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Abstract

Smallholder farmers in Africa typically only have access to blanket fertilizer recommendations which may not be optimal for local production conditions. The response to such recommendations has generally been poor. Using a randomized control trial in Ethiopia, we explore whether targeted recommendations lead farmers to align fertilizer usage to recommended levels and whether this impacts productivity. Results show that targeted recommendations closed the gap between the he recommended and actual amounts of fertilizer used and that this in turn increased productivity. We also consider whether coupling these recommendations with agricultural insurance further encourages fertilizer investment but find no differential effect.

JEL Codes: O12, O13, Q12, Q16

Key words: advisory services, smallholder agriculture, agricultural extension, ICT, fertilizer, agriculture

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1. Introduction

Agricultural productivity growth is one of the main components of the structural transformation process through which developing countries modernize and experience productivity and welfare improvements (Timmer 1988, Diao et al., 2010; Christiaensen et al., 2011).[1] Broad-based agricultural growth, by allowing greater participation by the poor in the growth process, has better poverty reducing characteristics than growth which is concentrated in the commercial farm sector (Diao et al., 2010). Key drivers of such growth include improved crop varieties, inorganic and organic fertilizers, and other complementary agronomic management practices.

Technology adoption by smallholder farmers in developing countries has remained persistently low over recent decades, however, even where such technologies are ostensibly profitable for farmers to use (Gollin et al, 2002; Duflo et al., 2008; Duflo et al., 2011, Suri, 2011; Emerick et al., 2016; Sheahan and Barrett, 2017). According to the World Bank (2007), fertilizer use in Africa is much lower than the rest of the world. Various reasons have been proposed for explaining such low adoption rates, including: technologies that are ill-suited to local conditions (Emerick et al., 2016); lack of information and difficulties in learning (Ashraf et al., 2009; Hanna et al., 2014); absence of formal insurance (Karlan et al., 2014); liquidity constraints (see for example, Croppenstedt et al., 2003; Gine and Klonner, 2006; Matsumoto and Yamano, 2010; Zerfu and Larson, 2010); high transaction costs due to poor infrastructure (Suri, 2011); and procrastination and time-inconsistent preferences (Duflo et al., 2011).

In this paper, we consider two specific constraints to technology adoption[2]: 1) the suitability of the technologies to local conditions; and 2) the downside risk associated with investing in a new technology due to potential crop failure. The context for our study is Ethiopia and the technology is a targeted site-specific fertilizer blend recommendation. We examine the impact of providing site-specific agronomic information (SSI) to smallholder farmers on fertilizer usage, farm productivity and household welfare using a two-level cluster randomized control trial. We conducted the field experiment in core maize producing zones of Ethiopia; namely West Gojjam, Jimma, East Showa, West Showa, and East Wellega zones. We randomized the provision of SSI

[1] Christiaensen et al. (2011) found that agricultural growth is up to 3.2 times better at reducing poverty at the one dollar a day level than growth in non-agricultural sectors.
[2] We use the term *adoption* to mean the adoption of site-specific fertilizer recommendation levels.

and access to crop insurance cover across 130 1km x 1km grid-cells which cover, on average, 6 households in each cell. The agronomic information provided to treated households consisted of a site-specific fertilizer blend recommendation, the expected yield outcome at the recommended rate, and the optimal timing of fertilizer application. In a second treatment arm we couple this information with a free insurance product that protects farmers against crop failure due to weather related events.

Soil degradation and nutrient depletion have been serious threats to agricultural productivity and food security in Ethiopia.[3] Over the years, soil fertility has also declined due to the increase in population size and decline in plot size. Nitrogen (N) and phosphorus (P) are the nutrients that are most lacking (Murphy, 1966; Kebede and Yomoch, 2009; Spielman et al., 2010). In 2007, the Ministry of Agriculture and Natural Resources (MoANR) and Agricultural Research Centers together developed regional or blanket fertilizer recommendations (fertilizer types and application rates for different crops). These recommendations inform farmers how much fertilizer in kilograms they should apply per hectare without performing any soil test and regardless of agro-ecological zones. Since nutrient management requirements of farms vary across crop type, soil type and other agro-ecological characteristics, these blanket fertilizer recommendations may not be suitable for all farmers. The adoption of fertilizer remains low and the average application rates by those who do use fertilizer are generally lower than recommended rates.[4]

Our main finding is that well targeted fertilizer recommendations induce greater fertilizer investments and improve the productivity of maize production. More specifically, we find that farmers who received SSI significantly closed the absolute gap between the actual total average macronutrient use and the recommended value by 18.6 kg/ha.[5] We find a similar effect for households who received the SSI coupled with the crop insurance cover but do not find any difference between the two treatment arms. This suggests that crop insurance cover does not matter for the adoption of the recommended level of fertilizer use within our study context. We also find a noticeable increase in maize production for plots cultivated by treated farmers, both for those who received the information only and those who received the information with the crop insurance

[3] Agriculture is the backbone of the Ethiopian economy and is the main source of livelihoods for rural households which accounts around 83 percent of the total population (Davis et al., 2010).
[4] Further details on the Ethiopian context and the blanket recommendations are provided in Appendix A.
[5] It closes the absolute gap for nitrogen, phosphorus, and sulfur by 13.2, 4.3 and 1.4 kg/ha, respectively.

cover. The effect is large, amounting to a 0.5 metric tons (MT) increase in average maize yield for plots cultivated by treatment farmers. Compared to the control group, the introduction of site-specific agronomic information improves maize productivity by around 15 percent.[6]

Our study adds to the existing literature in three main ways. First, despite extensive literature on the factors that determine the adoption of fertilizer use, to the best of our knowledge there is no empirical study that assesses whether the relevance of the agronomic information for local conditions is itself a constraint to technology adoption. To the extent that African smallholder farmers have access to fertilizer recommendations, these are typically blanket recommendations, where the application rate and type of fertilizer recommended for a particular crop does not vary over a large (often national) area. Since the nutrient management requirements of farms vary across crop type, soil type and agro-ecological zone, blanket fertilizer recommendations may not be well-matched to farmers' particular contexts, and may therefore give sub-optimal results, which may affect farmers' fertilizer adoption rates. This study tests whether fertilizer recommendations are more likely to be adopted when tailored to particular locations, and accompanied by detailed information on application methods, timing, and expected yields.

Second, in addition to the information channel, we examine the interactive effects of eliminating downside risk by providing insurance cover for crop failure with the site-specific agronomic information. Emerick et al. (2016), focus on the elimination of downside risk by providing a flood-tolerant rice variety to farmers. They find that the behavior of farmers changes once the downside risk is removed. They are willing to invest in more fertilizer and other inputs. Our study builds on this finding by providing additional evidence in a different context on the extent to which risk is a constraint to technology adoption when optimal information is available. That is, the elimination of downside risk may or may not be an important factor once farmers have the right information.

Third, our study is related to the recent literature exploring the demand for agricultural insurance and in particular, the reasons why the take-up of agricultural insurance is so low in developing countries. A number of studies have identified poor understanding of insurance mechanisms as a

[6] We do not find any evidence, however, that these productivity increases lead to higher net profits or household welfare improvements. This could be due to the relatively short time span between the intervention and end-line data collection periods.

key factor in the low demand for insurance by smallholder farmers (Njue et al., 2018; Sibiko et al., 2017). Other studies suggest that a lack of trust in the system and high premiums contribute to the low level of demand (Hongbin et al. 2009, Ceballos et al. 2018; Fonta et al., 2018). Our results suggest that even when agricultural insurance is given for free and its benefits explained clearly to farmers it does not seem to affect production decisions.

The rest of this paper is organized as follow. Section 2 presents a theoretical framework for understanding the relationship between information, insurance and technology adoption. In section 3, we provide the experimental design while the data and empirical approach are described in section 4. Section 5 presents the results and section 6 concludes.

2. Conceptual Framework

In this section, we develop a simple theoretical framework that maps the relationship between site-specific agronomic information, insurance, and technology adoption along the lines of Magruder (2018). For simplicity, we assume a two-period model where farmers decide their investment and saving decision in the first period and realize output in the second period. In the first period, a farmer decides to allocate his income (y) either to purchase an input (x) or invest in a savings asset (a) which has a return (R) in the second period. The amount of input to be purchased during the planting period depends both on the state of the world $(s \in S)$ that will be realized in the second period after the crop has been planted and the production function $(t \in T)$. Assume θ_s is the probability that the state of the world s occurs and θ_t is the probability that any technological realization t occurs. Incomplete information implies that farmers are uncertain about the state of the world and how their input choices will perform in each state. The state-specific production function is given by $f_{s,t}(x)$, where $f'_{s,t}(x) > 0$, and $f''_{s,t}(x) < 0, \forall s, t$. In period one, the farmer expects to produce $\mathrm{E}_{s,t}[f_{s,t}(x)]$.

The farmer maximizes utility as:

$$Max\ U = u(c^0) + \delta \sum_{s,t \in S \times T} \theta_s \theta_t\, u\left(c^1_{s,t}\right) \tag{1}$$

Subject to

$$c^0 = y - x - a \tag{2}$$

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

$$x \geq 0, a \geq 0, a \leq \overline{a} \qquad (4)$$

Where c^0 and $c^1_{s,t}$ are the levels of household consumption in the first and second period respectively, and δ is the discount factor.

