DIGITAL EXTENSION, PRICE RISK, AND FARM PERFORMANCE: EXPERIMENTAL EVIDENCE FROM NIGERIA

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Despite decades of investment in agricultural extension, technology adoption among farmers and agricultural productivity growth in Sub-Saharan Africa remain slow. Among other shortcomings, extension systems often make recommendations that do not account for price risk or spatial heterogeneity in farmers' growing conditions. However, little is known about the effectiveness of extension approaches for nutrient management that consider these issues. We analyze the impact of farmers' access to site-specific nutrient management recommendations and to information on expected returns, provided through a digital decision support tool, for maize production. We implement a randomized controlled trial among smallholders in the maize belt of northern Nigeria. We use three waves of annual panel data to estimate immediate and longer term effects of two different extension treatments: site-specific recommendations with and without complementary information about variability in output prices and expected returns. We find that site-specific nutrient management recommendations improve fertilizer management practices and maize yields but do not necessarily increase fertilizer use. In addition, we find that recommendations that are accompanied by additional information about variability in expected returns induce larger fertilizer investments that persist beyond the first year. However, the magnitudes of these effects are small: we find only incremental increases in investments and net revenues over two treatment years.

Key words: Advisory services, agricultural decision support tools, farm productivity, digital agronomy, extension, fertilizer, price uncertainty, site-specific nutrient management.

JEL codes: C93, D81, D83, O13, O33, Q12, Q16.

Agricultural productivity growth is considered crucial to reduce rural poverty, improve food security, and stimulate structural transformation in poor countries (Haggblade, Hazell, and Dorosh 2007; Barrett et al. 2017; Mellor 2017; Ligon and Sadoulet 2018). Agricultural productivity remains low in Sub-Saharan Africa (SSA), which is partially due to limited technology adoption (Bulte et al. 2014; Fafchamps et al. 2020). Crop yields in SSA are far below attainable yields and below yields in other regions, which limits upward income mobility for farmers and slows down agricultural and overall economic growth (Tittonell and Giller 2013; Benson

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We gratefully acknowledge the financial support for this research from the Bill and Melinda Gates Foundation (BMGF) through the project *Taking Maize Agronomy to Scale in Africa* (grant no: INV-008260), led by CIMMYT and supported in Nigeria by IITA and the Centre for Dryland Agriculture, Bayero University, Kano. We also acknowledge the International Plant Nutrition Institute for leading the co-development of the Nutrient Expert tool under this project. We thank the editor, Marc Bellemare, and three anonymous reviewers for their constructive comments and suggestions. We are also grateful to participants at the 20th BAAE PhD symposium, Brussels, 176th EAAE seminar, Montpellier, and 6th AAAE conference, Abuja, for their helpful comments.
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Amer. J. Agr. Econ. 00(00): 1–20; doi:10.1111/ajae.12242

and Mogues 2018; Alwang et al. 2019). Depletion of soil fertility contributes to this situation (Sanchez 2002; Barrett and Bevis 2015; Theriault, Smale, and Haider 2018). Yet the use of fertilizer is low in most parts of SSA (Xu et al. 2009; Burke, Jayne, and Black 2017; Michelson et al. 2021), which has been attributed in part to information constraints faced by farmers (Marenya and Barrett 2009; Benson and Mogues 2018; Jayne et al. 2019; Murphy et al. 2020).

Despite considerable variation in smallholders' growing conditions in SSA, such as soil quality and microclimate, traditional agricultural extension systems typically provide general or "blanket" fertilizer recommendations across wide and heterogeneous areas (Shehu et al. 2018; Theriault, Smale, and Haider 2018; Burke et al. 2019). Such recommendations are not tailored to the site-specific conditions of individual farmers and do not account for spatio-temporal variation in biophysical and socioeconomic conditions (Vanlauwe et al. 2015; Jayne et al. 2019; Rurinda et al. 2020). Blanket recommendations may be a good first approximation of agronomic needs, even in heterogeneous environments. Yet, a poor fit between general recommendations and local conditions may result in poor crop responses to recommended practices, which may negatively condition expectations about general agronomic recommendations (directly or through peer learning) and thereby contribute to limited uptake of recommended practices. New agricultural extension approaches, supported by digital tools, that account for spatial heterogeneity and provide site-specific recommendations tailored to farmers' fields are emerging. Although this ability to tailor extension advice is a key component of the expectations for a digital farming revolution in Africa, evidence on the impact of these approaches is still very limited (Fabregas, Kremer, and Schilbach 2019; Cole and Fernando 2020).

In addition, although national recommendations are sometimes accompanied by point estimates of expected agronomic responses or economic returns, they typically do not provide any information on the variability of the response or return. Yet the uncertainty surrounding agricultural yields and output prices can be considerable for smallholders in SSA, especially for staple crops such as maize with large seasonal price fluctuations (Minot 2014; Gilbert, Christiaensen, and Jonathan 2017; Assouto, Houensou, and Semedo 2020; Rosenzweig and Udry 2020). There is a substantial theoretical and empirical literature on output price risk (hereafter price risk), including evidence on its effects on producer behavior, productivity, welfare, and on associated policy responses (e.g., Sandmo 1971; Finkelshtain and Chalfant 1997; Bellemare, Barrett, and Just 2013; Haile, Kalkuhl, and von Braun 2016; Bellemare, Lee, and Just 2020). Variability in fertilizer investment returns—deriving in part from uncertainty about future market prices—is rarely integrated into extension recommendations, and the impact of providing such information on smallholders' input use decisions has not previously been empirically evaluated.

We analyze the impact of farmers' access to site-specific nutrient management recommendations and complementary information about expected returns, provided through a digital decision support tool, Nutrient Expert, for maize production in Nigeria. Our outcomes of interest are fertilizer application rates, fertilizer management practices, maize yields, and revenues. The tool is a tablet- or smartphone-mediated decision support tool that is designed for extension agents to provide tailored fertilizer recommendations on the right fertilizer type, the right rate, the right placement, and the right time of application (Pampolino et al. 2012; Johnston and Bruulsema 2014). The tool uses information about agronomic management history and growing conditions of an individual farmer's plot and input–output prices as relevant input data and applies the quantitative evaluation of the fertility of rropical soils model to develop site-specific nutrient requirements for the farmer's plot and the associated expected returns (Janssen et al. 1990; Pampolino et al. 2012). We implement a clustered randomized controlled trial (RCT) with 792 households in ninety-nine villages in the maize belt of northern Nigeria, with a random assignment of villages to one control (C) and two treatment groups (T1 and T2). Farmers in both treatment groups are exposed to site-specific recommendations and information about expected returns to fertilizer investment, and farmers in T2 received additional information about variability in prices and expected returns to fertilizer investment. Farmers in the control group receive blanket fertilizer recommendations and no information on prices or expected returns.[1] We

[1]The choice of using two treatment arms reflects the need for statistical power to detect differences between the groups as well as the finite resources available for implementing the research. The use of three treatment arms (e.g., T1 with site-specific nutrient management information, T2 with uncertainty information, and T3 with both site-specific nutrient management and uncertainty information), could have been more insightful but was not feasible given the resources available for this work.

use three-period panel data to estimate the immediate (after one year) and longer term (after two years) effects of the interventions on farmers' fertilizer investment and management decisions and the outcomes in terms of yields and revenues.

