Confidence and Information Usage: Evidence from Soil Testing in India *

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Abstract

Informational barriers are often considered to be a major constraint to the adoption of improved farming practices, inputs, and technologies by smallholder farmers. In the Indian context, it is widely believed that farmers misapply chemical fertilizers because they lack scientific information on soil conditions and corresponding fertilizer recommendations, thus resulting in imbalanced and potentially detrimental fertilizer application. Policymakers are frequently interested in providing farmers with various streams of information to overcome these informational barriers to optimize farming activities. However, such informational interventions frequently fail either because generic recommendations may be ill-suited for decisionmakers in highly heterogeneous agricultural environments or because farmers' beliefs may be so entrenched as to make them unresponsive to new information. We implemented a field experiment in Bihar, India to test whether plot-specific fertilizer recommendations affect farmers' fertilizer use. We find little evidence for sizable impacts on fertilizer use in general, though impacts are more apparent for low cost or costless recommendations such as increasing the use of highly subsidized fertilizers or shifting the timing of application. Despite modest evidence of such effects, even those fall short of their potential magnitude. We show that treated farmers that are less confident in their subjective beliefs about optimal fertilizer application rates (i.e., with more disperse priors) are more responsive to the recommendations and have a higher ex ante willingness to pay for soil testing. These results suggest that heterogeneity in beliefs may constrain the overall effectiveness of information provision, even when the information is tailored to individual farms.

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The imbalanced use of fertilizers is a major agricultural and environmental concern in emerging economies (FAO 2019; Vitousek et al. 2009). Under-application of fertilizers is tied to the persistence of yield gaps (Mueller et al. 2012), whereas over-application is not only inefficient, but damages soil health and pollutes water resources, leading to adverse public health impacts. Since over-utilized fertilizers are often subsidized, the consequences also involve substantial strain on public finance.

To address widespread fertilizer application imbalances (Bora 2022), the Government of India launched the Soil Health Card (SHC) program in 2015. The program sought to provide all 140 million farmers in the country with lab-derived soil health information and targeted fertilizer application recommendations on a triennial basis. The implicit assumption underlying this intent was that farmers misapply fertilizers because, at least in part, they lack scientific information and recommendations that are targeted to their specific soil attributes, and that providing them with this information will alter their fertilizer usage.

In this paper, we report results from an experimental evaluation of an intervention that mimics the SHC program in design and implementation. We find the program to have had modest effects, if any, on the total *amounts* of fertilizer usage, even though most farmers were advised to increase it. Farmers were more responsive to advice about the *timing* of fertilizer application. We then investigate the role that farmers' prior beliefs on the appropriate rate of fertilizer application played in mediating the impact of the information contained in the SHC.

India's Soil Health Card program is likely one of the largest informational interventions in the developing world. Although information provision interventions have become more common in various policy domains due to their relatively low cost, evidence on their effectiveness remains mixed, particularly in agricultural contexts (Haaland et al. 2022).[1] Even if informational barriers inhibit the adoption of improved farming practices, inputs and technologies by smallholder farmers (Fabregas et al. 2023, 2019; Jack 2013), various factors may limit the impacts of informational interventions.[2] The literature has explored issues such as the quality of the information and the manner in which it is disseminated, as well as the recipients of the information and potential biases in learning and information processing (Barham et al. 2018; Hanna et al. 2014).[3,4]

First, we present results from an experiment that covered 864 households across 48 villages in the Indian state of Bihar, and took place prior to the government launch of the national SHC program which it aimed to mimic. Following a baseline survey, trained enumerators collected soil samples from farmers in treatment villages. The samples were tested in a certified laboratory and the results were used by agronomists to prepare customized plot-specific recommendations for the usage rates of several common fertilizers. These recommendations were then provided to treated farmers prior to the *rabi* wheat season.

As mentioned above, we do not find robust evidence of an increase in total fertilizer application amounts, even though 71%, 85% and 100% of treated farmers received recommendations to increase their use of the three major fertilizers, urea, DAP and MOP. In addition, we can rule out an increase of more than 5% in total expenditure on fertilizer. Only for urea, the most heavily subsidized fertilizer, do we find significant indications of increases (amounting to about 5% of the mean value, or 40% of what full compliance would lead to), but confidence intervals that account for attrition include a null effect. Point estimates for DAP and MOP, which are subsidized to a much lesser degree, are insignificant (or even negative). Note that these results refer to levels of fertilizer use, rather than to adjustments in relation to the original plans or the recommendations, because we did not collect soil samples from the control group. In contrast, farmers were more responsive to advice about costless shifts in the timing of fertilizer application, which seems to have generated an increase in yields. The results are in line with findings in other contexts that provided plot specific soil quality information and recommendations, including Mexico (Corral et al. 2020), Tanzania (Harou et al. 2022), and Bangladesh (Beg et al. 2023).

While the pattern of these findings suggests the cost of compliance as one factor inhibiting responsiveness, it remains unclear why response remained modest even for highly subsidized inputs. To gain insight into the potential reasons, endline surveys asked treatment farmers to explain why they did not comply with the SHC recommendations. The most common response referred to farmers' own prior beliefs as the main reason, with cost appearing as a secondary factor and only for the more expensive fertilizers (DAP and MOP).

We investigate this possibility in greater depth through an analysis of heterogeneity in responsiveness to the SHC recommendations amongst treated farmers. The analysis makes use of three measures of farmers' baseline confidence in their usual fertilizer application choices. The first, and main one, is based on farmers' subjective belief distributions about optimal urea and DAP application rates on their *Kharif* rice crop (Delavande et al. 2011), which we elicited during the baseline survey. We construct a measure of confidence or uncertainty in their priors about optimal fertilizer application from the dispersion of the elicited belief distributions. Two other survey based measures of confidence include farmers' self-reported incidence of doubts about agricultural practices and a measure of their self-reported farming ability relative to their peers.[5] Consistent with recent work on within-person correlations of behavioral biases (Chapman et al. 2023; Stango and Zinman 2023), we show that there is a strong correlation across these three confidence measures.

We test whether farmers' confidence is correlated with the degree to which farmers adjust their pre-season fertilizer application plans in the direction of the recommendation of the SHC. The analysis is limited only to treated farmers, since we did not collect soil samples from the control samples, and therefore do not observe what their recommendations would have been.

We find that farmers that are less confident, by any of our three measures of confidence, adjust their endline urea usage in the direction of the SHC recommendation to a greater degree. This correlation is robust to the inclusion of a battery of farmer and plot characteristics that may be correlated with confidence and responsiveness to the information. For DAP usage, we find results of similar magnitudes, though the effects are marginally insignificant. In contrast, we find no effect of trust in extension agents or credit access on the degree to which farmers adjust fertilizer application. In addition, we find that farmers that are less confident and have more trust in existing extension services have a significantly higher stated willingness-to-pay for the soil health cards.[6] These results point to the importance of prior confidence in beliefs on responsiveness to the information in the SHC.