The first order conditions with respect to x and a are:

$$u'^{(c^0)} = \delta \sum_{s,t\epsilon S\times T} \theta_s \theta_t \, u'\left(c^1_{s,t}\right) f_{s,t}{}'(x\,) \qquad (5)$$

$$u'^{(c^0)} = \delta R\text{E}\left[u'\left(c^1_{s,t}\right)\right] + \lambda_a \qquad (6)$$

The two first order conditions imply:

$$\delta R + \frac{\lambda_a}{\text{E}[u\prime(c^1_{s,t})]} = \delta \text{E}\left[f_{s,t}{}'(x\,)\right] + \frac{cov[f_{s,t}\prime(x\,), u\prime(c^1_{s,t})]}{\text{E}[u\prime(c^1_{s,t})]} \qquad (7)$$

Equation (7) shows an optimal choice of input and savings that equates expected marginal benefits from the next period and marginal costs of forgone consumption in the current period. In this setup, farmers do not know which t of T is being realized and so have some uncertainty about the exact nature of the production function.

Now, let us consider a scenario which assumes farmers have full information on t but still do not know the exact state of the world s that will be realized. That is, there is no uncertainty around what technology t is realized but they remain uncertain about the state of the world s. This implies that $f_{s,t}{}'(x\,) = f_s{}'(x\,)$, $c^1_{s,t} = c^1_s$, $\theta_t \epsilon \{0,1\} \forall t$. Under this scenario, the first order conditions can be re-written as:

$$\delta R + \frac{\lambda_a}{\text{E}[u\prime(c^1_s)]} = \delta \text{E}[f_s{}'(x\,)] + \frac{cov[f_s\prime(x\,), u\prime(c^1_s)]}{\text{E}[u\prime(c^1_s)]} \qquad (8)$$

In both scenarios, the difference between the actual and expected output is higher if there is uncertainty about the state of the world, but in scenario 1, i.e. equation 7, there is also uncertainty about how input choices will perform in each state.[7] That is, $f_{s,t}{}'(x\,) - \text{E}(f_{s,t}{}'(x\,)) \geq f_s{}'(x\,) - \text{E}(f_s{}'(x\,))$ and $'\left(c^1_{s,t}\right) - \text{E}(u'\left(c^1_{s,t}\right)) \geq u'(c^1_s) - \text{E}(u'(c^1_s))$. As a result, $cov[f_s{}'(x\,), u'(c^1_s)] > cov[f_{s,t}{}'(x\,), u'\left(c^1_{s,t}\right)]$ and both terms are negative. This implies that, improved information by

[7] The key argument is that better information leads to lower outcome uncertainty and hence higher investments, ceteris paribus

reducing uncertainty on how input choices will perform in each state increases the amount of input used during the planting period.

Now let us assume another scenario where there is full information and perfect insurance cover to mitigate downside risk, $\theta_t \epsilon \{0,1\} \forall t$, $c_{s,t}^1 = c_s^1$, $f_{s,t}'(x) = f_s'(x)$, and $c_{s,t}^1 = c_s^1 = c_s^{1I} \forall s$. Equation (7) can be rewritten as:

$$\delta R + \frac{\lambda^I{}_a}{u\prime(c^{1\,I})} = \delta \mathrm{E}[f_s'(x)] \qquad (9)$$

If we compare equation (7) and (9), we can see that $cov[f_s'(x), u'(c_s^1)] < 0$, and $\lambda_a = 0$. This implies that the existence of (uninsured) risk reduces the input amounts used.

To sum up, incomplete information increases the uncertainty about the state of the world and how input choices will perform in each state. As a result, farmers will be reluctant to invest. On the other hand, better information leads to lower outcome uncertainty and hence higher investments, *ceteris paribus*. The design of our experiment allows us to link better information (site-specific agronomic information on the amount of fertilizer use, timing of fertilizer application and expected yield for the recommended amount) and perfect insurance (free crop insurance in the event of a weather-related shock) to farmers' investment decisions (adoption of fertilizer recommendation) and productivity.

3. Experimental Design

Our sample was drawn from the main maize growing areas of Ethiopia. We randomly generated four 10 x 10 km sampling grids within each of the four main maize growing zones (Jimma, Bako, West Gojjam, and East Shewa), with each grid subdivided into 100 1km^2 grid cells (Figure 1). Within each grid, eight grid cells were chosen randomly. If a randomly selected grid-cell could not be included (either because it was physically inaccessible or if there was no maize production taking place at or near that point), then a replacement location was drawn from the same 10km x 10km grid.

[INSERT FIGURE 1 HERE]

Within each of the randomly selected grid cells, 6 farmers were identified, using the following protocol. First, we identified the farm household closest to the selected point. For example, if the point fell within a field, we identified the farmer who owns this field. If this farmer grew maize in the current year, then this farmer entered the sample, as farmer number 1 for that location. If the farmer did not grow maize in the current year, then we identified the nearest neighbor to that farmer and repeated until farmer number 1 is identified for that location. Second, from farmer number 1 (for that location), 5 neighboring farmers were identified on the basis of spatial proximity and direction. We started with the nearest farmer in the direction due North (0 degrees), and proceeded to the nearest farmer in a clockwise direction at 72 degree intervals. Once it was confirmed that they grew maize in the current season, they were added to the sample. If any of these farmers did not grow maize, their nearest neighbor (not otherwise already included in the sample) was evaluated for suitability, until a total of 6 farmers for the selected point location were identified. If, at the time of the survey, a sample farmer was not available (or unable to be enumerated due to death, leaving the village or no longer planting maize), a replacement was made following the same spatial proximity rules as used in the initial selection. This replacement farmer was given the same household identification number as the drop-out farmer. In our baseline line data, around 27 originally selected households (3.6 percent of the sample) were replaced.

Table 1 summarizes the number of grid cells and households selected in each zone. From the total of 130 1km x 1km grid cells, 40 of them are located in West Gojjam, 34 in East Showa and 28 each in Bako and Jimma.

[INSERT TABLE 1 HERE]

The sample size was chosen on the basis of power calculations carried out for our main outcome variables.[8] These are the absolute difference between recommended and actual fertilizer use in kilogram per hectare (kg/ha) for the maize area planted, total maize production in kg per hectare, and average per-capita household income. Randomization took place at the grid-cell level with each grid-cell randomly assigned to one of three groups. We stratified by four blocks, defined by administrative zones. Since the total number of grid-cells cannot be evenly assigned to the three groups, we first randomly assigned an extra grid-cell to one of the three groups. The first treatment

[8] Detailed power calculations are provided in Appendix B.

arm was randomly selected to get one extra grid-cell. This means that treatment arm one has 44 grid-cells, whereas treatment arm two and the control group have 43 grid-cells each.

In addition, while each zone should have an equal number of grid-cells across the three groups, the uneven number of grid-cells prevents this (see Table 1 above). Hence, we randomly allocate the extra grid-cell in each zone to a particular group. Two zones take an extra grid-cell in treatment group one given that there is an extra grid cell assigned to this group, with the Bako and East Shewa zones randomly selected to have an extra grid-cell. Jimma and West Gojjam are randomly selected to have an extra grid-cell in treatment group two and the control group, respectively. Table 2 presents the number of grid-cells and households randomly selected to treatment and comparison groups in each zone.

[INSERT TABLE 2 HERE]

Households in the first treatment group received SSI, consisting of a recommended amount and blend of fertilizer to use on a particular maize plot, the optimal timing of the application of that fertilizer, and the expected yield outcome for that recommendation.[9] The information was provided both verbally and on paper. Comparing outcomes ex-post with the control group will allow us to test whether fertilizer recommendations are more likely to be adopted when accompanied by agronomic information.

Similarly, households in the second treatment group received the same SSI as in treatment arm one and insurance cover to mitigate the risk associated with potential crop failure. For each farmer in this group, we purchased crop insurance from Oromia Insurance Company (OIC) and informed them that they were insured while we provided the site-specific recommendation. The cover includes any crop failure associated with drought, flood, excess rain, fire, storms, and hail for the 2018 agricultural season. This information was explained face to face to farmers during the planting period. As discussed above, the aim of this treatment is to allow us to test whether the downside risk associated with fertilizer investment plays a role in the take-up of the site-specific

[9] The recommendations were defined on the basis of nutrient omissions trials carried out in the study region within the previous season. These trials are designed to empirically measure yield response to different fertilizer applications given soil nutrient status and other soil characteristics. See Pampolino et al. (2012) and Xu et al. (2016) for more detail on the calibration and validation methods used for the Nutrient Expert tool.

fertilizer use recommendation.[10] During our sample period, around 25.6 percent of farmers experienced exogenous production shocks (drought, flooding, pests and diseases). Moreover, in the 2017 agricultural season, farmers lost around 14.7 percent of their crop income due to weather related shocks. As such, weather related risks are salient for these farmers. Despite this, the rate of crop insurance in rural farm households in Ethiopia is very low. From the baseline Agronomic Panel Survey (APS) data, less than one percent of households bought crop insurance in the main maize producing areas of Ethiopia.[11]

Table 3 presents the main outcome variables used in our analysis. The main outcomes of interest are adoption of fertilizer recommendations, farm productivity and household welfare. We measure the adoption rate of fertilizer recommendations by calculating the absolute gap between the actual and recommended values of fertilizer use in kg/ha. Farm productivity is measured by average maize production per-hectare for all maize plots. Finally, we use average household level per-capita consumption expenditure as a proxy for household welfare. Consumption expenditure is constructed by taking the sum of the values of home production, purchased commodities, and gifts.

