Invited paper presented at the 6th African Conference of Agricultural Economists, September 23-26, 2019, Abuja, Nigeria

Can site-specific extension services improve fertilizer use and yields? Experimental evidence from Nigeria

Oyakhilomen Oyinbo[a*], Jordan Chamberlin[b], Abdoulaye Tahirou[d], Bernard Vanlauwe[c], Alpha Yaya Kamara[d], Peter Craufurd[e], Miet Maertens[a]

[a] Division of Bio-economics, Department of Earth and Environmental Sciences, KU Leuven, Celestijnenlaan 200E-box 2411, 3001 Heverlee, Belgium
[b] International Maize and Wheat Improvement Center (CIMMYT), Ethiopia
[c] International Institute of Tropical Agriculture (IITA), Kenya
[d] International Institute of Tropical Agriculture (IITA), Nigeria
[e] International Maize and Wheat Improvement Center (CIMMYT), Kenya
*Corresponding author: oyakhilomen.oyinbo@kuleuven.be

Abstract

Site-specific extension services are potentially more relevant for farmers than generalized extension recommendations that do not take into account localized variation in production conditions but this remains an empirical question. In this paper, we analyze the causal effects of farmers' exposure to site-specific nutrient management information for maize from an ICT-enabled extension tool in Nigeria**.** To estimate the causal effects, we implement a randomized controlled trial (RCT). We find evidence that the informational interventions improved farmers' fertilizer application rates but this is only significant for farmers whose application rates prior to the interventions are below the site-specific recommended rates for their growing conditions. Also, we find strong evidence of a significant increase in take-up of recommended fertilizer use management practices in response to the interventions. In terms of yield response, the interventions generated positive and significant maize yield gains which largely operate through better fertilizer management practices. Furthermore, we find that farmers exposed to site-specific nutrient management with additional information on the variability of expected returns have better responses in their input use decisions. This suggests that access to information on the riskiness of expected returns has consequences for farmers' behavioral responses to agronomic recommendations.

Key words: Adoption, Site-specific extension, Fertilizer use, Management practices, Maize yields

1. Introduction

Crop yields are often far below attainable yields, leading to substantial yield gaps with other regions (Guilpart et al., 2017; Benson and Mogues, 2018). A primary biophysical constraint is the depletion of soil fertility arising from poor soil fertility management (Sanchez, 2002; Berazneva et al., 2018). Yet, the use of fertilizer to address the poor fertility of soils is still on average low in SSA (Harou et al., 2017; Benson and Mogues, 2018; Jayne et al., 2019). It is well documented that informational inefficiencies on correct fertilizer use (e.g. what type, what rate, when, and how to apply) and soil fertility management in general contributes in limiting the use of fertilizer as well as the returns to fertilizer use (Liverpool-Tasie et al., 2017; Harou et al., 2017). Most agricultural extension systems in SSA provide only generalized or 'blanket' soil fertility management recommendations to farmers in large growing areas (Shehu et al., 2018; Oyinbo et al., 2019). Such recommendations are provided to farmers at scales beyond the farm, village, province, and/ or region and do not account for the substantial variation in biophysical and socioeconomic conditions of farmers. More effective soil fertility management will likely require relevant site-specific extension services, in which recommendations are tailored to the field-specific conditions of individual farmers but this remains an empirical question.

There is a growing interest in the use of information and communication technology (ICT) enabled decision support tools (DSTs) in provision of site-specific information. In the context of soil fertility, a nutrient management extension tool for maize, called 'Nutrient Expert' (NE) was developed for Nigeria to enable extension systems provide site-specific soil fertility information to farmers[1]. Empirical agronomic studies that have evaluated the use of NE for maize in some parts of Asia are mainly based on experimental plots monitored by researchers or researcher-farmer managed trials (Pampolino et al., 2012; Xu et al., 2016). Such experimental plots may not reflect real-world farm settings where farmers have full control over their resource allocations and management practices (Duflo et al., 2008; Beaman et al., 2013; Jayne et al., 2019).

In this paper, we undertake a rigorous evaluation of the impacts of farmers' access to site-specific nutrient management (SSNM) information enabled by the NE tool, which has hitherto not been addressed in Nigeria and SSA at large to the best of our knowledge. The outcomes of interest are fertilizer use rate, take-up of fertilizer use management practices and yield. Specifically, we test two hypotheses. First, we test whether or not farmers respond differently to SSNM versus blanket recommendations in terms of the outcomes of interest and secondly, we test whether or not complementary information about variability of returns also impacts farmers' responses to SSNM. To do so, we implement a clustered randomized controlled trial (RCT) with two treatment groups who are exposed to SSNM informational interventions using the tool and a control group who do not receive the interventions. This involves 792 farmers in the maize belt of northern Nigeria.

Our paper address the paucity of empirical evidence on farm-level effects of farmers' exposure to site-specific extension services for soil fertility management in a real-world farm condition beyond results from experimental plots, on-farm evaluation trials and demonstration plots. Also, we make the first attempt in the literature to provide evidence on farmers' behavioral response to site-specific extension services that offer complementary information on variability of expected returns on investment. In terms of causal identification, our paper contributes to the relatively scant literatures on the use of field experiments in development economics to explain farmers' behavioral responses to soil fertility-related informational interventions (e.g. Islam, 2014; Fishman et al., 2016). Furthermore, we contribute to the emerging literature on experimental evidence-based application of mobile technologies in agricultural extension (e.g. Larochelle et al., 2019). However, our study differs from previous studies in that our soil fertility informational interventions have both features of being site-specific and delivered

---

[1] The tool was also developed for Ethiopia and Tanzania as part of the project 'Taking Maize Agronomy to Scale in Africa' (TAMASA) in Nigeria, Ethiopia and Tanzania, funded by the Bill and Melinda Gates Foundation. This project is led by CIMMYT and supported in Nigeria by IITA, and Bayero University Kano.

to farmers using a DST. Finally, we extend the use of randomization inference which is highly recommended for randomized experiments with cluster design (Athey and Imbens, 2017).

The remainder of the paper is structured as follows. In section 2 we provide a conceptual framework. Section 3 presents the research design and identification strategy. In section 4 we present our main results and provide detailed discussion of the results in Section 5. Section 6 concludes the paper.

