Technology adoption and farmer beliefs: Experimental evidence from Tanzania

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Technology adoption and farmer beliefs: Experimental evidence from Tanzania*

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Abstract

Improved technologies can enhance agricultural productivity, yet their adoption remains limited in low-income countries. One under-explored factor affecting the adoption of inorganic fertilizers is farmer's beliefs about their soil quality, since returns to fertilizer depend on soil quality. We exploit a randomized controlled trial and find that farmers who learn they have higher quality soils are more likely to apply fertilizers, conditional on receiving a voucher. However, farmers who learn about their soil quality do not update their subjective soil beliefs (SSB), while farmers who receive vouchers only update their SSB upward. Our results suggest that input voucher programs failing to provide concomitant tailored recommendations may incorrectly encourage fertilizer application on poor, sometimes unresponsive soils.

Keywords: Subjective beliefs, Technology adoption, Agriculture, Fertilizer, Vouchers, Sub-Saharan Africa

JEL Classification:

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I Introduction

Agricultural yields in Africa remain disappointingly low relative to other parts of the world. One reason for these low yields is the lack of adoption of technologies and/or improved practices that have high expected returns, such as inorganic fertilizers. Many reasons have been proposed for the low observed adoption rates, including credit, insurance and/or information constraints, high transactions costs often associated with poor infrastructure, and imperfect land and labor markets (Conley and Udry, 2010; Duflo et al., 2011; Karlan et al., 2014; Burchardi et al., 2018; Fabregas et al., 2019; Magruder, 2018). Furthermore, the variability in returns to technologies can be high and likely contributes to lower adoption rates (Suri and Udry, 2022). Indeed, Marenya and Barrett (2009) find that fertilizers become unresponsive on poorer quality soils, making their application in some cases unprofitable.

Given the heterogeneity in expected returns to fertilizer application due to varying underlying soil quality, an important but often overlooked consideration is farmers' beliefs about their soil quality and how closely it aligns with their soil's true, or measured, quality. If farmers deem their soils to be poor, they may be unwilling to invest in inputs expecting the returns to be low. Alternatively, they may believe that applying fertilizers on poor soils will increase its fertility. If farmers perceive their soil quality to be high, they may decide that investing additional inputs is unnecessary, or they may think applying fertilizers is necessary to maintain its fertility. Or farmers may only think it is worthwhile to apply fertilizers if they believe their soils lie within a certain quality threshold. The returns to those farmers who deem it appropriate and apply fertilizers will depend on how closely their assessment of their soil aligns with the true soil quality. Thus, farmers' perceptions and beliefs about their soil quality seem to matter to the adoption decision.

We begin by testing whether farmer's true and revealed soil quality, as measured by soil electrical conductivity (EC), and how true soil quality compares to farmer's subjective assessment of their soil, affect farmer's decision to apply fertilizers. If true soil quality and farmers' beliefs matter to the fertilizer decision, then policymakers may be interested in knowing whether and how farmers update their beliefs. Thus, we are interested in knowing whether farmers learn and retain the information provided to them, and whether they update their SSBs closer towards the true soil quality. In other words, do farmers learn about their soil health, and do they believe those recommendations enough to update their beliefs? Finally, we are interested in knowing whether fertilizer use, specifically, is associated with SSB updating and information retention.

To study these issues we exploit a randomized controlled trial (RCT) designed to test the effect of information provision and subsidies on fertilizer use, yields and subjective soil beliefs with three treatment arms: farmers receive a voucher only, fertilizer recommendations only, or both a voucher and recommendations. We follow up with farmers approximately six months after treatment, at the end of the long rains season, and three years later. We find that farmer's subjective soil beliefs (SSBs) and true soil quality do matter to their decision to apply fertilizers. Farmers with underlying objectively good quality soils who received vouchers and recommendations apply more fertilizers six months after treatment, suggesting that farmers are aware that fertilizers are more responsive on better quality soils. In particular, farmers who have an initial low subjective belief of their soil quality and learn that their soil quality is good, are more likely to apply fertilizers and are more likely to apply a greater amount.

Only farmers who received a voucher to purchase fertilizer increase their SSB six months after the intervention. This effect is driven by farmers with poorer true soil quality. However, farmers with poor true soil quality who received a voucher are less likely to update their SSBs toward the true soil quality. The increase in SSB driven by receiving a voucher disappears five years after baseline, but persists, again, only for those farmers with poorer soils. Likewise, we find that applying fertilizer is associated with an increase in SSB at the end of the season, but not in the longer run. Finally, we find that farmers having received both recommendations and vouchers retain the recommendations both in the short and long run, though the magnitude of the information retained is much higher in the short run. Farmers who just received recommendations retain some of the information in the short run, but less than the farmers in the recommendations and voucher group, and not in the long run. Despite this increase in knowledge, farmers in the recommendations and voucher group do not update their SSBs accordingly.

The literature on technology adoption is vast covering research from several decades (Magruder, 2018). This paper draws from and contributes to two strands within this literature: the literature on information provision and technology adoption, and the role of belief updating and decision making. In particular, several recent randomized controlled trials examine the role of fertilizer recommendations on uptake and yields. Corral et al. (2022) test whether farmers adopt tailored recommendations, plot-specific or cluster-specific, under two types of grants, i.e., either farmers choose how to spend money they receive or they can only purchase specific inputs. They find that farmers who received recommendations and a grant adopted more fertilizers, but find no differentiation in the grant type. Farmers who only received recommendations and extension services also adopt more fertilizers, but not as much as those who received a grant. They find no difference in whether the recommendations were group or plot specific. Cole et al. (2020) test the effect of digitized and customized fertilizer recommendations on fertilizer adoption and yields and find greater fertilizer use among treated farmers. However, they find no difference in yields, whether they be farmer-reported or satellite-derived. As described in more detail below, this study uses the same data as **?** who examine the effect of tailored fertilizer recommendations and subsidized fertilizer on adoption and yields, and find that farmers having received vouchers only and both recommendations and vouchers increase input use. Other recent related studies look at the demand for fertilizers after giving farmers plot-specific recommendations by eliciting farmers' willingness to pay (Murphy et al., 2020), and the demand for soil recommendations by examining the contributions made in a public goods game for soil testing on a neighboring plot (Berazneva et al., 2023). Both studies corroborate the findings above, finding a positive effect of information provision on fertilizer use, and a demand for soil testing.

Most studies examining farmers' technology adoption decision begin with the model developed by Foster and Rosenzweig (1995). Some recent papers extend their model to incorporate different factors, including uncertainty, farmer beliefs and confidence. Oliva et al. (2020) model the multi-stage nature of the adoption of agroforestry trees in Zambia, seeing how new information, subsidies, and uncertainty affect the decision to continue adopting or abandoning a technology. Hoel et al. (2023) study how misattribution, where an agent mistakenly attributes a bad outcome to a specific input when the bad outcome was caused by natural variation or a different production process, and ambiguity, where the agents is unsure about the likelihood that a product is good or bad, affects the learning process. They find that misattribution and multiple priors beliefs may remain uncertain even after observing several data points, making it difficult for agents to learn. Nourani (2019) models how social influences alter profitability beliefs and learning effort. Maertens et al. (2020) study how farmers learn from extension services in two-stages, formulating yield expectations and then deciding how much effort to invest in the learning process. The authors find evidence that beliefs about potential yields hinges on first-hand and local experience and these beliefs impact learning effort.

We contribute to these literatures by explicitly examining the relationship between beliefs about soil quality, the adoption of fertilizers and belief updating. Only three studies we are aware of examine this relationship specifically. Berazneva et al. (2018) find that as Kenyan and Tanzanian farmers increase their subjective soil fertility beliefs from "bad" to "good", yields become higher, while input use does not change, suggesting that yields play an important role in affecting soil fertility perceptions while inputs do not. Marenya et al. (2008) also find that yields are a main correlate of soil beliefs, but it is not clear if farmers base their beliefs on productivity, or if they believe that better soils cause higher yields. Finally, Gars et al. (2023) study how farmers respond to fertilizer recommendations and how farmers' confidence, measured as the precision in farmer beliefs about optimal fertilizer use, affects their demand for fertilizer recommendations. The authors find that farmers who are more confident in their prior beliefs are willing to pay less for the information. In this study, we use randomization to establish identification, allowing us to study the impacts of information and vouchers on soil beliefs and retention. Furthermore, we examine how beliefs change over time, up to three years after an intervention designed to relax information and credit constraints ended. We are not aware of other studies examining the longer-term relationship between SSB and information provision in the context of agriculture.

II Experimental Design

We employ data collected in Harou et al. (2022) who conduct a randomized controlled with three treatment arms (two-by-two factorial design) to test the effect of providing farmers with site-specific soil recommendations and/or vouchers on farmer input decisions and yields. Of all maize-growing villages in Morogoro Rural District, Tanzania, 27 villages were randomly selected as control villages and 20 villages as treatment villages. Ten farmers were randomly selected in control villages while 40 farmers in treatment villages were randomly selected and assigned to one of four groups:

- *Voucher*: Farmers received a voucher worth 40 USD to purchase any input from an input dealer or to redeem for cash. These farmers were reminded of the government's regional fertilizer recommendations. After the 2016 midline survey, these farmers were provided with plot-specific soil recommendations for their main maize plot (MMP)[1]

- *Recommendations*: Farmers received plot-specific fertilizer recommendations for their MMP. Based on nitrogen, phosphorus, potassium, sulfur, pH, and electric conductivity (EC) tests, agronomists and soil scientists recommended suitable fertilizers to replenish the soils.

- *Voucher plus recommendations*: Farmers were given both of the aforementioned treatments.

- *Control*: Farmers in this group did not receive any treatment, but were given soil information and fertilizer recommendations after the 2016 data collection.

The baseline data was collected in August 2014 and included 1050 households. Between August and November 2014, agronomists collected and analyzed soil samples from farmers' MMPs. Based on these results, agronomists made recommendations of fertilizers to apply. The intervention occurred in January 2016, just before planting of the long rain season, and the midline was collected in August 2016, after the primary long rains season harvest, reaching 984 of the original households. Tamim et al. (2022) returned to the site in August 2019 reaching 920 households to collect the endline survey to test whether treatments had any effect three years and a half after the

[1]The main maize plot was defined as the plot most important for food security and income generation, and this plot's soil was tested as part of the Harou et al. (2022) study.

interventions concluded. In all surveys, collected in 2014, 2016, and 2019, we gathered detailed data on subjective soil beliefs, input use, maize yields, land tenure, and other household characteristics. As shown in Harou et al. (2022) and Tamim et al. (2022), treatment is orthogonal to attrition in 2016 and 2019, treatment take-up is high, and the sample is well-balanced on key observable characteristics when we exclude control villages. For completeness, Table A1 shows that the treatments did not impact attrition, and Table A2 presents treatment balance (Tamim et al., 2022). In the analysis that follows, we follow our previous studies and exclude control villages since one of the outcomes was imbalanced at baseline. We check the robustness of our results to including them.[2] [3]

Harou et al. (2022) find that farmers receiving vouchers only and both recommendations and vouchers increase their input use. However, only farmers receiving the voucher and recommendation treatment have increased maize yields in 2016. Tamim et al. (2022) extend Harou et al. (2022) and find that the treatment impacts dissipate in 2019, with fertilizer use returning to baseline levels, showing the limiting constraint of liquidity to farmers in this region and/or or that the initial experiment did not change farmers' beliefs about fertilizer profitability.