[INSERT TABLE 3 HERE]

4. Data and Empirical Approach

The baseline household and community level Agronomic Panel Survey (APS)[12] data was collected for 738 households at the harvest time of 2017, from October 11th to 4th December.[13] We collected detailed information on household composition, asset endowments, income sources, and farm-

[10] Since we offer agronomic information together with actual insurance cover to mitigate downside risk, our experiment is different from previous studies which investigate the impact of reducing downside risk on technology adoption of modern agricultural practices. For example, instead of providing actual insurance, Emerick et al. (2016) examine the impact of reducing downside risk on fertilizer use by introducing a new flood tolerant rice variety.

[11] This is likely due to a combination of demand and supply side factors including lack of awareness of farmers and insurance products that require large amounts of collateral that most farmers cannot afford.

[12] The Agronomic Panel Survey (APS) is a multi-component farm household survey designed to collect detailed and spatially-explicit agronomic management data from maize farmers. It also contains information on geographic, household and plot-level contextual conditions which are relevant to understand smallholder farm decisions and outcomes at the plot and household level.

[13] We used Open Data Kit (ODK) to collect plot, household and community level data. Since we used computer-assisted personal interviewing for internal validation control and well-experienced enumerators, our baseline data have very few observations with missing values. In the first week of October, we provided training to 20 enumerators and district level agricultural development agents on how to use ODK to collect the data. Since the survey covers four different zones that have different harvesting periods, we started collecting household, plot and community level data in the East Showa zone where harvesting begins earlier than in the other zones. Then we proceeded to Jimma, Bako and West Gojjam in line with the timing of the harvesting period in each zone.

level management. We also collected data on the agronomic information farmers received in the past including information on what fertilizer recommendation information they received and plot management history.[14] In addition, we collected physical data for one of the farm's maize plots on plot area, crop cuts (for yield estimates) and soil samples for laboratory analysis. The plot chosen was the largest maize plot farmed by the household. Within this plot, we estimated yields via crop-cuts.

The interventions were carried out from March 11th to April 1st 2018, just before the planting period started, for 248 and 245 households in treatment group one and two, respectively. The follow-up survey was collected during the harvest season of 2018, from October to December. Table 4 presents the pre-treatment descriptive statistics and balancing tests for each of the treatment arms and the control group.

[INSERT TABLE 4 HERE]

Column 1 presents the summary statistics for households in the control group (C), and columns 2 and 3 present the summary statistics for households in treatment groups one (T1) and two (T2), respectively. Columns 3 to 6 show the mean difference between households in the control and treatment arm one (C-T1), control and treatment two (C-T2), and treatment arms one and two (T1-T2), respectively. The groups are well balanced across all of the main characteristics with no significant differences in means detected. We also examine if there are significant differences in means between treatment and control groups within each zone. We do not find any differences in any of the outcome variables and most of the household demographic characteristics.[15]

We asked farmers at baseline whether they were aware of the current regional fertilizer recommendations given by the district-level agricultural development agents, and whether they followed the recommendation. In the baseline survey, around 65 percent of farmers knew these regional fertilizer recommendations. Among those who knew the recommendation, more than 87.5 percent reported that they followed the recommendation.

[14] This includes information on weeding, the application of organic fertilizer, the number of years that the plot was cultivated, whether the plot was left fallow in the last agricultural season, irrigation practices, etc.
[15] These tables are presented in Tables C1 to C4 of Appendix C.

Table 5 presents the summary statistics on the actual average baseline fertilizer application rates for farmers in each group relative to the coarse (zonal-level) fertilizer recommendation rates. Instead of using the total amount of inorganic fertilizer in kilogram per hectare (kg/ha), we focus on the level of macronutrients applied and the recommended amount. As revealed in the first panel of the table, farmers in treatment arm one (SSI only) used about 152.3 kg/ha of nitrogen, phosphorus and sulfur for maize production at baseline. This figure is lower than the average coarse macronutrient recommended rate of 208.4 kg/ha. The data also reveal that at baseline around 77.7 percent of farmers in treatment one applied macronutrients below the recommended rate. Similarly, in the second panel of Table 5, we see that farmers in treatment arm two (SSI coupled with insurance) used around 146 kg/ha of nitrogen, phosphorus and sulfur for maize production at baseline, lower than the blanket recommendation rate. On average, around 78.4 percent of farmers in treatment two applied a macronutrient rate below the site-specific recommended rate. Similarly, in the third panel of Table 5, we find that around 74.1 percent of farmers in the control group apply fertilizer at or below the recommended rate. The differences across groups are not statistically significant.

[INSERT TABLE 5 HERE]

The identification strategy relies on randomization across grid-cells. We compare outcomes at end-line between the treatment and control groups: farmers in those grid-cells that are given SSI, $T1$; farmers in those grid-cells that are given SSI with insurance, $T2$; and farmers in those grid-cells that are not given any SSI or insurance, the control group. While the randomization will allow us to detect the causal impact of the interventions on fertilizer adoption, to allow for possible unobserved differences between treatment and control groups we also control for baseline values of the outcome variables of interest along with baseline characteristics. The main specification is given in equation (10).

$$Y_{ib} = \beta_0 + \beta_1 T1_{ib} + \beta_2 T2_{ib} + \delta_1 Y_{ibt-1} + \boldsymbol{\delta}_2 \mathbf{X}_{ibt-1} + \alpha_b + e_{ib} \quad (10)$$

Where y_{ib} is the outcome variable for household i in block b at end-line; $T1_{ib}$ is a dummy indicator which takes a value of one if household i is in treatment arm 1; $T2_{ib}$ is a dummy indicator which takes a value of one if household i is in treatment arm 2; Y_{ibt-1} is the value of the outcome variable at baseline; X_{ibt-1} are household-specific control variables at baseline including gender, education, age and marital status of the household head, household size, type of maize seed planted, and number of adult household members; α_b are block-specific fixed effects that will capture any differences between the four administrative zones; and e_{ib} is a statistical noise term.

The coefficients β_1 and β_2 determine the causal impact of site-specific agronomic information alone and accompanied by insurance, respectively, on the outcome variable of interest. Standard errors are clustered at the level of the grid-cell, which is the unit of randomization.

We also explore some of the mechanisms through which the interventions impact on the outcomes of interest. To examine the effect of site-specific fertilizer recommendations on farm productivity, we use the random assignment of grid-cells into treatment and control groups as an instrument for fertilizer use. The exclusion restriction is that the randomization of grid-cells only affects farm productivity via fertilizer use. Similarly, we also use the randomization of grid-cells as an instrument for farm-productivity in examining the impact of site-specific fertilizer recommendations on household welfare.

5. Results

Our first outcome of interest is the total level of inorganic fertilizer used in kg/ha. The results for this outcome based on the specification presented in equation (10) are presented in Table 6. Columns 1 and 2 show the effect of the program on the average amount of inorganic fertilizer (urea and/or NPS) in kg/ha used for maize production by the household, whereas columns 3 and 4 show the effect on the amount of nitrogen used in kg/ha. In all estimations, we control for baseline outcome variables and block (zone) fixed effects.

Results show that well-targeted fertilizer recommendations increase fertilizer use for maize production. The first row in column 1 shows that SSI increases the amount of fertilizer used on average for households for maize production (in kg/ha) by around 15 percent. Column 2 shows that this effect increases slightly to 16 percent when we control for household-specific control variables at baseline including gender, education, age and marital status of the household head, household size, type of maize seed planted, number of adult household members, and credit take-up rate. In column 4 we find that provision of SSI increases the amount of nitrogen used for maize production by around 12 percent in kg/ha. We do not find any evidence that the provision of SSI on fertilizer use rates coupled with insurance has an effect on fertilizer application. That is, the results for treatment two are statistically insignificant in all three specifications.

[INSERT TABLE 6 HERE]

The null effect of treatment two could be due to heterogeneity in the actual and the recommended fertilizer application rates at the baseline. That is, farmers who applied inorganic fertilizer above the site-specific recommendation amount could reduce the amount of inorganic fertilizer used at the end-line, while those who used lower amounts of fertilizer relative to the recommended amount could increase their use. Pooling these impacts could suggest no effect on average. Moreover, these opposing effects could dampen the coefficient estimates for treatment arm one. To explore this possibility, we estimate a quantile regression model, focusing on nitrogen application rates.[16] The results are presented in Table 7. Estimates in column 1 and 2 show the effect of the program for the lower 10^{th} and 30^{th} percentiles of the distribution of the outcome variable (log N (kg/ha)), while columns 3, 4, and 5 show the results for the 50^{th}, 70^{th}, and 99^{th} percentiles of the distribution. We found find that for the lowest 10^{th} percentile of the distribution of log nitrogen use, farmers in treatment arm one and two increased their nitrogen application rate by 22 and 17 percent at end-line, respectively. The coefficients for treatment arm one and two are not statistically different. This effect decreased to 12 percent for farmers in treatment arm one for the 30^{th} quantile of the distribution with no statistically significant effect for treatment arm two. For treatment arm two, we find a negative effect for the top 99^{th} percentile of the distribution suggesting that farmers that were over-applying fertilizer at baseline in treatment arm two adjust their application rates downwards.

