Is Personalized Better: Digital Advisory and Productivity Differentials in Rice Farming in Nigeria

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Abstract

Personalized extension advisory deliver information that are more compatible with farmer production conditions and has a better chance of adoption and impacts. We exploit a rich four-round experimental panel data on RiceAdvice, a decision support app that provides personalized information on soil fertility management and other agricultural practices to rice farmers. We evaluate the impact of the app on technological, managerial, frontier yield, and fertilizer productivity differentials, while accounting for differences in production technologies possessed by the different treatment groups. Results based on the true random effects estimator suggest that exposure to RiceAdvice significantly increases the production possibilities and managerial performance of rice smallholders exposed to it (treated farmers), leading to an upward shift in the production frontier for those same farmers. Exposed farmers also have higher mean fertilizer productivity compared to the unexposed, especially when bundled with fertilizer inputs. The impacts are stronger in the early years but wanes over time. Ensuring consistent access to the app as well as fertilizer input could help sustain the gains.

Keywords: Digital extension, productivity, technology gap, technical efficiency, rice production, Nigeria

1 Introduction

Agricultural extension, along with evolving modes of information delivery and content, has long served as an avenue to disseminate new techniques, improve farmer know-how, and stimulate farm-level productivity growth. Advances in information and communication technology (ICT) tools (e.g., mobile electronic devices, apps, internet connectivity, remote sensing, etc.) have made agricultural information more accessible. Personalized extension advisory, which utilizes ICT tools, deliver information that are more compatible with farmer needs as they take into account the heterogeneity in farmer production conditions (MacCarthy et al., 2018; Tjernström et al., 2021; van Campenhout, 2022). The use of these tools to deliver tailored information in turn, has a better chance of actually improving smallholder decision-making and know-how. This mode of extension delivery presents a vital strategy for expediting and sustaining agricultural productivity growth on existing smallholder farmlands, and a strategy that is much needed for economic transformation (World Bank, 2017; Norton & Alwang, 2020; Jayne & Sanchez, 2021).

RiceAdvice, an ICT-based decision support tool developed by the Africa Rice Center (AfricaRice), allows field-specific information on nutrient management, cropping calendar, and good cultivation techniques to be disseminated to rice smallholder farmers (Saito et al., 2015; Arouna et al., 2020). Access to the RiceAdvice app is expected to enhance rice farmers' production possibilities, managerial skills, fertilizer use rates, and consequently, have an impact on output. While such ICT tools are increasingly popular in farm management, rigorous evidence of their influence on smallholder efficiency and productivity performance remains limited. We seek to broaden understanding of the productivity pathways of such tools by evaluating the technology, technical efficiency (TE), land, and fertilizer productivity impacts from using RiceAdvice.

Empirical studies on the role of ICT in agriculture have been increasing, and they have broadly focused on knowledge acquisition, innovation and input adoption, and marketing (e.g., Aker, 2010; Aker and Ksoll, 2016; Fu and Akter, 2016; van Campenhout, 2017; Maredia et al., 2018). A few studies have examined impacts on yields, profitability, soil nutrient management as well as technical efficiency, and poverty. Arouna et al. (2020) conducted randomized controlled trials (RCT) to evaluate the impact of digital extension information delivered through RiceAdvice in smallholder rice farming in Kano State, Nigeria. Based on a three-round panel data they found significant impact on farmers observed yields, profitability, and fertilizer use rate. In eastern Uganda, van Campenhout et al. (2021) also conducted a field experiment to assess the effectiveness of extension delivered through videos, interactive voice response (IVR) and short message services (SMS). They observed a significant yield impact with the use of videos, but very little impacts using IVR, and SMS. Oyinbo et al.

(2022) studied the impact of the Nutrient Expert tool for maize in an RCT setting in Nigeria and found significant improvements in fertility practices and yields, but no improvements for fertilizer use rates. In Zambia, Mwalupaso et al. (2019) utilized observational data to assess the impact of mobile phone use on TE and poverty, addressing only bias from observables and ignoring potential underlying differences in production technology between users and non-users. They reported significant TE improvements and poverty reduction associated with phone usage.

Our contribution in this study is three-fold. First, we go beyond looking narrowly at only the impact on observed yields (measured as observed output per unit area) as is the case in the received literature, to examine a more detailed set of productivity effects of ICT use. These effects include: 1) technology gap that comes from access to better information and/or inputs through RiceAdvice, 2) managerial performance improvement that arises from enhanced know-how on the implementation of farm-level practices, 3) frontier yield gain, which is a combination of the effects in (1) and (2), and 4) fertilizer productivity improvement coming from exposure to RiceAdvice. The production frontier framework employed to generate these effects reflects the stochastic nature of the production environment in which smallholders operate. Second, we hypothesize that access to RiceAdvice provides better technical information specific to users, enabling them to utilize the best-practice technology. If so, then, the analysis of managerial performance differentials needs to account for the possible differences in the underlying production technology between users and non-users. We accomplish this by constructing a shared benchmark frontier known as the stochastic metafrontier (Huang et al., 2014; Amsler et al., 2017; Owusu & Bravo-Ureta, 2021; Neubauer et al., 2022; Owusu & Bravo-Ureta, 2022), an approach largely ignored in the related literature. Third, our analysis of fertilizer productivity differentials relies on a single factor measure known as the fertilizer productivity index (FPI) that incorporates both conventional and non-conventional production inputs. The measure overcomes drawbacks of using single factor measures by adjusting for the possibility that managers of rice farms alter their input mix in response to changes in fertility management. The FPI also allows a decomposition of the productivity measure so as to track sources of fertilizer productivity growth. This is the first application of a more rigorous measure of fertilizer productivity in related literature, thus, constitutes a novel contribution.