We make three contributions to the literature. First, we contribute to the emerging literature on the effects of tailored fertilizer recommendations, particularly the literature describing RCT-based impact evaluations, which remains relatively thin. Fishman et al. (2016) find that access to soil health cards containing site-specific recommendations, based on traditional laboratory soil testing, does not affect farmers' fertilizer application rates in India, mainly due to a lack of farmers' confidence in the recommendations. Harou et al. (2020) find that provision of site-specific recommendations to maize farmers in Tanzania, using the SoilDoc on-farm soil testing kit, significantly increases fertilizer application rates and yields but only if the recommendations are paired with an input subsidy. In a context of overuse of urea in rice production in Bangladesh, Islam and Beg (2020) find that the receipt of tailored fertilizer recommendations, based on a simple leaf color chart tool and basic rules-of-thumb training, significantly reduces urea application rates without compromising yields. Murphy et al. (2020) also rely on the SoilDoc kit in Kenya and find that the receipt of site-specific recommendations significantly increases farmers' willingness to pay for fertilizer. The sparse empirical studies on the effectiveness of site-specific recommendations all rely on laboratory and on-farm soil testing approaches, which are time consuming, relatively expensive, often unavailable to smallholder farmers, and often inaccurate due to soil sampling and chemical analysis errors (Rurinda et al. 2020; Schut and Giller 2020). Our study explores an alternative means of delivering site-specific recommendations and provides innovative evidence on how site-specific advice delivered through a digital decision support tool affects fertilizer investment and management decisions of smallholder maize farmers in Nigeria. More generally, our study adds to the growing literature evaluating the effectiveness of information and communication technology-based tools for delivery of agricultural extension information (e.g., Fabregas, Kremer, and Schilbach 2019; Cole and Fernando 2020).

Our second contribution is to provide new insights about the effect of relaxing farmer uncertainty about returns to agricultural technology investments (Feder, Just, and Zilberman 1985; Saha, Love, and Schwart 1994; Koundouri, Nauges, and Tzouvelekas 2006; Genius et al. 2014). Previous studies have analyzed the effects of price risk on farm production and technology decisions (see Boyd and Bellemare 2020 for a recent review). For example, Haile, Kalkuhl, and von Braun (2016) document that price risk negatively affects the global acreage and yields of key staple commodities, especially of wheat and rice, which implies lower use of inputs on these crops to hedge against price risk. Assouto, Houensou, and Semedo (2020) find that farmers in Benin increase maize acreage and production in response to increased price risk, noting that the desire to ensure food self-sufficiency likely explains this unexpected behavioral response in the study setting. Using lab experiments in the US and lab-in-the-field experiments in Peru, Bellemare, Lee, and Just (2020) find that producers do not significantly change how much they produce in the presence of price risk, that is, at the extensive margin, but they do decrease production in response to an increased degree of price risk, that is, at the intensive margin. Although these studies examine production supply decisions as affected by price risk, the only study we are aware of that examines the influence of price risk on fertilizer usage is Finger (2012), who finds that output price volatility is associated with lower levels of nitrogen application by risk-averse Swiss maize farmers, as compared with risk-neutral farmers. However, we are aware of no study in an African smallholder context. Furthermore, we are aware of no study that distinguishes price risk from the parameterization of price risk in conditioning farmer input investment decisions. We provide evidence on how information about variability of expected returns to fertilizer investment, occasioned by price risk, influences the uptake of fertilizer recommendations. Our study provides an alternative explanation for smallholders' persistently low application rates of fertilizer in Nigeria.

Finally, in contrast to most agriculture-related RCTs that rely on a single post-intervention round, we use multiple rounds of post-intervention data to evaluate impact (c.f. Beaman et al. 2013; Bulte et al. 2014; de Brauw et al. 2018; Hossain et al. 2019; Omotilewa, Ricker-Gilbert, and Ainembabazi 2019, Fafchamps et al. 2020). With this approach, we are better able to estimate treatment effects under different weather and output price realizations over time, and to describe intertemporal heterogeneity in treatment effects (McKenzie 2012; Rosenzweig and Udry 2020).

Context

The research is conducted in three states in northern Nigeria (figure A1 in the online supplementary appendix), where maize is grown in a smallholder rainfed system under different agro-ecological conditions. Fertilizer use is low in this area, and maize yields amount to 1–2 tons per ha despite a yield potential of over 5 tons per ha (Liverpool-Tasie et al. 2017; Shehu et al. 2018; ten Berge et al. 2019; Oyinbo et al. 2019). The latter partially relates to soil nutrient deficiencies including macronutrients—nitrogen (N), phosphorus (P) and potassium (K)—with N as the most limiting nutrient (Shehu et al. 2018; Rurinda et al. 2020). As mentioned above, despite heterogeneous conditions in the area, the extension system relies on a general fertilizer recommendation of 120 kg N, 60 kg P_2O_5 and 60 kg K_2O per ha (Shehu et al. 2018).[2]

Within this context, a locally calibrated version of the Nutrient Expert tool was developed to provide site-specific nutrient management recommendations to smallholder maize farmers. The development of the tool is described in detail in appendix A1, the application of the tool in appendix A2, and the fertilizer recommendations provided by the Nutrient Expert tool in appendix A3. The Nutrient Export tool is a tablet- or smartphone-based decision support tool that allows extension agents to generate fertilizer recommendations tailored to the specific situation of an individual farmer's field (Pampolino et al. 2012). The tool is based on the site-specific nutrient management approach, which includes the 4R principles of nutrient management: the right fertilizer type, the right rate, the right placement and the right time of application (Pampolino et al. 2012; Johnston and Bruulsema 2014), and allows adjustment of the recommended fertilizer application based on crop-, plot- and season-specific conditions. Although the term "site-specific nutrient management" as an agronomic concept suggests that the 4Rs are site-specific features, we note that only the optimal nutrient rates (levels of N, P, K) and the associated fertilizer application rates and the fertilizer types that satisfy these nutrient requirements most cost effectively are site specific. Other features of the nutrient management (timing of fertilizer applications, methods of application, etc.) are not site specific. The tool applies the quantitative evaluation of the fertility of tropical soils model to estimate the optimal nutrient requirements for an economic maize yield target for a given field based on expected yield responses to fertilizer (Janssen et al. 1990; Pampolino et al. 2012). The model captures the major patterns of maize yield response to fertilizer and interactions among N, P, and K, and has been applied to other crops and other regions (Witt et al. 1999; Sattari et al. 2014; Schut and Giller 2020). For our study area, the model was calibrated and validated using data from multi-location nutrient omission trials carried out in the 2015 and 2016 cropping seasons, and is the basis of the tool's algorithm for estimating balanced fertilizer requirements (see more details in Shehu et al. 2019; Rurinda et al. 2020). Based on this model and relevant input data provided by a farmer and an extension agent, the tool predicts attainable yields and expected yield responses to fertilizer. The latter is used by the tool to determine the optimal plot-specific fertilizer requirements while accounting for market prices of inputs and output. The tool translates the nutrient recommendations (N, P and K) into the corresponding fertilizer application recommendations (e.g., NPK 15:15:15, NPK 20:10:10, Urea) given the fertilizer types locally available, in such a way that the cost of supplying the recommended nutrients is minimized. The resulting fertilizer application recommendations were made as the amount in kgs to be applied to the plot, after accounting for its size (e.g., x kg NPK 15:15:15, y kg Urea).