2. Conceptual framework

To conceptualize how SSNM information enabled by DSTs can induce investment in yield-increasing inputs such as fertilizer and complementary management practices, we employ a model of agricultural technology adoption under limited information-induced uncertainty adapted from Magruder (2018). In fertilizer investment decisions, we assume that smallholders' face uncertainty about the production function that can be realized in each possible state of nature, $t \in T$ and the probability of realizing a given production function t in T is denoted as π_t. This is in addition to the uncertainty from a realization of the state of the world, which varies over space and time (random weather or output price realizations), $s \in S$. The probability of state s in S is expressed as π_s. Following Magruder (2018), we specify a simplified model of farm-household decision making with two periods, two sources of uncertainty and a farmer's objective is to maximize utility from consumption in the two periods:

$$u(c^0) + \beta \sum_{s \in S, t \in T} \pi_s \pi_t u(c^1_{s,t}) \qquad (1)$$

Where $[u(c^0)]$ is utility from consumption in period 0 (planting season), $[u(c^1_{s,t})]$ is utility from expected consumption in period 1 (harvest season), β is a discount factor. With available cash (Y), a farmer can invest in risky farm inputs (x) such as fertilizer in period 0 to produce a state-conditioned output $[f_{s,t}(x)]$ in period 1, and a safe asset (a) to earn interest (R) in period 1. Thus, a farmer maximizes the objective function subject to the following constraints:

$$c^0 = Y - x - a \qquad (2)$$

$$c^1_{s,t} = f_{s,t}(x) + Ra \qquad (3)$$

The model portrays limited information-induced uncertainty via realization of t (subjective or endogenous uncertainty), and the inherent uncertainty arising from realization of s (exogenous uncertainty). Consequently, farm-households tend to reduce investments in risky farm inputs(x), such as fertilizer, in order to smooth consumption $[u(c^1_{s,t})]$ in either good or bad s of period 1 especially in the absence of perfect insurance markets (Dercon and Christiaenen, 2011).

Given that farmers' investment decisions on fertilizer$(x)$are made up-front before realization of the state of nature s, they often base their decisions on subjective beliefs about the production function due to incomplete information. We assume that a farmer will decide to invest more in fertilizer and complementary management practices(x)if the expected utility $u_{i1}(c^1_{s,t})$ under such investment is greater than the utility $u_{i0}(c^1_{s,t})$ under a low fertilizer investment, typical of smallholder farmers in SSA. The decision is denoted as a binary choice(Y_i), where a farmer can choose to invest more in fertilizer and management practices $(Y_i = 1)$ or not $(Y_i = 0)$:

$$Y_i = \begin{cases} 1 & if \quad E[u_{i0}(c^1_{s,t})] \; < \; E[u_{i1}(c^1_{s,t})] \\ 0 & if \quad E[u_{i1}(c^1_{s,t})] \; \leq \; E[u_{i0}(c^1_{s,t})] \end{cases} \qquad (4)$$

However, the expected utility is not a sufficient condition, as fertilizer use is still on average low. As shown in equation 1, the uncertainty about the realization of t due to limited information about fertilizer use behaves as an additional element of the risk space confronting farmers' decisions (Koundari et al., 2006; Magruder, 2018). Thus, limited information tends to reduce farmers' input use and uptake of optimal crop management practices (x) in the same manner as with the inherent risk, and can lead to sub-optimal allocation of resources and yield outcome. In this regard, any intervention that can allow for reduction in limited information-induced uncertainty can induce investment in fertilizer and complementary practices. This will likely require more relevant site-specific extension services, in which recommendations are tailored to the specific conditions of individual farmers over the existing generalized (blanket) recommendations. In this regard, an additional condition I_i is required for a farmer's investment decision in period 0:

$$Y_i = \begin{cases} 1 & if \quad E[u_{i0}(c^1_{s,t})] \; < \; E[u_{i1}(c^1_{s,t})] \quad | \quad I_i \; > \; 0 \\ 0 & if \quad E[u_{i1}(c^1_{s,t})] \; \leq \; E[u_{i0}(c^1_{s,t})] \quad | \quad I_i \; \leq \; 0 \end{cases} \tag{5}$$

Where $I_i$is an indicator for farmer i having site-specific information. With a randomized provision of SSNM information (T) to maize farmers in the planting season, we assume that the limited information-induced uncertainty about investment in fertilizer use is potentially relaxed and t notation is now t^* to show the reduced uncertainty:

$$Y_i = \begin{cases} 1 & if \quad E[u_{i0}(c^1_{s,t})] \; < \; E[u_{i1}(c^1_{s,t^*})] \quad | \quad I_i \; > \; 0 \; \equiv \; T = 1 \\ 0 & if \quad E[u_{i1}(c^1_{s,t^*})] \; \leq \; E[u_{i0}(c^1_{s,t})] \quad | \quad I_i \; \leq \; 0 \; \equiv \; T = 0 \end{cases} \tag{6}$$

In comparison to the generalized recommendations, we expect that farmers' access to the SSNM information help to update their prior subjective beliefs about the production relationship, which in turn reduces the uncertainty associated with their limited information about the expected returns. Given the reduction in uncertainty in response to the treatment, we anticipate increased investment in fertilizer and complementary management practices (direct effects) which can potentially improve yield responses. In a similar vein, access to SSNM with complementary information on the variability of expected returns (i.e. in addition to technical and average returns information), should result in reduced uncertainty about expected returns. In general, we expect increased fertilizer application rates for maize as current application rates are quite low, on average, with yields on farmers' fields around 1 to 2 tons per hectare (ha) despite potentials of over 5 tons per ha (Liverpool-Tasie et al., 2017; Shehu et al., 2018).

3. Methodology

3.1 Research area

We conducted this research in Kaduna, Katsina and Kano states of northern Nigeria, where maize is widely grown under a smallholder rain-fed system across the northern Guinea, southern Guinea and Sudan Savanna agro-ecological zones. These states were selected to pilot research activities for the development of the NE tool in the maize belt of Nigeria. We sampled maize producing farm-households in the research area using a two-stage sampling design. In the first stage, we randomly selected 99 villages belonging to 17 local government areas (LGAs). This was done by randomly generating 22 sampling grids of 10 x 10 km across the primary maize producing areas in the states to ensure spatial representativeness. The second stage was the construction of a sampling frame of households cultivating maize for each of the 99 selected villages. Lastly, eight households were randomly selected from the list of maize producing farm-households in each village, which gives a sample size of 792 households.