The rest of the paper is as follows: section two outlines the study context and the intervention, section three details the conceptual framework, section four deals with the data and the empirical strategy, section four presents the results and discussion, and section five concludes.

2 Context and Intervention

Rice is a popular food staple in Nigeria with consumption rapidly increasing owing to factors such as shifting consumer preferences, increasing population and incomes, and rapid urbanization (Kamai et al., 2020). Over the years, the increasing demand has been met through importation of about 3 million metric tonnes (MMT), which is equivalent to around 480 million US$ in foreign exchange annually. The increase demand in imports is due to the domestic production continuously falling short, accounting for just about 55% of total consumption (Saito et al., 2015; Kamai et al., 2020).

Although both public and private efforts (e.g., Growth Enhancement Support Program) have focused on increasing yields in order to reduce reliance on imports, the available data from FAO suggest a modest increase from the lowest of 0.9 t/ha in 1961 to a six-decade high of 2.7 t/ha in 2018 (see Figure 1).

To help increase rice productivity growth, AfricaRice and its collaborating national research centers developed an Android mobile application (app) known as RiceAdvice to disseminate plot-specific management information to rice farmers. This information is generated after the farmer has supplied information on expected production conditions such as, seed varietal choice, planned management practices, fertilizer availability, prevailing input prices, expected production costs, etc. For more information on the app Saito et al. (2015) and Arouna et al. (2020). The app has been introduced to rice farmers since 2015 in Kano State, which is in the northern part of the country where over 72% of national rice output originates.

To assess the performance of RiceAdvice in Kano State, AfricaRice implemented a randomized controlled trials (RCT) in which rice farmers were randomly assigned into one of three treatment groups: 1) control group (C) that received the traditional extension visits with blanket recommendations, 2) first treatment arm (T1) received the personalized information via RiceAdvice, and 3) second treatment arm (T2) received the personalized information plus fertilizer input subsidy (100%). The T1 and T2 treatments were administered after all farmers had received the traditional extension visits with blanket recommendations from the same set of extension agents. The quantity of fertilizer given to a T2 farmer depends on recommendations from the RiceAdvice app, and is delivered directly to the farmer. Contrasting T1 and C shows the productivity effects of RiceAdvice when liquidity constraint binds. T2 versus C gives the effect when the constraint is relaxed. It is worth mentioning that the provision of the in-kind fertilizer subsidy was done in only the first year or season of production.

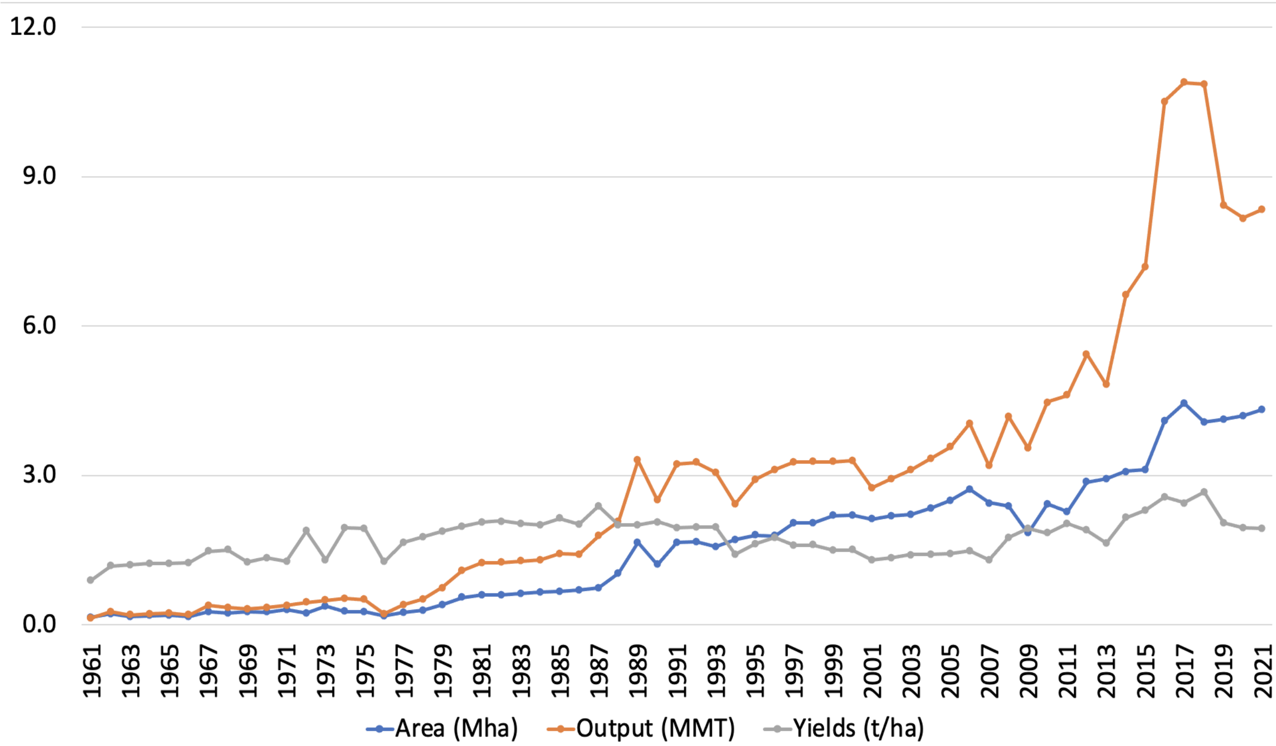


Figure 1. Rice production statistics over the past decade in Nigeria
(*Source: FAOSTAT, 2023*)
Notes: Mha - million hectares, MMT - million metric tonnes