III Empirical Strategy

To learn whether farmer input decisions depend on their initial SSBs, true soil quality, and/or the relationship between SSB and true soil quality, we estimate the following analysis of covariance (ANCOVA) specification with village fixed effects:

[2]For more details on the design, balance, attrition, and compliance, see Harou et al. (2022) and Tamim et al. (2022).

[3]The original pre-analysis plan included evaluating the treatment effects on farmers' subjective beliefs, and this has not been estimated in previous work using these data – in neither Harou et al. (2022) nor Tamim et al. (2022).

$$Y_i^t = \alpha + \varphi Y_i^{2014} + \sum_{k=1}^{3} \gamma_k TREAT_i^k + \sum_{j=1}^{3} \delta_j TREAT_i^j * Soil_i + \lambda Soil_i + d_v + \varepsilon_{iv} \quad (1)$$

where Y_i^t is fertilizer applied (kg/acre) or a fertilizer dummy (=1) if farmer i applied any fertilizer in the year $t = 2016$ or $t = 2019$, Y_i^{2014} is fertilizer (in kg/acre or dummy) applied at baseline, in 2014, $TREAT_i^k$ are dummy variables for the three treatment arms described above, d_v are village fixed effects to control for the initial village clustering, and ε_{iv} is an idiosyncratic error term that varies across individuals and between villages. We cluster standard errors at the village level to account for potential within-village correlation.

$Soil_i$ is one of three variables – farmers' SSB, true soil quality, and whether SSB is less than true soil quality. More specifically, to measure SSB, in each year the survey was administered, respondents were asked to rate their main maize plot soil quality on a scale from 1 to 5, 1 being very poor and 5 being very good. We regroup farmer responses into a binary variable taking the value of 0 ("poor") if farmers categorized their soil between 1 and 3, and 1 ("good") if they ranked their soil as 4 or 5.[4] Table A1 in the appendix shows both the original distribution of responses by year as well as its re-categorization as a binary variable. Next, we measure true soil quality using soil electrical conductivity (EC), a measure of soil fertility that captures salinity. During soil testing, agronomists classified soils into seven salinity levels: low salinity, medium salinity, slightly saline, very saline, severe salinity, very severe salinity, and few crops can grow. Soils are optimal for crop growth if they are slightly to very saline. So we categorize soils as "good quality" (=1) if they are slightly or very saline, else (=0) "poor quality". Third, we create a dummy variable

[4] Specifically, the survey question asked, "On a scale of 1 to 5, 1 being very poor and 5 being very good, how would you rate the quality of the soil of this MMP this year?".

taking the value of 1 if farmers' SSB is less than EC. In other words, this takes a value of 1 if SSB = 0 and EC = 1, 0 otherwise. We are interested in the coefficients δ_j which tell us whether SSB, EC or whether $SSB < EC$ differentially affects the decision to apply fertilizers in response to receiving vouchers, recommendations, or both.

McFadden et al. (2005) shows the difficulty in comparing Likert scale responses since respondents may interpret the scales differently. Furthermore, it is not clear whether farmer responses signify the mean, mode or median. Indeed, most of the recent literature eliciting subjective beliefs, elicits the distribution of beliefs or expectations, allowing the researcher to estimate any desired statistic (Manski, 2004; Attanasio, 2009; Delavande et al., 2011; Harrison et al., 2017). From this distribution, one can study how farmers update their expectations using a Bayesian updating framework after, for example, receiving new information (Lybbert et al., 2007). Eliciting the distribution of beliefs about farmers' subjective beliefs about soil quality is an important area for future research. The dispersion of priors, for example, might be useful to measure farmers' confidence in their beliefs (Lybbert et al., 2007; Gars et al., 2023).

We are also interested in learning whether farmers update their SSBs after receiving plot-specific fertilizer recommendations and/or vouchers. To do so, we estimate the following equation, again using ANCOVA with village fixed effects:

$$Y_i^t = \alpha + \varphi Y_i^{2014} + \sum_{k=1}^{3} \gamma_k TREAT_i^k + d_v + \varepsilon_{iv} \tag{2}$$

where Y_i^t is farmer i's subjective soil belief at time t = 2016 or 2019, and Y_i^{2014} is farmer i's baseline SSB. Here we measure SSB in two ways. We keep the same binary variable as defined above. Additionally, we categorize SSB into three groups, taking the value of 0 ("Poor) if the respondent categorized their SSB as 1 or 2 on a scale from 1 to 5, 1 ("Fair") if they answered 3, and 2 ("Good") if they answered 4 or 5. The remaining variables are the same as those defined above in equation 1. Here the main coefficients of interest are γ_k which represent the impact of treatment k (voucher, recommendations, and voucher plus recommendations) on farmer SSB. We estimate equation (2) in 2016 and 2019. We cluster standard errors at the village level to account for potential within-village correlation.

Not only are we interested in whether farmers change their SSB, but we are also interested in whether farmers update their SSB closer to its true soil quality. We define a new variable, $\mathbb{1}\{SSB_t = EC\}$, that takes the value 1 if a farmers' $SSB_t = EC$ at time t = 2016 or 2019. $SSB = EC$ takes a value of 0 if farmers increase, decrease or keep their SSB away from true soil quality. Table 1 shows the breakdown of farmers by year for which they increase, decrease or keep their SSB towards or away true soil quality, measured by EC. We see that a total of 47.6 % (47.0 %) of farmers have a SSB that matches EC in 2016 (2019). To measure the effect of receiving fertilizer recommendations and/or a voucher on whether SSBs matches EC, we estimate equation 2 above, where Y_{it} is a binary variable equal to 1 if $SSB = EC$ in year 2016 or 2019. Note, however, there is no baseline value for this variable so we estimate 2 without controlling for φY_i^{2014}.

To compare the effect of different treatments on farmers' retention of the fertilizer recommendations, we again estimate 2. Retention is relevant for learning since farmers may exert more effort to retain the information provided to them if they deem that information to be useful. We construct an index for retention of the recommended fertilizers. The 2016 index is constructed by assigning one point for every fertilizer type correctly recalled[5] . We normalize the index by subtracting the

[5]The question that we asked farmers in 2016 was "Can you please list the types of fertilizer that were recommended

control group mean and dividing by its standard deviation. In 2019, we collected farmer recall on both the type and quantity of recommended fertilizer(s) allowing us to construct three indices. The first measure replicates the 2016 index, assigning one point for every recommended fertilizer type that was correctly recalled. The second measure assigns one point for every fertilizer type recommended and two points for every fertilizer quantity recommended that were correctly recalled, accounting for the greater difficulty in recalling quantities. Finally, in the third index one point is given for each fertilizer type correctly recalled and one point for each quantity correctly recalled. For farmers who report not having received recommendations or who do not recall the recommendations, we assign them a score of zero.[6] Because we did not collect retention at baseline, we again do not control for baseline retention.

Finally, to examine whether applying fertilizer affects farmers' retention of the fertilizer recommendations and/or changes their SSB, we estimate the following equation using two-stage least squares:

$$Fertilizer_i^t = \beta + \mathbb{1}\{Voucher_i = 1\} + d_v + \nu_{iv} \tag{3}$$

$$Y_i^t = \pi + \lambda \widehat{Fertilizer}_i^t + d_v + \mu_{iv} \tag{4}$$

where $Fertilizer_i^t$ is either a binary variable that equals unity if a respondent i in village v applied fertilizer and zero otherwise, or the quantity of fertilizer applied in kg/acre. The variable $\widehat{Fertilizer}_{iv}$ in equation (4) is the predicted value of $Fertilizer_{iv}$ from the first-stage in equation

to you", and in 2019 was "Can you please list the types and quantities of ALL fertilizers (basal and top dressing) PER ACRE that were recommended to you for your 2014 main maize plot?"

[6] Since 3.6% of farmers were recommended to apply urea only, we double their scores to make them comparable to the majority of farmers who were recommended two fertilizers. Only two farmers were recommended to apply three fertilizers and neither of them recalled the recommendations in 2019, so their scores are zero. However, one farmer was able to recall the three fertilizers in 2016, and so we change the score from three to two points to be consistent with the majority of farmers who were recommended to apply two fertilizers.

(3). The outcome Y_i^t are the retention of the recommendations as proxied by the indices defined above, as well as farmers' SSB. This approach assumes that the voucher impacts SSB and WTP only through fertilizer adoption, but this need not be true if, for example, the voucher was redeemed to purchase other inputs. We therefore use caution in interpreting these results.

IV Results and Discussion

Since we find a negative relationship between farmers' SSB and true soil quality at baseline, [7]

The lack of effect of recommendations and vouchers on SSBs suggests that receiving information on soil quality reduces farmers' SSB, cancelling out the increase in SSB from receiving the voucher.

In fact, we find that farmers in the recommendations and voucher group are less likely to update their SSB closer to the true soil quality, albeit not statistically significantly. Households having received vouchers only are more likely to update their SSBs if they learn their true soil quality is good, whereas they are less likely to update their SSBs if they learn their soils are poor, statistically significant at the 5% level.

IV.1 Input decisions and soil quality

Farmers in 2016 having received only a recommendation apply more fertilizer (in kg/acre) if they believe, at baseline, their soil quality is good (Table 2, column 1, Panel A). On the other hand, farmers who learn their soil quality is good through soil testing do not apply more fertilizer (columns 3 and 4). Farmers who receive both vouchers and recommendations are more likely to apply fertil-

[7] SSB and true soil quality have a Pearson correlation coefficient of -0.133 and a Pearson Chi-square value of 13.304, statistically significant at the 1 % level.

izer after learning their soil quality is good (Table 2, column 4, Panel A). This result is stronger for farmers who initially believe their soil quality to be low, but learn that their soil quality is in fact better than they thought, both at the intensive and extensive margins (Table 2, Panel A, columns 5 and 6)[8]. We find no differential treatment effect on fertilizer use by underlying objective or subjective soil quality in 2019. This is not surprising since the treatment effects dissipate in 2019, seen in Panel B of Table 2. This corroborates the findings Harou et al. (2022) and Tamim et al. (2023) – in 2016, farmers receiving vouchers only increase fertilizer use, but not as much as those who receive both vouchers and recommendations; those effects dissipate three years later (Table 2, columns 1-6, Panels A and B). In sum, these results suggest that farmer beliefs about their soils' underlying quality matters to their decision to apply fertilizer, and how much fertilizer they apply. In particular, if farmers learn their soil quality is good and they receive a voucher, they are more likely to apply fertilizer and apply a greater amount.