The relevant input data include agronomic and market-related information, which is elicited through the interface of the tool (see figure A3 in the online supplementary appendix). This includes information on previous plot-level crop management practices, such as nutrient management (use of inorganic and organic fertilizer, application rates and splits), crop residue management, crop types, seed rate, etc.); on previous plot-level crop yields; on characteristics of the growing environment, such as water

[2]Elemental P is generally delivered via phosphate (P_2O_5), of which phosphorus constitutes 43.7%. Elemental potassium is delivered via water soluble potash (K_2O), of which potassium constitutes 83%.

availability (rainfed, fully irrigated and rainfed with supplemental irrigation), incidence of drought and/or flood in the last five years as a proxy for climate risk, etc.); on soil characteristics (color, texture, depth, etc.) through physical observation; on the plot location and size by a GPS receiver; and on costs of inputs (seed and fertilizer) and maize output prices. These input data are analyzed by the tool to produce a farmer-specific output. This includes plot-specific information on optimal nutrient rates (N, P, K), the fertilizer types and the appropriate fertilizer quantities that supply these nutrients as well as general advice on nutrient management practices, such as timing of fertilizer application (in particular on splitting the nitrogen application to match nutrient demands at different stages of the maize growth cycle) and fertilizer application method (in particular spot application is recommended as this reduces nutrient losses and ensures optimal nutrient uptake by the plant). In addition, the output includes a simple profit analysis to compare economic returns from a farmer's current and recommended practices, using information on maize yields, on prevailing seed and fertilizer prices at the village level, and on maize grain prices.

Previous Nutrient Expert impact studies under researcher-managed trail conditions report increases as well as decreases in fertilizer application, depending on the context. For example, Pampolino et al. (2012) find that Nutrient Expert-based site-specific recommendations increase average nutrient (N, P, and K) application rates by 40 kg/ha, yields by 1.6 tons/ha and profits by 379 USD/ha in the Philippines. Xu et al. (2016) find that Nutrient Expert-based site-specific recommendations reduce overall nutrient application rates by 36 kg/ha and greenhouse gas (GHG) emissions by 17% while increasing yields by 0.9 ton/ha and profits by 303 USD/ha in China, in a context of high baseline fertilizer application rates.

Methods

Experimental Design

A two-stage spatial sampling design was used to sample maize farmers across the primary maize-producing areas in the three states. In the first stage, we randomly generated twenty-two spatial sampling grids of 100 km^2 within all non-marginal agricultural areas within the three states (based on satellite-derived estimates from the Africa Soils Information System).[3] Within the randomly allocated twenty-two sampling grids, a total of ninety-nine villages were identified. These villages are distributed across seventeen different Local Government Areas (LGAs), the administrative unit below the state. In the second stage, we constructed lists of all farm households in each village, from which we randomly selected eight, resulting in a total sample of 792 households. We randomly assigned the ninety-nine villages to one control (C) and two treatment groups (T1 and T2, described below), resulting in thirty-three villages and 264 households in each group, which allows three pairwise comparisons: T1 versus C, T2 versus C, and T1 versus T2.

We opted for an allocation ratio of 1:1 to maximize statistical power, following Glennerster and Takavarasha (2013). A power calculation was performed with maize yield as the primary outcome variable and a meaningful effect size—a 25% increase in maize yields. This is equivalent to a standardized minimum detectable effect of 0.3, based on a mean of 2032.7 kg/ha and a standard deviation of 1675.6 for maize yields in the study area (as derived from the 2015/2016 round of the Living Standard Measurement Survey–Integrated Survey on Agriculture [LSMS-ISA]). With a power of 80%, a 5% significance level and a conservative intracluster correlation coefficient of 0.05, a minimum sample size of sixty-one villages and 488 households (244 in the treatment and in the control group) is needed for each pairwise comparison. With two treatments and one control, this implies a minimum of thirty-one villages (eight households per village) and 244 households in each group, resulting in ninety-three villages and 732 households. With a sample of ninety-nine villages and 792 households, our design is sufficiently powered. For each household, a focal maize plot was identified as the maize plot perceived by the head to be most important for food security and/or income generation. All treatment interventions were targeted to the focal plot.

Treatment Interventions

We provided site-specific nutrient management interventions and information on

[3]Marginal areas, defined on the basis of having population densities below 25 persons/km^2 and further than four hours travel by road from the nearest local market, were excluded from the sampling frame, as such areas have only sparse sporadic maize production, and little input or output market engagement.

expected returns in both 2017 and 2018, before the start of the planting season in April and May.[4] Farmers in T1 were exposed to site-specific nutrient management information including a site-specific fertilizer application rate to obtain a target yield, optimal fertilizer management practices (sources, timing, placement), the rationale behind the recommendations and a detailed explanation on how to implement them as well as the expected return from uptake of the recommendations. This site-specific intervention is expected to increase farmers' fertilizer application if current rates are below the optimal requirements, to improve the efficiency of applied fertilizer via optimal fertilizer practices and to improve the associated yield and net revenue as depicted in figures A4 and A5, and described in the online supplementary appendix A4. The expected economic return of T1 is a naïve estimate based on the prevailing (average) maize market price in a community at the time of providing the information, before planting (April to May 2017 and 2018). The prevailing market prices were used to proxy for expected post-harvest maize prices in the tool's estimation of expected returns for T1 farmers. This is akin to most agronomic recommendations and to the price risk farmers face due to the time lag between planting decisions and outcomes at harvest time.

Farmers in T2 were exposed to the same information as T1 farmers but received additional information on the variability of expected returns. This includes a more robust estimate based on the 25th, 50th and 75th percentiles of the distribution of the monthly real maize price during post-harvest months over the last nine years in the research area[5]: respectively 6,625, 8,086, and 10,569 NGN per 100 kg bag for the 2017 intervention, and 7,799, 9,360, and 12,980 NGN per 100 kg bag for the 2018 intervention. For T2 we are limited to only capture price or market uncertainty and not production uncertainty related to weather variability, as the present design of the Nutrient Expert tool could not accommodate spatially explicit historical rainfall data. T2 represents the situation as depicted in figure A6 and described in the online supplementary appendix A4.

Farmers in C are exposed, in both 2017 and 2018 cropping seasons, to general recommendations prevailing in the traditional extension systems—120 kg N, 60 kg P_2O_5 and 60 kg K_2O per ha with no associated information on optimal fertilizer management practices nor information on economic returns. Overall, we hypothesize that T1 and T2 in comparison with C, and T2 in comparison with T1, induce farmers to adopt management recommendations and to increase fertilizer use, and result in higher yields and revenues.

The site-specific nutrient management recommendations and information on expected returns were provided to farmers using the Nutrient Expert tool by public extension agents. These extension agents were trained intensively to ensure a proper understanding of how to use the tool, to generate recommendations, and to interpret the results to farmers; and were supervised in the field to ensure that recommendation protocols were correctly followed. As described in more detail above, the tool requires input data, which includes information on plot management history, growing conditions, and market prices of inputs and output. The output generated by the tool includes fertilizer use guidelines (amount, type, timing and placement), crop management practices, and a simple profit analysis to compare returns from current and recommended practices. The expected maize prices and the expected economic returns were presented to farmers as numbers with supporting text in a recommendation sheet in the local language and explained to farmers in detail by the extension agents. At the end, a summary of the recommendation in the local language is given to every farmer in a recommendation sheet to enable farmers to implement the recommendations during the cropping season. A sample of the recommendation sheet is presented in figures A8 and A9 in the online supplementary appendix. We pro-actively avoided potential contamination

[4]Although it would be possible to rely on a design with treatments only in 2017, we opted for a design with treatments in 2017 and 2018 to account for season-specific yield responses to fertilizer, residual nutrient balance from the preceding season, agronomic management practices, and plot size, which are likely to vary over different cropping seasons. This allows us to provide season-specific recommendations and to better understand season-specific treatment effects and intertemporal heterogeneity in treatment effects.

