*- or *q*-values for the multiple regressions presented in the paper. Columns (1) and (2) present ANCOVA estimates, while columns (3) and (4) present kernel matching ANCOVA estimates. Bonferroni and Holm adjusted *p*-values are calculated following List et al. (2019). The sharpened *q*-values are calcualted using the Stata code from Anderson (2008).

Table A.10: Treatment effects on the quantity of fertilizer

	(1)	(2)	(3)	(4)
Treatment effect (T-C)				
Mean dependent variable in control	367.4			
Quartile: 0.25	-1.524	-1.524	-1.524	-1.524
	(15.91)	(15.91)	(15.91)	(15.91)
Quartile: 0.5	4.209	4.209	4.209	4.209
	(8.121)	(8.121)	(8.121)	(8.121)
Quartile: 0.75	4.742	4.742	4.742	4.742
	(19.70)	(19.70)	(19.70)	(19.70)
Treatment effect (T1-C)				
Mean dependent variable in control	367.4			
Quartile: 0.25	6.857	6.857	6.857	6.857
	(10.74)	(10.74)	(10.74)	(10.74)
Quartile: 0.5	13.21	13.21	13.21	13.21
	(8.941)	(8.941)	(8.941)	(8.941)
Quartile: 0.75	12.60	12.60	12.60	12.60
	(12.94)	(12.94)	(12.94)	(12.94)
Treatment effect (T2-C)				
Mean dependent variable in control	367.4			
Quartile: 0.25	-13.90	-13.90	-13.90	-13.90
	(18.65)	(18.65)	(18.65)	(18.65)
Quartile: 0.5	-18.39	-18.39	-18.39	-18.39
	(20.55)	(20.55)	(20.55)	(20.55)
Quartile: 0.75	-26.91	-26.91	-26.91	-26.91
	(18.57)	(18.57)	(18.57)	(18.57)
Treatment effect (T2-T1)				
Mean dependent variable in T1	359.1			
Quartile: 0.25	-42.65*	-42.65*	-42.65*	-42.65*
	(22.43)	(22.43)	(22.43)	(22.43)
Quartile: 0.5	-21.00	-21.00	-21.00	-21.00
	(20.28)	(20.28)	(20.28)	(20.28)
Quartile: 0.75	-38.00	-38.00	-38.00	-38.00
	(26.93)	(26.93)	(26.93)	(26.93)

Note: Coefficient estimates are only reported for the treatment effect. All regressions include year and LGA fixed effects. Odd numbered columns are from regressions without covariates while even numbered columns include covariates. Household covariates include household size, age of household head, number of days in agricultural training, and indicators for if the household head has formal education, if farming is the household's main activity, and if they have access to credit. Columns (1) and (2) present ANCOVA estimates while columns (3) and (4) present the kernel matching ANCOVA estimates. Robust standard errors, clustered at the village level, are shown in parentheses. (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

Table A.11: Treatment effects on the quantity of NPK fertilizer

	(1)	(2)	(3)	(4)
Treatment effect (T-C)				
Mean dependent variable in control	176.7			
Quartile: 0.25	5.333	10.03	-17.40***	-16.08***
	(8.080)	(7.416)	(5.342)	(5.162)
Quartile: 0.5	-3.808	-5.380	-16.70***	-15.34***
	(4.665)	(6.497)	(5.371)	(5.254)
Quartile: 0.75	-7.000	-14.70	-16.82***	-15.42***
	(14.06)	(14.01)	(5.358)	(5.235)
Treatment effect (T1-C)				
Mean dependent variable in control	176.7			
Quartile: 0.25	16.67*	13.92*	-16.16**	-15.18**
	(10.10)	(7.755)	(5.893)	(5.673)
Quartile: 0.5	-2.000	-2.000	-16.04**	-15.11**
	(4.866)	(3.557)	(5.898)	(5.731)
Quartile: 0.75	-8.333	-19.45*	-16.03**	-15.11**
	(12.57)	(10.11)	(5.890)	(5.710)
Treatment effect (T2-C)				
Mean dependent variable in control	176.7			
Quartile: 0.25	1.588	7.569	-21.85***	-17.56***
	(6.846)	(9.708)	(6.239)	(6.007)
Quartile: 0.5	-23.88***	-21.11**	-21.75***	-17.40***
	(6.066)	(10.66)	(6.235)	(6.025)
Quartile: 0.75	-10.13	-15.69	-21.80***	-17.52***
	(16.37)	(18.69)	(6.202)	(5.986)
Treatment effect (T2-T1)				
Mean dependent variable in T1	169.0			
Quartile: 0.25	-18.85**	-18.67**	-1.636	-3.243
	(8.960)	(8.794)	(4.793)	(6.634)
Quartile: 0.5	-17.00**	-17.00**	-2.835	-1.556
	(6.584)	(8.392)	(5.625)	(5.974)
Quartile: 0.75	0.000	4.197	-3.509	-2.479
	(17.38)	(12.62)	(4.556)	(5.864)