IV.2 Subjective Soil Belief updating

Farmers having received any treatment update their SSB upward (Table 3), although only by a statistically significant amount for farmers receiving vouchers. Farmers who receive vouchers (recommendations) update their SSB with a magnitude of 0.155 (0.027) standard deviation units, while farmers receiving both recommendations and vouchers update their SSBs by 0.089 standard deviation units. The positive SSB updating for farmers in the voucher group continues to hold in 2019 for farmers with poor underlying soil quality. In 2016 (column 3), farmers who received vouchers had not learned their true soil quality, while in 2019, farmers had learned their true soil

[8]Note, this is statistically significant at the 5 % for the extensive margin (column 6) if we do not restrict the sample size to the number of observations present in each column of Table 2, see Appendix **??**

quality since all farmers received recommendations after the 2016 intervention. Therefore, farmers update their SSB upward when they receive vouchers whether they know their true soil quality or not. These results suggest that applying fertilizers leads to farmers believing their soil quality has improved. Below, we test explicitly whether applying fertilizers has an effect on SSB. Interestingly, when vouchers are coupled with recommendations, farmers only increase their SSB by a modest and not statistically significant amount. These results suggest that receiving recommendations may decrease farmers' expectations about their soil quality, resulting in a smaller V+R treatment impact compared to V only.

We next want to see whether farmers update their SSB after learning about their true soil quality and/or receiving vouchers, whether it be changing their SSB upward, downward or staying the same. In Table 4, we see that farmers receiving vouchers are more likely to update their SSB closer to its true soil quality when their underlying soil quality is good, statistically significant at the 10% level (column 2). On the other hand, when farmers' underlying quality is bad, farmers receiving vouchers are less likely to update their SSB to match true soil quality, statistically significant at the 5% level (column 3). The sign of these effects – a decrease in likelihood of matching objective and subjective soil quality measures on bad soils and an increase in likelihood on good soils – holds for farmers receiving both recommendations and vouchers, albeit not as strongly in magnitude and not statistically significantly. These results suggest that respondents are more (less) likely to update their SSB closer to the true soil quality when they learn their soils are good (bad). In 2019, farmers having received vouchers in 2016 are still less likely to have SSB matching their true soil quality. In the case of vouchers, where we see the strongest effects, farmers did not receive information on their underlying soil quality until after the completion of the survey in 2016. Since farmers having received vouchers increased fertilizer application, these results suggest that farmers believe applying fertilizers increases their soil quality. We test this explicitly next – whether the use of fertilizer increases SSB in Section IV.3 below.

IV.3 Fertilizer use, subjective beliefs, and retention

We can explicitly test whether farmers who apply fertilizers change their SSB. Because the decision to apply fertilizers is endogenous, we instrument fertilizer application with the randomized voucher receipt (either in the voucher group or the recommendation and voucher group). The impacts are reported in Table 7 and the first-stage results are available in Table A3 in the Appendix. The first column of Table 7 shows the impact of applying fertilizer (Panel A) and the quantity fertilizer applied (Panel B) have a positive effect on SSB in 2016. This increase in SSB from applying fertilizers is driven by farmers whose underlying soil quality is poor (column 3, Panel A) at the extensive margin. These results corroborate our results above, suggesting that applying fertilizers increase farmers' SSB especially when farmers' underlying soil quality is poor.

We next turn to see whether farmers retain the recommendations. This matters for several reasons. First, whether farmers update their SSBs closer to their soils' true value intrinsically depends on whether farmers can remember the recommendations. Second, if SSBs vary significantly to true soil quality, and the returns to fertilizer are positive, which Harou et al. (2021) show is the case for farmers in the V+R treatment group, farmers can be expected to make an effort to retain the information. Finally, we are interested in knowing whether there may have been spillover effects, e.g., if farmers having received vouchers only may have learned about their true soil quality from neighbors with potentially similar soil types. In Table 5 we see that all treatment groups have a higher retention index in 2016. However, the magnitude on the effect in the voucher group is only 0.29

standard deviation units and only statistically significant at the 10% level. Farmers in the recommendations and recommendations and voucher group have retention scores of approximately 2.9 and 4.3 standard deviation units, respectively, higher than the control group, statistically significant at the 1% level. The retention of the recommendations disappears for all groups three years after treatment, except for the recommendations and voucher group who have a statistically significantly higher retention score of 0.39-0.42 in 2019, statistically significant at the 1% level. These results suggest that farmers retain the recommendations in the shorter-term, and that experimenting with fertilizers increases the accuracy and duration of the information retained. Indeed, we see in Table 7, columns 4 and 5 that fertilizer application at both the intensive and extensive margins increase retention. There seems to be little spillover of the information on fertilizer recommendations to farmers in the voucher group.

IV.4 Heterogeneity

We next test whether our results differ among farmers whose main maize plot is greater than or equal to 1.5 acres since Tamim et al. (2023) find.., and/or better-off households, as measured by an asset index[9]. Our results are shown in Appendix Tables A4-A6. In Table A4, we see that farmers with plots greater than or equal to 1.5 acres who believe their soil quality is good apply more fertilizer at the intensive and extensive margins, statistically significant at the 1 and 5 % levels, respectively, if they received recommendations only. This result holds true for better-off farmers. It is not clear, however, why farmers having received both recommendations and a voucher do not also apply more fertilizer if recommendations alone induce farmers to apply more fertilizer. The increase in fertilizer use for farmers who learn their soil is good is positive, but only statistically

[9]say something here about generating the asset index

significant at the 10 % level for farmers in the R+V treatment group. Again, this holds for better off farmers (Panel B in table A4). That we find weaker results for the R+V treatment group makes sense since farmers with larger plots and better-off farmers are less likely to be credit-constrained.

We also disaggreggate the 2016 analysis of Table A5 by plot size and asset index. Interestingly, we see that the increase in SSB we observe for all treatments, especially farmers in the Voucher treatment, is driven by worst-off farmers. This suggests that poorer farmers are more likely to believe that applying fertilizers increases their soil quality. When we look at the treatment effects on SSB by plot size, we see that farmers with plots less than 1.5 acres having received the R+V treatment have a higher SSB. Finally, we look at Table A6 by plot size and asset index. We see that, again, our main results – a decrease in likelihood that of correct updating for the V group with bad underlying soil quality and an increase in updating when the underlying soil quality is good – is driven by worst off farmers and farmers with plots less than 1.5 acres. We also see that farmers having received recommendations and whose plot is greater than or equal to 1.5 acres are less likely to update their SSB to the true soil quality when their soil is good. This supports the previous finding that worst-off farmers are more likely to believe that applying fertilizers will increase their soil quality.

IV.5 Robustness

We test the robustness of our results by including all households who participated in the original study, including the previously dropped control villages. Our results, shown in Tables A7-A10, are qualitatively similar.

V Conclusion

We examine the impact of farmers' subjective soil beliefs (SSBs) on their decision to apply fertilizer. We find that farmers' SSBs and true soil quality matter to their decision to apply fertilizer. Farmers who received plot-specific fertilizer recommendations and a voucher are more likely to apply fertilizers if they learn their underlying soil quality is good. This suggests that farmers may know, as Marenya and Barrett (2009) show, that the returns to fertilizer are higher on soils that are not deficient in nutrients. We also find that farmers who receive vouchers to purchase fertilizers increase their beliefs about their soil fertility, especially if they previously believed their soil quality to be poor. This result is driven by poorer households and, to a lesser degree, farmers whose main maize plot is less than 1.5 acres. These results suggest that farmers believe they are improving their soil fertility by applying fertilizers. Indeed, when we explicitly test the effect of fertilizer use on SSB, we see that fertilizer use is associated with an increase in SSB.

These results highlight the importance of considering farmer subjective beliefs in the adoption decision. In the case of fertilizer application, farmers seem aware that the returns to fertilizer will be more successful on plots with better soil quality, yet farmers do not accurately gauge their own soil fertility. At the same time, farmers receiving vouchers only are more likely to apply fertilizers, which increases their SSB. This is particularly true for poorer farmers. Therefore, giving farmers only vouchers could encourage farmers to apply fertilizers when in fact the returns to fertilizer application could be low.

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Table (1) SSB updating relative to EC

	Variable values	2016 n	2016 %	2016 $SSB = EC$	2019 n	2019 %	2019 $SSB = EC$
Increase SSB closer to EC	SSB_{2014} = 0; SSB_{2016} = 1; EC_{good} = 1	78	12.5	Yes	75	11.4	Yes (=1)
Decrease SSB closer to EC	SSB_{2014} = 1; SSB_{2016} = 0; EC_{good} = 0	52	8.3	Yes	67	10.2	Yes (=1)
Unchanged, right SSB	SSB_{2014} = 1; SSB_{2016} = 1; EC_{good} = 1	168	26.8	Yes	167	25.4	Yes (=1)
	SSB_{2014} = 0; SSB_{2016} = 0; EC_{good} = 0						
Unchanged, wrong SSB	SSB_{2014} = 1; SSB_{2016} = 1; EC_{good} = 0	208	33.2	No	220	33.5	No (=0)
	SSB_{2014} = 0; SSB_{2016} = 0; EC_{good} = 1						
Decrease SSB further from EC	SSB_{2014} = 1; SSB_{2016} = 0; EC_{good} = 1	63	10.1	No	83	12.6	No (=0)
Increase SSB further from EC	SSB_{2014} = 0; SSB_{2016} = 1; EC_{good} = 0	57	9.1	No	45	6.9	No (=0)
Total		626			657		

Notes: This table shows the distribution of farmers by year who update their SSB closer to or further away from or do not update true soil quality, proxied by electrical conductivity (EC).