3.2 Experimental design

Our experiment consists of two treatment arms and a control. We employ a two-step trial design. The first step in the design was the random sampling of clusters (villages) in the research area, and the second step was village-level randomization to randomly assign villages into treatment and control. The first step aims at promoting external validity and the second is for internal validity. The use of village-level randomization over individual-level randomization is to avoid unintended behavioral and spillover effects that can interfere with causal identification (Athey and Imbens, 2017). With 99 randomly selected villages, we randomly assigned the villages into three distinct groups of 33 villages per group using a random number generator. This results in 264 households in each of the three groups who are on average expected to be comparable in both observed and unobserved characteristics. The first group of farmers belong to treatment one (T1), the second to treatment two (T2) and the third to control (C).

The farmers in T1 are exposed to site-specific informational intervention on soil fertility management. This entails recommendations on SSNM for a target yield, rationale for the recommendations, detailed explanation on how to implement these recommendations (technical information) and the average expected returns (returns information). The returns on investment is estimated based on a naïve expectation of post-harvest average price of maize using the prevailing market price at the time of providing the information which is prior to the planting time. This appears less credible and raises a lot of uncertainty for farmers' investment decisions. This is akin to agronomic recommendations and extension services in general with information on average expected outcomes for farmers but no further information on the variability or riskiness of expected outcomes. Due to time lag between production decisions and realization of output, access to information on variability of expected outcomes may enhance farmers' decision-making and matter for the take-up of optimal fertilizer use and farming practices.

The farmers in T2 receive information on the variability of the expected returns from uptake of the recommendations (variance information) in addition to the technical and returns information. To provide more credible information and take into account the uncertainty of expected returns on investment using expected prices of maize, we estimate a more robust expectation of maize prices based on weekly real prices of maize (prices are only for the post-harvest months of maize marketing which represents the marketing periods farmers often sell their produce after harvest) over the last eight years in the research area. The variability in expected returns is based on variation in expected market prices of maize taken at the 25th, 50th and 75th percentiles of the average monthly real prices of maize over the 8-year period in addition to the prevailing market prices. Due to a much higher uncertainty associated with new technologies and farming practices such as SSNM, exposing farmers to information on riskiness of expected outcomes is more informative and could potentially enhance their input use decisions. The farmers in the control villages are not exposed to the interventions and their fertilizer use and management practices is based on the general recommendations prevailing in the extension systems.

3.2.1 Source of intervention

We provide the site-specific information intervention to farmers using the pre-release version of a nutrient management extension tool known as Nutrient Expert (NE), which allows extension agents to generate fertilizer and management recommendations tailored to the specific situation of an individual farmer's field in real-time (Pampolino et al., 2012). The tool is based on the SSNM principle of dynamically adjusting fertilizer application based on crop-, field- and season-specific conditions referred to as the 4Rs of nutrient stewardship: the right fertilizer source, the right rate, the right placement and the right time of application. The provision of site-specific fertilizer recommendation by the tool is based on an individual farmer's target yield and expected yield responses, and it relies on the QUEFTS (Quantitative Evaluation of the Fertility of Tropical Soils) model to predict maize yield responses. The model was calibrated for the study area using nutrient omission trials data collected in the previous two seasons. The tool works with farmer-supplied information about his plot and growing conditions and produces plot-specific information as output.

3.2.2 Implementation of intervention

The implementation of the intervention took place prior to the planting period of the 2017 season (April to May) using public agricultural extension agents. Prior to the implementation, there was intensive training and pre-test sessions to ensure that the extension agents properly understood how to use the tool, generate recommendations and interpret the results to farmers. Agents were also supervised in the field to ensure that the recommendation protocols were correctly followed. In the use of the tool by an extension agent, each farmer is fully engaged in the process and provides detailed information required for the tool to generate an output. This information includes the farmer's previous season's crop management practices on the plot (use of inorganic fertilizer and organic resources, seed type, cropping system, yield, etc.), characteristics of the growing environment (water availability, incidence of drought, flood, etc.), as well as the prevailing prices of inputs and maize. Additional information on soil characteristics (soil color, soil texture, etc.) is elicited by the extension agent through physical observation of the soil in the plot. Finally, a GPS-based plot area measurement is collected. The output generated for each farmer includes fertilizer use guidelines (amount, type, timing, placement) and optimal crop management practices to achieve a target yield (technical information), a simple profit analysis to compare returns under farmers current practice and the recommended (returns information). After generating recommendations, the extension agent clearly explains the details of the output to the farmer and provides a summary of the recommendations in a report sheet in the local language to serve as a reminder for the farmer during the course of the growing season.

3.3 Data collection

We implement two rounds of a farm-household panel survey: a baseline survey conducted in 2016 and a follow-up visit in 2017. Both survey rounds were conducted during the maize harvest season (September to October). We collected baseline data from 792 households and follow-up data from 788 households, giving an attrition rate of 0.5%. Despite the low attrition rate, we still test for possible selective or differential attrition across treatments by regressing a dropout indicator variable against treatment dummies (Özler et al., 2018). The results show that there is no evidence of selective or differential attrition of farmers from any of the two treatment arms, which indicate that the attrition in our sample does not pose a threat to the validity of our results.

3.3 Identification strategy

A simple comparison of the average post-treatment outcomes between the treated and control groups will suffice for causal identification under randomized experiments (Athey and Imbens, 2017). Since we have a panel data, we estimate the intention-to-treat (ITT) effect using difference-in-difference (DD) specification, which compares the average change in outcomes over time for the treated and control groups. It accounts for possible imbalances in pre-treatment outcomes and time-invariant unobserved heterogeneity not controlled for by randomization. We present a specification of our DD in equation (7).

$$y_{ijt} = \beta_0 + \beta_1 \mathrm{T1}_{iJt} + \beta_2 \mathrm{T2}_{iJt} + \beta_3 \mathrm{Post}_t + \beta_4 \mathrm{T1}_{iJt} * \mathrm{Post}_t + \beta_5 \mathrm{T2}_{iJt} * \mathrm{Post}_t + \varepsilon_{ijt} \qquad (7)$$

In an alternative specification, equation (8), we include baseline controls for plot-, farmer and household characteristics that are potentially correlated with outcomes of interest to improve precision of estimates.

$$y_{ijt} = \beta_0 + \beta_1 \mathrm{T1}_{iJt} + \beta_2 \mathrm{T2}_{iJt} + \beta_3 \mathrm{Post}_t + \beta_4 \mathrm{T1}_{iJt} * \mathrm{Post}_t + \beta_5 \mathrm{T2}_{iJt} * \mathrm{Post}_t + \beta_6 \mathrm{X}_{iJ} + \varepsilon_{ijt} \qquad (8)$$

Where y_{ijt} is the outcome for focal plot of household i in village j at year t (fertilizer application rates (kg/ha), adoption of optimal fertilizer use management practices in terms of combined application of inorganic and organic fertilizer (1/0), split N application (1/0), fertilizer application at sowing time, spot application of fertilizer (dibbling (1/0)), and maize yields (tons/ha)), $\mathrm{T1}_{iJt}$ and $\mathrm{T2}_{iJt}$ are binary indicators for farmers in treatment one and two respectively, β_4 and β_5 are the coefficients of interest that captures the effects of treatment one and treatment two interventions respectively, Post_t is an indicator equaling zero for observations in the baseline year and one for observations in the follow-up round, X_{iJ} is a vector of baseline control variables, ε_{ijt} is a random error term clustered at the village level to account for the cluster design, β_0 is the average value of the outcomes of interest for the control group at the baseline. The binary outcome variables are estimated using a linear probability model (LPM).