[INSERT TABLE 7 HERE]

Next, we consider the impact of the interventions on the absolute difference between the recommended and the actual fertilizer use. The results are presented in Table 8. Columns 1 and 2 show the effect of the interventions on the household level average absolute difference between the recommended and actual use of nitrogen in kilograms per hectare used for maize production,

[16] Due to the availability of different fertilizer types with different nutrient composition, we use amounts of nutrient use in kg per hectare as an outcome variable rather than total fertilizer use in kg per hectare to better capture adherence to our specific recommendations.

while column 3 and 4 show the absolute gap for phosphorus and sulfur used for maize production. Column 5 presents the results for the overall average of all three nutrients. For the treatment households, the fertilizer use gap is calculated by using the absolute difference between the actual macronutrient in kg/ha that farmers applied for maize production and the site-specific recommended values, whereas for the control households we used the absolute deviation of the actual macronutrients used by farmers and the regional recommendation values. In all estimations, we control for baseline outcome variables, household-specific control variables at baseline (with the exception of column (1)), and block (zone) fixed effects.

[INSERT TABLE 8 HERE]

Results show that well-targeted fertilizer recommendations improve fertilizer use for maize production in terms of better alignment with locally optimal rates. The first row in column 1 shows that site-specific information on how much fertilizer to use, when to use it and the expected outcomes reduces the absolute gap of actual and the recommended use of nitrogen by around 13.2 kilogram or 15 percent in kg/ha. Column 2 shows the same effect after we control for household-specific control variables at baseline including gender, education, and marital status of the household head, household size, number of adult household members, credit take-up rate, and drought flood incidence dummies. Similarly, in column 3 and 4, we find a reduction in the absolute gap between the farmers' actual phosphorus and sulfur use and recommended values by around 4.3 and 1.4 kilograms per-hectare, respectively. Over all, in column 5, we see that on average, the provision of SSI closed the absolute gap between the actual and recommended amount of macronutrients by around 18.7 kg/ha or 12.3 percent compared to the baseline amount. This supports our hypothesis that households are more likely to adopt fertilizer recommendations when accompanied by SSI.

The findings for treatment arm two, where information is coupled with insurance, are very similar. The second row in columns 1 and 2 show that the combined information-insurance treatment closed the absolute gap between the actual and recommended use of nitrogen use by around 13.45 kilograms per hectare, or 15.2 percent. This effect is not statistically different from the effect of the information-only treatment. Similarly, the results in the second row of columns 3 to 5 show that the combined treatment reduces phosphorus, sulfur and total macronutrient values (nitrogen, phosphorus and sulfur) by 7.2, 1.85, and 22.04 kilograms per hectare, respectively. These coefficients are also not statistically different from those for the information-only treatment. This suggests that the addition of the insurance product does not affect the impact of SSI.

During the end-line data collection, we asked farmers who received crop insurance cover on the relevance of the insurance scheme in making their production decisions. Only 35 percent of farmers found the insurance cover useful. Farmers reported that the main reasons behind the low perceived usefulness of the insurance cover included the fact that they never experienced shocks (40 percent), they did not trust that claims could be made in the event of shock (48 percent), and that they did not understand what insurance was (22.5 percent). This is in line with recent literature which identifies both lack of trust that payouts would be made (Hongbin et al., 2009; Ceballos et al., 2018) and poor understanding of insurance mechanisms (Njue et al. 2018, Sibiko et al. 2017) as key factors in the low demand for insurance by smallholder farmers. Dercon et al. (2014), Fonta et al. (2018), and Njue et al. (2018) all find, however, that awareness and training in crop insurance enhances uptake.[17] While we cannot speak to the factors affecting the uptake of insurance, our results suggest that giving agricultural insurance for free and explaining its benefits to farmers does not impact on production decisions. This suggests that in this context either the downside risk of making agricultural investments is not important for farmers in making their production decisions or agricultural insurance is not the appropriate mechanism.[18]

Overall, we find that households are more likely to adopt fertilizer recommendations when accompanied by SSI. The next question is whether these adjustments to fertilizer use lead to improved productivity. In Table 9, we examine the impact of the two treatments on maize yields measured in kilogram per hectare. As revealed in columns (1) and (2), there is a noticeable increase in yields for plots cultivated by farmers who received the SSI, both in treatment arms one and two.[19] We find around a 0.5 MT/ha yield difference between plots cultivated by farmers in the

[17] It should be noted that other studies, for example, Takahashi et al. (2016), find that improving knowledge about agricultural insurance products does not affect uptake

[18] It is also possible that farmers did not understand the benefits of the insurance product. We made every effort to minimise this possibility. Enumerators were given in-depth training on how to explain the insurance to participants. In addition to an oral explanation participants were also given a piece of paper which stated that they would be reimbursed if they lose their crop due to drought, fire, storm or flooding. Extensive training of enumerators suggests that this is not the case but it cannot be ruled out.

[19] We do not find any differential effect of the information coupled with the insurance treatment.

treatment and control groups. Compared to the control group whose average maize production at the baseline was around 3.3 MT per hectare, the introduction of SSI improves average maize productivity of the treatment group by around 15 percent.

To provide some reassurance that the increase in productivity is related to improved application of fertilizer we also examine whether there is a difference in the number of labor hours allocated for maize production by farmers' in treatment and control groups. It is possible, for example, that the information about the appropriate level of fertilizer and the expected yields motivates farmers to worker harder thus leading to higher productivity. Our results, presented in columns (3) and (4) of Table 9, show, however, that there is no statically significant difference between treatment and control farmers in the number of labor hours allocated for maize production.[20]

[INSERT TABLE 9 HERE]

In Table 9 we also consider whether the increase in productivity has knock on effects for household welfare by exploring the impact of the treatments on per-capita consumption expenditure of households. The results are presented in columns (5) and (6) and show that there is no significant difference in the average per-capita consumption expenditure between treatment and control households at end-line suggesting that productivity increases have not translated into improvements at end-line. This could be due to very short time span between harvest period and the end-line data collection.

In the final part of our analysis we consider whether there are any spillover effects of the program on input allocation decisions for crops other than maize. We test whether there is a difference in the usage of fertilizer for non-maize crop production. While we only provide site-specific recommendations and crop insurance cover for maize production, we might expect farmers to also change their fertilizer use for non-maize production. Table 10 shows the effect of the two treatments on the absolute gap between the farmers' actual and recommended fertilizer values for non-maize crop production at end-line. Unlike maize production, we do not find any statistically

[20] We also find no statistically significant difference in the effect of the treatment on the allocation of labour hours to other crops suggesting that farmers are not changing the focus of the labour efforts in response to the treatment. Results are presented in Table D1 of Appendix D.

significant difference between treatment and control farmers in closing the gap between actual and recommended values.[21]

[INSERT TABLE 10 HERE]

6. Conclusion

Adoption of modern agricultural practices, including increased use of improved inputs, are crucial for enabling agricultural productivity growth and structural transformation. However, the existing literature shows that adoption rates for new agricultural technologies in developing countries have remained persistently low, particularly among smallholder farmers. This could be due to a variety of different constraints including liquidity constraints, information failure and risk. In this paper, we examine whether the relevance of the technology to local conditions is a constraining factor. The context for our study is Ethiopia where blanket fertilizer recommendations are used to try to encourage farmers adopt particular blends of fertilizer. These recommendations, however, are often not suitable for particular soil types of different agro-climatic conditions. Using a two-level cluster randomized control trial, we test whether providing smallholder farmers with targeted information on the specific blend of fertilizer to use on their maize growing plots makes them more likely to adjust their fertilizer use in line with the recommendation. We also test whether coupling this information with a free insurance product that protects farmers against crop failure due to weather related events impacts on adoption rates.

Our results show that site-specific fertilizer recommendations improve fertilizer usage and this in turn has meaningful effects on the productivity of maize production. Our findings suggest that poorly defined extension information may constitute an important constraint to technology adoption. As such, our work suggests that one of the ways in which the ongoing digital transformation of agriculture in developing countries may impact growth is through better alignment of agronomic recommendations with localized production contexts. This is certainly not limited to fertilizer recommendations: many other types of agronomic management information may also be enhanced by better spatial targeting. More empirical work will also help to better understand how the uptake of information from improved and better-targeted advisory services

[21] Similarly, the results in table D2 and D3 of the Appendix D show that there is no statistically significant difference in pesticide and herbicide application rates between farmers in treatment and control groups for non-maize production.

may conditioned by complementary interventions, such as insurance and credit. While we did not find evidence that insurance affected information uptake in our study context, it is possible that the combined provision of improved advisory services with insurance may have important complementary effects in other contexts. In the current era of ICT-enabled innovations in the provision of advisory and other services to smallholder farmers, there exist many possible modes of presenting and bundling such services, and additional experimental research will help to further clarify the opportunities with the greatest potential impacts on smallholder production and welfare outcomes in particular settings.