Our work contributes to and bridges the literature studying the effects of information provision on technology adoption, and the literature analyzing the role of information on belief updating and decision making. Previous work that evaluates the effectiveness of various forms of extension and information provision to farmers in developing countries include, but are not limited to: Arouna et al. (2021); Beaman et al. (2021); BenYishay and Mobarak (2018); Casaburi et al. (2019); Cole and Fernando (2021); Emerick and Dar (2021); Van Campenhout et al. (2021).[7] Several recent studies investigate the effectiveness of targeted soil information, as we do. Using a field experiment in Mexico, Corral et al. (2020) vary the specificity of the soil-test based recommendations (own plot vs a local average) as well as the flexibility of an in-kind grant of recommended fertilizers. While recommendations and extension services resulted in a small but persistent adoption of practices, averaged soil information was as effective as providing plot-specific recommendations. Similarly, Harou et al. (2022) find that plot-specific information in Tanzania was insufficient to increase fertilizer adoption on its own, though vouchers for fertilizer purchase or a combination of both vouchers and information increased usage and yields. In contrast to these studies, farmers in our context operated under a fertilizer subsidy regime that reduced the costs of complying with recommendations and is argued to have incentivized excessive application of urea and under-application of phosphorus and potassium fertilizers (Kishore et al. 2021). In India, Cole et al. (2021) investigate the effects of hand delivered SHCs combined with customized recommendations delivered through mobile phones for cotton farmers. They show that aid materials can help improve low levels of comprehension of SHCs, and experimentally demonstrate that the SHCs are able to affect fertilizer usage, though they find no evidence of a change in cotton yields. In Bangladesh, where fertilizers are also subsidized, Beg et al. (2023) find that farmers responded only to recommendations to decrease one fertilizer (TSP) by stopping application altogether, with negative impacts on rice yields. The authors attribute the lack of response on the intensive margin to limited attention. We complement this work by evaluating a large scale plot-specific soil testing program in a context where farmers commonly apply the recommended fertilizers, which are argued to be imbalanced. In addition, we examine how farmers' beliefs - particularly the strength of their beliefs - affect demand for and responsiveness to tailored advice like the SHCs.

This study also contributes to the comparatively thinner literature that uses information provision to study belief updating and barriers to responsiveness to information. Recent evidence from survey experiments documents that firms and individuals update their expectations in response to information about home prices (Armona et al. 2019; Fuster et al. 2022) and GDP growth (Coibion et al. 2018; Roth and Wohlfart 2020) and that policymakers and practitioners update their beliefs about policy effectiveness in response to research findings (Hjort et al. 2021; Vivalt and Coville 2023). Across these domains, heterogeneity in updating arises due to a variety of individual characteristics and biases. These include numeracy and "taste" for information (Fuster et al. 2022), as well as variance neglect and asymmetric updating in favor of good news (Vivalt and Coville 2023).[8] Increasingly, research on belief updating has included measures of prior uncertainty to test its impact on Bayesian updating (Armona et al. 2019; Roth and Wohlfart 2020) though evidence of its effect is mixed. While previous papers have shown that respondents with higher stated prior uncertainty tend to react more to information about inflation (Armantier et al. 2016; Coibion et al. 2018), research on house price expectations find either no effect (Armona et al. 2019) or the opposite effect (Fuster et al. 2022). Using a large-scale information intervention, we extend the existing literature by examining how quantitative measures of prior uncertainty affect actual investment choices and responsiveness to advice in the context of developing country agriculture.[9]

Finally, we make a further contribution to the growing literature that uses beliefs to analyze farmer decision making. The relatively simple method of belief elicitation we use, summarized in Delavande et al. (2011), requires respondents to allocate tokens across bins to represent probabilities of events occurring. Recent work using elicited expectations analyzes how farmers' beliefs affect their investment in learning about new technologies (Maertens et al. 2021), frictions in learning about input quality (Bold et al. 2017; Hoel et al. 2024), and how perceived output price risk (Hill 2009, 2010) and rainfall expectations (Lybbert et al. 2007) affect farmer decisions.[10] Our paper complements this work by incorporating the dispersion of beliefs into farmer decision making and responsiveness to information. We provide some of the first field evidence that the strength of farmers' prior beliefs – regardless of whether those beliefs are right or wrong – can indeed reduce both demand for and responsiveness to an informational intervention. Our results suggest that identifying and targeting advice to farmers with low confidence may produce the highest returns to information diffusion efforts. We further show that the elicited beliefs measures, which are costly and time consuming to collect, are correlated with survey-based measures of confidence that similarly predict responsiveness to the fertilizer recommendations.

Context and Experimental Design

We implemented our field experiment with the assistance of scientists from Department of Soil Science at Rajendra Agricultural University (RAU). RAU is the oldest and most prestigious institution for agricultural research and extension in Bihar and has the greatest capacity to carry out the soil testing, analysis, and derive nutrient recommendations. The study area comprised three districts in Bihar with a predominant rice-wheat cropping system: Bhojpur, Madhubani, and Nawada. In these districts, rice is the predominant *Kharif* (monsoon season; spanning from June to October) crop. Wheat is the predominant *Rabi* (dry, winter season; spanning from December to February) crop, accounting for nearly 60 percent of gross sown area.

At the time of the study, the state of Bihar was lagging behind other states in implementing its SHC scheme (Gujarat, for example, had already claimed testing of all plots in the state). In our baseline survey, only 2 percent of respondents reported ever having their soil tested, although 95 percent indicated that they would like to have it tested, suggesting high demand for the program. The reasons cited for wanting soil testing were to learn the appropriate quantity of urea to use (17%), which other fertilizers to use apart from urea (27%), when to apply fertilizers (6%), and all of the above (50%). The declared targets in the state were to analyze nearly 1.31 million soil samples and provide more than 11 million SHCs to farmers in Bihar within three years.

Sampling, Randomization, and Treatment

To select households, we used a multistage sampling approach. In the first stage, we selected three districts with a predominant rice-wheat cropping system from which to sample households: Bhojpur, Madhubani, and Nawada. In the second stage, we randomly selected 16 high-rice-producing blocks (subdistrict administrative units) across the three districts, with the number of blocks drawn from each district proportional to the share of rice production attributable to that district: seven blocks were selected from Bhojpur, 6 from Madhubani, and 3 from Nawada. Treatment was randomized at the village level within each of these 16 blocks (strata). Within each block, we randomly selected 2 villages from which to draw households for treatment and 1 village from which to draw households for a control group. Within each of the 48 villages, we randomly selected 18 rice- and wheat-growing households from village rosters prepared by enumerators through door-to-door listing. The baseline sample therefore included 864 farmers, of which 576 are treatment farmers and 288 are control farmers.

Figure 1 illustrates the timeline of the SHC intervention and data collection activities. In April and May of 2014, we conducted a baseline survey with all households to collect information on household and farm characteristics and the use of farm inputs for the 2013 *Kharif* rice crop on farmers' two primary paddy plots.[11] During the baseline survey, we elicited survey based confidence measures and subjective beliefs regarding optimal application rates of urea and DAP for the upcoming 2014 *Kharif* rice crop on farmers' primary paddy plot. We also collected information about farmers' past experience with soil testing and their stated willingness-to-pay for soil tests. The belief elicitation process and willingness-to-pay are explained in greater detail in Section below.