To consistently estimate the effects of the interventions on fertilizer application rates especially for farmers who are currently using rates below the recommended application rates, we use a Heckman two-step procedure (Heckman, 1979) to correct for possible selection bias. This procedure estimates an Inverse Mills Ratio (IMR) from a probit estimation of the probability of farmers' current fertilizer use rates being below the recommended fertilizer use rates (first stage). The IMR is included as an additional regressor in the outcome equations 9 and 10 (second stage) to control for possible selection bias from correlation of unobservables in the selection and the outcome equations.

We perform several robustness checks of our results. First, to control for the proportion of false treatment effects due to multiple outcomes and pairwise comparisons, we perform multiple hypothesis corrections on our outcomes of interest using False Discovery Rate (FDR)-adjusted q-values (Anderson, 2008). These q-values are computed following Anderson (2008) and related empirical implementations (Özler et al., 2018). The second robustness check is with respect to the type of statistical inference employed. Although, statistical inference in randomized experiments is commonly by sampling-based inference (asymptotic inference), it is increasingly recommended to use randomization-based inference especially for clustered designs or finite samples (Athey and Imbens, 2017; Heß, 2017; Young, 2018). Randomization inference is not sensitive to the number of clusters or observations, size of clusters, ratio of treated and control clusters and yields consistent estimates solely based on the randomization assumption (Heß, 2017). As a robustness check to our hypothesis testing by conventional inference p-values, we perform same tests of statistical significance using randomization inference p-values. In general, the results are robust to alternative statistical inference and corrections for multiple hypothesis testing.

4. Results

4.1 Baseline summary statistics and treatment balance

Table 1 shows the baseline summary statistics by treatment status of farmers and orthogonality tests. Across the treatment groups (column 1), the farmers are on average 44 years old, have about 5 years of formal schooling and 19 years of maize farming experience. They live in households with an average of about 9 members, 3 ha of farmland and 2 tropical livestock units. We perform randomization checks by testing equality of means of the baseline characteristics between the three groups (T1=C, T2=C and T1=T2) which is equivalent to a simple regression of each baseline characteristic on a treatment dummy. The p-values of the pairwise comparisons in columns 5, 6 and 7 show that there are no significant differences in almost all the baseline characteristics between the three groups. Overall, the p-values for the chi-squared tests of joint orthogonality between the three groups show that we cannot reject the null hypothesis that the baseline observables are orthogonal to the treatment status and thus conclude that our randomization design produced comparable groups. Only in three cases out of the 69 orthogonality tests (23 variables for each group) across the three groups do we find significant differences. These are household size for T2=C and access to extension as well as yield for T2=C. We can control for these imbalances with our difference-in-difference model estimation especially for yield outcome, which could lead to upward bias if we rely only on post-treatment maize yields.

Table 1: Baseline characteristics and balance tests

	Overall sample (1)	Treatment one (T1) (2)	Treatment two (T2) (3)	Control (C) (4)	T1=C p-value (5)	T2=C p-value (6)	T1=T2 p-value (7)
Farmer/household characteristics							
Age of head (years)	44.24	44.51	44.25	43.96	0.599	0.774	0.807
	(0.42)	(0.76)	(0.73)	(0.71)			
Education of head (years)	5.20	5.36	4.83	5.41	0.916	0.268	0.326
	(0.22)	(0.38)	(0.37)	(0.37)			
Household size (no.)	9.12	8.96	9.77	8.62	0.426	0.016	0.113
	(0.19)	(0.33)	(0.39)	(0.27)			
Group membership (1/0)	0.31	0.34	0.29	0.289	0.190	0.924	0.225
	(0.02)	(0.03)	(0.03)	(0.03)			
Access to credit (1/0)	0.23	0.22	0.24	0.24	0.679	0.839	0.536
	(0.02)	(0.03)	(0.03)	(0.03)			
Maize farming experience (years)	18.96	19.50	18.45	18.92	0.524	0.601	0.260
	(0.37)	(0.65)	(0.67)	(0.62)			
Access to extension (1/0)	0.39	0.43	0.39	0.35	0.050	0.281	0.378
	(0.02)	(0.03)	(0.03)	(0.03)			
Maize contract farming (1/0)	0.19	0.18	0.18	0.21	0.440	0.509	0.910
	(0.01)	(0.02)	(0.02)	(0.03)			
Livestock holding (TLU)[1]	2.14	2.11	2.35	1.95	0.677	0.184	0.555
	(0.15)	(0.34)	(0.21)	(0.22)			
Number of plots cultivated	2.70	2.75	2.66	2.69	0.528	0.763	0.356
	(0.04)	(0.07)	(0.07)	(0.07)			
Total farm area (hectare)	3.11	3.08	3.26	2.98	0.728	0.370	0.560
	(0.12)	(0.20)	(0.24)	(0.20)			
Assets (1,000 NGN)[2]	545.66	557.12	598.99	480.88	0.232	0.103	0.579
	(28.83)	(47.53)	(58.48)	(42.40)			
Annual income (1,000 NGN)[3]	184.21	178.74	196.12	177.77	0.969	0.539	0.517
	(11.09)	(14.71)	(22.43)	(19.73)			
Access to off-farm income (1/0)	0.88	0.86	0.91	0.86	0.900	0.105	0.135
	(0.01)	(0.02)	(0.02)	(0.02)			
Plot-level characteristics							
Focal plot area (hectare)	0.80	0.84	0.81	0.76	0.345	0.609	0.719
	(0.04)	(0.06)	(0.07)	(0.06)			
Plot ownership (1/0)	0.96	0.94	0.97	0.97	0.108	1.000	0.108
	(0.01)	(0.02)	(0.01)	(0.01)			
Plot distance (time in minutes)[4]	15.33	14.72	16.02	15.25	0.646	0.627	0.372
	(0.57)	(0.70)	(1.27)	(0.93)			
Use organic fertilizer (1/0)	0.78	0.76	0.78	0.79	0.404	0.673	0.680
	(0.02)	(0.03)	(0.03)	(0.03)			
Use improved seed (1/0)	0.29	0.27	0.31	0.28	0.627	0.506	0.250
	(0.02)	(0.03)	(0.03)	(0.03)			
Use mineral fertilizer (1/0)	0.97	0.96	0.97	0.97	0.484	1.000	0.484
	(0.01)	(0.01)	(0.01)	(0.01)			
NPK fertilizer (kg/ha)	127.29	128.51	131.77	121.60	0.465	0.287	0.740
	(3.92)	(6.87)	(7.00)	(6.50)			
Urea fertilizer (kg/ha)	85.89	83.99	88.94	84.75	0.925	0.616	0.539
	(3.34)	(5.52)	(5.87)	(5.95)			
Maize yield (tons/ha)	2.06	1.98	2.08	2.11	0.091	0.704	0.201
	(0.03)	(0.06)	(0.06)	(0.06)			
Joint orthogonality test p-value					0.840	0.502	0.282
N	792	264	264	264			