3 Conceptual Framework

Evaluating the impact of RiceAdvice on productivity outcomes requires defining the counterfactual for users of the app (the treated groups), which is their outcomes had they not used it. Randomization has long been a standard approach to defining the counterfactual as it ensures that treatment status is independent of potential outcomes, thus, eliminating the possibility that selection bias taints the impact estimate (Duflo et al., 2007; Angrist & Pischke, 2009).

To define the measure of impact, suppose the binary variable will $D_i = \{0, 1\}$ describes treatment status so the $D_i = 1$ represents exposure to RiceAdvice and $D_i = 0$ denotes the unexposed state. Let corresponding outcomes with and without exposure be denoted by Y_{1i}

and Y_{0i}. Given random assignment of treatment, we measure impact of RiceAdvice as the average treatment effect on the treated (ATET) based on the observed difference in exposure status as:

$$\begin{aligned} \Delta Y_i &= E[Y_{1i}|D=1] - E[Y_{0i}|D=0] \\ &= \tau_{ATET} + \{E[Y_{0i}|D=1] - E[Y_{0i}|D=0]\} \\ &= \tau_{ATET} \qquad \{\because \text{by randomization} \quad E[Y_{0i}|D_i=1] = E[Y_{0i}|D_i=0]\} \end{aligned} \tag{1}$$

3.1 Randomized Evaluation and Stochastic Frontiers

The application of stochastic frontier methods in impact evaluation is straight forward when treatment assignment is randomized as is the case of participants' exposure to RiceAdvice. Derived productivity measures can be directly compared between the treated and control groups. Here, we focus on defining the productivity measures employed in the evaluation, which are technical efficiencies relative to the group frontier for each farmer (i.e., group TE), and relative to the metafrontier (MTE); technology gap ratio (TGR) which are deviations of the group frontiers from the metafrontier; frontier yield which is the ratio of the predicted frontier output to cultivated area; and fertilizer productivity index (FPI) which is the product of six indices namely, input deepening index (IDI), output-oriented scale efficiency index (OSEI), environmental index (EI), output-oriented technology index (OTI), output-oriented technical efficiency index (OTEI), and statistical noise index (SNI).

The stochastic production frontier (SPF) expresses the maximum output attainable from a vector of inputs, the technology, and environment, and explicitly delineates exogenous random shocks from technical inefficiency (Aigner et al., 1977; Meeusen & van den Broeck, 1977; O'Donnell, 2016; Njuki & Bravo-Ureta, 2018). For the period-t technology set,

$$\mathcal{T}^t = \{(X, q) : X \text{ can produce } q \text{ in period } t\} \tag{2}$$

where, $X \in \Re^K_+$ and $q \in \Re_{++}$, the production technology of farmer i in treatment group

$d \in \{C, T1, T2\}$ can be represented by the SPF model,

$$q_{itd} = f^t(x_{itd}; \theta_d) exp(\varepsilon_{itd}); \quad \varepsilon_{itd} = v_{itd} - u_{itd} \tag{3}$$

where, q_{itd} is observed output; x_{itd} is a vector of inputs; ε_{itd} is the error term composed of a two-sided symmetric noise, v_{itd}, and a non-negative technical inefficiency, u_{itd}; θ_d is the parameter vector. From eq. (3), the time-varying group-specific TE for farmer i is expressed as,

$$TE_{itd} = \frac{q_{itd}}{f^t(x_{itd}; \theta_d) exp(v_{itd})} = exp(-u_{itd}) \tag{4}$$

If production technologies are systematically different among the three groups, then cross-group examination of managerial performance using TE in eq. (4) is untenable. Instead, a TE index computed relative to the metafrontier (i.e., the MTE) needs to be used (Battese et al., 2004; O'Donnell et al., 2008; Owusu & Bravo-Ureta, 2021).

3.2 Stochastic Metafrontier

The SMF emanated from the meta-production function of Hayami and Ruttan (1970) and as an extension of the deterministic metafrontier (DMF) of Battese and Rao (2002). It has the benefit of consistency with the stochastic nature of the group frontiers it envelops, possesses statistical properties, and accommodates idiosyncratic shocks. Two approaches are identified in the literature. The first is by Huang et al. (2014) and involves parametric estimation of the SMF in two-stages. It does require the composed error term to have the correct skewness in order for technical inefficiency to be identified. This approach is more common in the literature (e.g., Lawin and Tamini, 2018; Alem et al., 2019; Bravo-Ureta et al., 2020; Owusu and Bravo-Ureta, 2021). The second approach by Amsler et al. (2017) is semi-parametric relying on simulations. Unlike the first, this approach has received less attention with only three applications to the best of our knowledge (Owusu & Bravo-Ureta, 2021; Neubauer et al., 2022; Owusu & Bravo-Ureta, 2022). We implement the second approach in this study as the first did not work given wrong skew of the residuals. Following O'Donnell (2018) and Owusu and Bravo-Ureta (2022), we compute TGR as,