[5]Price data include weekly nominal maize prices, collected from grain markets in the study area by the National Agricultural Extension and Rural Liaison Services (NAERLS), Ahmadu Bello University, Nigeria. We consider only prices for the months that farmers most frequently sell their harvested maize (October to February). The 2017 intervention covered eight-year period and the 2018 intervention covered nine-year period. Figure A7 in the online supplementary appendix shows considerable variation in real maize prices over the nine-year period.

by the extension agents through extensive training sessions, pre-tests, and close supervision during implementation in the field.

Data Collection

We implemented three rounds of a farm-household survey: a baseline survey conducted in 2016 before any intervention and two follow-up surveys in 2017 and 2018, after a first and second site-specific intervention among T1 and T2 households (HHs). The surveys were conducted during the maize harvest season (September to October). The questionnaire includes general household information, production data and detailed agronomic data for the focal plot, and community-level information on prices and access to institutions and services. At baseline, data were collected from the full sample of 792 HHs, but this dropped to 788 and 786 HHs in the first and second follow-up rounds, reflecting very low attrition rates of 0.5% and 0.8%, respectively. An additional attrition of 13% (in 2017) and 16% (in 2018) arises due to HHs not cultivating maize on the sampled plot in subsequent seasons.

For both types of attrition, we test for possible differential attrition across treatment groups and baseline observable characteristics (online supplementary appendix, tables A3 and A4). We find no strong evidence of non-random attrition, apart from attrition due to not cultivating maize being negatively correlated with T1 in the first follow-up (table A4).[6] We check for possible imbalances in baseline characteristics that could arise from attrition (Athey and Imbens 2017). We find no pairwise differences between treatment groups, which indicates that attrition does not undermine the randomization (table 1 and table A5 in the online supplementary appendix). Finally, we perform a robustness check for possible attrition bias using the non-parametric bounds approach of Lee (2009) as in other randomized evaluations (de Brauw et al. 2018; Omotilewa, Ricker-Gilbert, and Ainembabazi 2019) (online supplementary appendix, tables A6 to A8). In our model estimation, we use a balanced panel of 690 HHs who cultivate maize for the first 2016–2017 panel period, which we refer to as panel A and contains one year of treatment, and a balanced panel of 666 HHs who cultivate maize for the second 2016–2018 panel period, which we refer to as panel B and contains two years of treatment.

Estimation Strategy

We estimate the intent-to-treat (ITT) effect with and without baseline control variables using an analysis of covariance (ANCOVA) specification, which guarantees statistical power when outcomes of interest have low autocorrelation (McKenzie 2012). The specification in equation 1 includes baseline plot, farmer and household characteristics that are potentially correlated with outcomes of interest, which can improve the precision of the estimates.

$$(1) \quad y_{ij,follow-up} = \beta_0 + \beta_1 T1_{ij} + \beta_2 T2_{ij} + \beta_3 y_{ij,baseline} + \beta_4 \boldsymbol{X}_{ij} + \varepsilon_{ij}$$

Various outcome variables $y_{ij,follow-up}$ for the focal plot of HH i in village j in the follow-up year, 2017 or 2018 are used: 1/adoption of optimal fertilizer management practices, including binary variables for combined application of inorganic and organic fertilizer, split N application, application at sowing time, and spot application or dibbling; 2/fertilizer application rates (kg/ha), including N, P_2O_5 and K_2O rates and the overall rate; 3/maize yield (ton/ha); and 4/production costs, and gross and net revenue (NGN/ha). The variables $T1_{ij}$ and $T2_{ij}$ are binary indicators for farmers in T1 and T2 respectively, and $y_{ij,baseline}$ is the outcome variable in the baseline year, 2016. $\boldsymbol{X}_{ij}$ is a vector of baseline control variables, including age of HH head, education of HH head, HH size, group membership, access to credit, access to off-farm income, access to contract farming, value of assets, plot ownership, and plot distance. The vector $\boldsymbol{X}_{ij}$ is excluded in the estimations without baseline control variables. The term ε_{ij} is a random error term clustered at the village level to account for the use of cluster randomization (Abadie et al. 2017). The

[6]T1 is associated with a slightly higher likelihood of cultivating maize in 2017. If this is driven by the entrepreneurship of T1 farmers, a bias may arise. We note that the interaction terms of T1 with baseline characteristics (except for household size) and the joint F-tests of the interaction terms are not significant (table A4). Hence, T1 farmers who are more (less) likely to cultivate maize are not systematically different from control farmers who are less (more) likely to cultivate maize, pointing to no systematic attrition. This suggests that the correlation between T1 and attrition is not driven by entrepreneurship. Randomization is not compromised as there are no pairwise differences between the treatment groups who cultivate maize (table 1 and table A5 in the online supplementary appendix). We perform a robustness check using Lee bounds, which further allays concerns about attrition causing a potential threat to identification.

Table 1. Baseline Household and Plot 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)
Age of head (years)	44.28	44.20	44.23	44.41	0.856	0.871	0.984
	(0.45)	(0.79)	(0.78)	(0.77)			
Education of head (years)	5.23	5.34	4.93	5.42	0.881	0.385	0.462
	(0.23)	(0.39)	(0.40)	(0.41)			
Household size	9.27	8.93	9.87	9.01	0.863	0.105	0.086
	(0.21)	(0.34)	(0.44)	(0.31)			
Group membership (1/0)	0.31	0.35	0.30	0.291	0.208	0.912	0.245
	(0.02)	(0.03)	(0.03)	(0.03)			
Access to credit (1/0)	0.23	0.22	0.25	0.23	0.698	0.692	0.425
	(0.02)	(0.03)	(0.03)	(0.03)			
Maize experience (years)	18.80	19.14	18.24	19.01	0.885	0.431	0.356
	(0.39)	(0.67)	(0.71)	(0.66)			
Access to extension (1/0)	0.40	0.43	0.40	0.36	0.180	0.429	0.583
	(0.02)	(0.03)	(0.03)	(0.03)			
Maize contract farming (1/0)	0.19	0.19	0.18	0.20	0.735	0.640	0.892
	(0.02)	(0.03)	(0.03)	(0.03)			
Livestock holding (TLU)[a]	1.94	1.80	2.29	1.73	0.751	0.041	0.067
	(0.10)	(0.15)	(0.22)	(0.16)			
Number of plots cultivated	2.70	2.73	2.69	2.67	0.602	0.865	0.730
	(0.04)	(0.08)	(0.08)	(0.08)			
Total farm area (hectare)	3.15	3.08	3.37	3.00	0.800	0.277	0.384
	(0.13)	(0.22)	(0.27)	(0.21)			
Assets (1,000 NGN)[b]	534.09	516.46	608.36	475.67	0.503	0.096	0.225
	(29.58)	(40.75)	(64.47)	(45.52)			
Annual income (1,000 NGN)[c]	188.51	182.49	206.50	176.26	0.820	0.377	0.420
	(12.44)	(15.90)	(25.46)	(22.70)			
Off-farm income (1/0)	0.88	0.86	0.90	0.87	0.859	0.367	0.272
	(0.01)	(0.02)	(0.02)	(0.02)			
Focal plot area (hectare)	0.82	0.84	0.82	0.81	0.688	0.898	0.813
	(0.04)	(0.06)	(0.08)	(0.07)			
Plot ownership (1/0)	0.96	0.94	0.97	0.96	0.200	0.928	0.165
	(0.01)	(0.02)	(0.01)	(0.01)			
Plot distance (minutes)[d]	15.11	14.33	16.05	14.96	0.604	0.536	0.277
	(0.63)	(0.70)	(1.44)	(1.00)			
Use organic fertilizer (1/0)	0.78	0.76	0.77	0.80	0.396	0.580	0.770
	(0.02)	(0.03)	(0.03)	(0.03)			
Use improved seed (1/0)	0.29	0.27	0.33	0.27	0.884	0.218	0.159
	(0.02)	(0.03)	(0.03)	(0.03)			
Use mineral fertilizer (1/0)	0.97	0.96	0.97	0.97	0.401	0.647	0.698
	(0.01)	(0.01)	(0.01)	(0.01)			
NPK fertilizer (kg/ha)	130.89	131.83	132.89	127.77	0.697	0.627	0.920
	(4.29)	(7.40)	(7.53)	(7.34)			
Urea fertilizer (kg/ha)	87.25	83.35	91.61	86.94	0.677	0.612	0.343
	(3.60)	(5.77)	(6.55)	(6.44)			
Maize yield (ton/ha)	2.07	2.01	2.09	2.12	0.217	0.711	0.390
	(0.04)	(0.06)	(0.06)	(0.06)			
Joint orthogonality test *p*-value					0.985	0.648	0.398
N	690	240	230	220			