p-values are from t-tests of equality of means and the joint test p-values are from chi-squared tests, [1]One tropical livestock unit (TLU) is equivalent to 250 kg (cattle=0.7, sheep/goat=0.1, pig=0.2, chicken=0.01, duck=0.02, rabbit=0.01), [2]Value of non-land assets, including farm equipment and machinery, [3]Per-adult equivalent household annual income from all sources, [4] Time to walk from homestead to the plot, Standard errors are reported in parentheses, NGN: 305 NGN (Nigerian Naira) is equivalent to 1 USD at the survey time

4.2 Farmers' actual and recommended fertilizer application rates and yields

We examine farmers' baseline fertilizer application rates and maize yields, and compare these with the recommended rates and corresponding expected yield level from the treatment (table 2). Table 2 shows that on average farmers in treatment one apply about 93 kg of N, P_2O_5 and K_2O per ha in comparison with the average recommended site-specific rate of 242 kg of N, P_2O_5 and K_2O per ha resulting in a nutrient gap of 149 kg (61%). This nutrient gap may not be unconnected to the yield gap of an average of 3.3 tons per ha (63%) as macronutrients deficiencies are considered the primary yield-limiting factors of maize production. For treatment two farmers, they apply on average 99 kg of N, P_2O_5 and K_2O per ha with an associated yield of 2.1 tons per ha in comparison with the average recommended site-specific rate of 238 kg of N, P_2O_5 and K_2O with an expected yield of 5.3 tons per ha. This amounts to a nutrient gap of 139 kg (58%) and a yield gap of 3.3 tons per ha (61%) for farmers in treatment two. Across the two treatment arms, the farmers' application rate of N is about two-thirds of the average N, P_2O_5 and K_2O nutrients applied per ha. The observed higher application of N is expected, as it is the most limiting nutrient of maize production in Nigeria and SSA in general which necessitates application of more N to meet its requirement. In a similar vein, the site-specific recommended rates prescribe a higher N application of about one-third of the average N, P_2O_5 and K_2O nutrients per ha for a target maize yield. Across the treatment arms, the majority (95%) of farmers apply nutrients rates below the recommended rates (95% of farmers in treatment one and 91% of farmers in treatment two).

Table 2: Descriptive statistics on farmers' actual and recommended fertilizer use rates and yields

	N (kg/ha)	P_2O_5 (kg/ha)	K_2O (kg/ha)	All (kg/ha)	Yield (tons/ha)
Treatment one (T1)					
Baseline nutrient rates[1] and yields	58.49	17.42	17.42	93.34	1.98
	(48.86)	(14.54)	(14.54)	(65.61)	(0.90)
Recommended nutrient rates and expected yields	129.10	56.65	56.36	242.11	5.30
	(23.11)	(25.81)	(25.86)	(72.10)	(1.07)
Nutrient gap and yield gap	70.61	39.23	38.94	148.77	3.32
	(50.72)	(28.20)	(28.23)	(89.14)	(1.49)
Nutrient gap and yield gap (%)	55	69	69	61	63
Nutrient rate below the recommended (%)[2]	91	95	95	95	
Treatment two (T2)					
Baseline nutrient rates[1] and yields	60.55	19.30	19.30	99.15	2.08
	(49.02)	(17.94)	(17.94)	(72.92)	(0.96)
Recommended nutrient rates and expected yields	128.81	54.59	54.38	237.78	5.34
	(20.65)	(23.78)	(23.89)	(64.92)	(1.10)
Nutrient gap and yield gap	68.26	35.29	35.08	138.63	3.26
	(52.60)	(30.04)	(29.26)	(97.43)	(1.43)
Nutrient gap and yield gap (%)	53	65	65	58	61
Nutrient rate below the recommended (%)[2]	90	91	91	91	

The macronutrients are based on the fertilizer blends used by farmers, which include NPK 15:15:15 (contains 15% N, 15% P and 15% K), NPK 20:10:10 (20% N, 10% P and 10% K) and urea (46% N),

[1] Farmer's actual nutrient application rates, [2] Share of farmers who apply nutrients below the recommended site-specific rates, Standard deviations are reported in parentheses, N = 264 farmers in each treatment.

4.3 Effects of farmers' exposure to site-specific extension services

4.3.1 Effect on farmers' fertilizer application rates

Table 3a shows the ITT effects of farmers' exposure to SSNM information on their fertilizer application rates. Column 7 shows that access to SSNM information increases macronutrient application rates by an average of 6 kg of N, P_2O_5 and K_2O per ha which corresponds to around 6% increase for treatment one farmers and 12 kg (around 12%) for treatment two farmers. However, the magnitudes of these increases are small and statistically insignificant at conventional probability levels. In practice, we do not expect an increase in fertilizer application rates for all farmers exposed to site-specific fertilizer application rates as some farmers are expected to reduce their current application rates as prescribed by the site-specific recommendations. We only expect an increase in fertilizer application rates for farmers whose current fertilizer application rates prior to the interventions are below the site-specific recommended rates.