Table (2) Treatment impact on fertilizer by baseline subjective soil beliefs and true soil quality

	SSB is good (dummy)		EC is good (dummy)		SSB less than EC (dummy)	
	(1)	(2)	(3)	(4)	(5)	(6)
	Fertilizer (kg/acre)	Fertilizer Dummy	Fertilizer (kg/acre)	Fertilizer Dummy	Fertilizer (kg/acre)	Fertilizer Dummy
Vouchers	9.929**	0.291***	12.565**	0.274***	10.075***	0.299***
	(3.871)	(0.081)	(5.107)	(0.094)	(3.320)	(0.079)
Recommendations	-3.146**	-0.015	0.187	0.022	1.452	0.032
	(1.306)	(0.050)	(1.890)	(0.030)	(1.409)	(0.023)
Voucher+Recommendations	30.248***	0.754***	22.392***	0.645***	22.812***	0.699***
	(4.771)	(0.050)	(3.209)	(0.052)	(2.441)	(0.037)
Variable	-0.884	0.008	-3.739*	-0.062	-0.238	-0.019
	(1.125)	(0.043)	(2.128)	(0.040	(1.646)	(0.053)
Vouchers × Variable	-1.266	-0.005	-5.015	0.030	-2.980	-0.034
	(4.468)	(0.089)	(4.933)	(0.086)	(3.770)	(0.095)
Recommendations × Variable	5.690**	0.056	1.338	0.004	-3.182	-0.043
	(2.075)	(0.057)	(1.682)	(0.047)	(1.917)	(0.054)
Voucher+Recommendations × Variable	-6.946	-0.044	6.635	0.157**	15.492*	0.135*
	(5.989)	(0.058)	(4.765)	(0.068)	(8.145)	(0.069)
2014 Fertilizer (kg/acre)	0.200		0.192		0.198	
	(0.149)		(0.157)		(0.151)	
2014 Fertilizer Dummy		0.246		0.272		0.252
		(0.269)		(0.263)		(0.264)
Observations	580	580	580	580	580	580
R-squared	0.224	0.413	0.226	0.417	0.235	0.416
Mean dep. var.	10.780	0.316	10.780	0.316	10.780	0.316

Notes: This table shows the analysis of covariance results for the following model: $Y_i^t = \alpha + \varphi Y_i^{2014} + \sum_{k=1}^{3} \gamma_k TREAT_i^k + \sum_{j=1}^{3} \delta_j TREAT_i^j * Variable_i + \lambda Variable_i + d_v + \varepsilon_{iv}$. The $Variable$ in columns 1 and 2 is an indicator variable taking the value of 1 if the respondent believes his/her soil is good at baseline, in 2014. The $Variable$ in columns 3 and 4 takes a value of 1 if the true soil quality, revealed for treatment "R" in 2016 and revealed for all farmers after 2016, is good. In columns 5 and 6, the dependent variable takes a value of 1 if SSB is poor/fair in 2014 and the true soil quality is good in 2016. SSB stands for subjective soil beliefs and EC stands for electrical conductivity, proxying true soil quality. Robust standard errors, clustered at the village-level, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All regressions control for village fixed effects.

Table (3) Treatment Impact on Beliefs

	(1) SSB	(2) SSB|Good EC	(3) SSB|Bad EC	(4) SSB	(5) SSB|Good EC	(6) SSB|Bad EC
	2016	2016	2016	2019	2019	2019
Vouchers	0.155**	0.119	0.184**	0.055	0.016	0.154**
	(0.059)	(0.086)	(0.078)	(0.083)	(0.117)	(0.066)
Recommendations	0.027	-0.032	0.069	0.069	0.033	0.051
	(0.063)	(0.088)	(0.088)	(0.077)	(0.135)	(0.115)
Voucher+Recommendations	0.089	0.068	0.059	0.046	0.069	0.024
	(0.071)	(0.118)	(0.096)	(0.071)	(0.092)	(0.109)
Baseline Value	0.060	0.130**	-0.080	0.122**	0.127*	0.075
	(0.045)	(0.049)	(0.071)	(0.045)	(0.072)	(0.053)
Constant	1.485***	1.351***	1.769***	1.239***	1.201***	1.381***
	(0.072)	(0.078)	(0.137)	(0.100)	(0.149)	(0.093)
V vs. R (p-value)	0.055	0.123	0.160	0.880	0.897	0.421
V vs. V+R (p-value)	0.297	0.546	0.111	0.883	0.511	0.267
R vs. V+R (p-value)	0.325	0.283	0.896	0.772	0.763	0.838
Observations	646	350	276	677	365	292
R-squared	0.015	0.027	0.022	0.012	0.013	0.013
Mean dep. var.	1.652	1.594	1.710	1.474	1.422	1.562
Village FE	YES	YES	YES	YES	YES	YES

Notes: This table shows the analysis of covariance results for the following model: $Y_i^t = \alpha + \varphi Y_i^{2014} + \sum_{k=1}^{3} \gamma_k TREAT_i^k + d_v + \varepsilon_{iv}$. Columns 2 and 5 (3 and 6) condition on good (bad) true soil quality. SSB stands for subjective soil beliefs and takes the values of poor (0), fair (1) or good (2). EC stands for electrical conductivity, proxying true soil quality. Robust standard errors, clustered at the village-level, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All regressions control for village fixed effects.

Table (4) Treatment impact on SSB updating relative to EC

	(1) SSB=EC	(2) SSB=EC|Good EC	(3) SSB=EC|Bad EC	(4) SSB=EC	(5) SSB=EC|Good EC	(6) SSB=EC|Bad EC
	2016	2016	2016	2019	2019	2019
Vouchers	0.019	0.118*	-0.166**	-0.014	0.012	-0.112*
	(0.062)	(0.067)	(0.067)	(0.048)	(0.071)	(0.056)
Recommendations	-0.052	-0.022	-0.063	0.028	0.007	0.033
	(0.061)	(0.071)	(0.078)	(0.073)	(0.084)	(0.091)
Voucher+Recommendations	-0.048	0.053	-0.098	0.026	0.039	0.016
	(0.070)	(0.086)	(0.080)	(0.051)	(0.067)	(0.075)
V vs. R (p-value)	0.277	0.080	0.134	0.604	0.953	0.198
V vs. V+R (p-value)	0.170	0.307	0.185	0.409	0.610	0.125
R vs. V+R (p-value)	0.943	0.400	0.572	0.982	0.732	0.874
Observations	626	350	276	657	365	292
R-squared	0.004	0.014	0.019	0.001	0.001	0.014
Mean dep. var.	0.476	0.654	0.250	0.470	0.573	0.342

Notes: This table shows the results of the following model: $\mathbb{1}\{SSB_t = EC\}_i^t = \alpha + \sum_{k=1}^{3} \gamma_k TREAT_i^k + d_v + \varepsilon_{iv}$ in 2016 (columns 1-3) and in 2019 (columns 4-6). Columns 2 and 5 (3 and 6) condition on good (bad) true soil quality. SSB=EC takes the value 1 if a farmers' $SSB_t = EC$ at time $t =$ 2016 or 2019, else SSB=EC takes the value of 0. SSB stands for subjective soil beliefs and EC stands for electrical conductivity, proxying true soil quality. Robust standard errors, clustered at the village-level, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All regressions control for village fixed effects.

Table (5) Treatment Impact on Information Retention

	(1)	(2)	(3)	(4)
	Retention Index (z-score)			
	2016	2019	2019	2019
Vouchers	0.29*	0.09	0.09	0.09
	(0.15)	(0.09)	(0.08)	(0.09)
Recommendations	2.87***	0.05	0.02	0.03
	(0.38)	(0.09)	(0.08)	(0.08)
Voucher+Recommendations	4.25***	0.45***	0.39***	0.42***
	(0.25)	(0.10)	(0.11)	(0.11)
Control mean	0.00	0.00	0.00	0.00
(std. dev.)	(1.00)	(1.00)	(1.00)	(1.00)
V vs. R (p-value)	0	0.74	0.52	0.58
V vs. V+R (p-value)	0	0	0.02	0.01
R vs. V+R (p-value)	0.01	0	0	0
Observations	733	680	680	680
R-squared	0.339	0.031	0.025	0.028
Village FE	YES	YES	YES	YES

Notes: This table show the effects of treatments on fertilizer recommendations retention for 2016 (column 1) and 2019 (columns 2-4) by estimating the following model: $Retention_i^t = \alpha + \sum_{k=1}^{3} \gamma_k TREAT_i^k + d_v + \varepsilon_{iv}$. To construct the 2016 index and the first 2019 index (column 2), we assign one point for every recommended fertilizer type the farmer correctly recalls. To construct the second index in 2019 (column 3), we assign one point for every fertilizer type recommended and two points for every fertilizer quantity recommended the farmer correctly recalls. The third 2019 index (column 4) assigns one point for each fertilizer type correctly recalled and one point for each quantity correctly recalled. Robust standard errors, clustered at the village-level, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All regressions control for village fixed effects.

Table (6) Effect of fertilizer application on SSB and retention, two stage least squares

	(1)	(2)	(3)	(4)	(5)
	SSB	SSB$\vert$Good EC	SSB$\vert$Bad EC	Retention	
	2016	2016	2016	2016	2019
Panel A: Decision to Adopt					
Fertilizer (=1)	0.226**	0.199	0.251**	0.423***	-16.039
	(0.096)	(0.145)	(0.115)	(0.100)	(33.002)
Observations	618	332	267	620	301
Mean dep. var.	1.659	1.608	1.708	0.531	0.548
F-stat (first-stage)	124.017	119.537	79.252	122.938	0.274
Panel B: Quantity Applied					
Fertilizer (kg/acre)	0.006**	0.007	0.004	0.014***	0.532
	(0.003)	(0.005)	(0.003)	(0.003)	(1.910)
Observations	630	337	273	632	301
Mean dep. var.	1.648	1.588	1.707	0.522	0.548
F-stat (first-stage)	98.981	49.497	68.896	99.407	0.011

Notes: This table shows the effects of fertilizer use on SSB (columns 1-3) and retention (columns 4-5) by estimating the following two-stage least squares model: 1) $Fertilizer_i^t = \beta + \mathbb{1}\{Voucher_i = 1\} + d_v + \nu_{iv}$; 2) $Y_i^t = \pi + \lambda \widehat{Fertilizer_i^t} + d_v + \mu_{iv}$. Column 2 (3) conditions on good (bad) true soil quality. SSB stands for subjective soil beliefs and EC stands for electrical conductivity, proxying true soil quality. Robust standard errors, clustered at the village-level, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All regressions control for village fixed effects.