Note: p-values in columns 5, 6, 7 are from t-tests of equality of means except the joint test *p*-values from chi-squared tests, [a]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), [b]Value of household assets, [c]Per-adult equivalent household annual income from all sources, [d]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.

coefficients β_1 and β_2 capture the ITT effects of T1 and T2 respectively.

As a robustness check, we estimate the ITT effects using a difference-in-difference (DiD) specification (equation 2), which compares the average change in outcomes over time for the treated and control groups and accounts for possible time-invariant unobserved heterogeneity not controlled for by randomization. The DiD specification is not sensitive to whether or not outcomes of interest exhibit autocorrelation, unlike the ANCOVA specification, which improves power relative to DiD only if outcomes of interest have low autocorrelation.

$$(2) \quad y_{ijt} = \delta_0 + \delta_1 T1_{ij} + \delta_2 T2_{ij} + \delta_3 Post_t + \delta_4 T1_{ij}{*}Post_t + \delta_5 T2_{ij}{*}Post_t + \delta_6 \boldsymbol{X}_{ij} + \varepsilon_{ij}$$

Where y_{ijt} is an outcome variable for the focal plot of HH i in village j in year t, 2016, and 2017 or 2018, $Post_t$ for observations in the follow-up year (2017 or 2018), and the coefficients of interest δ_4 and δ_5 capture the ITT effects of T1 and T2 respectively. Other variables are as defined in equation 1.

Two sets of estimations are reported, for the first one-year period, panel A (using baseline and 2017 data) and for a second two-year period, panel B (using baseline and 2018 data); we do not pool the data of 2017 and 2018. This allows us to explore immediate and more gradual effects. Although we do not pool the data for the followups (2017 and 2018) in equation 1, we specify only one equation for the two sets of estimations. For binary outcome variables, a linear probability model is used. Based on the estimates of the ITT effects in equations 1 and 2, we test whether the effects of T2 are larger than the effects of T1, and whether the effects in panel B are larger than the effects in panel A. In line with the conceptual discussion in the online supplementary appendix A4, we hypothesize that T2 and panel B effects are larger than respectively T1 and panel A effects. We estimate quantile regressions for continuous outcome variables (fertilizer application rate, maize yield and net revenue) to explore heterogeneity in treatments effects across the outcome distribution. In addition, we use treatment-by-covariate interactions to examine heterogeneous effects with respect to baseline fertilizer application status and with respect to a wealth index. The former allows us to examine how treatment effects vary with pre-treatment fertilizer use and to test the hypothesis that effects of site-specific advice are larger for farmers using fertilizer below the optimal rate, as put forward in the conceptual discussion in the appendix. The latter reveals the role of cash constraints in fertilizer investment responses to site-specific advice.

In addition to the robustness checks for attrition bias and the use of alternative ITT estimation strategies, we perform multiple hypothesis corrections using False Discovery Rate (FDR) sharpened q-values to control for the proportion of false treatment effects due to multiple outcomes and treatments (Anderson 2008). These q-values are computed following Benjamini, Krieger, and Yekutieli (2006) procedure as described in Anderson (2008) and empirical implementations (McKenzie 2017; Omotilewa et al. 2018). Moreover, we perform hypotheses tests using randomization inference p-values as a robustness check to conventional inference p-values. Although statistical inference in RCT is commonly done by sampling-based (asymptotic) inference, it is recommended to use randomization-based inference to test the sharp null hypothesis of no treatment effect for all respondents (Athey and Imbens 2017; Heß 2017; Hossain et al. 2019; Young 2019). This yields consistent estimates solely based on the randomization assumption and is not sensitive to the number of clusters or observations.

The results of the robustness checks are reported in the supplementary appendix. In general, our results are robust to potential attrition bias (tables A6 to A8), to alternative model specifications (tables A9 to A17), to alternative statistical inference (tables A18 to A20), and to corrections for multiple hypotheses testing (table A21).

Results

Baseline Characteristics and Recommendations

In the overall sample, the maize focal plot of farmers is on average 0.9 ha; most (97%) of the plots are cultivated with inorganic fertilizer, and the plots produce an average yield of around 2 tons per ha (table 1). We perform randomization checks by testing equality of means of the baseline characteristics between the three groups (T1 = C, T2 = C and T1 = T2). 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 groups. Only in three out of sixty-nine orthogonality tests (twenty-three variables for each group) across the three groups we find significant differences: for livestock holdings and assets for T2 = C comparison, and for household size for T1 = T2 comparison. Overall, the p-values for the chi-squared tests of joint orthogonality between the groups fail to reject the null hypothesis that the baseline observables are orthogonal to the treatment status.

We examine farmers' baseline fertilizer application rates and maize yields, and compare these with the recommended rates and corresponding expected yield levels from the treatments (table 2). In the 2016–2017 panel period, farmers in T1 apply on average 93 kg of nutrients (including N, P_2O_5 and K_2O per ha) at baseline while the average recommended site-specific rate is 242 kg per ha. This results in an average nutrient gap of 149 kg (or 61%) and 95% of farmers initially (at baseline) using less fertilizer than recommended for their plot specific situations. This is associated with a low initial average yield (2 ton per ha) and a yield gap of an average of 3.3 tons per ha (or 63%). The comparison of baseline and recommended nutrient applications and of baseline and attainable yields is very similar for panel B and for T2 farmers.

Treatment Effects

We report results from ANCOVA specifications with baseline control variables (equation 1) in tables 3, 4, and 5 for different outcome variables. These estimates are very similar to estimates from ANCOVA specifications without baseline control variables, reported in the online supplementary appendix, tables A9 to A11 and to estimates from DiD specifications with and without baseline control variables (equation 2), reported in tables A12 to A17 in the appendix. We base our discussion on ANCOVA specifications because these result in more precise estimates.