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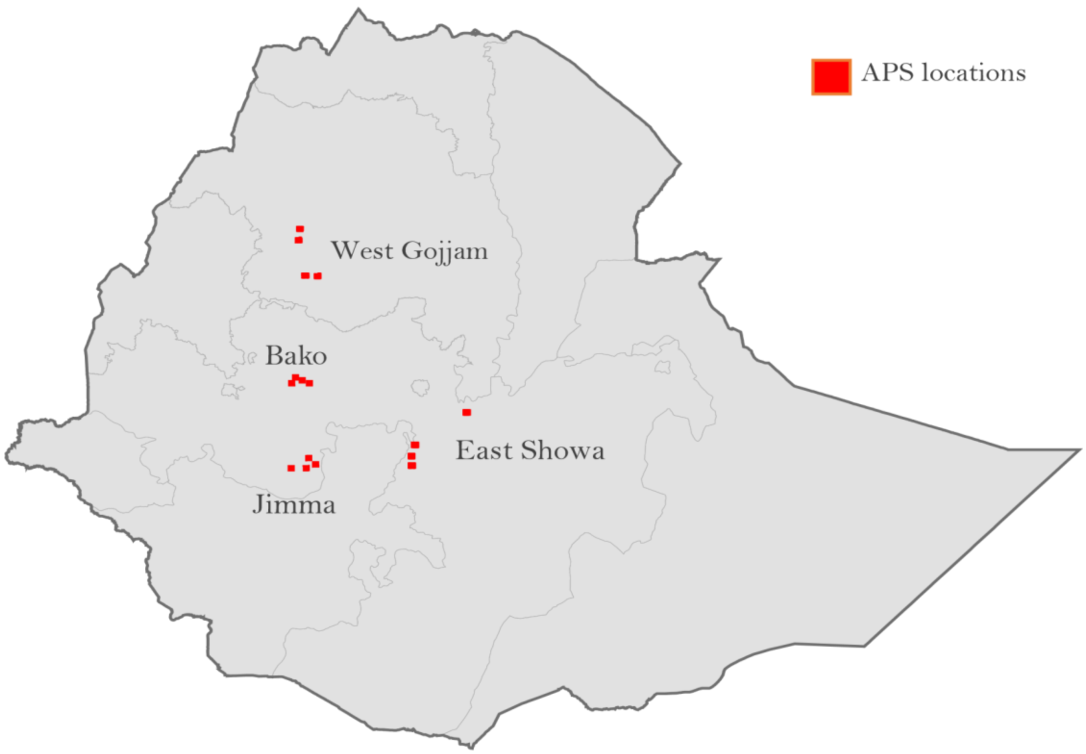
Figures

Figure 1: Map of the study area



Source: 2017 Agronomic Panel Survey (APS) data

Tables

Table 1: Summary of number of grid-cells and households by zone

Administrative zones	Number of grid-cells	Number of households
West Gojjam	40	240
East Shewa	34	166
Jimma	28	165
Bako	28	167
Total number of grid cells	130	738

Table 2: Summary of the randomization by zone

Group	West Gojjam	East Showa	Jimma	Bako	Total	Number of grid -cells
Treatment one (T1)	40	40	58	58	248	44
Treatment two (T2)	34	34	53	53	245	43
Comparison (C)	28	28	54	54	245	43
Total	130	130	165	165	738	130

Table 3: Summary of main outcome variables

Outcome	Measurement
Adoption rate of fertilizer recommendation	Absolute gap between actual farmers' fertilizer use and the recommended value.
Farm productivity	Average maize yields in kg per hectare.
Household welfare	Average per-capita consumption expenditure and change in gross profit margins of maize production.

Table 4: Mean difference between households in treatment one, two and the comparison groups

Variables	C	T1	T2	[C-T1]	[C-T2]	[T1-T2]
Maize production (kg per hectare)	3,247	3,246	3,205	1.41	42.27	40.86
				[0.990]	[0.726]	[0.735]
Per-capita income	4,349	4,123	3,989	225.8	359.7	133.9
				[0.527]	[0.301]	[0.700]
Fertilizer use (kg per hectare)	276.1	274.1	263.2	2.01	10.89	10.89
				[0.921]	[0.445]	[0.571]
Household size	6.01	6.29	6.37	-0.28	-0.09	-0.09
				[0.175]	[0.080]	[0.677]
Number of adult members	3.40	3.36	3.48	0.04	-0.12	-0.12
				[0.763]	[0.518]	[0.351]
Household head sex	0.93	0.94	0.91	-0.00	0.02	0.02
				[0.835]	[0.394]	[0.288]
Household head age	45.67	44.60	45.02	1.07	-0.42	-0.42
				[0.337]	[0.564]	[0.705]
Maximum years of education	13.96	14.88	13.85	-0.92	1.03	1.03
				[0.685]	[0.960]	[0.654]
Fertilizer use dummy	0.96	0.97	0.98	-0.01	-0.01	-0.01
				[0.445]	[0.191]	(0.574]
Credit take-up rate	0.33	0.31	0.38	0.02	-0.07	-0.07
				[0.633]	[0.257]	[0.106]
Flood dummy	0.08	0.05	0.06	0.03	-0.00	-0.00
				[0.195]	[0.287]	[0.818]
Drought dummy	0.05	0.04	0.04	0.01	-0.00	-0.00
				[0.486]	[0.663]	[0.795]

Note: All data are from the 2017 APS data set. Columns 1 to 3 present the summary statistics for households in the comparison (C), treatment one (T1) and treatment two (T2) groups, respectively. Columns 4 to 6 show the mean difference between control group and treatment arm one [C-T1], the control group and treatment two [CT2], and treatment arm one and treatment arm two [T1-T2], respectively. P-values are reported in parenthesis.

Table 5: Descriptive statistics on farmers' actual and recommended fertilizer application rates

	N (kg/ha)	P_2O_5 (kg/ha)	S (kg/ha)	All (kg/ha)
Treatment one (T1)				
Farmers baseline actual nutrient application rates	90.3	52.4	9.7	152.3
	(83.6)	(48.9)	(9.0)	(136.7)
Coarse (zonal level) recommended value	122.6	71.8	14	208.4
	(13.8)	(7.9)	(0.0)	(21.7)
Nutrient gap	32.3	19.1	4.3	55.6
	(77.8)	(46.5)	(9.0)	(128.3)
Share of farmers below the recommended rate (%)	74.8	76.0	76.5	77.7
Treatment two (T2)				
Baseline nutrient application rates	84.7	52.2	9.6	146
	(60.3)	(32.9)	(6.0)	(94.3)
Coarse (zonal level) recommended value	122.3	72.0	14	209
	(13.5)	(7.8)	(0.0)	(21.3)
Nutrient gap	38.6	19.9	4.4	62.9
	(53.6)	(30.4)	(6.0)	(84.3)
Share of farmers below the recommended rate (%)	75.8	74.1	75.0	78.4
Control (C)				
Baseline nutrient application rates	88.2	53.6	(9.9)	152
	(68.0)	(37.7)	(7.0)	(107.3)
Coarse (zonal level) recommended value	122.8	71.8	14	208.7
	(13.6)	(7.9)	(0.0)	(21.5)
Nutrient gap	35.0	18.2	4.1	57.0
	(61.5)	(34.9)	(7.0)	(97.4)
Share of farmers below the recommended rate (%)	73.2	71.5	72.0	74.1

Note: The macronutrients are based on the fertilizer blends used by farmers, which include urea (46% N) and NPS (19% N, 38% P and 7% S). Standard deviations are reported in parentheses.

Table 6: Effects on farmers' fertilizer application rates

	Log fertilizer (kg/ha)		Log N (kg/ha)	
	(1)	(2)	(3)	(4)
Treatment one	0.15*	0.16*	0.11	0.12*
	(0.09)	(0.09)	(0.07)	(0.06)
Treatment two	0.03	0.02	0.04	0.03
	(0.10)	(0.10)	(0.07)	(0.06)
Baseline outcome variables	Yes	Yes	Yes	Yes
Baseline control variables	No	Yes	No	No
Block/zone fixed effects	Yes	Yes	Yes	Yes
Observations	718	717	711	710

Note: The dependent variable in column (1) and (2) is the log household level average use of total inorganic fertilizer (urea and NPS) in kilogram per hectare used for maize production at the end-line, whereas the dependent variable in columns (3) and (4) is the log of nitrogen in kg/ha used at the end-line. In columns (2) and (4), we control for outcome variables at the baseline, household specific control variables at the baseline including gender, education, age and marital status of the household head, household size, type of maize seed planted, and number of adult household members, and block (zone) specific fixed effects. Kebele (village) level clustered standard errors are reported in parenthesis, with significance denoted as * $p < 0.1$, ** $p < 0.05$ and *** $p < 0.01$.

Table 7: Effects on farmers' fertilizer application rates (quantile regression results)

	Log N (kg/ha)				
	(1)	(2)	(3)	(4)	(5)
	10th	30th	50th	70th	99th
Treatment one	0.22***	0.12**	0.04	0.01	-0.14
	(0.08)	(0.05)	(0.06)	(0.07)	(0.11)
Treatment two	0.17*	0.07	0.04	-0.01	-0.20*
	(0.09)	(0.06)	(0.06)	(0.06)	(0.12)
Controls	Yes	Yes	Yes	Yes	Yes
Block/Zonal fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	710	710	710	710	710

Note: The dependent variable in all columns is the household level average log nitrogen use for maize production in kilogram per hectare at the end-line. Estimates in column 1 and 2 show the effect of the program for the lower 10th and 30th percentile of the distribution of the outcome variable, whereas estimates in column 3, 4, and 5 present the effect of SSI on fertilizer application rate for the 50th, 70th, and 99th percentile of the distribution of the outcome variable. In all columns, we control for outcome variables at the baseline: drought, flooding, household specific control variables at the baseline including gender, education, marital status of the household head, household size, credit take-up rate, and number of adult household members, and block (zone) specific fixed effects. Bootstrap standard errors are reported in parenthesis, with significance denoted as * $p < 0.1$, ** $p < 0.05$ and *** $p < 0.01$.