$$TGR_{it} = \frac{1}{R}\sum_{r=1}^{R} exp[-u_{it}^{\tau}(r)] \tag{5}$$

where, R is the number of replications chosen, $u_{it}^{\tau}(r) = u_{it}(r) - u_{itd}(r)$, $u_{itd}(r)$ is time-varying inefficiency relative to the group frontier in the rth replication, and $u_{it}(r)$ is time-varying inefficiency relative to the maximum output across the three groups. The MTE is then given by the product of eqs. (4) and (5):

$$MTE_{it} = TE_{itd} \times TGR_{it} \tag{6}$$

Frontier yield is calculated as follows:

$$\text{Frontier yield} = \frac{\hat{q}_{itd}}{area} \tag{7}$$

where, $\hat{q}_{itd}$ is predicted frontier output.

3.3 Fertilizer Productivity Index

Following Njuki and Bravo-Ureta (2019), we derive a fertilizer productivity index (FPI) that addresses the drawback of single-factor measures, which ignore the effect of other factors of production. To do so, let the technology represented in eq. (3) be approximated by the Cobb-Douglas functional form and the input vector be comprised of conventional (x_{kitd}) and non-conventional factors (Z_{jitd}). Then, multiplying both sides of eq. (3) by $\frac{1}{x_{1itd}}$, where, x_{1itd}

is quantity of fertilizer in kilograms, gives an expression for FPI as;

$$\begin{aligned} FPI_{itd} &= (\frac{q_{itd}}{x_{1itd}}) \\ &= [\prod_{k=1}^{K-1}(\frac{x_{kitd}}{x_{1itd}})^{\beta_{kd}}][(x_{1itd})^{\epsilon_d - 1}][exp(\sum_{l=1}^{L}\gamma_l Z_{litd})][exp(\sum_{t=1}^{T}\lambda_t t)][exp(-u_{itd})][exp(v_{itd})] \end{aligned} \tag{8}$$

where: $\epsilon_d = \sum_k \beta_{kd}$ is the scale elasticity. From eq. (8), fertilizer productivity of farmer i in period t treatment d relative to farmer j in period s treatment b is given by:

$$\begin{aligned} FPI_{id(t)/jb(s)} = \{\prod_{k=1}^{K-1}(\frac{x_{kitd}}{x_{1itd}} \times \frac{x_{1jsb}}{x_{kjsb}})^{\beta_{kd}}\} \times \{(\frac{x_{1itd}}{x_{1jsb}})^{\epsilon_d - 1}\} \times \{\frac{exp(\sum_{l=1}^{L}\gamma_l Z_{litd})}{exp(\sum_{l=1}^{L}\gamma_l Z_{ljsb})}\} \\ \times \{\frac{exp(\sum_{t=1}^{T}\lambda_t t}{exp(\sum_{s=1}^{S}\lambda_s s}\} \times \{\frac{exp(-u_{itd})}{exp(-u_{jsb})}\} \times \{\frac{exp(v_{itd})}{exp(v_{jsb})}\} \end{aligned} \tag{9}$$

There are six terms on the right-hand side of eq. (9), which are interpreted as follows: 1) Input-deepening index (IDI): Accounts for changes in FPI owing to adjustments in the quantities of other factors relative to fertilizer. 2) Output-oriented scale efficiency index (OSEI): Captures productivity gains from a unit change in all the conventional factors of production. 3) Environmental index (EI): Accounts for the effect of ecology, soil, institutional support, and time-invariant attributes of the production environment. 4) Output-oriented technology index (OTI): Quantifies fertilizer productivity effects due to dynamic shifts in the production frontier. 5) Output-oriented technical efficiency index (OTEI): Reflects changes in FPI associated with changes in managerial capabilities. 5) Statistical noise index (SNI): Represents the effect of random shocks and measurement errors on FPI.

4 Data and Estimation

The analysis uses a four-round panel dataset generated from an RCT conducted in Kano State, Nigeria. Power analysis was conducted to inform the selection of 700 households in 35 villages across five local government areas (LGAs). The sample was distributed across the treatment categories as follows: $C = 320$, $T1 = 280$, and $T2 = 100$. The baseline was in 2015 and the endline in 2016. Two follow-up data collection efforts occurred. The first in 2017, and the second in 2018.

We specify a Cobb-Douglas (CD) SPF considering that, unlike the translog, it satisfies global properties of the production frontier, and is consistent with requirements for computing proper productivity indices:

$$ln\, q_{itd} = \alpha_i + \sum_{k=1}^{K} \beta_{kd} ln\, x_{kitd} + \sum_{l=1}^{L} \gamma_l Z_{litd} + \sum_{t=2015}^{2018} \lambda_t t + v_{itd} - u_{itd} \tag{10}$$

where:$\alpha_i = \alpha + \omega_i$, α is a constant, ω_i is the unobserved time-invariant farm-specific heterogeneity; q_{itd} is rice output in kilogram; x_{kitd} is the vector of conventional inputs - land area in hectares, seed in kilogram, labor in person-days, fertilizer in kilogram, and other chemicals in liters; Z_{jitd} is a vector of non-conventional inputs including rice ecology, soil type, extension, credit access, and group membership; t is a vector of year dummies; v_{itd} is the symmetric error assumed to be independently and identically distributed (i.i.d); u_{itd} is a one-sided time-varying inefficiency assumed to follow a half-normal distribution. α, β_{kd}, γ_{ld}, and λ_t are parameters to be estimated.