Table 3b shows the ITT effects on fertilizer application rates conditional on farmers' current application rates being below the recommended application rates. We control for possible sample selection bias using the Heckman selection model as reported in columns 2, 4, 6 and 8. The estimated coefficients of Inverse Mills Ratio (IMR) are not significantly different from zero, which implies that we do not reject the null hypothesis of no selection bias. Correspondingly, we also observe that the estimates with no control for selection bias in columns 1, 3, 5 and 7 differ little from the estimates from the Heckman selection model (Wooldridge, 2010). Based on the estimates in column 8, the results show that exposure to SSNM information increases macronutrient application rates by an average of 9 kg of N, P_2O_5 and K_2O per ha (around a 9% increase) for treatment one farmers and 22 kg (around 21%) for treatment two farmers. The observed increase for treatment two farmers is statistically significant at the 5% probability level and not significant for treatment one farmers, which means that exposing farmers to information on SSNM and riskiness of expected returns produces better response than recommendations with no information on riskiness of expected returns. In terms of the treatment effects for each of the nutrients, the observed increase is consistent across the nutrients.

Table 3a: ITT effects on farmers' fertilizer application rates

Variables	N (kg/ha)		P_2O_5 (kg/ha)		K_2O (kg/ha)		All (kg/ha)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment one	0.976	0.714	2.360	2.188	2.398	2.224	5.736	5.127
	(6.637)	(6.792)	(2.467)	(2.510)	(2.459)	(2.502)	(9.867)	(10.155)
Treatment two	8.200	8.020	2.153	2.101	2.054	2.001	12.405	12.120
	(5.638)	(5.652)	(2.465)	(2.473)	(2.436)	(2.444)	(8.888)	(8.933)
HH controls	No	Yes	No	Yes	No	Yes	No	Yes
[1]F-statistic	1.11	1.13	0.01	0.00	0.03	0.01	0.46	0.50
Baseline control mean	62.19	62.19	20.35	20.35	20.35	20.35	102.88	102.88
Observations	1380	1380	1380	1380	1380	1380	1380	1380

Estimates in columns 1, 3, 5 and 7 (results without HH controls), estimates in columns 2, 4, 6 and 8 (results with control for baseline covariates: age of farmer, education of farmer, household size, group membership, access to credit, access to off-farm income, access to contract farming, value of assets, plot ownership, plot distance),

[1]F-test of equality of treatment effects (treatment one=treatment two)

Table 3b: ITT effects on farmers' fertilizer application rates

Variables	N (kg/ha)		P_2O_5 (kg/ha)		K_2O (kg/ha)		All (kg/ha)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment one	3.807	3.805	2.458	2.437	2.492	2.468	8.759	8.710
	(6.444)	(5.896)	(2.585)	(2.193)	(2.571)	(2.188)	(10.290)	(9.191)
Treatment two	13.162**	13.167**	4.482*	4.516**	4.357*	4.395**	22.000**	22.078**
	(5.448)	(6.006)	(2.362)	(2.237)	(2.327)	(2.233)	(8.538)	(9.367)
IMR (Lambda)	-	1.438	-	10.728	-	12.058	-	24.226
		(48.617)		(17.964)		(17.892)		(75.645)
HH controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
[1]F-statistic	2.50	1.10	0.96	0.89	0.83	0.77	2.15	2.10
Baseline control mean	62.19	62.19	20.35	20.35	20.35	20.35	102.88	102.88
Observations	1312	1380	1312	1380	1312	1380	1312	1380

Estimates in columns 1, 3, 5 and 7 (results with no control for sample selection), estimates in columns 2, 4, 6 and 8 (second stage regression of Heckman selection model: control for sample selection),

Standard errors clustered at the village level reported in parentheses, with significance denoted as * $p < 0.1$, ** $p < 0.05$ and *** $p < 0.01$

[1]F-test of equality of treatment effects (treatment one=treatment two)

4.3.2 Effect on farmers adoption of optimal fertilizer use management practices

In table 4, we report the results of the effects of exposing farmers to SSNM information on adoption of optimal fertilizer use management practices. These practices relate to the source of nutrients, timing of nutrients application and method of nutrients application that are recommended to increase the efficiency of fertilizer use. Columns 1 and 2 of the table show that access to the interventions increases the likelihood of adopting combined use of inorganic fertilizer and organic manure as nutrient sources by an average of 15% and 16% points for treatments one and two farmers respectively. The effects are significant at the 1% probability level. This is expected as the treated farmers may have received better information about the complimentary effects of the combined use of inorganic fertilizer and organic manure in improving response to fertilizer application. Columns 3 and 4 shows that on average, the likelihood of adopting the practice of splitting N application increases by 13-14% points for farmers in treatment one and the observed effects with and without baseline controls are significant at the 10% probability level. The likelihood of adopting this practice increases by an average of 17% points for farmers in treatment two at the 5% probability level. Splitting application of N is strongly recommended in SSNM to ensure that N is available when needed at different stages in the growth cycle of maize. In terms of fertilizer application at sowing, columns 5 and 6 shows that the farmers in treatments one and two are on average 17% and 19% points respectively more likely to apply fertilizer at the time of sowing and the effects are statistically significant at 1%. Fertilizer application at sowing as an element of timing of nutrient application contributes in making nutrients available at the early stage of crop development. This is an uncommon practice in the research area as indicated by the baseline mean of 14% for the control group. For the use of dibbling or spot application as a method of nutrients application, columns 7 and 8 shows that access to the interventions increases the likelihood of using this practice by an average of 14-15% points and 20% points for treatments one and two farmers respectively. The effects are significant at the 10% and 1% probability levels for treatments one and two farmers respectively. This implies that incorporating nutrients into the soil rather than applying on the soil surface is more appealing to the treated farmers due to their exposure to SSNM information. This practice reduces nutrient losses and ensures optimal uptake of nutrients applied to crops.

4.3.3 Effect on maize yields

The results in columns 1 and 2 of table 5 show that exposing farmers to the informational interventions leads to an increase in yields for treatment one farmers by an average of 0.2 tons per ha which corresponds to around 10% increase in yield over the baseline yield of the control farmers. For the treatment two farmers, the interventions increase yields on average by 0.3 tons per ha (around 14%). These observed effects are statistically significant at the 1% and 5% probability levels for farmers in treatment one and two respectively. These results imply that providing fertilizer recommendations targeted at the specific needs of individual farmers can produce considerable yield gains for farmers. A potential confounding factor to the observed treatment effects is the incidence of fall army worm (FAW) infestation during the 2017 maize growing season in Nigeria and other parts of SSA (Nagoshi et al., 2018). Although, we find a relatively low incidence of 17%, we control for this to consistently estimate the causal effect of the interventions. The results in column 3 are consistent with those of columns 1 and 2, which imply that the incidence of FAW does not interfere with our causal inference. In columns 4 and 5, we report the results of the yield effects of the interventions conditional on farmers' current application rates being below the recommended application rates. The coefficient of Inverse Mills Ratio (IMR) is not statistically significant, indicating no evidence of sample selection bias. The results are very similar to those of columns 1, 2 and 3. However, the yield gains for farmers in treatment one is slightly lower and statistically insignificant at the conventional probability levels. In general, the results show that conveying SSNM information to farmers is potentially effective in improving yield response.