Table 8: ITT effects on absolute difference between recommended and actual fertilizer use

Variables	N (kg/ha)		P2O5 (kg/ha)	S (kg/ha)	All nutrients (kg/ha)
	(1)	(2)	(3)	(4)	(5)
Treatment one	-13.22***	-13.24***	-4.28*	-1.35***	-18.68***
	(4.10)	(4.14)	(2.37)	(0.45)	(6.47)
Treatment two	-13.45***	-13.72***	-7.20**	-1.85***	-22.04***
	(4.08)	(4.12)	(2.65)	(0.49)	(7.07)
Baseline control mean	88.5	88.5	53.6	9.9	151.3
F-statistic	0.00	0.01	1.19	0.98	0.22
Prob > F	(0.96)	(0.91)	(0.28)	(0.32)	(0.64)
Baseline outcome variable	Yes	Yes	Yes	Yes	Yes
Baseline control variables	No	Yes	Yes	Yes	Yes
Block (zone) fixed effect	Yes	Yes	Yes	Yes	Yes
Observations	702	701	701	701	711

Note: The dependent variable in columns 1 and 2 is the household level average absolute difference between recommended and actual use of nitrogen in kilograms per hectare used for maize production. In columns 3 and 4 the dependent variable is the household average absolute difference between recommended and actual use of phosphorus and sulfur used for maize production. Column 5 presents the results for the average absolute difference for all macronutrients combined. In all estimations, we control for baseline outcome variables, household-specific control variables at baseline including gender, education, age and marital status of the household head, household size, type of maize seed planted, and number of adult household members, dummy for fertilizer use, and block (zone) fixed effects. The F-statistic tests the quality of the coefficients for treatment arms one and two. Village level clustered standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 9: ITT effects on productivity and household welfare

Variables	Aggregate farm-level output (kg/ha)		Farmer labor hours allocated to maize (hr/ha)	Log per-capita consumption expenditure	
	(1)	(2)	(3)	(4)	(5)
Treatment one	437.4***	468.1***	3.18	0.04	0.04
	(162.2)	(162.9)	(27.5)	(0.06)	(0.06)
Treatment two	430.0 **	485.5***	-14.1	-0.04	-0.03
	(174.5)	(173.0)	(27.9)	(0.06)	(0.06)
Baseline control mean	3,247	3,247	327.7	16,857	16,857
F-statistic	0.00	0.01	0.31	1.83	1.68
Prob > F	(0.97)	(0.92)	(0.58)	(0.18)	(0.19)
Baseline outcome variable	Yes	Yes	Yes	Yes	Yes
Baseline control variables	No	Yes	Yes	No	Yes
Block (zone) fixed effect	Yes	Yes	Yes	Yes	Yes
Observations	896	892	723	703	702

Note: The dependent variable in columns 1 and 2 is the household level average maize production in kg/ha. The dependent variable in column 3 is the average amount of labor hour per hectare used for maize production. In columns 3 and 4 the dependent variable is average per-capita income in Ethiopian Birr. The unit of analysis in columns 1 and 2 is the plot while in columns 3 and 4 it is the household, which explains the difference in the number of observations. Household-specific control variables at baseline include gender, education, age and marital status of the household head, household size, maize seed variety, indicator for credit take-up, amount of inorganic fertilizer used in kg/ha, incidence of flooding and drought. The F-statistic tests the quality of the coefficients for treatment arms one and two. Village level clustered standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 10: ITT effects on gap between actual farmers' fertilizer use and recommended amount

Variables		N (kg/ha)	P2O5 (kg/ha)	S (kg/ha)	All nutrients (kg/ha)
	(1)	(2)	(3)	(4)	(5)
Treatment one	-6.07*	-5.28	-3.64	-0.67	-7.19
	(3.17)	(3.33)	(2.39)	(0.44)	(5.34)
Treatment two	-2.19	-1.61	-0.63	-0.14	-2.46
	(3.54)	(3.56)	(2.59)	(0.47)	(5.82)
Baseline control mean	88.4	88.4	54.0	10.0	152.3
Baseline outcome variable	Yes	Yes	Yes	Yes	Yes
Baseline control variables	No	Yes	Yes	Yes	Yes
Block (zone) fixed effect	Yes	Yes	Yes	Yes	Yes
Observations	679	634	634	634	628

Note: The dependent variable in columns 1 and 2 is the household level average absolute difference between the recommended and actual use of nitrogen in kilogram per hectare used for non-maize production. In columns 3 and 4 the dependent variables are the household average absolute differences between the recommended and actual use of phosphorus and sulfur used for non-maize production, respectively. In column 5 the dependent variable is the household level average of the absolute difference between the recommended and actual use of all nutrients (nitrogen, phosphorus and sulfur) for non-maize production. In all estimations, we control for baseline outcome variables and block (zone) fixed effects. Household-specific control variables at baseline include gender, education, age and marital status of the household head, household size, type of maize seed planted, and number of adult household members, and dummy for fertilizer use. Village level clustered standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendices

Appendix A: Fertilizer recommendations in Ethiopia

Agriculture is the backbone of the Ethiopian economy and is the main source of livelihoods for rural households. More than 83 percent of the population depend directly on agriculture and many others on agriculture-related cottage industries, such as food oil processing, leather, and textiles (Davis et al., 2010). The sector also contributes 44 percent of the nation's Gross Domestic Product (GDP), 85 percent of exports and 85 percent of employment (Spielman et al., 2010; UNDP, 2016; World Bank, 2016).

Before the 1960s, the soil in Ethiopia was rich in nutrients. This was due to sufficient per-capita arable land and a small population growth rate.[22] Consequently, farmers traditionally used a very low amount of fertilizer. As time progressed, the nation's population grew and the total land holding declined. For example, between 1960 and 2008, the total per-capita land area fell from 0.5 ha to 0.2 ha (Spielman et al., 2010). As a result, soil degradation and nutrient depletion have become a serious threat to agricultural productivity and food security in Ethiopia (Kebede and Yomoch, 2009). Murphy (1968) found that nitrogen (N) and phosphorus (P) were identified as being the most deficient plant nutrients in almost all Ethiopian soils. According to the International Food Policy Research Institute (2010), around 5 to 7 million people in Ethiopia are chronically food insecure. Despite diverse and complex reasons for this, declining soil fertility and soil degradation are primary contributing factors.

To keep the soil nutrient balance[23] at sufficient levels, in the late 1960s, the Ministry of Agriculture and Natural Resources (MoANR) introduced a national-level blanket recommendation for use of urea and Diammonium phosphate (DAP) on the land to boost the N and P content (Murphy, 1968; Kassahun, 2015).[24] However, the application rate has still remained at a low level. For example, the amount of fertilizer used in 1997 and 1999 was only 13 and 16 kg per hectare on average, respectively (World Bank, 2008; FAOSTAT, 2005). Fertilizer use increased slightly to 17 and 18.5 kg per hectare in 2002 and 2015, respectively (World Bank, 2018). Spielman et al. (2010) reported that only 37 percent of farmers were using inorganic fertilizer in 2008 and the amount being applied was very low compared to other parts of the world. For instance, between 1997 and 2005 the average fertilizer use in South Asian countries was

[22] From the total of land area of around 1.13 million, Ethiopia has an estimated 55 million hectares of arable land (Makombe et al., 2007).

[23] Soil nutrient balance is the difference between nutrient inputs through, for example, organic or inorganic fertilizer, minus the nutrient loss through erosion and crop production.

[24] A 'blanket recommendation' is a 'one size fits all' solution where all farmers use the same amount of fertilizer blend recommendation in kg per-hectare without taking into account crop type, soil type or agro-ecological zones. For example, it may recommend that all farmers use 100 kg Urea and 100 kg NPS per hectare for all crops in all parts of the country.

more than six times higher than the average use of fertilizer in Ethiopia. In addition to the low adoption rate, the blanket application of nutrients, regardless of the crop type, soil type or agro-ecological zone, limited the effectiveness of its use (Lulseged *et al.*, 2017). It is therefore not surprising that farmers are reluctant to invest in fertilizer given the poor response of crops to its application in the past as a result of recommendations that were not specifically relevant to local conditions.

Indeed, in 2007, the Ethiopian Ministry of Agriculture (MoE) and Agricultural Research Centers developed regional fertilizer recommendation rates in Ethiopia. These recommendations have been disseminated to all farmers through district level agricultural extension workers and development agents for free. However, farmers have not adopted these blanket recommendations. For example, from our baseline survey in 2017, the average fertilizer use of farmers for maize production in all zones was below the average recommended rates for most zones at 120 kg of urea and 120 kg of NPS per hectare.[25] This setting provides the ideal context for testing farmers' adoption responses to a new technology that tailors the fertilizer recommendation to each individual farmer.

Since the existing fertilizer recommendations in Ethiopia are blanket, there is uncertainty about how well the recommendation will work in particular area. This could led to a sub-optimal use of fertilizer with little impact on farm productivity. In this study, we provide site-specific recommendations that are adjusted to local soil and climate conditions which, if adopted, should lead to a higher productivity and welfare benefit. We use the Nutrient Expert (NE) tool to generate the locally relevant recommendations (Pampolino et al., 2012; Xu et al., 2016).[26] The NE tool is a simple, quick and easily implemented tool that helps an agricultural agent to generate up to 20 nutrient management recommendations per-day. Moreover, it will generate predictions of both yield and profit. To roll-out site-specific recommendations, android phones are required and local agricultural extension workers require training on how to use the NE tool. The existing blanket recommendation is disseminated to farmers by local agricultural extension workers and so costs are relatively lower. As such, it is important to understand the extent of the benefits associated with the site-specific recommendations to ensure that they outweigh the cost of implementation.