In May and June 2014, following the baseline survey, we collected soil samples from one plot of every *treatment* farmer. Farmers nominated their two most important plots and one was randomly selected for testing. Eight soil science graduates from local agricultural universities were selected to deliver the SHCs for this study. These agents received a three-day training from experts from the department of soil science at RAU and the regional office of the Indian Council of Agricultural Research on the proper procedures for collecting soil samples for subsequent testing. The agents then visited each of the treatment households, collected soil samples according to the recommended practices, and deposited them with the soil testing laboratory at RAU. This execution of soil testing and its delivery to the laboratory was meant to simulate the intended execution of the central government's SHC program, albeit at an individual plot level rather than on a gridded basis.[12] We discuss further details of the soil testing process and the development of fertilizer use recommendations in Section .[13]

Technical delays in conducting all soil tests prevented us from distributing the SHCs prior to the planting of the 2014 *Kharif* paddy rice crop. We therefore shifted the delivery of the SHC to the 2014-15 *Rabi* season, and had fertilizer recommendations prepared for the wheat crop, the main crop of that season.

We carried out a midline survey to collect information on cultivation practices and fertilizer application on farmers' wheat crop for the previous 2013-14 *Rabi* season. The midline was conducted in November 2014, prior to distributing the SHCs with soil test results and recommendations to treatment farmers. The majority of farmers in the study area and in our sample (85%) also regularly cultivate wheat during the *Rabi* season, though there is variation from year to year in the decision to cultivate. During the midline data collection, we reminded farmers of their experimental plot, and data for all inputs were collected for their experimental plot as well as their secondary plot if they cultivated more than one plot. For control farmers, we randomly selected their comparison plot prior to the midline survey and collected data during both the midline and endline surveys for both the selected plot as well as their secondary plot (if applicable). We restrict our analysis of the SHC intervention and heterogeneous responses to the recommendations to the selected plot, which we refer to as the experimental plot.

Following the midline survey, SHCs (printed in Hindi) were hand-delivered by the eight field agents to treatment farmers prior to the sowing of the wheat crop.[14] Enumerators collected treatment farmers' planned fertilizer application rates in the coming 2015 season and subsequently delivered the SHCs. The agents were trained in the proper interpretation and explanation of the SHC to farmers. Finally, we conducted an endline survey of fertilizer application rates in June-July 2015 following the harvest of the the 2014-15 *Rabi* wheat crop. Together, the data includes a household panel of agricultural practices and fertilizer application in both the *Kharif* rice and *Rabi* wheat crops that were harvested in 2014 and 2015 on the experimental plot and the secondary plot if farmers cultivated two or more plots.

We note several aspects of the study implementation and their implications for our analysis. First, we opted not to test soils for farmers in control villages, due both to the cost of sampling and testing soils as well as concerns that not receiving the SHC after testing could diminish their future trust in soil health card programs. Consequently, we do not know what the fertilizer recommendations *would have been* for farmers in the control villages and are unable to directly compare whether farmers in treatment villages move in the direction of the recommendations relative to farmers in the control villages. Rather, we are only able to compare the levels of fertilizer use across treatment and control groups. Second, the original goal was to provide farmers with recommendations for their paddy rice crop prior to the 2014 *Kharif* season, but technical delays forced us to delay delivery of the SHCs until just before planting of the 2014-15 *Rabi* wheat crop. Thus, a potential limitation of our analysis is that measures of confidence and observations of responsiveness to the SHC recommendations were collected for different crops (i.e., our measure of confidence was collected with respect to fertilizer application for rice, whereas the observed fertilizer applications in response to receipt of the SHC was for the wheat crop). All of the farmers in our sample have experience growing wheat during the *Rabi* season, though 15% of the farmers in our sample opted not to cultivate wheat in the 2014-15 *Rabi* season, and consequently were excluded from our analysis. Finally, while the original treatment sample consisted of 576 farmers, the research team failed to deliver SHCs to 79 of these farmers, due to a combination of technical reasons (samples that were either too small or contaminated) or a lack of cooperation in a handful of cases. Our local implementing partners were reluctant to visit these farmers to collect endline data without being able to also provide them with SHCs. This only affected the size of the treatment group, by definition, and resulted in lower availability of endline data in that group (data is available for 497 treated farmers, or 86% of the original treatment sample). To account for any possible bias stemming from these and other potentially unobservable differences, we employ the bounding approach of Lee (2009) to construct upper and lower bounds for the estimated treatment effects (additional details are discussed in the online supplementary appendix). The initial sample size provided 80 percent statistical power to identify effects of $0.25 - 0.5$ standard deviations in fertilizer application rates, depending on the range of intracluster correlation (ICC) in the observed range from baseline data. These effect sizes fall within the range of positive outcomes found in similar studies on soil testing interventions including in Corral et al. (2020) and Harou et al. (2022). However, due to the technical delays described above, the sample size decreased in the treatment group following the baseline which further reduced power.[15]

Belief elicitation and confidence measures

During the baseline survey, we collected farmers' prior belief distributions about optimal fertilizer application rates (urea and DAP) in the upcoming 2014 *Kharif* rice season using hypothetical, visually-aided elicitation method.[16] Farmers were asked to allocate beans across bins according to how likely they think that each fertilizer application rate bin would lead to the highest yields on their primary agricultural plot. Whereas much of the early work using similar visually-aided experiments to elicit subjective beliefs avoided explicit references to probability or likelihood (e.g., due to idiosyncratic differences in the interpretation these terms), we followed the example of Delavande and Kohler (2009) and explicitly framed our experiment in probabilistic terms.

After participants were comfortable representing probabilities with the beans, they were asked to allocate 20 beans to represent their subjective beliefs regarding the optimal urea and DAP application rates (in kg per katha) for the upcoming (2014) *Kharif* rice season on their primary plot.[17][18] The bins of fertilizer application rates were predetermined using data collected with a subsample of treatment farmers in 2013, as well as conversations with farmers and extension agents in the region. The DAP support consists of 5 bins spread over the empirical distribution of DAP application rates while the urea support consists of 7 bins spread over the empirical distribution of urea application rates. We chose varying bin sizes in order to cover the whole empirical support of fertilizer use while allowing for variation where the majority of application occurs.[19]

Eliciting the beliefs distributions entailed two questions for each bin. Before starting, respondents were reassured that there were no incorrect answers and that we were only interested in their thoughts regarding optimal fertilizer use. Specifically, for each bin, respondents were asked:

> Do you think that this range of total urea (DAP) applied throughout the season could result in the maximum possible yield in the upcoming season on your primary rice-growing plot? If yes, what is the likelihood that this range of application rates will result in the maximum possible yield in the upcoming season?

After answering these questions for each bin, respondents were allowed to reconsider their choices and re-allocate beans accordingly, using the entire support and all beans.

Figure 2 shows the range of values for urea and DAP application rates (kg per katha), respectively, and the proportion of total beans (or probability) allocated to each bin. The figures show that some probability is allocated over the full support for both fertilizers, though a relatively small share of the total probability is placed on the highest possible values for both urea and DAP. The slight skewness may be attributed to local beliefs about the amount of excessive urea resulting in crop failure. There is no apparent bunching at particular values of the distribution, and only two bins for which fewer than 10 percent of respondents believed there is at least *some* possibility that the corresponding range of fertilizer application will result in the highest yield.