Several panel SPF estimators for eq. (10) have been proposed in the panel stochastic frontier literature starting with Pitt and Lee (1981) random effects model. However, the inherent limitations of the received models motivated Greene (2005a, 2005b) to propose the "true" fixed and random effects (TFE and TRE) estimators. Although both the TFE and TRE can be attractive options, we implement the TRE owing to the incidental parameter problem that leads to inconsistent parameter estimates with the TFE (Farsi et al., 2005;

Greene, 2005a, 2005b; Filippini & Greene, 2016; Karagiannis & Kellermann, 2019).

5 Results and Discussion

In Table 1, we present estimates of the technology parameters of the "true" random effects (TRE) stochastic production frontier (SPF) model estimated using maximum simulated likelihood. The coefficients and standard errors are shown for all groups combined (All) in the second column, for the control group (C) in the third column, the first treatment group ($T1$) in the fourth, and the second treatment group ($T2$) in the fifth.

The variation in inefficiency (σ_u) relative to that of the symmetric noise (σ_v), given by λ, is about 3.9 to 5.7 higher across the samples, and translates into about 80% or more of the total residual variation for technical inefficiency (bottom of Table 1). This supports the choice of the SPF model. Also, the variation in the random farm effects (σ_ω) is statistically significant, but only for the $T1$ group, indicating that the TRE estimator correctly delineates time-invariant unobserved heterogeneity from time-varying inefficiency as is evident from the shift in variation from the inefficiency to the random farm effects. This justifies the implementation of the TRE as opposed to the pooled estimator, which is subject to heterogeneity bias.

Across all samples the coefficients of the conventional variables (land, seed, labor, fertilizer, and other chemicals) are positive and less than one suggesting a well-behaved production technology consistent with economic theory and valid for examining managerial performance (Henningsen & Henning, 2009). The model for the "All" sample assumes that the same production technology is in use by all farmers regardless of treatment, except for the shift parameters for the variables $T1$: Advice and $T2$: Advice + input. These two coefficients point to 4.6% and 13.7% output increase associated with only RiceAdvice and RiceAdvice bundled with fertilizer input, respectively. However, the results of the likelihood ratio test shown below Table 1 suggest that different production technologies are in use across all three treatment groups. Consequently, analyses with estimates from the separate technologies are favored.

Scale elasticities are statistically significantly less than 1 for C and $T1$, but not different from 1 for the $T2$ (see bottom of Table 1). This implies that while the technologies for the C and $T1$ exhibit diminishing returns to scale, that for the $T2$ displays constant returns. Production elasticities for land are statistically significant at the 1% across the three groups, ranging from 0.66 to 0.78. The values are also the largest among the five production factors. This is consistent with results obtained elsewhere underscoring the importance of land for smallholders (e.g., Munthali and Murayama, 2013; Jayne et al., 2014; Owusu and Bravo-Ureta, 2022). Elasticity for seed is significant for the treated groups and not the control. Elasticity for labor is not significant across all groups suggesting that labor may not be a binding constraint in rice production in the study area. Production elasticities for fertilizer and other chemicals are both statistically significant for only the control and $T1$ groups.

Summaries of the productivity indicators namely, TE relative to the group frontier (group TE), technology gap ratio (TGR), TE relative to the metafrontier (MTE), frontier yield, and fertilizer productivity index (FPI) are presented in Table 2. Columns 2-4 report the means (across the four study years) and standard deviations for the three groups while columns 5-7 report the differences in means between the groups and their associated standard errors.

The mean TE relative to the group frontier is 64.8% for the $T1$ and 59.9% for $T2$. Compared to the control group, the difference is statistically significant for the $T1$ (4.4 percentage point) and not the $T2$. However, given the existence of separate and systematically different production technologies evidenced by the TGR differences, the group TEs do not provide a valid basis for comparing managerial performance. The results show that the mean TGR is significantly higher for the $T2$ compared to C, and to $T1$. The difference in mean TGR between $T1$ and C. The MTE, unlike the group TE, accounts for technology gaps. The mean MTE is statistically significant for both the $T1$ (3.7 percentage points) and $T2$ (6.4 percentage points) relative to C.

These findings suggest that access to only RiceAdvice increases managerial skills of rice farmers despite producing the same amount of the potential output embodied in the best-practice technology as the control group (about 81%). However, coupling RiceAdvice with fertilizer input increases both the production potential and managerial performance of rice farmers. This highlights the positive role of input bundling, and in this case, relaxing the liquidity constraint for farm-level productivity gains. Results on the mean frontier yields are consistent with the MTE and TGR gains of the treated group. Frontier yields increase by about 4.2% (245/5845.9*100) and 10.9% (635/5845.9*100) for the $T1$ and $T2$, respectively.

Also, means of FPI are significantly higher for the $T2$ and $T1$ compared C, indicating that treated farmers increase fertilizer productivity by 3.3 times for the T2 and 1.7 times for the T1. In Figure 2, we plot the components of FPI which show that although the differences in FPI between the groups are driven by the input deepening, environmental, technology, and technical efficiency indices, IDI has an outsized role in driving the FPI differences. Thus, RiceAdvice does influence the input mix by causing farmers to adjust the quantities of other conventional inputs relative to that of fertilizer.