Table (7) Effect of fertilizer application on 2016 yields, two stage least squares

	(1) All 2016 yields	(2) Yields if EC is good	(3) yields if EC is bad	(4) Yields if SSB is good	(5) Yields if SSB is bad
fert_dum_2016	142.886** (56.016)	139.964* (73.186)	145.757 (104.521)	180.443** (90.309)	133.325** (52.597)
N	602.000	320.000	263.000	395.000	204.000
ymean	302.455	319.773	283.398	306.384	298.444

Notes: XXX

Appendix

Figures

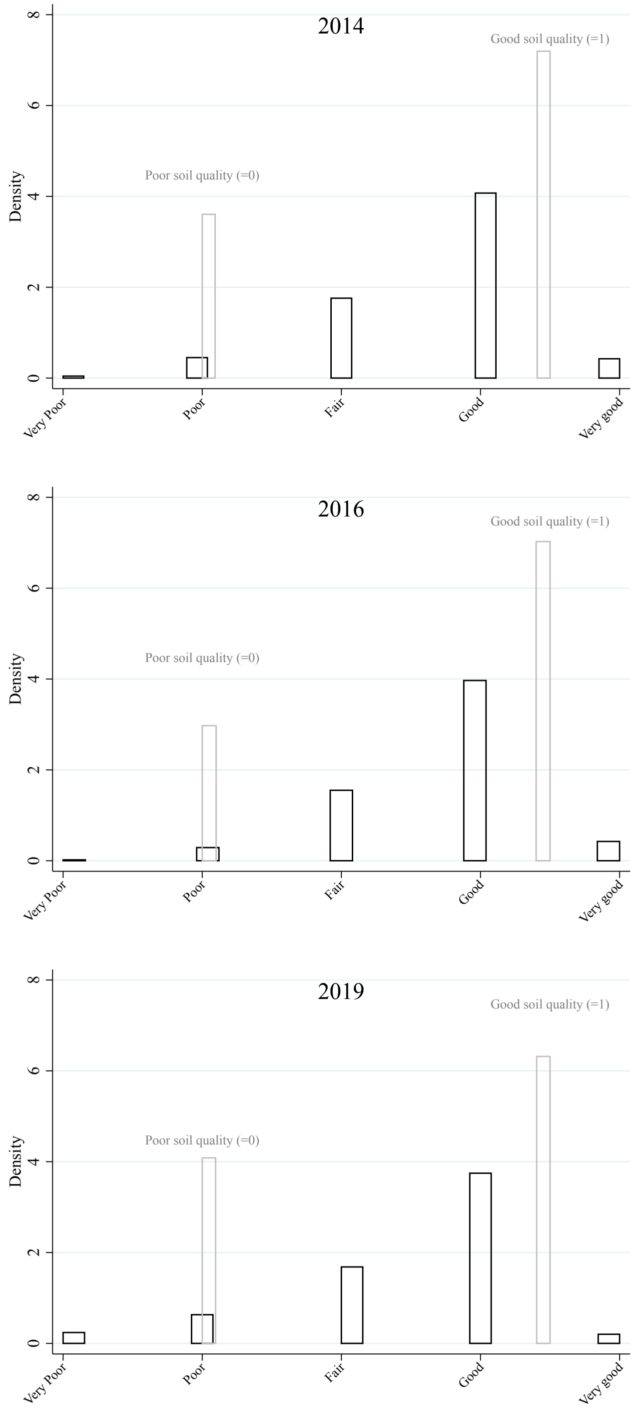

Figure (A1) Subjective soil beliefs, by year

NOTES: This table shows the subjective soil beliefs by year under the original five-point likert scale, as well as its re-categorization into a binary variable (in grey). We re-categorize farmers who described their soil as being "very poor", "poor" or "fair" to be "poor", and farmers who describe their soil as "good" or "very good" to be considered "good".

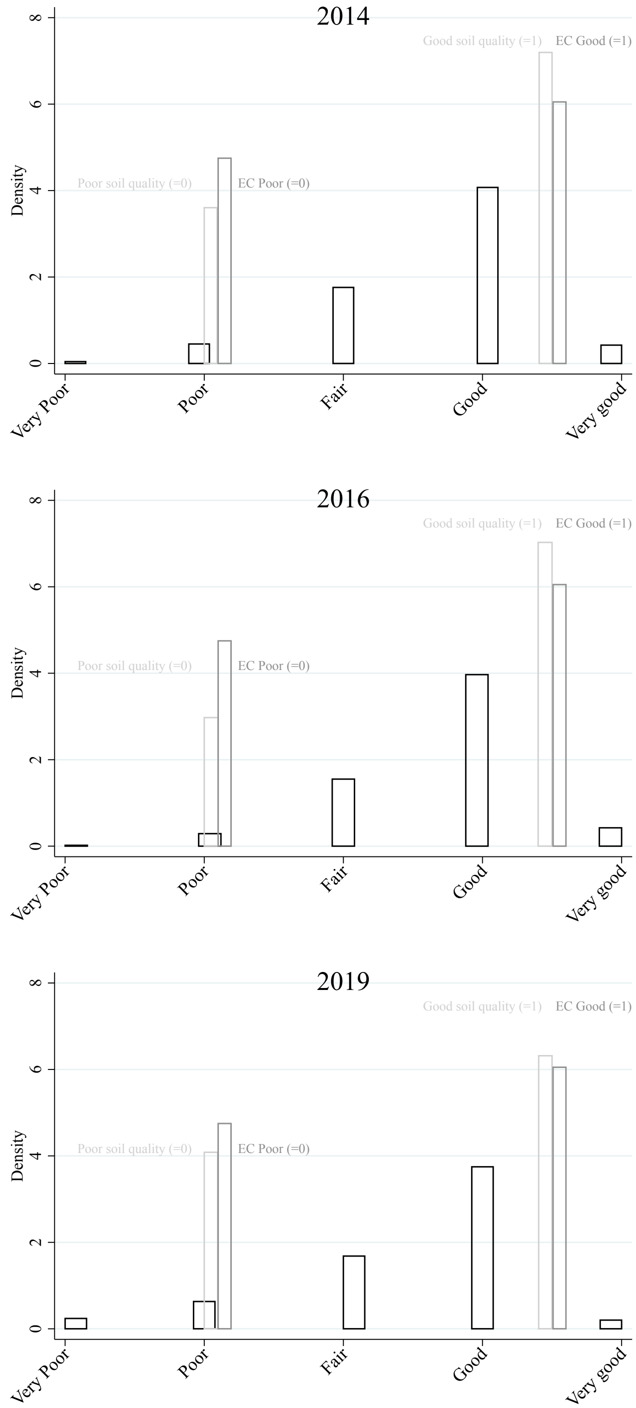

Figure (A2) Subjective soil beliefs, by year, compared to true soil quality (binary)
NOTES: This table shows the subjective soil beliefs by year under the original five-point likert scale, as well as its re-categorization into a binary variable (in grey) commpared to the binary true soil quality. We re-categorize farmers who described their soil as being “very poor”, “poor” or “fair” to be “poor”, and farmers who describe their soil as “good” or “very good” to be considered “good”.

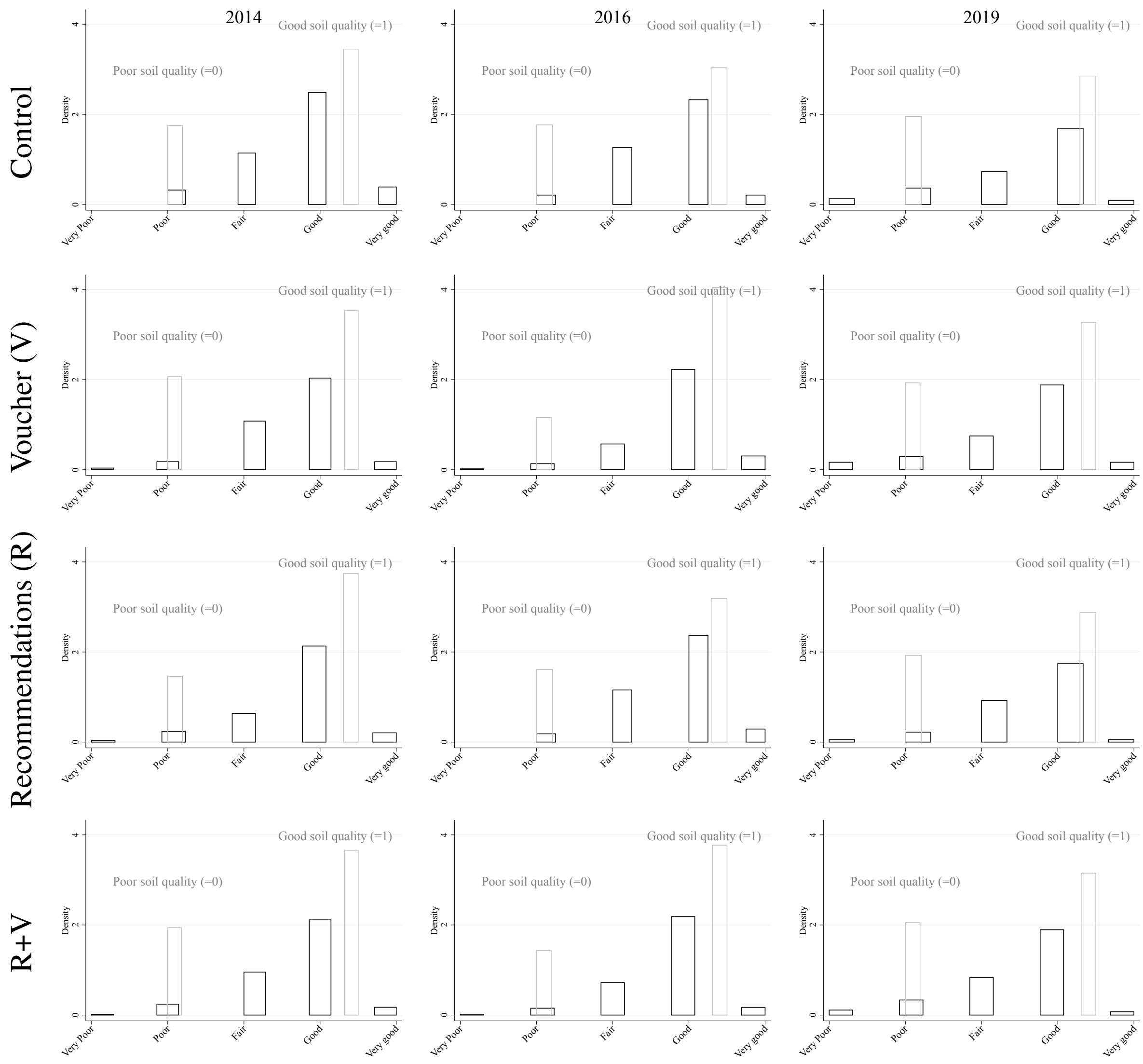

Figure (A3) Subjective soil beliefs, by year and treatment

NOTES: This table shows the subjective soil beliefs by year and treatment under the original five-point likert scale, as well as its re-categorization into a binary variable (in grey). We re-categorize farmers who described their soil as being "very poor", "poor" or "fair" to be "poor", and farmers who describe their soil as "good" or "very good" to be considered "good". The rows show the different treatments while the columns show the different years.