Table 4: ITT effects on farmers' fertilizer use management practices

Variables	Inorganic-organic fertilizer (1/0)		N split application (1/0)		Fertilizer at sowing date (1/0)		Fertilizer application method (dibbling (1/0))	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment one	0.147***	0.148***	0.135*	0.134*	0.170***	0.167***	0.149*	0.138*
	(0.052)	(0.052)	(0.076)	(0.076)	(0.056)	(0.056)	(0.077)	(0.077)
Treatment two	0.164***	0.163***	0.173**	0.171**	0.187***	0.186***	0.202***	0.198***
	(0.052)	(0.051)	(0.068)	(0.069)	(0.061)	(0.061)	(0.073)	(0.073)
HH controls	No	Yes	No	Yes	No	Yes	No	Yes
[1]F-statistic	0.10	0.08	0.38	0.37	0.09	0.13	0.45	0.57
Baseline control mean	0.77	0.77	0.79	0.79	0.14	0.14	0.36	0.36

Estimates in columns 1, 3, 5 and 7 (results without HH controls), estimates in columns 2, 4, 6 and 8 (results with control for baseline covariates: age of farmer, education of farmer, household size, group membership, access to credit, access to off-farm income, access to contract farming, value of assets, plot ownership, plot distance), Standard errors clustered at the village level reported between parentheses, Significant coefficients at * $p < 0.1$, ** $p < 0.05$ and *** $p < 0.01$

[1]F-test of equality of treatment effects (treatment one=treatment two)

Table 5: ITT effects on maize yields

	Yield (tons/ha)				
	(1)	(2)	(3)	(4)	(5)
Treatment one	0.201*	0.201*	0.205*	0.194	0.193
	(0.120)	(0.120)	(0.120)	(0.122)	(0.123)
Treatment two	0.256**	0.256**	0.257**	0.262**	0.265**
	(0.121)	(0.121)	(0.121)	(0.127)	(0.125)
FAW (1/0)		0.019			
		(0.075)			
IMR (Lambda)					0.693
					(1.004)
HH controls	No	No	Yes	Yes	Yes
[1]F-statistic	0.23	0.23	0.19	0.31	0.34
Baseline control mean	2.12	2.12	2.12	2.12	2.12
Observations	1380	1380	1380	1312	1380

Column 1 (results without HH controls) column 2 (results with control for fall army worm (FAW) infestation during the maize production season, column 3 (results with control for baseline covariates: age of farmer, education of farmer, household size, group membership, access to credit, access to off-farm income, access to contract farming, value of assets, plot ownership, plot distance), column 4 (results without control for sample selection), column 5 (Heckman selection model: control for sample selection, Standard errors clustered at the village level reported between parentheses,

Significant coefficients at * $p < 0.1$, ** $p < 0.05$ and *** $p < 0.01$

[1]F-test of equality of treatment effects (treatment one=treatment two)

5. Discussion

We find that exposing farmers to site-specific nutrient management information in a tablet-based decision support tool improves fertilizer application rates for maize cultivation but for farmers who are using rates below the recommended rates. This indicates that overly coarse information on fertilizer use (i.e. the typical case of "blanket" recommendations) explains an important part of the observed low intensity of fertilizer use for some farmers in our research area. This finding is consistent with the literature on the role of limited knowledge in conditioning fertilizer use (Jayne et al., 2019). Moreover, the provision of a recommended fertilizer application rate for a target yield, combined with additional information on the distribution of expected returns, appears to increase fertilizer use by reducing farmers' uncertainty about fertilizer investment outcomes. We see evidence for this in the fact that fertilizer application rate treatment effects are only significant for farmers in treatment two (i.e. who received additional information on the riskiness of expected returns). Our findings contrast somewhat with the findings of closely-related randomized experiments. Fishman et al. (2016) found that access to site-specific fertilizer recommended rates from soil testing in India did not affect fertilizer application for rice, mainly due to the treated farmers' lack of confidence in the recommendations. Islam (2014) found that the receipt of fertilizer application guide from leaf color chart in Bangladesh significantly *reduced* the application rates of urea for rice, but this was in a context where most of the farmers had been over-applying urea prior to site-specific advice.

We find strong evidence that receipt of the interventions improves fertilizer use management practices in terms of combined use of fertilizer and organic manure, fertilizer application timing (split applications of N, including application at sowing), and application method (spot application aka "dibbling"). This is not surprising as the informational interventions are not only about optimal fertilizer application rates but strongly emphasize the use of optimal fertilizer use management practices to enhance yield responses to fertilizer. This is predicated on the idea that efforts to improve yield responses to fertilizer does not only depend on fertilizer use rates but optimal crop management practices (Burke et al., 2017; Jayne et al., 2019). This result is consistent with Pan et al. (2018) who find that information via extension services significantly increased the uptake of improved cultivation practices in Uganda.

We find evidence of yield increasing effects of the farmers' receipt of the informational interventions, and the impact pathway for the observed yield gains largely occurs through the improved fertilizer use management practices of farmers. This indicates that although increased investment in external inputs such as fertilizer can be risk increasing, the knowledge of correct use in the context of SSNM can relax the risk of low yield response arising from poor technical knowledge of fertilizer use (Benson and Mogues, 2018). Furthermore, access to information on the expected returns as well as the variability of the expected returns possibly improves the farmers input use decisions and management practices resulting in yield gains. This is expected as such information reduces the perceived uncertainty about the expected benefits of the recommended site-specific fertilizer application practices over the traditional practices of farmers in line with our conceptual framework.