In table 3, we report the ITT effects on farmers' adoption of optimal fertilizer management practices, which are associated with improved agronomic efficiency of fertilizer applications (and which are assumed in the yield responses underlying the recommendations). The results show that in both panels A and B, the treatments increase the likelihood of adopting combined use of inorganic fertilizer and manure with on average 10 to 13 percentage points (pp), the likelihood of using a split N application with 12 to 19 pp, the likelihood of applying fertilizer at sowing time with 15 to 18 pp, and the likelihood of using a spot fertilizer application with 15 to 23 pp. Given that baseline adoption is around 77% to 79% for combined inorganic–organic fertilizer application and for split N application, the estimated effects translate into absolute increases of around 8% to 10%. Baseline use of fertilizer at sowing and of spot application is much lower, and estimated effects translate into absolute increases of around 2% for the former and around 5% to 8% for the latter. There are only small differences between the estimated ITT effects for T1 and T2, and between the estimated ITT effects for panels A and B. None of these differences are statistically significant, except for spot fertilizer application being significantly larger in panel B. In general, these observed effects are in line with the expectations, given that T1 and T2 farmers are exposed to information on optimal fertilizer management practices.

Table 4 shows the ITT effects of farmers' access to site-specific nutrient management interventions on fertilizer application rates based on ANCOVA specifications with baseline control variables (equation 1). Only the effect of T2 in panel B is statistically significant and is mainly driven by an increased application of nitrogen. This relates to the fact that nitrogen is generally the most limiting nutrient for maize production and the nutrient with the largest impact on yields in the research area (Shehu et al. 2018) and SSA in general (Kihara et al. 2016). The estimated effects on nitrogen and overall macronutrients application differ significantly between T1 and T2, but not between the panels.

Heterogeneity in treatment effects is explored in tables A23 and A24 in the online supplementary appendix. We find significant treatment effects for T2 in both panel periods and for all nutrients—with an increase in overall macronutrients of 26 kg per ha—for farmers using fertilizer below the optimal rate (table A23). For farmers using fertilizer at or above the recommended rate, effects are lower and even negative. This is in line with our expectations and nuances results in table 4. In general, an increase of 26 kg of nutrients per ha for those farmers who used to apply fertilizer below the recommended rate, is a small impact—it is only about one-fourth of the average baseline application rate. Table A24 shows that only the treatment effects of T2 on nitrogen and overall macronutrients in panel A are significantly positive for households in the upper half of the

Table 2. Descriptive Statistics on Farmers' Baseline and Recommended Fertilizer Application Rates and Yields

	N (kg/ha)	P_2O_5 (kg/ha)	K_2O (kg/ha)	All (kg/ha)	Yield (ton/ha)	N (kg/ha)	P_2O_5 (kg/ha)	K_2O (kg/ha)	All (kg/ha)	Yield (ton/ha)
	Panel A (one year): 2016–2017					Panel B (two years): 2016–2018				
Treatment one (T1)										
Baseline (2016) nutrient rates and yields[a]	57.77	17.41	17.41	92.58	2.01	59.58	17.58	17.58	94.73	1.96
	(48.00)	(14.65)	(14.65)	(65.27)	(0.92)	(49.90)	(14.60)	(14.60)	(67.07)	(0.90)
Recommended nutrient rates and expected yields[b]	128.96	56.50	56.18	241.64	5.28	132.07	59.40	59.40	250.88	5.89
	(23.31)	(25.84)	(25.89)	(72.23)	(1.07)	(22.21)	(18.62)	(18.62)	(56.46)	(1.33)
Nutrient gap and yield gap	71.19	39.09	38.77	149.06	3.27	72.49	41.83	41.83	156.15	3.93
	(50.12)	(27.93)	(27.96)	(88.79)	(1.52)	(55.71)	(23.89)	(23.89)	(89.48)	(1.70)
Nutrient gap and yield gap (%)	55	69	69	61	62	55	70	70	62	67
Farmers (%) applying nutrients below the recommended rate	92	95	95	95		90	95	95	95	
Treatment two (T2)										
Baseline (2016) nutrient rates and yields[a]	58.77	18.81	18.81	96.40	2.08	60.03	19.50	19.50	99.04	2.11
	(46.93)	(16.71)	(16.71)	(67.15)	(0.95)	(49.46)	(18.33)	(18.33)	(75.04)	(0.95)
Recommended nutrient rates and expected yields	128.56	53.19	53.03	234.79	5.35	134.80	56.13	56.13	247.06	5.90
	(19.53)	(22.16)	(22.24)	(60.82)	(1.10)	(24.28)	(21.71)	(21.71)	(62.77)	(1.19)
Nutrient gap and yield gap	69.80	34.38	34.21	138.39	3.27	74.76	36.63	36.63	148.01	3.80
	(50.92)	(28.54)	(28.68)	(92.49)	(1.45)	(57.90)	(29.51)	(29.51)	(104.34)	(1.60)
Nutrient gap and yield gap (%)	54	65	65	59	61	55	65	65	60	64
Farmers (%) applying nutrients below the recommended rate	90	91	91	92		90	93	93	93	

Note: The macronutrients are based on the fertilizer blends used by farmers, which include NPK 15:15:15 (contains 15% N, 15% P_2O_5 and 15% K_2O), NPK 20:10:10 (20% N, 10% P_2O_5 and 10% K_2O), urea (46% N) and SSP (18% P_2O_5). [a]Baseline values refer to 2016 for both panel periods and differ for the two panel periods because of differences in the balanced sample size. [b]Values refer to 2017 (first year of treatment) for panel A and to 2018 (second year of treatment) for panel B. N = 240 and 230 in T1 and T2 respectively for 2017; N = 225 and 220 in T1 and T2 respectively for 2018. Standard deviations are reported in parentheses.

Table 3. ITT Effects on Fertilizer Management Practices

	Inorganic–organic fertilizer (1/0)	Split N application (1/0)	Fertilizer at sowing (1/0)	Spot fertilizer application (1/0)
Panel A: 2016–2017				
Treatment 1	0.099***	0.123***	0.145***	0.153***
	(0.035)	(0.044)	(0.051)	(0.052)
Treatment 2	0.130***	0.140***	0.152***	0.207***
	(0.038)	(0.046)	(0.058)	(0.053)
Baseline control mean	0.77	0.79	0.14	0.36
N	690	690	690	690
Panel B: 2016–2018				
Treatment 1	0.107***	0.154***	0.173***	0.140***
	(0.039)	(0.048)	(0.047)	(0.047)
Treatment 2	0.119***	0.194***	0.177***	0.234***
	(0.036)	(0.049)	(0.048)	(0.045)
Baseline control mean	0.76	0.78	0.14	0.35
N	666	666	666	666
p-values two-sided tests:				
$T2_{2017} \neq T1_{2017}$	0.413	0.661	0.901	0.297
$T2_{2018} \neq T1_{2018}$	0.709	0.268	0.935	0.017
$T1_{2018} \neq T1_{2017}$	0.887	0.633	0.582	0.854
$T2_{2018} \neq T2_{2017}$	0.826	0.432	0.640	0.698

Note: Estimates with baseline control variables as specified in equation (1). Standard errors clustered at the village level reported between parentheses. Asterisks ***, **, and * denote any variable significant at 1%, 5%, and 10% levels respectively.