We calculate the first and second moments for each individuals' subjective beliefs distribution assuming that the allocation of beans across bins approximates a stepwise uniform distribution (Attanasio and Augsburg 2016). The mean and standard deviation of the elicited beliefs are used as proxies for the corresponding priors of the farmers' true fertilizer application belief distributions prior to receiving soil testing (θ_1 and $\sigma^2_{\theta_1}$, respectively). We include the standard deviation of farmers beliefs in our estimations and control for the mean. Farmers' confidence can be interpreted as the inverse of the dispersion of their prior beliefs ($\rho_{\theta_1} = \frac{1}{\sigma^2_{\theta_1}}$).

Figure 3 shows the relationship between the elicited expectations (mean values) of the subjective beliefs distributions and actual fertilizer application rates on the experimental plot during the 2013 *Kharif* season. In general, there is a high correlation between expectations of optimal fertilizer use and actual behavior. The relationship is weaker for DAP than for urea, and for farmers who are at or above about the 90th percentile of mean beliefs. These correlations demonstrate that (1) the elicitation procedure captures meaningful information about farmers' beliefs and (2) that the majority of farmers are able to achieve their perceived optimal fertilizer application rates and are not constrained by other factors such as fertilizer cost or availability. The distributions of the means and standard deviations of farmers' beliefs are presented in Figure C1 in the online supplementary appendix.

In addition to subjective beliefs, we asked questions that provide survey-based measures of confidence. The first question asks: *Given the same soil quality and access to inputs, how would your yields compare to others in your village?* The second question asks: *How often do you have doubts about agricultural practices?* For both questions, farmers respond on a Likert scale corresponding to judgments from "much less than others" to "much more than others." From this scale, we construct a measure of confidence that is equal to one if they responded that they would have less or much less yields relative to their peers. Similarly, using their incidence of doubts we construct a binary measure that is equal to one if farmers have a little more or much more doubts than their peers. The first question (regarding yields) is meant to capture the respondent's perceived farming ability relative to other farmers in their village.[20] The second question (regarding doubts about agricultural practices) is meant to capture general uncertainty about farming and is akin to qualitative confidence questions that measure how confident respondents are about beliefs that are being elicited (Haaland et al. 2022).[21]

The subjective beliefs we collected pertained to the 2014 *Kharif* season rice crop, as mentioned above, but technical delays in the preparation of SHCs forced us to focus our experiment on the subsequent 2014-15 *Rabi* season wheat crop. While we have not measured the dispersion of farmers' priors for the wheat crop, we rely on the priors for the rice crop as a proxy for the dispersion of farmers' priors of fertilizer usage. Empirical confidence experiments find that within-agent confidence tends to be highly correlated across tasks (Klayman et al. 1999) and that measures of overconfidence exhibit positive correlation within person (Chapman et al. 2023; Stango and Zinman 2023). Given the similarity in experimental tasks in the present study, and that 92% all farmers in our sample have at least ten years of experience with both rice and wheat crops, we believe that confidence in beliefs for fertilizer application for the *Kharif* rice crop is a reasonable, though imperfect, proxy for underlying confidence in beliefs for fertilizer application for the *Rabi* wheat crop.[22] Table 1 shows that the dispersion (standard deviation; SD) in beliefs for both urea and DAP are highly and positively correlated, providing some evidence that confidence is correlated across different fertilizers for the same crop. Further, the dispersion measures from the belief distributions are correlated with our survey-based measures of confidence (i.e., their potential yields compared with neighbors with similar soil quality, or the frequency that farmers have doubts about agricultural practices relative to their peers), suggesting that we are indeed capturing meaningful heterogeneity in underlying confidence.

Tables C1 and C2 in the online supplementary appendix investigate correlates of prior dispersion using farmer and characteristics of the experimental plot. We find suggestive evidence that farmers that are more trusting, have a higher WTP for soil tests, and have access to credit have higher dispersion in their beliefs (less confident), while female farmers and those with plots that are flat (rather than sloped) have tighter prior beliefs (more confident). Confidence does not seem to be correlated with experience or wealth. We also estimate the relationship jointly in Table C3. The effects of trust, WTP, gender and the slope of the plot persist, though having access to credit is no longer significant. As the belief dispersion measures may be capturing a combination of farmers' beliefs about optimal fertilizer usage as well as stochasticity in production, we include village fixed effects in all estimates to account for potential variation across villages in underlying uncertainty due to weather or pests that may be correlated with farmers' elicited beliefs.

Soil tests and recommendations

The soil samples were analyzed using wet chemistry methods by soil scientists at RAU. Tests included the levels of three key macronutrients available in the soil – nitrogen (N), phosphorus (P), and potassium (K) – as well as organic carbon content, electrical conductivity (to measure soil salinity), and soil pH (i.e., whether the soil is alkaline, acidic, or neutral), as well as levels of micronutrients including sulfur, zinc, copper, boron, and manganese. Based on the soil analyses, scientists at RAU generated plot-specific SHCs reporting soil nutrient composition (i.e., the levels of various nutrients and comparison relative to agronomic benchmarks) for each of the tested components. In addition to the levels of the nutrient and comparison relative to its threshold (high/medium/low), the SHCs included recommendations (in kg/ha) for the application of macro fertilizers urea (the main source of N), DAP (the main source of P), MOP (the main source of K). Because Bihari soils are widely believed to suffer from sulfur (S) and zinc (Zn) deficiencies (Shukla and Behra 2019), and because both of these micronutrients are considered to be important for soil health and crop yields, we included fertilizer specific recommendations (in kg/ha) for these two micronutrients in the SHCs.

All farmers in our sample use urea and DAP, though MOP is less commonly used (30% report using MOP on their *Rabi* wheat crop in the previous season). The Government of India ensures a uniform price of N, P, and K fertilizers across India, including subsidizing the transport costs of fertilizers to make sure that fertilizers do not cost more in inland areas or those further away from fertilizer plants (Government of India 2022). At the time of the experiment, all three fertilizers were subsidized by the government. Urea was the most heavily subsidized, costing around Rs.5/kg, with DAP and MOP costing around 8 and 5 times more per kg, respectively.[23] Only 2% of farmers in our sample had previously applied sulfur and 11% had applied zinc.

An example of the SHC in Hindi is presented in Figure 4. The front side of the SHC contained information on soil nutrients and their measured levels, categorized as low (deficient), medium (within the acceptable range), or high (excessive), while the back side of the SHC provided farmers with the plot specific recommended application rates of different nutrients (N, P, and K), specific fertilizers (urea, DAP, and MOP), and a two micronutrient fertilizers (Zinc and S) to apply to their *Rabi* wheat crop. The back side of the SHC also included information on the timing of urea application, stating that farmers should apply half of the total nitrogen (urea) amount at the time of sowing, and the remaining half split into two equal parts, with one part applied at the time of first irrigation and the other applied at tillering. The practice of splitting nitrogen fertilizer application at these times is recommended to enhance nutrient efficiency by synchronizing nitrogen supply with the plant's ability to utilize the applied nutrients. An example of the back side of the SHC in English is provided in Figure 5.

A complicating factor in the determination of fertilizer application recommendations is that they depend on the desired yield, which could vary by crop, variety, access to supplemental irrigation, and other factors. The typical practice in Bihar is to calibrate the recommendations to a fixed yield rate (in our specific case, 4 tonnes per hectare). The average wheat yield in our sample at the time of project baseline was 3 t/ha, 25 percent lower than the target yield used for the recommendations. The relatively high target yield was chosen by local partners, who face the trade off of encouraging balanced nutrient management to decrease environmental impacts with the need to increase yields to meet growing population and consumption demands. Farmers may have viewed the yields, conditional on recommended fertilization rates, as unprofitable. This is unlikely the case for urea, due to its low cost, or the recommendation on the timing of urea application which is revenue neutral. However, for DAP and MOP, roughly 40% farmers that applied less than the recommended amounts cited cost as a primary reason for not following the recommendations, but lower profits were only a primary concern for 6% and 2% of farmers, respectively (Table 8).