Note: Coefficient estimates are only reported for the treatment effect. All regressions include year and LGA fixed effects. Odd numbered columns are from regressions without covariates while even numbered columns include covariates. Household covariates include household size, age of household head, number of days in agricultural training, and indicators for if the household head has formal education, if farming is the household's main activity, and if they have access to credit. Columns (1) and (2) present ANCOVA estimates while columns (3) and (4) present the kernel matching ANCOVA estimates. Robust standard errors, clustered at the village level, are shown in parentheses. (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

Table A.12: Treatment effects on the quantity of urea fertilizer

	(1)	(2)	(3)	(4)
Treatment effect (T-C)				
Mean dependent variable in control	137.5			
Quartile: 0.25	16.05**	15.51*	14.28***	11.34*
	(6.524)	(8.774)	(5.206)	(5.634)
Quartile: 0.5	19.17***	17.19***	13.69**	10.88*
	(4.530)	(6.608)	(5.262)	(5.731)
Quartile: 0.75	-0.000	0.000	13.68**	10.87*
	(10.59)	(9.876)	(5.261)	(5.729)
Treatment effect (T1-C)				
Mean dependent variable in control	137.5			
Quartile: 0.25	20.00***	18.78**	18.08***	15.64***
	(7.187)	(7.979)	(5.014)	(5.611)
Quartile: 0.5	26.61***	25.02***	18.40***	15.71**
	(6.700)	(6.183)	(5.060)	(5.703)
Quartile: 0.75	0.000	2.321	18.54***	15.87***
	(15.95)	(10.52)	(5.045)	(5.720)
Treatment effect (T2-C)				
Mean dependent variable in control	137.5			
Quartile: 0.25	-0.952	-3.055	1.384	1.239
	(7.494)	(5.967)	(6.853)	(8.283)
Quartile: 0.5	0.000	6.080	1.358	1.245
	(9.723)	(8.094)	(6.842)	(8.286)
Quartile: 0.75	0.000	0.322	1.393	1.239
	(2.681)	(6.573)	(6.856)	(8.281)
Treatment effect (T2-T1)				
Mean dependent variable in T1	165.6			
Quartile: 0.25	-25.00***	-26.34**	-16.15***	-15.86***
	(9.135)	(10.493)	(4.062)	(4.705)
Quartile: 0.5	-19.34*	-20.53***	-16.04***	-15.69***
	(10.02)	(6.935)	(4.114)	(4.711)
Quartile: 0.75	0.000	-4.912	-16.06***	-15.71***
	(10.48)	(12.86)	(4.110)	(4.714)

Note: Coefficient estimates are only reported for the treatment effect. All regressions include year and LGA fixed effects. Odd numbered columns are from regressions without covariates while even numbered columns include covariates. Household covariates include household size, age of household head, number of days in agricultural training, and indicators for if the household head has formal education, if farming is the household's main activity, and if they have access to credit. Columns (1) and (2) present ANCOVA estimates while columns (3) and (4) present the kernel matching ANCOVA estimates. Robust standard errors, clustered at the village level, are shown in parentheses. (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).