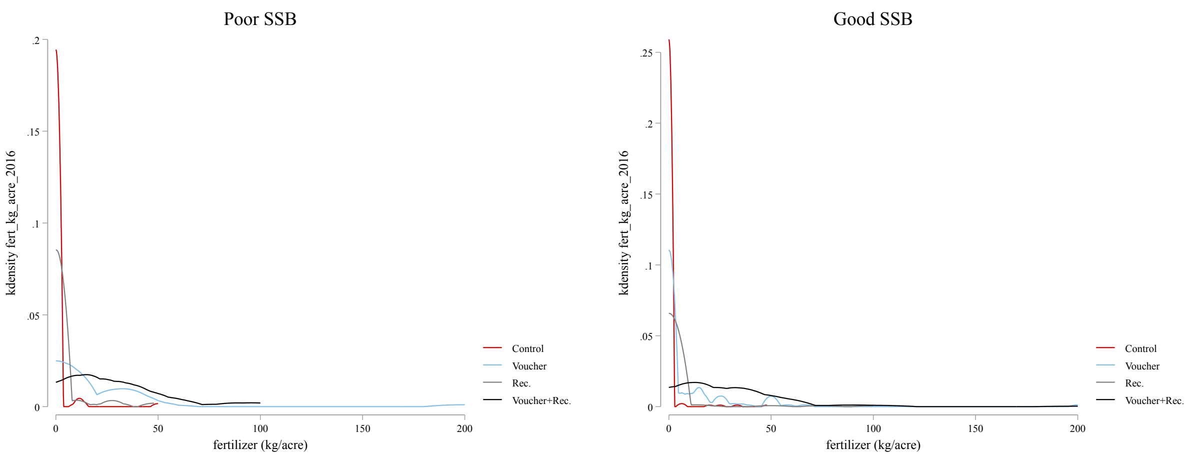

Figure (A4) Fertilizer Application by SSB

Table (A1) Probability of Attrition by Treatment

	Attrition (=1 if attrited)			
	2016	2016	2019	2019
Voucher	-0.00234	-0.00326	-0.0306	-0.0314
	(0.0219)	(0.0217)	(0.0294)	(0.0300)
Recommendations	0.0154	0.0157	0.0203	0.0201
	(0.0220)	(0.0220)	(0.0333)	(0.0332)
Voucher+Recommendations	0.00614	0.00539	0.00635	0.00423
	(0.0179)	(0.0180)	(0.0262)	(0.0264)
Constant	0.0579***		0.132***	
	(0.0142)		(0.0231)	
N	782	782	782	782
Village FE		✓		✓

Notes: This table shows the probability of attrition by treatment by regressing an indicator variable, where =1 if the household attrited, on treatment. Robust standard errors, clustered at the village-level, are shown in parentheses. Control villages are excluded. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table (A2) Within-Village Balance Tests

		Control	Treatment coefficient			F-Test (p-value)			N
		Mean	V	R	V+R	V = R	V = V+R	R = V+R	
Panel A: Outcomes									
(1)	Fertilizer (kg/ SR acre)	0.02	0.54	0.30	-0.07	0.7	0.17	0.38	491
			(0.41)	(0.37)	(0.06)				
(2)	Fertilizer (kg/ GPS acre)	0.01	0.21	0.47	-0.07	0.68	0.27	0.35	486
			(0.24)	(0.52)	(0.07)				
(3)	Fertilizer (=1)	0.01	0.00	0.01	-0.00	0.83	0.66	0.51	491
			(0.01)	(0.01)	(0.01)				
(4)	Yields (kg/ SR acre)	403.2	-34.53	50.77	-37.19	0.09	0.91	0.05	435
			(31.37)	(59.71)	(37.35)				
(5)	Yields (kg/ GPS acre)	410.02	-58.12	-36.78	-36.84	0.53	0.54	1	433
			(58.55)	(64.69)	(78.18)				
Panel B: Covariates									
(6)	Male-Head (=1)	0.87	-0.04	-0.01	-0.00	0.46	0.31	0.77	491
			(0.04)	(0.05)	(0.05)				
(7)	Head Age (Years)	44.29	-1.45	1.36	1.61	0.09	0.03	0.88	491
			(1.74)	(1.37)	(1.35)				
(8)	Head Education (=1 if some education)	0.9	0.02	0.00	-0.03	0.57	0.26	0.53	491
			(0.03)	(0.04)	(0.03)				
(9)	Head Education (=1 if beyond primary)	0.05	-0.00	-0.04*	0.00	0.09	0.94	0.03	491
			(0.04)	(0.02)	(0.03)				
(10)	Distance to plot in minutes	34.02	-0.82	-6.13	2.39	0.18	0.35	0.1	458
			(2.36)	(3.82)	(4.78)				
(11)	Credit Access (=1)	0.12	-0.03	-0.05	-0.07*	0.59	0.33	0.58	491
			(0.03)	(0.03)	(0.04)				
(12)	Remittances (=1)	0.14	0.01	-0.03	0.04	0.49	0.55	0.07	491
			(0.05)	(0.06)	(0.06)				
(13)	Asset Index	-.17	0.07	0.06	-0.00	0.96	0.6	0.8	491
			(0.21)	(0.28)	(0.18)				
(14)	Livestock Ownership (=1)	0.82	-0.13**	-0.10**	-0.11*	0.52	0.73	0.86	491
			(0.06)	(0.04)	(0.06)				
(15)	Household Size	5.1	-0.21	0.09	0.10	0.38	0.38	0.97	491
			(0.34)	(0.31)	(0.36)				
(16)	Area Owned (SR acres)	5.59	-0.17	0.13	-0.47	0.54	0.56	0.21	491
			(0.64)	(0.76)	(0.77)				
(17)	Close to Chairman (=1)	0.33	0.00	-0.01	-0.03	0.82	0.49	0.71	491
			(0.05)	(0.05)	(0.06)				
(18)	Received Training (=1)	0.07	0.01	-0.01	0.04	0.32	0.42	0.11	491
			(0.02)	(0.02)	(0.03)				
(19)	Visited by Extension (=1)	0.17	0.02	-0.03	0.01	0.4	0.91	0.52	491
			(0.05)	(0.06)	(0.07)				
(20)	Maize Area (SR acres)	2.11	0.07	-0.13	-0.33	0.34	0.02	0.18	487
			(0.22)	(0.15)	(0.21)				
(21)	Improved Seeds (=1)	0.15	0.01	-0.01	0.02	0.57	0.83	0.46	491
			(0.05)	(0.04)	(0.05)				

Notes: This table reports the results of baseline balance tests in which we estimate $b_{iv} = \alpha_0 + \sum_{k=1}^{3} \theta_k TREAT_i^k + d_v + \varepsilon_{iv}$ (columns 2-4). Columns 5-7 test the equality of coefficients between the three treatments. V stands for the Voucher treatment; R for the Recommendations treatment; V+R for the Voucher plus Recommendations treatment. Robust standard errors clustered at the village-level are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All regressions control for village fixed effects.

Table (A3) First Stage

	(1) SSB	(2) SSB$\mid$Good EC	(3) SSB$\mid$Bad EC	(4) Retention	(5)
	2016	2016	2016	2016	2019
Panel A: Decision to Adopt (Fertilizer = 1)					
Voucher = 1	0.503***	0.515***	0.497***	0.504***	-0.007
	(0.045)	(0.047)	(0.056)	(0.045)	(0.013)
Observations	618	332	267	620	301
F-statistic	124.017	119.537	79.252	122.938	0.274
R-squared	0.293	0.300	0.281	0.294	0.001
Village FE	YES	YES	YES	YES	YES
Panel B: Quantity Applied (Fertilizer = kg/acre)					
Voucher = 1	16.350***	15.705***	18.034***	16.401***	0.066
	(1.643)	(2.232)	(2.173)	(1.645)	(0.637)
Observations	630	337	273	632	301
F-statistic	98.981	49.497	68.896	99.407	0.011
R-squared	0.136	0.144	0.135	0.137	0.000
Village FE	YES	YES	YES	YES	YES

Notes: This table shows the first stage results of the following two-stage least squares model: 1) $Fertilizer_i^t = \beta + \mathbb{1}\{Voucher_i = 1\} + d_v + \nu_{iv}$; 2) $Y_i^t = \pi + \lambda \widehat{Fertilizer}_i^t + d_v + \mu_{iv}$. The results, shown in Table 6, examine the effect of applying fertilizers on SSB (columns 1-3) and retention (columns 4-5). Column 2 (3) conditions on good (bad) true soil quality. SSB stands for subjective soil beliefs and EC stands for electrical conductivity, proxying true soil quality. Robust standard errors, clustered at the village-level, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table (A4) Heterogeneous treatment impact on fertilizer by baseline subjective soil beliefs and true soil quality (2016)

	SSB is good (dummy)		EC is good (dummy)		SSB less than EC (dummy)	
	(1)	(2)	(3)	(4)	(5)	(6)
	Fertilizer (kg/acre)	Fertilizer Dummy	Fertilizer (kg/acre)	Fertilizer Dummy	Fertilizer (kg/acre)	Fertilizer Dummy
Panel A: Plot size is greater than 1.5 acres						
Vouchers	16.206	0.333**	13.778*	0.249**	9.858**	0.339***
	(12.056)	(0.143)	(7.961)	(0.102)	(4.509)	(0.089)
Recommendations	-5.070*	-0.081	-0.130	0.041	2.831**	0.098***
	(2.466)	(0.069)	(1.059)	(0.050)	(1.346)	(0.032)
Voucher+Recommendations	33.846***	0.867***	21.174***	0.668***	20.531***	0.724***
	(8.046)	(0.075)	(4.742)	(0.091)	(3.159)	(0.065)
Variable	-0.520	-0.001	-1.745	-0.038	3.383	0.083
	(2.015)	(0.073)	(1.703)	(0.065)	(2.905)	(0.142)
Vouchers × Variable	-8.803	-0.015	-7.816	0.129	-4.149	-0.143
	(12.308)	(0.129)	(8.304)	(0.138)	(6.015)	(0.204)
Recommendations × Variable	8.929***	0.201**	3.340	0.072	-8.454*	-0.213
	(2.993)	(0.081)	(2.733)	(0.096)	(4.261)	(0.150)
Voucher+Recommendations × Variable	-15.184	-0.174	5.713	0.189*	17.853	0.127
	(9.125)	(0.102)	(8.613)	(0.097)	(15.224)	(0.135)
2014 Fertilizer (kg/acre)	-0.025		-0.065		-0.045*	
	(0.019)		(0.040)		(0.023)	
2014 Fertilizer Dummy		0.097		0.273		0.107
		(0.254)		(0.333)		(0.243)
Observations	296	296	287	288	296	296
R-squared	0.180	0.416	0.154	0.407	0.174	0.411
Mean dep. var.	9.742	0.334	9.995	0.337	9.742	0.334
Panel B: Better off households						
Vouchers	12.575*	0.333**	12.621	0.394***	9.639**	0.391***
	(6.300)	(0.134)	(9.575)	(0.133)	(4.350)	(0.095)
Recommendations	-4.244**	-0.041	1.414	0.045	2.459	0.056
	(1.918)	(0.085)	(3.063)	(0.073)	(2.315)	(0.053)
Voucher+Recommendations	26.599***	0.697***	20.548***	0.698***	22.308***	0.740***
	(6.795)	(0.067)	(3.169)	(0.078)	(2.806)	(0.055)
Variable	-3.138*	-0.059	-3.563	-0.018	0.707	0.039
	(1.752)	(0.060)	(3.596)	(0.071)	(2.858)	(0.088)
Vouchers × Variable	-7.352	0.036	-5.999	-0.062	-4.169	-0.126
	(6.452)	(0.130)	(9.965)	(0.159)	(5.109)	(0.166)
Recommendations × Variable	8.522**	0.116	0.826	-0.008	-4.381	-0.080
	(3.121)	(0.089)	(3.373)	(0.113)	(3.400)	(0.139)
Voucher+Recommendations × Variable	-2.343	0.077	8.642	0.099	11.692	0.033
	(7.771)	(0.069)	(7.881)	(0.089)	(10.126)	(0.085)
2014 Fertilizer (kg/acre)	0.183		0.166		0.174	
	(0.115)		(0.123)		(0.124)	
2014 Fertilizer Dummy		0.104		0.157		0.104
		(0.206)		(0.245)		(0.206)
Observations	306	306	300	300	306	306
R-squared	0.217	0.424	0.210	0.430	0.215	0.426
Mean dep. var.	11.257	0.382	11.148	0.383	11.257	0.382