Table 4. ITT Effects on Farmers' Fertilizer Application Rates

	N (kg/ha)	P_2O_5 (kg/ha)	K_2O (kg/ha)	Overall (kg/ha)
Panel A: 2016–2017				
Treatment 1	−3.296	−0.407	−0.356	−3.700
	(4.871)	(1.921)	(1.926)	(8.017)
Treatment 2	5.053	0.797	0.695	6.775
	(4.978)	(2.055)	(2.047)	(8.416)
Baseline control mean	62.19	20.35	20.35	102.88
N	690	690	690	690
Panel B: 2016–2018				
Treatment 1	1.746	0.952	0.604	3.392
	(3.596)	(1.908)	(1.696)	(6.449)
Treatment 2	10.745***	2.035	2.602	15.387**
	(4.001)	(1.603)	(1.586)	(6.332)
Baseline control mean	62.13	19.97	19.97	102.09
N	666	666	666	666
p-values two-sided tests:				
$T2_{2017} \neq T1_{2017}$	0.072	0.466	0.524	0.156
$T2_{2018} \neq T1_{2018}$	0.026	0.558	0.244	0.072
$T1_{2018} \neq T1_{2017}$	0.376	0.584	0.672	0.440
$T2_{2018} \neq T2_{2017}$	0.276	0.586	0.388	0.300

Note: Estimates with baseline control variables as specified in equation (1). Standard errors clustered at the village level reported between parentheses. Asterisks ***, **, and * denote any variable significant at 1%, 5%, and 10% levels respectively.

wealth distribution and are not significantly different from zero for households in the lower half of the wealth distribution. In addition, in panel B the effects of both T1 and T2 on nitrogen and overall macronutrients are significantly positive only for households in the upper half of the wealth distribution.

Table 5 shows the ITT effects of farmers' access to site-specific nutrient management interventions on maize yields, production

Table 5. ITT Effects on Maize Yields, Production Costs, Gross Revenue, and Net Revenue

	Yield (ton/ha)		Production costs (NGN/ha)	Gross revenue (NGN/ha)	Net revenue (NGN/ha)
Panel A: 2016–2017					
Treatment 1	0.106	0.109	3,368	10,566	6,212
	(0.083)	(0.083)	(5,292)	(8,279)	(8,185)
Treatment 2	0.245***	0.251***	9,320*	24,456***	14,776*
	(0.082)	(0.082)	(5,269)	(8,165)	(7,937)
FAW (1/0)		0.100			
		(0.100)			
Baseline control mean	2.12	2.12	75,053	222,395	147,341
N	690	690	690	690	690
Panel B: 2016–2018					
Treatment 1	0.189**	0.197***	8,237**	16,977**	7,454
	(0.074)	(0.074)	(3,562)	(6,663)	(5,580)
Treatment 2	0.371***	0.378***	12,414***	33,427***	20,827***
	(0.074)	(0.074)	(3,736)	(6,617)	(5,166)
FAW (1/0)		−0.200**			
		(0.098)			
Baseline control mean	2.13	2.13	75,118	223,365	148,247
N	666	666	666	666	666
p-values two-sided tests:					
$T2_{2017} \neq T1_{2017}$	0.070	0.066	0.226	0.070	0.222
$T2_{2018} \neq T1_{2018}$	0.022	0.022	0.266	0.022	0.020
$T1_{2018} \neq T1_{2017}$	0.314	0.634	0.416	0.420	0.878
$T2_{2018} \neq T2_{2017}$	0.114	0.116	0.588	0.246	0.418

Note: Estimates with baseline control variables as specified in equation (1). Net revenue is the gross revenue (value of output) less the variable costs of production, which include cost of inorganic fertilizer, seed, organic fertilizer, labor (both hired and imputed cost of family labor valued at the average daily wage rate for an adult for maize farming activities, obtained via a community-level questionnaire), and agrochemicals such as herbicides and insecticides. In addition, the revenues are based on average maize prices at the village level during the harvest seasons, collected via a community-level questionnaire. The use of harvest season prices helps to avoid confounding potential net revenue effects from increased output, with the returns to storage (Beaman et al. 2013). Standard errors clustered at the village level reported between parentheses. Asterisks ***, **, and * denote any variable significant at 1%, 5%, and 10% levels respectively.

costs, and gross and net revenues. The results show that the interventions lead to statistically significant increases in maize yield, except for T1 farmers in panel A. We find that T1 increases maize yield with 0.2 ton for panel B, whereas T2 increases yield with 0.2 and 0.4 ton per ha in respectively panel A and B. These are small but somewhat important effects, corresponding to increases of 9% to 19% from the average baseline yield. The estimated yield effects of T2 are somewhat larger than the effects of T1, and the differences are significant in both panel periods. In addition, we find that the yield effect of T2 is significantly larger for panel B than for panel A. The observed effects might be influenced by the incidence of fall army worm (FAW) infestation during the 2017 and 2018 cropping seasons in Nigeria and other parts of SSA (Nagoshi et al. 2018). The incidence of FAW infestation in our sample is 17% and 8% in 2017 and 2018 respectively. Column 2 of table 5 shows that the results are robust to controlling for FAW infestation.

The results in table 5 further show that the yield increase associated with site-specific nutrient management treatment translates into a significant increase in gross and net revenues for T2 farmers in both panels A and B, and a significant increase in gross revenue for T1 farmers in panel B. The economic importance of these net revenue increases is rather modest, with effects amounting to 10% to 14% of baseline revenue values. T2 results in significantly larger production costs in both panel periods, and T1 only in panel B, which points to gradual investments by farmers. After two years (panel B), production costs increase on average with 8,237 NGN per ha or 11% for T1 farmers and with 12,414 NGN per ha or 17% for T2 farmers. The observed effects of T1 on yield and production costs in 2018 are likely explained by a combination of significant changes in the management practices (that might increase yields and labor costs) and the slight but insignificant increase in fertility quantity (that might translate into a significant cost increase). In addition, weather variability might play a role in explaining different yield effects in 2017 and 2018. The estimated effects on yield, gross, and net revenues are significantly larger for T2 than for T1.

Following the suggestion of de Janvry, Sadoulet, and Suri (2017), we value family labor using a range of wage rates from the average market wage rates (akin to lower bound estimates and a lower likelihood to overestimate ITT, reported in table 5) to a fraction of the wage rates (columns 1–4 in table A22, online supplementary appendix) and to a more conservative assumption of zero family labor costs, that is, family labor is a fixed factor (upper bound estimates and a higher likelihood to overestimate ITT, columns 5–6 in table A22, online supplementary appendix). Overall, our results are robust to these variations in labor cost valuation.

Discussion

Our results indicate that smallholders' access to site-specific nutrient management advice increases maize yields with 0.2 to 0.4 ton per ha or with 9% to 19% over one to two years. These effects are small relative to an existing maize yield gap of over 60% (i.e., the average gap between farmers' baseline maize yields and expected yields under optimal management conditions). The observed impact on net revenue is also small: 21,000 NGN (about 69 USD) or 14% increase in net revenue for the most informative treatment after two years. Yet our observation of gradual increases in yield and revenue effects over the two years suggests that impacts of access to site-specific nutrient management advice become more substantial over time.

We find more substantial and more immediate effects of access to site-specific nutrient management advice on the adoption of improved management practices than on the adoption of higher fertilizer application rates. This could imply that smallholder maize farmers in the research area more readily adopt labor intensive technology changes (fertilizer management practices) than capital intensive technology changes (higher fertilizer application rates) because cash constraints are more binding than labor constraints. This could also imply that farmers perceive a higher risk from expanding fertilizer use (e.g., because of the climate variability in fertilizer responsiveness) than from improved management practices and adopt the least risky components of the advice first. Our treatments do not allow us to explicitly test if cash constraints and/or attitudes toward risk influence farmers' responses to site-specific recommendations. We find that only more wealthier farmers (in the upper half of the wealth distribution) intensify fertilizer use toward economically efficient levels in response to site-specific recommendations. This is consistent with both cash constraints and risk aversion acting as limiting factors in the uptake of site-specific recommendations among poorer farmers, who are typically more cash constrained as well as more risk averse. Findings are in line with our conceptual discussion on binding cash constraints and risk that may limit the expansion of fertilizer use, and with findings in the empirical literature on fertilizer adoption (Croppenstedt, Demeke, and Meschi 2003; Lambrecht et al. 2014; Koussoubé and Nauges 2017).