Table 2 compares treatment farmers' self-reported planned fertilizer application rates on their experimental plot (Columns 1-5) in the 2014-15 *Rabi* wheat season (collected prior to receiving the SHC) to the recommendations (i.e. calibrated uniformly to 4t/ha, Columns 6-10). The average recommendations for the use of urea and DAP were 22 and 46 percent higher, respectively, than farmers' planned application rates. The recommended use of MOP was more than six fold larger than planned use, related to the fact that only 38% of farmers in our sample planned to use MOP at all (Column 1). Considering farmers that planned to apply any MOP, the corresponding recommendations were 224% larger. Overall, 71% (85%) of farmers received a recommendation to increase their use of urea (DAP), while 98% of farmers were told to increase their use of MOP (Column 11). Figure 6 plots the distribution of these differences between planned and recommended application rates of urea and DAP.

Summary Statistics and Balance

Table 3 presents comparisons of baseline attributes between control farmers (Column 1), treatment farmers that received SHCs (Column 2) and treatment farmers that did not receive SHCs (Column 3) and were also not surveyed at endline. Columns 4-6 report p-values of t-tests comparing each pair of these three groups. The average farmer in our sample is around 45 years of age, and 65% of the sample are literate. The average stated willingness to pay for a SHC was about USD 1.6. 31% of farmers report trusting information from extension agents until there is evidence that it is effective, suggesting that trust in existing extension services is low in our sample.[24]

While treated and control farmers were mostly similar statistically, treated farmers were a little more likely to be female (8.5 vs 5.2 percent points). To ensure against the possibility that this difference might bias the interpretation of our results, we control for gender in all regressions, and find this to have little effect. An F-test of joint orthogonality fails to reject the null hypothesis that treatment is jointly orthogonal to all baseline variables (p-values reported at the bottom of the table).[25]

Treatment farmers for which soil tests were collected incorrectly or failed to be collected are very similar to the rest of the treatment sample in terms of soil properties, baseline fertilizer use, yields, as well as their priors. However, they are somewhat more likely to be female. Since our ITT estimates of the effect of SHC distribution compare the samples in Columns 1 and 2 (no endline data is available for farmers in Column 3), in order to account for any possible bias stemming from these and other potential unobservable differences, we employ the bounding approach of Lee (2009) to construct upper and lower bounds for the estimated treatment effects (additional details are discussed in the online supplementary appendix). We report summary statistics and balance tests of farmer characteristics, input use, and yields the previous *Rabi* season using the sample that was surveyed at midline in Table C4 in the online supplementary appendix.

Table 4 examines attrition by treatment group. Column 1 shows that treatment farmers were 14 percentage points less likely to be interviewed in the endline survey. This includes the full sample of baseline farmers including those treatment farmers that were not interviewed in the endline because they did not receive their SHCs. In column 2, we remove treatment farmers that did not receive soil tests and examine attrition with the remaining sample. Of this sample, 94% of farmers that were present at baseline were interviewed at endline and we do not find any differences in attrition by treatment status. Because the SHC we distributed were specific to wheat cultivation, we further restrict our sample to the 85% of farmers at endline that cultivated wheat in the primary plot. In column 3, we show that the likelihood of cultivating wheat did not differ across control and treatment farmers. Our final sample for estimating treatment effects on wheat cultivators consists of 621 farmers.

Impacts of the SHC Program

Treatment effects on fertilizer use, yields, and expenditures

We estimate the causal impacts of the SHC distribution on farmers' experimental plots in the 2014-15 *Rabi* season using the following ANCOVA specification:

$$y^1_{iv} = \beta_0 + \beta_1 T_v + X^{'}_{iv}\gamma + y^0_{iv} + \mu_b + \nu_e + \epsilon_{iv} \tag{1}$$

where y^1_{iv} is the endline measure for the outcome of interest for farmer i's experimental plot in village v, T_v is a binary treatment indicator for being in a village that received the SHCs, and X_i is a vector of individual and household baseline characteristics (gender, age, literacy, landholding size, and size of the experimental plot). Following McKenzie (2012), we include the baseline value of the outcome variable when available, y^0_{iv}, to improve statistical power. Block (strata) fixed effects are captured by, μ_b, and we include enumerator fixed effects (ν_e) in the regression. Standard errors are clustered at the village level, the unit of randomization. The sample includes all farmers who planted wheat on their experimental plot at endline. The estimated parameter β_1 captures the intent-to-treat effect of receiving the SHC. We report the 95% confidence intervals of Lee bounds to account for potential selection bias due to attrition (Lee 2009).[26]

We estimate treatment effects on the application rates of the three major macro fertilizers: urea, DAP and MOP, measured in kg per hectare. While urea and DAP are used by all farmers, only 30% of sampled farmers applied MOP on their wheat crop. We include a binary indicator of MOP use to estimate the treatment effect on MOP use along the extensive margin. We also examine the effects of the information treatment on the recommended practice of applying half of the overall amount of urea at the time of sowing.[27] Unlike other SHC recommendations, this practice did not necessitate changes in overall fertilizer application rates – only in its temporal distribution – and consequently is cost-neutral. Finally, we measure the effects of the information treatment on self-reported wheat yields and total fertilizer expenditures. We calculate expenditures as the sum of the price of each fertilizer multiplied by the reported application rate per hectare.[28] Ostensibly, the stated objectives of India's national Soil Health Card program were to address negative environmental externalities associated with imbalanced fertilizer application and to improve soil health over the long-term; not to increase agricultural productivity. However, at the local level, wheat yields in Bihar lag well behind the national average (Government of India 2018). Thus, the recommendations were calibrated to a yield of 4 t/ha (33% higher than the sample average in the previous season) to simultaneously encourage yield growth while improving nutrient balance and fertilizer use efficiency.

Table 5 presents estimates of treatment effects on the intensive margin of urea, DAP, and MOP fertilizer use (columns 1-3), the extensive margin of MOP use (column 4), and a binary indicator for whether farmers applied half of their urea at sowing (column 5). Farmers that received the SHCs increased urea application by 10.2 kg/ha (4.7% of mean urea use in the control group). The increase in urea is significant at the 5% level. For DAP and MOP, the more costly (less subsidized) fertilizers, the coefficients are not statistically significant at conventional levels. The coefficient on the extensive margin of MOP usage suggests a 16% increase in the probability of farmers using MOP, though the effect is marginally insignificant (p=0.12). In contrast, we find stronger evidence of an effect of the SHC on the recommended practice of applying half of the total urea amount at the time of sowing. The adoption of this practice increased by 9 percentage points, a 46% increase relative to control farmers, and the effect is statistically significant at the 5% level.

While the Lee bounds for urea usage are positive, due to the relatively small treatment effect, the 95% confidence interval for the lower bound includes a null effect.[29] Therefore, we cannot confidently conclude that SHCs lead to an increase in urea application. However, the Lee intervals are strictly positive for the likelihood of applying half of total urea at the time of sowing.