Notes: This table shows the analysis of covariance results for the following model: $Y_i^t = \alpha + \varphi Y_i^{2014} + \sum_{k=1}^{3} \gamma_k TREAT_i^k + \sum_{j=1}^{3} \delta_j TREAT_i^j * Variable_i + \lambda Variable_i + d_v + \varepsilon_{iv}$. The $Variable$ in columns 1 and 2 is an indicator variable taking the value of 1 if the respondent believes his/her soil is good at baseline, in 2014. The $Variable$ in columns 3 and 4 takes a value of 1 if the true soil quality, revealed for treatment "R" in 2016 and revealed for all farmers after 2016, is good. In columns 5 and 6, the dependent variable takes a value of 1 if SSB is poor in 2014 and the true soil quality is good in 2016. Panel A (B) shows results for households whose main maize plot size is greater than (less than or equal to) 1.5 acres. SSB stands for subjective soil beliefs and EC stands for electrical conductivity, proxying true soil quality. Robust standard errors, clustered at the village-level, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All regressions control for village fixed effects.

Table (A5) Heterogeneous 2016 treatment impact on fertilizer by baseline subjective soil beliefs and true soil quality

	(1) SSB	(2) SSB|Good EC	(3) SSB|Bad EC	(4) SSB	(5) SSB|Good EC	(6) SSB|Bad EC
Panel A: By asset index	Worst-off farmers			Better-off farmers		
Vouchers	0.181*	0.110	0.259**	0.135	0.208	0.010
	(0.093)	(0.119)	(0.111)	(0.094)	(0.146)	(0.098)
Recommendations	0.071	0.031	0.160	-0.027	0.021	-0.042
	(0.095)	(0.150)	(0.112)	(0.089)	(0.152)	(0.168)
Voucher+Recommendations	0.148	0.195	0.098	0.020	0.015	-0.036
	(0.087)	(0.159)	(0.147)	(0.106)	(0.160)	(0.148)
Baseline Value	0.105	0.221**	-0.039	0.008	0.031	-0.110
	(0.068)	(0.082)	(0.072)	(0.047)	(0.086)	(0.089)
V vs R (p-value)	0.243	0.567	0.389	0.025	0.088	0.688
V vs. V+R (p-value)	0.711	0.510	0.193	0.224	0.109	0.754
R vs. V+R (p-value)	0.466	0.408	0.634	0.559	0.953	0.973
Observations	328	160	156	318	190	120
R-squared	0.029	0.069	0.036	0.012	0.024	0.013
Mean dep. var.	1.655	1.562	1.744	1.648	1.621	1.667
Village FE	YES	YES	YES	YES	YES	YES
Panel B: By plot-size	Plot $<$ 1.5 acres			Plot $>=$ 1.5 acres		
Vouchers	0.225*	0.197	0.175	0.084	-0.025	0.174*
	(0.120)	(0.142)	(0.185)	(0.068)	(0.092)	(0.084)
Recommendations	0.106	0.129	-0.004	-0.033	-0.272**	0.178
	(0.098)	(0.141)	(0.164)	(0.081)	(0.095)	(0.104)
Voucher+Recommendations	0.212**	0.171	0.152	-0.035	-0.066	-0.040
	(0.101)	(0.169)	(0.159)	(0.092)	(0.108)	(0.143)
Baseline Value	0.113*	0.169**	-0.064	-0.061	-0.005	-0.154**
	(0.063)	(0.062)	(0.128)	(0.060)	(0.101)	(0.056)
V vs. R (p-value)	0.250	0.660	0.251	0.134	0.023	0.968
V vs. V+R (p-value)	0.901	0.839	0.877	0.216	0.738	0.100
R vs. V+R (p-value)	0.232	0.745	0.271	0.984	0.127	0.026
Observations	343	203	130	303	147	146
R-squared	0.032	0.043	0.027	0.017	0.059	0.061
Mean Dep. Var.	1.557	1.483	1.654	1.759	1.748	1.760
Village FE	YES	YES	YES	YES	YES	YES

Notes: This table shows the analysis of covariance results for the following model: $Y_i^t = \alpha + \varphi Y_i^{2014} + \sum_{k=1}^{3} \gamma_k TREAT_i^k + d_v + \varepsilon_{iv}$. Panel A differentiates better (columns 1-3) and worst-off (columns 4-6) households measured by an asset index. Panel B divides the sample by plot size less than (columns 1-3) and greater or equal to (columns 4-6) 1.5 acres. Columns 2 and 5 (3 and 6) condition on good (bad) true soil quality. SSB stands for subjective soil beliefs and EC stands for electrical conductivity, proxying true soil quality. Robust standard errors, clustered at the village-level, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table (A6) Heterogeneous 2016 treatment impact on SSB updating relative to EC

	(1) SSB=EC	(2) SSB=EC|Good EC	(3) SSB=EC|Bad EC	(4) SSB=EC	(5) SSB=EC|Good EC	(6) SSB=EC|Bad EC
Panel A: By asset index	Worst-off farmers			Better-off farmers		
Vouchers	-0.101	0.107	-0.260**	0.189**	0.187	0.013
	(0.079)	(0.086)	(0.090)	(0.088)	(0.119)	(0.090)
Recommendations	-0.122	0.057	-0.170	0.072	-0.031	0.056
	(0.095)	(0.126)	(0.104)	(0.094)	(0.102)	(0.158)
Voucher+Recommendations	-0.021	0.188	-0.114	-0.036	-0.015	-0.036
	(0.108)	(0.128)	(0.113)	(0.084)	(0.120)	(0.099)
V vs. R (p-value)	0.781	0.660	0.296	0.166	0.011	0.758
V vs. V+R (p-value)	0.379	0.527	0.118	0.002	0.044	0.619
R vs. V+R (p-value)	0.375	0.498	0.520	0.189	0.877	0.503
N	316	160	156	310	190	120
R-squared	0.011	0.020	0.051	0.033	0.039	0.006
Mean Dep. Var.	0.434	0.637	0.224	0.519	0.668	0.283
Village FE	YES	YES	YES	YES	YES	YES
Panel B: By plot-size	Plot $<$ 1.5 acres			Plot $>=$ 1.5 acres		
Vouchers	0.070	0.176*	-0.127	-0.055	-0.026	-0.157
	(0.077)	(0.099)	(0.113)	(0.086)	(0.087)	(0.093)
Recommendations	0.049	0.116	0.020	-0.200**	-0.242**	-0.171
	(0.093)	(0.107)	(0.131)	(0.081)	(0.093)	(0.100)
Voucher+Recommendations	-0.029	0.139	-0.127	-0.099	-0.072	-0.063
	(0.103)	(0.112)	(0.112)	(0.067)	(0.107)	(0.107)
V vs. R (p-value)	0.828	0.627	0.233	0.104	0.034	0.875
V vs. V+R (p-value)	0.149	0.697	0.993	0.593	0.709	0.233
R vs. V+R (p-value)	0.425	0.851	0.192	0.209	0.204	0.117
N	333	203	130	293.000	147.000	146.000
R-squared	0.006	0.020	0.026	0.021	0.049	0.029
Mean Dep. Var.	0.465	0.581	0.285	0.488	0.755	0.219
Village FE	YES	YES	YES	YES	YES	YES

Notes: This table shows the results of the following model: $\mathbb{1}\{SSB_t = EC\}_i^t = \alpha + \sum_{k=1}^{3} \gamma_k TREAT_i^k + d_v + \varepsilon_{iv}$ in 2016. Panel A differentiates better (columns 1-3) and worst-off (columns 4-6) households as measured by an asset index. Panel B divides the sample by plot size less than (columns 1-3) and greater or equal to (columns 4-6) 1.5 acres. Columns 2 and 5 (3 and 6) condition on good (bad) true soil quality. SSB stands for subjective soil beliefs and EC stands for electrical conductivity, proxying true soil quality. Robust standard errors, clustered at the village-level, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All regressions control for village fixed effects.