The two treatments result in diverging effects. Although both treatments improve fertilizer management practices already over one year, only T2 significantly increases the use of fertilizer, over two years. The latter effect is small in absolute value, 26 kg per ha, but does amount to an expansion of 25%. This implies that information on the variability of expected returns to fertilizer use might induce farmers to invest in fertilizer and intensify production.[7] In addition, this lends credence to the argument that risk attitudes shape farmers' responses to site-specific recommendations. The estimated increase in fertilizer application rates of 26 kg per ha, combined with the estimated yield effect of 0.4 ton per ha for T2 after two years, implies a return of 15 kg maize per kg nutrient. This compares to some extent with survey-based estimates of 8 to 25 kg maize per additional kg N in Nigeria and other parts of SSA (Marenya and Barrett 2009; Matsumoto and Takashi 2013; Sheahan, Black, and Jayne 2013; Koussoubé and Nauges 2017; Liverpool-Tasie et al. 2017; Ragasa and Chapoto 2017; Theriault, Smale, and Haider 2018; Chamberlin, Jayne, and Snapp 2021) but is far below the potential of more than 40 kg maize per kg N under researcher-managed farm trials (Vanlauwe et al. 2011, 2015; Ichami et al. 2019). Our results are consistent with

[7]Although reducing the uncertainty of expected returns by providing information about maize price distributions has clear impacts on fertilizer investment, we cannot differentiate which of the percentiles is most relevant for this effect. Empirical work indicates that downside risk is particularly important to farmer decision making (Cardell and Michelson 2020), which suggests that expected returns at the 25th percentile price may be most important, but additional empirical work would be required to confirm this.

other empirical studies pointing to low and variable maize yield responses to fertilizer in Nigeria and elsewhere in SSA (Marenya and Barrett 2009; Burke, Jayne, and Black 2017; Liverpool-Tasie et al. 2017; Theriault, Smale, and Haider 2018).

For the specific context of smallholder maize production in Nigeria, our results imply that improving technical efficiency of fertilizer use through information on optimal fertilizer management practices should be a first priority for extension programs, especially as such practices do not necessarily imply larger cash investments. Traditional extension systems could benefit from low-cost agronomic decision support tools that provide better-targeted information about optimal fertilizer and crop management practices. In addition, our results imply that intensifying fertilizer use without corresponding efforts to improve yield responses is unlikely to substantially improve the profitability of maize production in the research area. This is consistent with the conclusions of other empirical studies (Marenya and Barrett 2009; Burke, Jayne, and Black 2017; Liverpool-Tasie et al. 2017; Burke et al. 2019; Jayne et al. 2019; ten Berge et al. 2019; Chamberlin, Jayne, and Snapp 2021). More research is needed to further clarify the underlying causes of low yield responses to fertilizer (Kihara et al. 2016; Burke, Jayne, and Black 2017; Njoroge et al. 2017; Jayne et al. 2019).

Our study highlights the role of price uncertainty in conditioning smallholder investment decisions. Our findings imply that uncertainty in economic returns deriving from price uncertainty partly explains the persistent underutilization of fertilizer in the research area. This is consistent with studies arguing that farmers may not adopt agricultural technologies if they are uncertain about the returns to investments (Koundouri, Nauges, and Tzouvelekas 2006; Genius et al. 2014; Magruder 2018). Yet, policy interventions to encourage fertilizer investments in Nigeria and other SSA countries have largely focused on relaxing liquidity constraints through subsidy programs (Liverpool-Tasie et al. 2017; Ragasa and Chapoto 2017; Jayne et al. 2019). Extension systems should provide better information on price uncertainty-induced variability in economic returns (in addition to information on average returns) associated with fertilizer recommendations, which may signal greater credibility and foster trust in recommendations (Fishman et al. 2016).

We acknowledge some methodological limitations. First, inclusion of optimal fertilizer management practices as a separate treatment would have allowed stronger conclusions about the role of management practices. Second, uncertainty about seasonal variation in return to fertilizer was only captured by price variation (i.e., market uncertainty) and not by climate-induced yield variation (i.e., production uncertainty) as in other studies (e.g., Finkelshtain and Chalfant 1997; Bellemare, Barrett, and Just 2013; Bellemare, Lee, and Just 2020). Some farmers may be aware of variation in prices or have subjective expectations about this, but they may be more uncertain about yield variation when applying new practices or expanding input use. A third caveat has to do with the time horizon of our analysis. Although our inclusion of three seasons in the analysis is an important innovation and has generated insights on the lagged effects of information impacts on farm decisions, it would be useful for future studies to consider even longer periods in order to better understand how improved extension efforts may affect farmers' investment and management decisions over longer trajectories. Fourth, we estimate only direct effects, although we acknowledge that indirect effects may also be substantial, for example, site-specific recommendations may create environmental benefits through reduced soil nutrient mining and degradation. Last, although our experimental design allows us to address internal validity concerns, we cannot make strong claims about the external validity of our estimates given that our study covered a single context, that is, the maize belt of northern Nigeria. This is one oft-cited criticism of randomized evaluations (Athey and Imbens 2017). Nonetheless, our findings may be informative for other similar contexts in the region, particularly with respect to guiding further research on tailored extension interventions with uncertainty in expected returns. Given that previous studies (e.g., Minot 2014; Gilbert, Christiaensen, and Jonathan 2017; Assouto, Houensou, and Semedo 2020) show that maize prices vary substantially in much of SSA and are often more volatile than the prices of other crops, our findings on the role of information about variation in expected returns through price uncertainty may be particularly relevant to other settings in SSA.

Conclusion

Our study contributes to the nascent empirical literature on how newly emerging digital and farmer-tailored agronomy tools affect the performance of smallholder farms in developing countries and to understanding the role of price risk in farmers' adoption of extension advice.

Using an experimental approach and panel data from three years, we estimate the impact of information and communication technology-enabled plot-specific fertilizer recommendations for smallholder maize farmers in northern Nigeria. We find that access to site-specific nutrient management advice gradually improves maize yields and farm revenues. We find more immediate and stronger impacts on the uptake of fertilizer management practices, such as timing and mode of application in response to site-specific advice, than fertilizer investments. In addition, we show that reducing farmers' uncertainty by providing additional information on the variability in expected returns induced by price uncertainty results in gradual investments and expansion of fertilizer use, and renders agricultural extension more effective. The latter provides an alternative explanation for the persistently low application rates of fertilizer in the research area. Estimated effects are rather small, with the treatment resulting after two years in, on average, a 2% to 15% higher adoption of various improved fertilizer management practices, an expansion of fertilizer application of 25%, a yield increase of 19%, and a net revenue increase of 14%.

In general, our results support an extension approach that uses digital support tools and provides site-specific nutrient management advice to smallholder farmers. Yet expectations about the impact of such an approach must be realistic. They should not be seen as a "silver bullet" solution to closing yield gaps and improving smallholder farm revenue but rather as a catalyst to gradually move farmers to higher yield and revenue levels through improved nutrient management.

Supplementary Material

Supplementary material are available at American Journal of Agricultural Economics *online.*

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