Finally, we provide some policy implications of our findings for agricultural extension systems and larger development community. Our empirical evidence supports the use of DSTs such as NE in agricultural extension systems to improve provision of site-specific nutrient management information to farmers. However, there are areas of concern that need to be addressed. For the development of nutrient management and other agronomic DSTs, farmers are not only interested in the agronomic recommendation and the associated average expected returns, but are also interested in the variability of expected returns. Conveying site-specific information to farmers with predicted returns based on average yields without information on variance around the average yields (riskiness of expected returns) can be misleading and less informative for farmers (Vanlauwe et al., 2016). The use of weather data such as rainfall should be explored to simulate possible distribution of expected yields and returns on investment in the use of site-specific recommendations over the existing practice of farmers, which will be more informative, particularly for risk-averse farmers. Despite the potentials of current agronomic advisory tools, another area of concern is that the use of the tools requires physical contact of extension agents with farmers, which may limit farmers' access given the poor extension coverage due to the very low agents-to-farmers ratio that is typical in the region. This calls for increased investments in extension systems to scale out the use of these innovative tools for better service delivery to farmers. In other words, investments in DST development should not be seen as substitutes for investments in extension systems and other modes of scaling advisory services. Lastly, with so much emphasis on intensifying fertilizer application rates in environments where the returns to fertilizer investments are often low and variable, extension systems could benefit from DSTs which better inform farmers about optimal fertilizer use and crop management practices beyond simply making fertilizer application rate recommendations. This is consistent with empirical studies (Burke et al., 2017; Jayne et al., 20119), on promoting complementary measures and services to improve yield response to fertilizer application and returns on investment.

6. Conclusion

In this paper, we empirically evaluate the impact of farmers' exposure to site-specific nutrient management recommendations for maize from an ICT-enabled extension tool 'Nutrient Expert' in the maize belt of Nigeria**.** To do so, we implement a clustered RCT with two treatment groups and a control group. We find evidence of improved fertilizer application rates specifically for farmers whose application rates prior to the interventions are below the site-specific recommended rates for their growing conditions. However, this is only significant for farmers exposed to the full range of information, i.e. the site-specific fertilizer recommendations, average expected returns and distribution of expected returns. There is substantial evidence of significant increase in the use of optimal fertilizer use management practices in response to the receipt of site-specific nutrient management informational interventions by the farmers. Also, the receipt of site-specific nutrient management informational interventions by the farmers resulted in significant yield increasing effects. The impact pathway for the yield gains largely occurs through complementary fertilizer use management practices. In terms of the magnitude of response to the informational interventions, the farmers exposed to additional information on variance of expected returns have better response than farmers who did not receive the additional information. This suggests that the provision of information on the uncertainty of expected returns (rather than simply providing the average expected returns, as most tools do) matters for farmers given the time lag between investment decisions and realization of returns. To avoid relying solely on predicted returns based on average yields, this calls for further improvement of tools to allow for provision of information on variability of expected returns on the use of recommended site-specific fertilizer management practices for better informed input use decision-making. Our findings lend credence to the use of ICT-enabled tools for extension, and strongly suggest that extension and development organizations as well as policy institutions interested in improving maize yields and food security should support and promote the use of DSTs to improve the delivery of relevant soil fertility advisory services to farmers.

References

Athey, S. & Imbens, G.W. (2017). The econometrics of randomized experiments. In A. Banerjee, A. V. & Duflo, E. (Eds.), *Handbook of Economic Field Experiments* (vol. 1, pp. 73-140).

Beaman, L., Karlan, D., Thuysbaert, B. & Udry, C. (2013). Profitability of fertilizer: Experimental evidence from female rice farmers in Mali. *American Economic Review*, 103 (3), 381-86.

Benson, T. & Mogues, T. (2018). Constraints in the fertilizer supply chain: Evidence for fertilizer policy development from three African countries. *Food Security*, 10(6), 1479-1500.

Berazneva, J., McBride, L., Sheahan, M. & Güereña, D. (2018). Empirical assessment of subjective and objective soil fertility metrics in east Africa: Implications for researchers and policy makers. *World Development*, 105, 367-382.

Burke, W.J., Jayne, T.S. & Black, T.J.R. (2017). Factors explaining the low and variable profitability of fertilizer application to maize in Zambia. *Agricultural Economics*, 48, 115-126.

Dercon S. & Christiensen L. (2011). Consumption risk, technology adoption and poverty traps: Evidence from Ethiopia. *Journal of Development Economics*, 96 (2), 159-173.

Duflo, E., Kremer, M. & Robinson, J. (2008). How high are the returns to fertilizer? Evidence from field experiments in Kenya. *American Economic Review*, 98(2), 482-88.

Harou, A.P., Liu, Y., Barrett, C.B. & You, L., (2017). Variable returns to fertilizer use and the geography of poverty: Experimental and simulation evidence from Malawi. *Journal of African Economics*, 26, 342-371.

Heckman, J. J. (1979). Sample selection bias as a specification error. *Econometrica*, 47 (1), 153-161.

Jayne, T.S., Snapp, S., Place, F. & Sitko, N. (2019). Sustainable agricultural intensification in an era of rural transformation in Africa. *Global Food Security*, 20, 105-113.

Koundouri, P., Nauges, C. & Tzouvelekas, V. (2006). Technology adoption under production uncertainty: theory and application to irrigation technology. *American Journal of Agricultural Economics,* 88, 657-670.

Larochelle, C., Alwang, J., Travis, E., Barrera, V.H. & Andrade, J.M.D. (2019). Did you really get the message? Using text reminders to stimulate adoption of agricultural technologies. *Journal of Development Studies*, 55, 4, 548-564.

Liverpool-Tasie, L.S.O., Omonona, B.T., Sanou, A. & Ogunleye, W.O. (2017). Is increasing inorganic fertilizer use for maize production in SSA a profitable proposition? Evidence from Nigeria. *Food policy*, 67, 41-51.

Magruder, J. (2018). An assessment of experimental evidence on agricultural technology adoption in developing countries. *Annual Review of Resource Economics*, 10, 19.1-19.18

Özler, B., Fernald, L.C.H., Kariger, P., McConnell, C., Neuman, M. & Fraga, E. (2018). Combining pre-school teacher training with parenting education: A cluster randomized controlled trial. *Journal of Development Economics*, 133, 448-467.

Oyinbo, O., Chamberlin, J., Vanlauwe, B., Vranken, L., Kamara, A.Y., Craufurd, P. & Maertens, M. (2019). Farmers' preferences for high-input agriculture supported by site-specific extension services: Evidence from a choice experiment in Nigeria. *Agricultural Systems*, 173, 12-26.

Pan, Y., Smith, S.C. & Sulaiman, M. (2018). Agricultural extension and technology adoption for food security: Evidence from Uganda. *American Journal of Agricultural Economics*, 100(4), 1012-1031.