Table (A7) Robustness: Treatment impact on fertilizer by baseline subjective soil beliefs and true soil quality, **all villages**

	SSB is good (dummy)		EC is good (dummy)		SSB less than EC (dummy)	
	(1)	(2)	(3)	(4)	(5)	(6)
	Fertilizer (kg/acre)	Fertilizer Dummy	Fertilizer (kg/acre)	Fertilizer Dummy	Fertilizer (kg/acre)	Fertilizer Dummy
Panel A: 2016						
Vouchers	10.122***	0.292***	13.583**	0.297***	10.155***	0.301***
	(3.710)	(0.074)	(5.125)	(0.091)	(3.274)	(0.078)
Recommendations	-2.954***	-0.015	1.224	0.046	1.530	0.034
	(1.076)	(0.042)	(1.741)	(0.029)	(1.353)	(0.023)
Voucher+Recommendations	30.442***	0.754***	23.427***	0.669***	22.892***	0.701***
	(4.896)	(0.049)	(3.006)	(0.049)	(2.385)	(0.035)
Variable	-0.594	0.008	-1.649	-0.015	0.167	-0.008
	(0.742)	(0.028)	(1.218)	(0.028)	(1.047)	(0.034)
Vouchers × Variable	-1.552	-0.006	-6.897	-0.013	-3.368	-0.045
	(4.161)	(0.077)	(4.837)	(0.077)	(3.560)	(0.085)
Recommendations × Variable	5.405***	0.055	-0.581	-0.040	-3.568**	-0.053
	(1.891)	(0.049)	(1.657)	(0.044)	(1.663)	(0.045)
Voucher+Recommendations × Variable	-7.233	-0.044	4.750	0.114	15.104*	0.125**
	(6.116)	(0.055)	(4.482)	(0.068)	(7.987)	(0.058)
2014 Fertilizer (kg/acre)	0.200		0.192		0.198	
	(0.147)		(0.155)		(0.149)	
2014 Fertilizer dummy		0.246		0.267		0.252
		(0.264)		(0.260)		(0.259)
Observations	764	764	764	764	764	764
R-squared	0.223	0.402	0.223	0.405	0.233	0.405
Mean dep. var.	8.289	0.245	8.289	0.245	8.289	0.245
Panel B: 2019						
Vouchers	0.557	0.005	3.630	0.053	1.929	0.031
	(2.237)	(0.045)	(2.778)	(0.044)	(1.525)	(0.024)
Recommendations	-1.142	0.015	-0.594	-0.012*	-0.395	-0.007
	(1.129)	(0.049)	(0.369)	(0.007)	(0.594)	(0.012)
Voucher+Recommendations	-1.610	-0.034	-0.611	-0.006	-0.344	0.001
	(1.180)	(0.024)	(0.576)	(0.008)	(0.536)	(0.009)
Variable	-1.682	-0.035	0.388	0.003	1.965	0.040
	(1.107)	(0.023)	(0.867)	(0.018)	(1.454)	(0.030)
Vouchers × Variable	0.572	0.008	-4.347	-0.070	-3.581**	-0.072**
	(2.442)	(0.045)	(2.682)	(0.042)	(1.757)	(0.032)
Recommendations × Variable	0.848	-0.018	-0.204	0.022	-0.998	0.031
	(0.824)	(0.047)	(1.049)	(0.038)	(1.115)	(0.064)
Voucher+Recommendations × Variable	1.190	0.034	-0.258	-0.008	-1.884	-0.049*
	(1.132)	(0.022)	(0.770)	(0.014)	(1.423)	(0.029)
2014 Fertilizer (kg/acre)	-0.020***		-0.022***		-0.019***	
	(0.004)		(0.004)		(0.004)	
2014 Fertilizer dummy		-0.063***		-0.095***		-0.062***
		(0.015)		(0.028)		(0.012)
Observations	396	396	396	396	396	396
R-squared	0.018	0.023	0.027	0.022	0.020	0.030
Mean dep. var.	0.619	0.013	0.619	0.013	0.619	0.013

Notes: This table shows the analysis of covariance results for the following model: $Y_i^t = \alpha + \varphi Y_i^{2014} + \sum_{k=1}^{3} \gamma_k TREAT_i^k + \sum_{j=1}^{3} \delta_j TREAT_i^j * Variable_i + \lambda Variable_i + d_v + \varepsilon_{iv}$. The $Variable$ in columns 1 and 2 is an indicator variable taking the value of 1 if the respondent believes his/her soil is good at baseline, in 2014. The $Variable$ in columns 3 and 4 takes a value of 1 if the true soil quality, revealed for treatment "R" in 2016 and revealed for all farmers after 2016, is good. In columns 5 and 6, the dependent variable takes a value of 1 if SSB is poor in 2014 and the true soil quality is good in 2016. SSB stands for subjective soil beliefs and EC stands for electrical conductivity, proxying true soil quality. Robust standard errors, clustered at the village-level, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All regressions control for village fixed effects.

Table (A8) Robustness: Treatment impact on beliefs, **all villages**

	(1) SSB	(2) SSB|Good EC	(3) SSB|Bad EC	(4) SSB	(5) SSB|Good EC	(6) SSB|Bad EC
	2016	2016	2016	2019	2019	2019
Vouchers	0.156**	0.119	0.184**	0.055	0.016	0.154**
	(0.058)	(0.085)	(0.076)	(0.081)	(0.115)	(0.066)
Recommendations	0.026	-0.031	0.068	0.069	0.033	0.052
	(0.062)	(0.086)	(0.086)	(0.076)	(0.132)	(0.113)
Voucher+Recommendations	0.089	0.068	0.063	0.045	0.069	0.023
	(0.070)	(0.116)	(0.094)	(0.070)	(0.091)	(0.107)
Baseline Value	0.073*	0.128***	-0.050	0.105**	0.117*	0.068
	(0.041)	(0.045)	(0.067)	(0.042)	(0.063)	(0.051)
V vs. R (p-value)	0.041	0.106	0.137	0.871	0.891	0.409
V vs. V+R (p-value)	0.279	0.535	0.104	0.870	0.496	0.247
R vs. V+R (p-value)	0.301	0.267	0.945	0.751	0.759	0.828
Observations	863	460	370	916	493	390
R-squared	0.014	0.025	0.015	0.009	0.011	0.011
Mean dep. var.	1.650	1.600	1.711	1.481	1.430	1.567
Village FE	YES	YES	YES	YES	YES	YES

Notes: This table shows the analysis of covariance results for the following model: $Y_i^t = \alpha + \varphi Y_i^{2014} + \sum_{k=1}^{3} \gamma_k TREAT_i^k + d_v + \varepsilon_{iv}$. Columns 2 and 5 (3 and 6) condition on good (bad) true soil quality. SSB stands for subjective soil beliefs and EC stands for electrical conductivity, proxying true soil quality. Robust standard errors, clustered at the village-level, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All regressions control for village fixed effects.

Table (A9) Robustness: Treatment impact on SSB updating relative to EC, **all villages**

	(1) SSB=EC	(2) SSB=EC|Good EC	(3) SSB=EC|Bad EC	(4) SSB=EC	(5) SSB=EC|Good EC	(6) SSB=EC|Bad EC
	2016	2016	2016	2019	2019	2019
Vouchers	0.019	0.118*	-0.166**	-0.014	0.012	-0.112**
	(0.061)	(0.066)	(0.066)	(0.048)	(0.070)	(0.055)
Recommendations	-0.052	-0.022	-0.063	0.028	0.007	0.033
	(0.060)	(0.070)	(0.077)	(0.072)	(0.083)	(0.090)
Voucher+Recommendations	-0.048	0.053	-0.098	0.026	0.039	0.016
	(0.069)	(0.085)	(0.079)	(0.050)	(0.066)	(0.074)
V vs. R (p-value)	0.261	0.066	0.119	0.595	0.952	0.183
V vs. V+R (p-value)	0.154	0.290	0.170	0.395	0.600	0.111
R vs. V+R (p-value)	0.941	0.386	0.562	0.982	0.725	0.871
Observations	830	460	370	883	493	390
R-squared	0.003	0.012	0.016	0.001	0.001	0.011
Mean dep. var.	0.476	0.659	0.249	0.472	0.576	0.341

Notes: This table shows the results of the following model: $\mathbb{1}\{SSB_t = EC\}_i^t = \alpha + \sum_{k=1}^{3} \gamma_k TREAT_i^k + d_v + \varepsilon_{iv}$ in 2016 (columns 1-3) and in 2019 (columns 4-6). Columns 2 and 5 (3 and 6) condition on good (bad) true soil quality. SSB stands for subjective soil beliefs and EC stands for electrical conductivity, proxying true soil quality. Robust standard errors, clustered at the village-level, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All regressions control for village fixed effects.

Table (A10) Robustness: Treatment Impact on Information Retention, **all villages**

	(1)	(2)	(3)	(4)
	Retention Index (z-score)			
	2016	2019	2019	2019
Vouchers	0.40**	0.09	0.09	0.09
	(0.20)	(0.10)	(0.08)	(0.09)
Recommendations	3.93***	0.05	0.02	0.03
	(0.52)	(0.09)	(0.08)	(0.08)
Voucher+Recommendations	5.82***	0.48***	0.40***	0.43***
	(0.34)	(0.11)	(0.11)	(0.11)
Control mean	0.00	0.00	0.00	0.00
(std. dev.)	(1.00)	(1.00)	(1.00)	(1.00)
V vs. R (p-value)	0	0.74	0.51	0.57
V vs. V+R (p-value)	0	0	0.01	0.01
R vs. V+R (p-value)	0	0	0	0
Observations	984	920	920	920
Village FE	YES	YES	YES	YES

Notes: This table show the effects of treatments on fertilizer recommendations retention for 2016 (column 1) and 2019 (columns 2-4) by estimating the following model: $Retention_i^t = \alpha + \sum_{k=1}^{3} \gamma_k TREAT_i^k + d_v + \varepsilon_{iv}$. To construct the 2016 index and the first 2019 index (column 2), we assign one point for every recommended fertilizer type the farmer correctly recalls. To construct the second index in 2019 (column 3), we assign one point for every fertilizer type recommended and two points for every fertilizer quantity recommended the farmer correctly recalls. The third 2019 index (column 4) assigns one point for each fertilizer type correctly recalled and one point for each quantity correctly recalled. Robust standard errors, clustered at the village-level, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table (A11) Robustness: Effect of fertilizer application on SSB and retention, all villages

	(1)	(2)	(3)	(4)	(5)
	SSB	SSB|Good EC	SSB|Bad EC	Retention	
	2016	2016	2016	2016	2019
Panel A: Decision to Adopt					
Fertilizer (=1)	0.199**	0.157	0.195*	0.638***	-68.000
	(0.085)	(0.124)	(0.107)	(0.089)	(315.922)
Observations	818	431	355	820	416
Mean dep. var.	1.658	1.615	1.710	0.405	0.500
F-stat (first-stage)	127.82	123.46	81.56	126.71	0.28
Panel B: Quantity Applied					
Fertilizer (kg/acre)	0.005**	0.005	0.004	0.018***	0.432
	(0.003)	(0.004)	(0.003)	(0.003)	(0.832)
Observations	846	447	366	848	416
Mean dep. var.	1.647	1.595	1.708	0.393	0.500
F-stat (first-stage)	102.02	51.12	70.90	102.45	0.01

Notes: This table shows the effects of fertilizer use on SSB (columns 1-3) and retention (columns 4-5) by estimating the following two-stage least squares model: 1) $Fertilizer_i^t = \beta + \mathbb{1}\{Voucher_i = 1\} + d_v + \nu_{iv}$; 2) $Y_i^t = \pi + \lambda \widehat{Fertilizer_i^t} + d_v + \mu_{iv}$. Column 2 (3) conditions on good (bad) true soil quality. SSB stands for subjective soil beliefs and EC stands for electrical conductivity, proxying true soil quality. Robust standard errors, clustered at the village-level, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All regressions control for village fixed effects.