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[25] The current blanket fertilizer recommendation rate for maize production in West Gojjam, East Wollega and West Shoa are 130 kilogram nitrogen and 76 kilogram phosphate per-hectare.

[26] Nutrient Expert is a decision-support tool (program), developed by the International Plant Nutrition Institute, that enables farmers and extension providers to quickly generate fertilizer recommendations for individual fields or for larger but similar areas, depending on the user's requirements. It is based on the QUEFTS (Quantitative Evaluation of the Fertility of Tropical Soils) model described by Janssen et al. (1990). To make a site-specific recommendation, the tool uses information on the available fertilizer blends in Ethiopia, current farmers' practices, relevant inputs and field history, and local conditions. Then, it provides advice on improved crop management practices, such as site-specific fertilizer blend recommendations, the potential or attainable yield a farmer can get from the same land, planting density, timing of fertilizer application, and weeding.

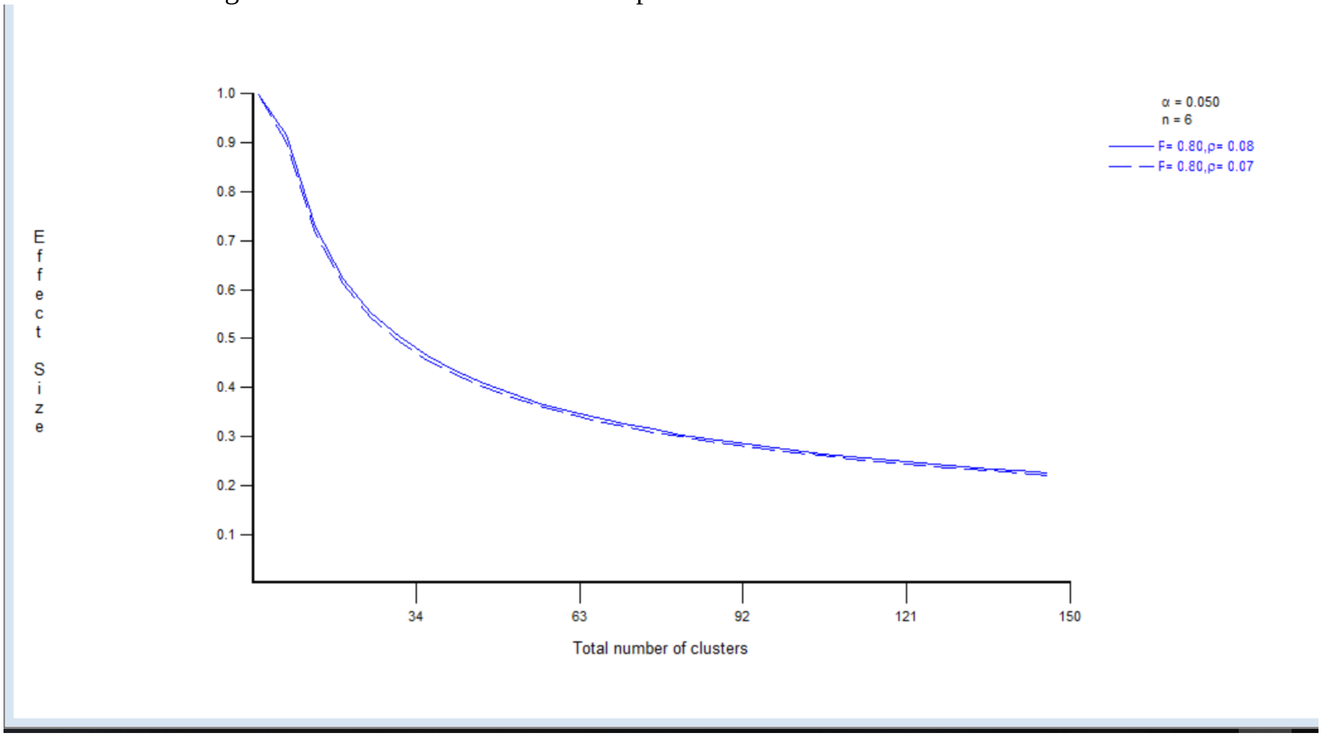
Appendix B: Power Calculations

We conducted power calculations for our main outcome variable - the absolute deviation of farmers' nitrogen applications from recommended rates in kilogram per hectare (kg/ha) – as well as other productivity and welfare outcomes of interest, i.e. farm-level maize productivity (kg/ha), net value of maize production per capita in Ethiopian birr (ETB), and average per capita consumption expenditure (ETB).

B1. Absolute deviation of farmers' actual and recommended amount of macronutrient use (kg/ha)

To calculate the minimum detectable effect of the absolute deviation of farmers' actual fertilizer application and the recommended amount, we estimate the intra-cluster correlation coefficient using the baseline data. The intra-cluster correlation between the control and treatment farmers is 0.065, whereas 0.075 for treatment arm one and two. Figure B1 presents the relationship between the number of clusters and the minimum detectable effect associated with the absolute deviation between actual farmers practice and the recommended value. The solid line shows the relationship between minimum detectable effect and cluster size between treatment and control farmers, whereas the dashed line presents the relationship between farmers in treatment arm one and two. For a power of 0.8, cluster size of 6, test size of 0.05 and intra cluster correlation of 0.08, we found a minimum detectable effect of 0.237 for 130 clusters. That is, we will be able to detect a treatment induced reduction of nutrient supply gaps of at least 23.7 percent with only a 20% chance of a type II error, assuming a test size of 0.05. This effect is more or less the same between treatment arm one and two.

Figure B1: Power calculation for adoption of fertilizer recommendations

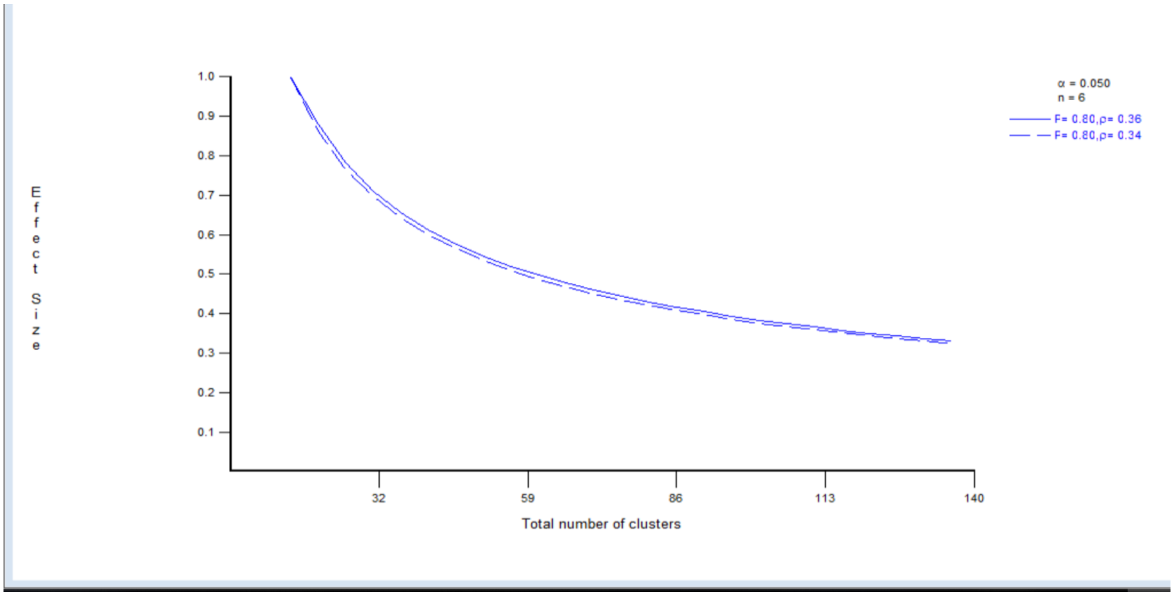


B2. Productivity and welfare indicator variables

Figure B2 shows the relationship between the number of clusters and the minimum detectable effect for productivity and welfare measures. The solid line shows the relationship between minimum detectable effect and cluster size between treatment and control farmers, whereas the dashed line presents the relationship between farmers in treatment arm one and two. We estimate the minimum detectable effect for a power of 0.8, cluster size of 6 and cluster number of 130. For intra cluster correlation of 0.36 and 0.34, we found a minimum detectable effect of 0.338 and 0.335 between farmers in treatment and control groups, and farmers in treatment arm one and two respectively. That is, we will able to detect treatment induced improvement of farm productivity of at least 33.5 percent for plots managed by treatment farmers with only a 20% chance of a type II error, assuming a test size of 0.05. Similarly, we found a minimum detectable effect of 0.30 for the average per capita net cost maize value production and consumption expenditure.