In Figures 3 and 4, we plot the treatment effects for $T1$ and $T2$ across years. We see that in general, the effects increase until 2017 after which they dissipate. This suggests the need for efforts that will help to at least sustain the impact over time.

Table 1. Maximum likelihood estimates of parameters using the TRE SPF estimator

Variables	All	C	T1	T2
Constant	7.678***	7.906***	7.350***	7.728***
	(0.101)	(0.194)	(0.140)	(0.413)
T1: Advice	0.045**			
	(0.019)			
T2: Advice + input	0.128***			
	(0.023)			
Land	0.738***	0.784***	0.661***	0.701***
	(0.018)	(0.030)	(0.027)	(0.068)
Seed	0.076***	0.033	0.141***	0.124***
	(0.013)	(0.021)	(0.021)	(0.047)
Labor	0.009	0.009	0.001	0.019
	(0.006)	(0.011)	(0.011)	(0.024)
Fertilizer	0.054***	0.039**	0.098***	0.05
	(0.011)	(0.018)	(0.016)	(0.032)
Other chemicals	0.055***	0.064***	0.031**	0.041
	(0.012)	(0.022)	(0.015)	(0.043)
Extension	0.026	0.024	−0.018	0.088
	(0.021)	(0.041)	(0.035)	(0.070)
Credit	0.007	0.002	0.027	−0.086
	(0.029)	(0.052)	(0.033)	(0.115)
Group	0.023	0.045	0.031	−0.038
	(0.020)	(0.030)	(0.033)	(0.098)
Moderate soil	−0.024	0.046	−0.091**	−0.062
	(0.037)	(0.133)	(0.044)	(0.164)
Rich soil	0.001	0.07	−0.037	−0.073
	(0.040)	(0.133)	(0.048)	(0.167)
Upland irrigated	0.001	−0.004	−0.010	−0.082
	(0.028)	(0.044)	(0.038)	(0.162)
Lowland non-irrigated	−0.010	0.022	−0.013	−0.183
	(0.038)	(0.063)	(0.057)	(0.172)
Lowland irrigated	0.046	0.058	0.03	−0.065
	(0.030)	(0.051)	(0.040)	(0.166)
Scale elasticity	0.932***	0.930***	0.933***	0.936
LGA fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes

Table 1. *Cont.*

Variables	All	C	T1	T2
Dummies(=1) for non-use of fertilizer & other chemicals†	Yes	Yes	Yes	Yes
σ_ω	0.002	0.003	0.035***	0.009
σ_u	0.761	0.814	0.651	0.837
$\lambda(=\sigma_u/\sigma_v)$	4.5	5.4	3.9	5.7
Log-likelihood	−1700.6	−809.1	−558	−269.7
N	2724	1220	1106	398

Notes:

The dependent variable is log of rice output. Standard errors are clustered at the panel level. σ_u and σ_ω are the standard deviations of technical inefficiency and the random farm effects, respectively. C=control group (received the traditional blanket extension recommendation); $T1$=treatment arm 1 (received traditional advice plus RiceAdvice recommendation); $T2$=treatment arm 2 (received traditional advice plus RiceAdvice recommendation plus in-kind input subsidy (100%) in year 2016).

† Following Battese (1997), a dummy is included for each variable to account for the zero-valued observations after adjusting the zero values of the continuous variables.

Test of same production technology between $T1$ and C: $LR \sim \chi^2_{23} = 86.523; p = 0.000$

Test of same production technology between $T2$ and C: $LR \sim \chi^2_{23} = 76.223; p = 0.000$

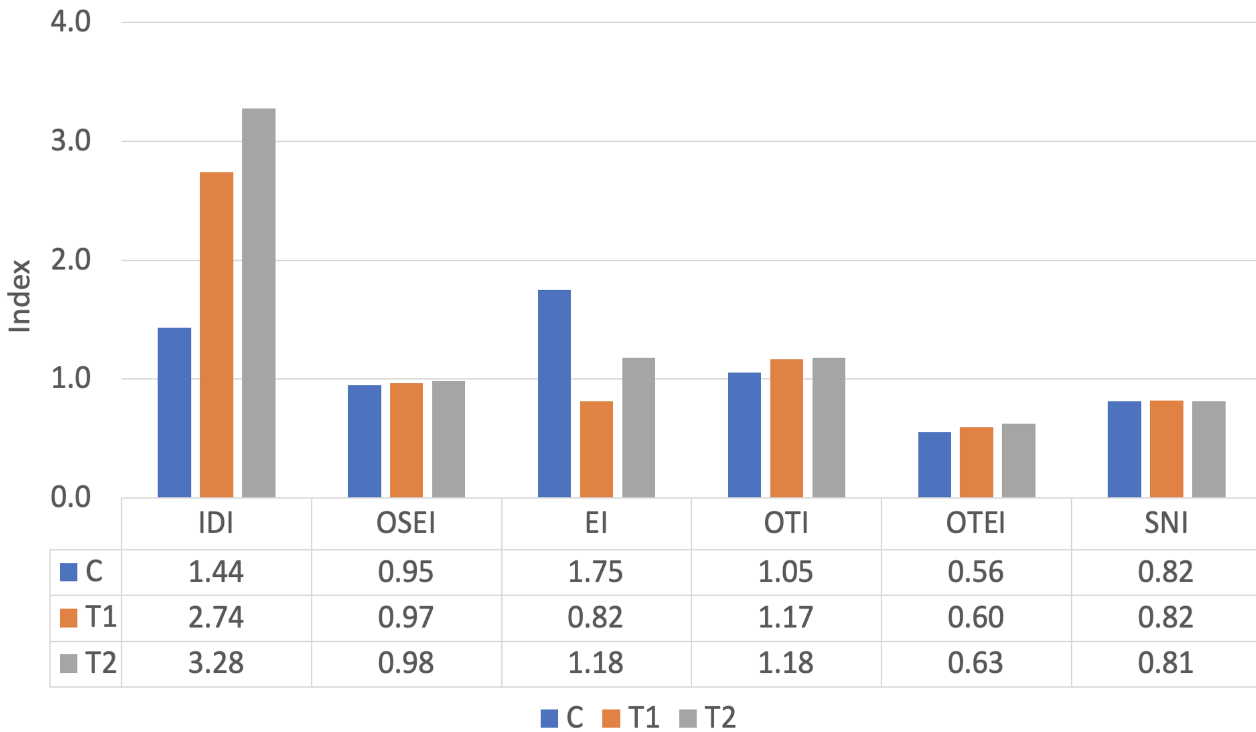
Test of same production technology between $T2$ and $T1$: $LR \sim \chi^2_{23} = 68.623; p = 0.000$