In order to benchmark the estimated impacts, at the bottom row of Table 5 we report the hypothetical impacts the SHC would have had if all treatment farmers had fully complied with the SHC recommendations. To calculate this benchmark, we replace the outcome variable for treatment farmers with the *recommended* application rate on the SHC and re-estimate equation (1). The bottom row of the table reports the coefficients estimated in these regressions. For urea, the observed effect amounts to 41% of the potential effect (10.2 kg/ha compared to a potential effect of about 25.6 kg/ha). For all other indicators, the observed effects are smaller than 10% of their potential. Thus, the impacts are modest relative to what would have been possible under full compliance with the recommendations. [30]

In column (1) of Table 6, we report the effects of the SHCs on self-reported wheat yields. We find that providing the SHC increased yields by 10.6% relative to the control mean of 18.3 quintals/ha (1.83 tons/ha), and the effect is statistically significant at the 5% level. We note that the average yields that we find in the control group were nearly identical to official yield estimates for Bihar during the 2014-15 *Rabi* season (1.85 tons/ha) (Government of India 2018), which provides some confidence about the reliability of the data. The Lee intervals are strictly positive, suggesting that the yield effect persists even after adjusting the confidence intervals for attrition. The yield impacts are similar in both absolute and relative magnitude to those reported in Corral et al. (2020) and Harou et al. (2022), with the notable distinction that the yield effects we observe are attributable only to the information treatment, rather than jointly attributable to information *and* financial support. In contrast to the contexts they study, farmers in Bihar operated under a fertilizer subsidy regime that reduced the costs of complying with recommendations and is argued to have incentivized excessive application of urea in particular (Kishore et al. 2021).

In column (2) of Table 6, we report the effects of the SHCs on fertilizer expenditures per hectare. Treatment farmers spent 197.3 less rupees/ha than farmers in the control group. Although the point estimate is negative, and suggests expenditure decreases of 3%, they are insignificant at conventional levels. Based on the 95% confidence interval, we can rule out increases in fertilizer expenditures larger than 4%.

The modest effect on total fertilizer uses leads us to attribute the impacts on yields to changes in the timing of fertilizer application. It is also possible that changes in the fertilizer mix that did not affect total expenditure could also have contributed, but we find no evidence of this when examining separate fertilizer application rates. Alternatively, the overall small effect on fertilizer application amounts could mask heterogeneity in which some farmers increased and some decreased urea application rates in line with the SHC, with all farmers benefiting.

Potential Explanations

Our results indicate a rather modest overall response to the SHC recommendations on total fertilizer use. These findings are consistent with previous evaluations of interventions that provided plot-specific soil tests and recommendations to farmers, which tend to find relatively small impacts on adoption and fertilizer usage when they are not coupled with vouchers or in-kind grants (Corral et al. 2020; Harou et al. 2022).

What could explain the limited response? One possibility is that farmers may not have understood or taken note of the recommendations. Cole and Sharma (2017), for example, show that a lack of understanding can inhibit the usefulness of SHCs in other areas in India. To examine whether farmers understood the recommendations, we asked farmers in the endline survey whether they had applied more or less urea, DAP, and MOP than the recommended amount. In Table 7, we cross-tabulate farmers' responses about over or under application with the mean difference between the actual rate of application and the recommendation in the SHC. Consistency between these two measures is indicative that farmers took sufficient note of and understood the recommendations.

In the case of urea, the mean value of the difference between actual and recommended application is positive for self-reported over-appliers, and negative for self-reported under-appliers, suggesting farmers had a good understanding of the recommendations. For DAP and MOP, the indications are less clear. Most farmers have in fact under-applied these fertilizers relative to the recommendations and most have also correctly stated under-applying, but there are significant numbers of farmers who inaccurately report applying the recommended amount. The pattern of recall may be due in part to limited attention to certain aspects on the SHC (Beg et al. 2023; Gabaix 2019; Hanna et al. 2014).

Overall, farmers seem to be both most aware of, and most responsive to, the SHC recommendations for urea in relation to DAP and MOP. This difference might be related to cost. While all three fertilizer are subsidized in India, subsidies for DAP and MOP declined in the years prior to the intervention, resulting in steep price differences between urea on the one hand, and DAP and MOP on the other hand (Kishore et al. 2021). For example, the price of DAP and MOP in 2015 was INR 1,200 and INR 800 per 50 kg bag, while the price for urea was INR 270. For DAP, applying the average recommendation (165kg/ha) would cost roughly INR 4000 compared to INR 1312 for urea. It is therefore perhaps not surprising that, when farmers received recommendations to increase their application of urea, DAP, and MOP, they may have only chosen to increase their application of the far cheaper of the three fertilizers. This might also contribute to the sizable effect on the adoption of the recommended shift in the timing of urea application, which is cost neutral. Another possible explanation in the difference in responsiveness across the three fertilizers, however, is that farmers may also overestimate the yield return to nitrogen and underestimate the return to phosphorus and potassium because their effects on yields are not observable during the growing stages (Lin 2022).

Low trust in extension agents (as we find in the baseline survey) may also have led farmers to disregard the SHC recommendations. However, trust in traditional extension agents (Krishi Vigyan Kendra) may not necessarily translate into lack of compliance with the recommendations in the SHC. Previous evidence from India suggests that farmers display high levels of willingness to trust SHCs customized for their field that are generated by the government (Cole and Sharma 2017; IDinsight 2019) and that 95% of Indians report trusting in scientists to do what is right (PEW 2020).

Table 8 summarizes farmers' self-reported primary reasons for applying more or less than the recommended levels. Cost factors (high prices or liquidity constraints) were mentioned as reasons for applying less than the recommended amount by only 12% of under-appliers in the case of urea, but by 38% in the case of DAP and 36% in the case of MOP. This is consistent with the hypothesized role of cost in determining responsiveness to the SHC. However, the results also highlight the importance of farmers' confidence in their own practices and beliefs as affecting their willingness to comply with the recommendations. This factor is highlighted by farmers applying both more or less than the recommendations. Ninety six percent of the farmers who reported having used more than the recommended amount of urea cite belief based reasons, including statements that the usual amount they use is correct (66%) or that using less will reduce yields (30%). Similarly, 72 percent of those who used less than the recommended amount of urea said they did so because they did not want to adjust their practices because of their beliefs that the usual amount they use is correct (58%), yields or returns would not increase by using more (9%), or using more would damage the crop (5%). Similar responses were observed for DAP and MOP.

In the next section, we examine more closely to what degree confidence, trust, and cost were correlated with farmers' demand for and responsiveness to the SHCs. We investigate how responsive treatment farmers were to the recommendations and indicate farmer characteristics that are correlated with how much individual farmers adjust in response to the SHC.