Figure B2: Power calculation of productivity and welfare measures

(i) Aggregate farm-level average maize production



Appendix C: Baseline covariate balance tests at zonal level

Table C1: Mean difference between households in treatment one, two and the comparison groups in the West Gojjam zone

Variables	C	T1	T2	[C-T1]	[C-T2]	[T1-T2]
Maize production (kg per hectare)	2804	3143	3007	-339	-202	136.8
Per-capita income	3391	3502	3304	-111	86.8	197.7
Fertilizer use (kg per hectare)	433	461	403	-28.3	30.2	58.43
Household size	5.64	5.81	5.86	-0.16	-0.22	-0.05
Number of adult members	3.29	3.33	3.31	-0.05	-0.02	0.03
Household head sex	0.98	0.97	0.94	0.00	0.04	0.04
Household head age	46.37	45.7	46.28	0.68	0.09	-0.59
Marital status	2.06	2.19	2.04	-0.13	0.02	0.15
Maximum years of education	15.68	17.9	19.72	-2.19	-4.04	-1.85
Fertilizer use dummy	1.00	1.00	1.00	0.00	0.00	0.00
Credit take-up rate	0.42	0.29	0.41	0.12	0.01	-0.12
Flood dummy	0.05	0.03	0.04	0.02	0.01	-0.01
Drought dummy	0.00	0.00	0.00	0.00	0.00	0.00

Note: All data taken from the 2017 APS data set. Column 1 to 3 present the summary statistics of households in the comparison (C), treatment one (T1) and two (T2), respectively. Column 4 to 6 show the mean difference between control and treatment arm one [C-T1], comparison and treatment two [CT2], and treatment arm one and two [T1-T2] groups respectively. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C2: Mean difference between households in treatment one, two and the comparison groups in the East Shoa zone

Variables	C	T1	T2	[C-T1]	[C-T2]	[T1-T2]
Maize production (kg per hectare)	6603	5880	5427	723.3	1174	450.8
Per-capita income	2975	2590	2826	385.7	149.4	-236.3
Fertilizer use (kg per hectare)	70.8	68.5	75.8	2.34	-4.98	-7.32
Household size	6.19	6.48	6.57	-0.30	-0.39	-0.09
Number of adult members	3.22	3.05	3.67	0.17	-0.44	-0.61*
Household head sex	0.89	0.88	0.80	0.01	0.09	0.08
Household head age	42.8	41.6	47.7	1.16	-4.96*	-6.12**
Marital status	2.46	2.47	2.70	-0.00	-0.24	-0.24
Maximum years of education	7.04	8.14	14.6	-1.10	-7.54*	-6.44
Fertilizer use dummy	0.85	0.88	0.91	-0.03	-0.06	-0.03
Credit take-up rate	0.28	0.31	0.33	-0.03	-0.06	-0.02
Flood dummy	0.28	0.09	0.07	0.19**	0.20**	0.01
Drought dummy	0.11	0.12	0.11	-0.01	0.00	0.01

Note: All data taken from the 2017 APS data set. Column 1 to 3 present the summary statistics of households in the comparison (C), treatment one (T1) and two (T2), respectively. Column 4 to 6 show the mean difference between control and treatment arm one [C-T1], comparison and treatment two [CT2], and treatment arm one and two [T1-T2] groups respectively. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C3: Mean difference between households in treatment one, two and the comparison groups in the West Shoa and West Wollega zones (Bako area)

Variables	C	T1	T2	[C-T1]	[C-T2]	[T1-T2]
Maize production (kg per hectare)	5830	5183	6104	647	-273	-920
Per-capita income	3889	3940	4067	-51.6	-178	-178
Fertilizer use (kg per hectare)	341	315	325	25.9	15.37	15.37
Household size	5.70	6.24	6.04	-0.54	-0.33	-0.33
Number of adult members	3.67	3.59	3.49	0.08	0.18	0.18
Household head sex	0.89	0.95	0.92	-0.06	-0.04	-0.04
Household head age	47.9	46.8	42.00	1.04	5.85*	5.85*
Marital status	2.48	2.19	2.36	0.29	0.12	0.12
Maximum years of education	18.4	19.9	10.28	-1.49	8.09*	8.09*
Fertilizer use dummy	1.00	1.00	1.00	0.00	0.00	0.00
Credit take-up rate	0.37	0.41	0.43	-0.04	-0.06	-0.06
Flood dummy	0.02	0.10	0.08	-0.08	-0.06	-0.06
Drought dummy	0.00	0.00	0.02	0.00	-0.02	-0.02

Note: All data taken from the 2017 APS data set. Column 1 to 3 present the summary statistics of households in the comparison (C), treatment one (T1) and two (T2), respectively. Column 4 to 6 show the mean difference between control and treatment arm one [C-T1], comparison and treatment two [CT2], and treatment arm one and two [T1-T2] groups respectively. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C4: Mean difference between households in treatment one, two and the comparison groups in the Jimma zone

Variables	C	T1	T2	[C-T1]	[C-T2]	[T1-T2]
Maize production (kg per hectare)	3108	2600	2245	508	863.2	355.3
Per-capita income	2652	2820	2672	-168	-19.5	148.6
Fertilizer use (kg per hectare)	170.9	181.1	195.6	-10.1	-24.7	-14.5
Household size	6.72	6.81	7.15	-0.10	-0.43	-0.34
Number of adult members	3.49	3.50	3.53	-0.01	-0.04	-0.03
Household head sex	0.96	0.94	0.98	0.02	-0.02	-0.04
Household head age	45.32	43.91	43.60	1.41	1.72	0.31
Marital status	2.23	2.39	2.13	-0.16	0.09	0.26*
Maximum years of education	13.79	12.46	8.72	1.33	5.08	3.75
Fertilizer use dummy	0.96	1.00	1.00	-0.04	-0.04	0.00
Credit take-up rate	0.19	0.20	0.32	-0.02	-0.13	-0.11
Flood dummy	0.00	0.00	0.05	0.00	-0.05	-0.05
Drought dummy	0.11	0.04	0.05	0.08	0.06	-0.01

Note: All data taken from the 2017 APS data set. Column 1 to 3 present the summary statistics of households in the comparison (C), treatment one (T1) and two (T2), respectively. Column 4 to 6 show the mean difference between control and treatment arm one [C-T1], comparison and treatment two [CT2], and treatment arm one and two [T1-T2] groups respectively. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix D: Additional results

Table D1: ITT effects on farmers' amount of labor hour allocation

Variables	All crops (hr./ha)		Non-maize production (hr./ha)
	(1)	(2)	(3)
Treatment one	6.44	3.62	-49.26
	(24.23)	(23.80)	(69.20)
Treatment two	-5.42	-8.23	-110.04
	(24.41)	(24.41)	(69.55)
Baseline control mean	263.9	263.9	380.9
Baseline outcome variable	Yes	Yes	Yes
Baseline control variables	No	Yes	Yes
Block (zone) fixed effect	Yes	Yes	Yes
Observations	731	730	637

Note: The dependent variable in column 1 and 2 is the household level average amount of labor hour per-hectare used for all crops, while in column 3 the dependent variable is the household level average amount of labor hour per-hectare used for non-maize production. In all estimations, we control baseline outcome variables and block (zone) fixed effects. Household-specific control variables at baseline include gender, education, age and marital status of the household head, household size, type of maize seed planted, and number of adult household members, and dummy for fertilizer use. Village level clustered standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table D2: ITT effects on farmers' pesticides application rate

Variables	All crops		Maize	Non-maize
	(1)	(2)	(3)	(4)
Treatment one	0.01	0.02	0.08	0.00
	(0.03)	(0.03)	(0.09)	(0.00)
Treatment two	-0.13	-0.12	-0.32	0.00
	(0.16)	(0.15)	(0.36)	(0.00)
Baseline control mean	0.01	0.01	0.03	0.05
Baseline outcome variable	Yes	Yes	Yes	Yes
Baseline control variables	No	Yes	Yes	Yes
Block (zone) fixed effect	Yes	Yes	Yes	Yes
Observations	731	730	723	682

Note: The dependent variable in columns 1 and 2 is the household level dummy variable for pesticides use for all crops, while in columns 3 and 4 the dependent variable is a household level dummy variable for pesticides application for maize and non-maize production respectively. In all estimations, we control for baseline outcome variables and block (zone) fixed effects. Household-specific control variables at baseline include gender, education, age and marital status of the household head, household size, type of maize seed planted, and number of adult household members, and dummy for fertilizer use. Village level clustered standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table D3: ITT effects on farmers' herbicides application rate

Variables	All crops		Maize	Non-maize
	(1)	(2)	(3)	(4)
Treatment one	-0.06	-0.06	-0.06	-0.06
	(0.04)	(0.04)	(0.04)	(0.04)
Treatment two	-0.01	-0.01	-0.02	-0.01
	(0.04)	(0.04)	(0.05)	(0.04)
Baseline control mean	0.69	0.69	0.42	0.61
Baseline outcome variable	Yes	Yes	Yes	Yes
Baseline control variables	No	Yes	Yes	Yes
Block (zone) fixed effect	Yes	Yes	Yes	Yes
Observations	731	730	730	730

Note: The dependent variable in columns 1 and 2 is the household level dummy variable for herbicide use for all crops, while in columns 3 and 4 the dependent variable is a household level dummy variable for herbicides application for maize and non-maize production, respectively. In all estimations, we control for baseline outcome variables and block (zone) fixed effects. Household-specific control variables at baseline include gender, education, age and marital status of the household head, household size, type of maize seed planted, and number of adult household members, and dummy for fertilizer use. Village level clustered standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.