$^{**}\, p < 0.05$, $^{***}\, p < 0.01$

Table 2. Means and differences of productivity indicators across treatment

Indicator	Mean			Difference		
	C	T1	T2	T1-C	T2-C	T2-T1
Group TE	0.604	0.648	0.599	0.044^{***}	-0.005	-0.049^{***}
	[0.199]	[0.178]	[0.199]	(0.008)	(0.011)	(0.011)
TGR	0.813	0.811	0.929	-0.001	0.116^{***}	0.117^{***}
	[0.095]	[0.077]	[0.057]	(0.004)	(0.005)	(0.004)
MTE	0.496	0.533	0.56	0.037^{***}	0.064^{***}	0.027^{**}
	[0.187]	[0.174]	(0.196]	(0.008)	(0.011)	(0.011)
Frontier yield	5845.9	6091.3	6480.7	245.0^{***}	635^{***}	389.0^{***}
	[936.1]	[1145.2]	[1317.0]	(43.0)	(60.0)	(70.0)
FPI	1.269	2.123	4.133	0.854^{**}	2.864^{***}	2.009^{**}
	[6.462]	[12.858]	[19.993]	(0.416)	(0.657)	(0.881)

Notes:
Standard deviations are in square brackets and standard errors in parenthesis. C=control group (received the traditional blanket extension recommendation); $T1$=treatment arm 1 (received traditional advice plus RiceAdvice recommendation); $T2$=treatment arm 2 (received traditional advice plus RiceAdvice recommendation plus in-kind input subsidy (100%) in year 2016).** $p < 0.05$, *** $p < 0.01$.



	IDI	OSEI	EI	OTI	OTEI	SNI
C	1.44	0.95	1.75	1.05	0.56	0.82
T1	2.74	0.97	0.82	1.17	0.60	0.82
T2	3.28	0.98	1.18	1.18	0.63	0.81

Figure 2. Means of the FPI components by treatment

Notes: C=control group (received the traditional blanket extension recommendation); $T1$=treatment arm 1 (received traditional advice plus RiceAdvice recommendation); $T2$=treatment arm 2 (received traditional advice plus RiceAdvice recommendation plus in-kind input subsidy (100%) in year 2016). IDI - input deepening index, OSEI - output-oriented scale efficiency index, EI - environmental index, OTI - output-oriented technology index, OTEI - output-oriented technical efficiency index, SNI - statistical noise index