Responsiveness and Demand for the SHCs Among Treated Farmers

Responsiveness and its Correlates

To examine whether farmers account for the recommendations in adjusting their fertilizer usage, we follow a similar strategy to that used in recent experiments across a variety of contexts to test for Bayesian updating. Examples include belief updating about expectations about house prices (Fuster et al. 2022), salaries (Cullen and Perez-Truglia 2022), and inflation (Cavallo et al. 2017; Coibion et al. 2018).[31] Our main estimating equation for fertilizer responsiveness is as follows:

$$Endline_i - Plan_i = \alpha(SHC_i - Plan_i) + X_i\gamma + \nu_v + u_{iv} \tag{2}$$

where $Endline_i - Plan_i$ is farmer i's revision in fertilizer usage on their experimental plot, and $SHC_i - Plan_i$ is the signal gap, or the difference between the recommendation and planned fertilizer usage prior to receiving the SHC. We include village fixed effects (ν_v) and controls (X_i) that include access to credit, plot size, experience, literacy, and age. Standard errors are clustered at the village level.

Figure 7 presents binned scatter plots with a linear regression fit line of equation 2 for urea, DAP, and MOP (both including and excluding farmers that use any MOP) for all farmers in the treatment group that planted wheat during both the 2013-14 and the 2014-15 *Rabi* seasons. The y-axis measures the revision in usage (the difference between the endline and planned fertilizer application) and the x-axis measures the difference between the SHC recommendation and the plan.

The slopes of the plots represent the estimated coefficient α from Equation 2, which captures farmers' responsiveness to the signal in the SHC.[32] If farmers fully reacted to the signal provided on the SHC (placed all weight on the signal), the coefficient would be 1.[33] If farmers did not respond at all to the signal, the coefficient would be equal to zero (e.g. they received a recommendation to apply more but actually applied less than they planned). We also present scatter plots that are not binned (Figure C2 in the online supplementary appendix) and scatter plots of the residuals after removing village fixed effects (Figure C3 in the online supplementary appendix).

Panel A presents the scatter plot for urea usage, which shows a clear correlation between the direction of the recommendation and the adjustment, with an estimated slope of $\hat{\alpha} = 0.78$. Amongst farmers that received a recommendation to increase their urea application relative to the planned amount, 72% ended up increasing urea relative to their original (pre-SHC) plans. Amongst those that received a recommendation to decrease it, 79% did so. When estimating α separately for farmers that received recommendations to increase or decrease urea usage, we find a significantly stronger response to recommendations to decrease ($\hat{\alpha} = 0.89$) urea usage than to increase it ($\hat{\alpha} = 0.54$) (Table C5 in the online supplementary appendix).

Farmers were less likely to increase DAP usage, even if recommended to do so (Panel B). Amongst the 84% of farmers who received a recommendation to increase DAP, only 36% did so, while roughly the same share (34%) decreased usage or did not adjust (28%). In contrast, the majority of farmers who received a recommendation to decrease their DAP usage did so (86%). The overall slope is lower than that for Urea, with $\hat{\alpha} = 0.71$, but amongst those recommended to decrease DAP, $\hat{\alpha} = 0.92$, implying that they put 92% weight on the recommendation and 8% on their baseline plan. The linear fit suggests that for farmers to increase their DAP usage, they would have had to receive a recommendation to do so by more than 50kg/ha, on average.

Panel C presents the scatter for MOP, for which the estimated slope is lowest at $\hat{\alpha} = 0.56$. Almost all farmers were recommended to increase their MOP application rate, and most did so, but the correlation between the sizes of the recommendations and the adjustment is quite low. When we limit the sample to farmers that actually applied MOP ($N = 141$), the slope becomes higher ($\hat{\alpha} = 0.87$) and significant (Panel D). In this sub-sample, 64% increased their MOP usage relative to their planned application rate when they received a recommendation to do so, and only 12% decreased it. While some farmers decreased DAP and MOP usage when the SHCs recommended to increase them, they did so by less than farmers that were told to decrease usage.

Next, we turn to heterogeneity in responsiveness. We estimate the following regression, where β captures reversion to the signal and α is the parameter of interest:

$$\text{(3)} \qquad \mathit{Endline}_i - \mathit{Plan}_i = \gamma + \alpha(\mathit{SHC}_i - \mathit{Plan}_i) \cdot Characteristic_i + \beta(\mathit{SHC}_i - \mathit{Plan}_i) + X_i^{'}\gamma + \nu_v + u_{iv}$$

First, we investigate the role of confidence.[34] Conditional on the signal gap $\mathit{SHC}_i - \mathit{Plan}_i$, farmers that are more uncertain about their input usage or farming practices should be more responsive to the recommendations on the SHC. Similarly, farmers that are less confident in their farming abilities should be more responsive to the recommendations. To test this, we use three measures of confidence: the SD of the elicited beliefs distribution about optimal urea and DAP during the *Kharif* season, a binary indicator that is equal to 1 if farmers reported have much more doubts than their peers about input usage, and a binary indicator that is equal to 1 if farmers reported that they would have much lower yields relative to their peers if they cultivated on the same plot with equal access to inputs.[35] For ease of interpretation, all of the confidence measures are scaled so that higher values imply that farmers have lower confidence.

Table 9 reports farmers' responsiveness to the recommendations for urea. If less confident farmers respond more to the information and place more weight on the SHC recommendation, then the interaction terms should be positive ($\alpha > 0$). We indeed find that less confident farmers tend to revise their urea usage by more. In column 1, moving from the bottom quartile to the top quartile of prior belief dispersion increases the weight that farmers place on the SHC signal by 19 percentage points. In columns 2 and 3, we report similar results using interactions with survey-based measures of confidence. Under both of these survey-based measures of farmer confidence, less confident farmers appear much more responsive to the

SHC recommendations. Farmers that responded that they would get much lower yields than others given the same inputs placed 19 percentage points more weight on the recommendations, and those that report having much more doubts than their peers about input usage placed 29 percentage points more weight on the recommendations. The results broadly confirm that more confident farmers place less weight on the signal and that the effects are economically meaningful in size. Table 10 reports farmers' DAP responsiveness by measures of confidence. Similar to urea, the coefficients are sizable and in the expected direction, though they are insignificant. We also note that 30% of farmers did not change their DAP from their planned application rate while only 9% of did not change their urea usage. In Table C8 in the online supplementary appendix, we provide suggestive evidence that confidence is correlated with farmer's willingness to change their planned DAP usage in the direction of the recommendation on the extensive margin, particularly when they receive a recommendation to decrease DAP usage.

In short, when presented with new soil quality information and recommendations, farmers revise their input usage towards the recommendations they receive and do so more when they are less confident. This is true using both elicited measures of prior uncertainty as well as survey based measures of confidence. This adjustment is primarily evident for urea, which may reflect a higher willingness to experiment with urea due to its lower costs, and potentially the availability of DAP in the local market.

In Tables C6 and C7 in the online supplementary appendix, we investigate heterogeneity in responsiveness by farmer and plot characteristics. Wealthier and male farmers place less weight on their priors and more weight on the recommendations, which suggests that liquidity constraints may affect farmers' ability to respond to the information. For DAP, we also find that farmers that own their plots (77%) are substantially less responsive to the recommendations. In contrast, trust in extension agents or our measure of credit access do not have a systematic relationship with response to the SHCs. We note that only 5.5% of farmers attempted to access credit in previous seasons. In addition to information, there may be a number of factors that cause farmers to deviate from their planned input usage including weather shocks, pests, and credit constraints. For example, recent research suggests that farmers may adjust planting times (Cui and Xie 2022; Jagnani et al. 2021), as well as area planted and crop mix (Aragón et al. 2021) throughout the season in response to unanticipated heat or rainfall.