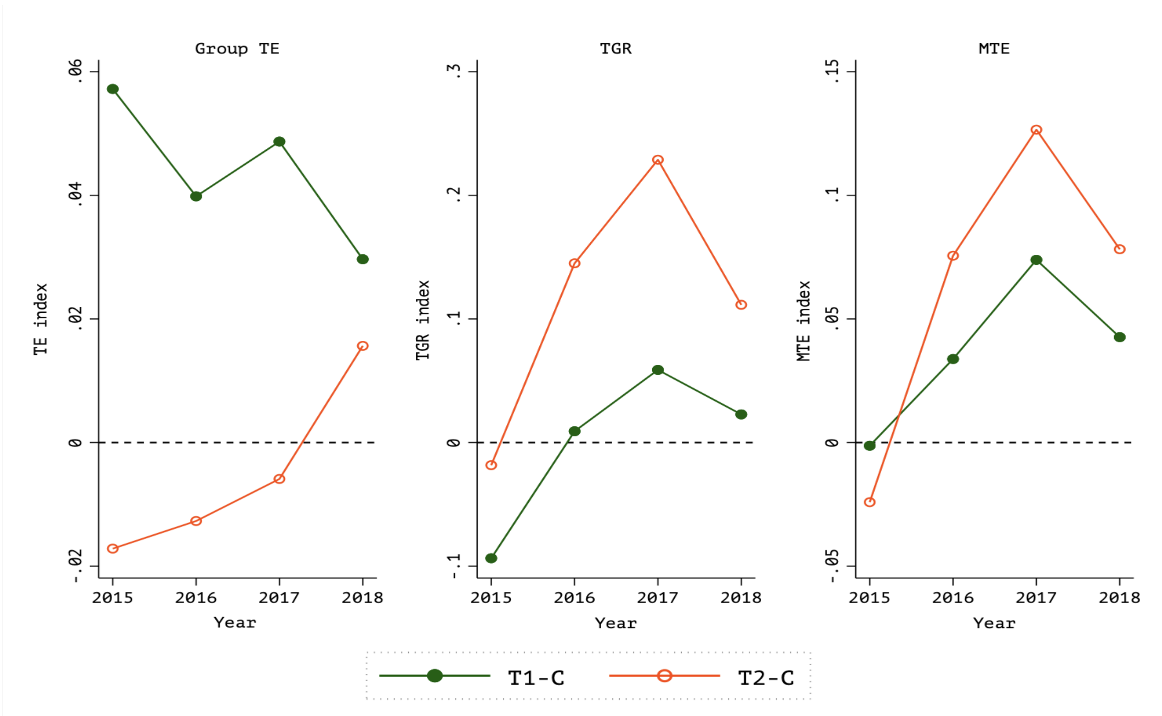


Figure 3. Treatment effect on TE, TGR, and MTE by year

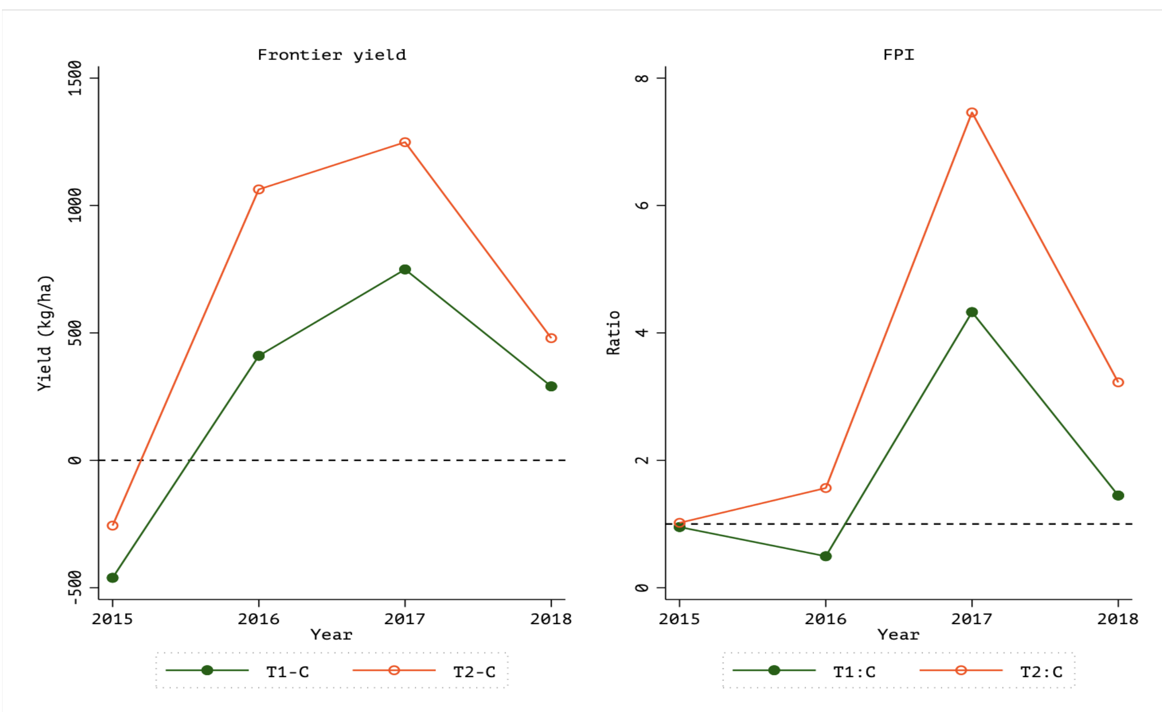


Figure 4. Treatment effect on frontier yield and FPI by year

6 Concluding Remarks

This study analyzes the impact of RiceAdvice app introduced in rice farming in Kano State, Northern Nigeria on smallholders technological endowment, managerial performance, yield and fertilizer productivity. We couple the stochastic frontier technique with the randomized evaluation framework to examine the causal impact of the app on various aspects of smallholder productivity and then examine the persistence of impacts over time. The analysis is then extended to address production technology differences among the three treatment groups to be able to conduct valid comparisons of managerial performance. We also analyze fertilizer productivity impacts by computing an index that accounts for the effects of both conventional and non-conventional factors of production.

We find that the RiceAdvice app significantly increases both technical efficiency and technological advantages of smallholder rice farmers allowing them to significantly increase their output and economize on fertilizer use without compromising output. The effect tends to be larger for farmers offered in-kind fertilizer subsidy, which shows that relaxing liquidity constraints, often binding for smallholders, has robust productivity gains. Although, the impact associated with the app increased in the first two years, in general, the last year of follow-up data point to the initial impact having a waning effect.

These findings call for a need to improve farmers' access to the app. In this study, the in-kind fertilizer subsidy was only given in the first treatment year. In the future, it will be good to find ways to make fertilizer more accessible for farmers in the absence of the direct subsidy.

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