Demand for the SHC

Figure 8 displays the distribution of the stated WTP for the SHC, asked to farmers during the baseline survey. Overall, WTP was quite low. Thirty percent of farmers answered that they were not willing to pay any money for SHCs. Further, 72% of farmers stated a WTP which was below the approximately $2 charged by public facilities to perform soil health tests (prior to the introduction of the SHC program) which was the price of soil testing using the available public service at the time of the intervention. The model presented in the online supplementary appendix predicts that farmers with greater confidence should display lower demand for the SHC recommendations.

Table 11 reports regressions of the inverse hyperbolic sine transformation of stated WTP on confidence, trust, and literacy.[36] In Columns 1 and 2, confidence is measured through the SD of the farmers' belief distribution regarding optimal urea application (SD urea). In Columns 3 and 4, confidence is measured through the corresponding measure for DAP (SD DAP). Columns 2 and 4 control for additional farmer characteristics, including wealth, and farming ability. The results indicate that higher levels of dispersion in beliefs on the optimal level of urea or DAP (indicative of lower levels of confidence in subjective beliefs) are both associated with increased WTP for the SHC. Moving from the bottom quartile (most confident) to the top quartile (least confident) of urea beliefs dispersion is associated with an increase of \$0.96 in WTP, or roughly 58% of the mean WTP. Similarly, moving from the bottom quartile to the top quartile of DAP beliefs dispersion is associated with an increase of \$0.54 in WTP. We find similar results in Table 12 using survey-based measures of confidence.[37] Across both of these survey-based measures of confidence, results suggest that greater confidence is associated with a lower WTP for fertilizer recommendations. Farmers that responded that they would get much higher yields than others given the same inputs have a WTP that is 35% lower than the mean WTP, and those that report having much less doubts than their peers about input usage have a WTP that is 34% lower than the mean WTP. Further, both literacy and trust are positively correlated with WTP and correspond to increases in WTP by 11% and 26%, respectively.

Overall, these results lend support to the predictions of the theoretical model. They indicate substantial levels of heterogeneity in farmers' interest in the information provided by the SHC that is correlated with baseline confidence. While the predictions on demand for information follow from a standard model of belief updating, recent empirical evidence on information demand finds that agents may also vary in their taste for information, in which case farmers with higher belief precision could potentially demand information regardless of whether they plan to use it (Fuster et al. 2022). We do not find evidence that this is the case in our context. One important caveat in interpreting the results is that we cannot rule out that experimenter demand effects could have influenced self-reported hypothetical WTP and fertilizer usage (De Quidt et al. 2018).

Conclusion

In this paper, we present the results from a randomized controlled trial in three districts of Bihar, India, that provided Soil Health Cards (SHCs) to farmers based on individualized soil tests in order to promote balanced use of fertilizers. The intervention closely mirrored the operational approach of a large scale government soil testing program in India that intended to provide more than 145 million SHCs to all farmers in India. We estimate modestly sized effects of SHCs on urea use, but negligible effects on use of DAP and MOP, and with our most conservative specification, we are not able to reject the null hypothesis of zero change in total amount of any of the fertilizers we examine. Although we find compelling evidence that farmers altered the timing of their urea application to increase fertilizer use efficiency, and that wheat yields increased by more than 10% among treatment farmers, heterogeneity analysis with treatment farmers suggests that the intervention may have led to further nutrient imbalances. The yield effects are similar in magnitude to those found in Mexico (Corral et al. 2020) and Tanzania (Harou et al. 2022), when plot specific recommendations are combined with vouchers to increase adoption. Together, the findings suggest that simply providing information is an insufficient policy intervention to adequately move the needle toward socially optimal farm management, if farmers face a subsidy regime that encourages nutrient imbalances. An obvious policy implication of our work is that information treatments that target multiple inputs may need to be coupled with other policy instruments to overcome additional barriers to the adoption of economically and socially beneficial agricultural practices, such the judicious and balanced application of chemical fertilizers.

We further document significant heterogeneity in beliefs about optimal fertilizer application levels prior to receiving the SHC information. We show that confidence is associated with lower demand for SHCs and lower responsiveness to the recommendations provided on the SHCs: less confident farmers were more likely to adjust their input use in the direction of the recommendations. These findings are robust for urea application, which is highly subsidized and unlikely to be affected by other constraints including cost or availability. Our results highlight the potential role of confidence in who is most likely to respond to expert information, with implications for targeted interventions such as India's SHC scheme as well as information provision more generally. While a large body of literature has shown that information experiments can be effective, including in the context of developing country agriculture (Fabregas et al. 2019; Haaland et al. 2022), our findings suggest that identifying and targeting low confidence and high marginal value of information respondents – including using survey based confidence measures – may produce the largest returns to the program's investment, especially if there are cost constraints to providing information.

Notes

[1] There is a large literature that studies the impacts of information provision on health behavior and outcomes (Bennett et al. 2018; Dupas 2011; Guiteras et al. 2016), job search (Abebe et al. 2021; Belot et al. 2019), education investments (Dizon-Ross 2019; Jensen 2010), and increasingly in public policy (Banuri et al. 2019; Hjort et al. 2021; Vivalt and Coville 2023) under the assumption that lack of information about costs and benefits is a binding constraint on optimal investments and behaviors.

[2] Numerous constraints affect learning and technology adoption including liquidity and credit constraints, low input quality, risk, and various behavioral biases. See Magruder (2018) and Jack (2013) for excellent overviews of the literature on barriers to technology diffusion in developing countries.

[3] For example, in a highly heterogeneous environment typical of smallholder farming, generic or insufficiently targeted recommendations may be of little value (Suri 2011). Furthermore, extension agents, who are typically charged with delivering information to farmers, are often overtaxed, poorly trained, and poorly incentivized (Anderson and Feder 2007). Secondary sources of information (e.g., so-called "lead farmers") may not be incentivized to diffuse information through social networks or may be sub-optimally placed within them to reach most farmers (Beaman et al. 2021; BenYishay and Mobarak 2018).

[4] For example, Hanna et al. (2014) points to the difficulty of noticing crucial dimensions of productivity as an impediment to learning from experience or from others. Barham et al. (2018) show that receptiveness to advice sped up adoption of GM maize among farmers in the U.S with low cognitive ability, but slowed adoption among farmers with high cognitive ability.

[5] See Moore and Healy (2008) for further discussion of how confidence has been measured in both the psychology and economics literature. Our measure is closest to the concept of "overprecision," or the excessive certainty regarding the accuracy of one's beliefs. Recent overviews of the literature include (Benjamin 2019; Moore and Dev 2020; Moore and Schatz 2017)

[6] The farmers in our sample were not asked to pay for the soil tests and recommendations. During the baseline survey, we asked farmers""What are you willing to pay for soil testing?" Farmers did not see an example of the SHC, however, farmers in Bihar were aware of soil health cards at the time of our study.

[7] See Fabregas et al. (2019) and Spielman et al. (2021) for recent overviews of information provision and digital extension in developing countries.

[8] Vivalt and Coville (2023) find evidence for both biases amongst policymakers and practitioners. Further, they consider the overweighting of positive impact evaluation results compared to negative results as a form of overconfidence

[9] Previously cited literature connects prior uncertainty to belief updating, though no studies to our knowl-

edge move beyond the direct effects on beliefs to real-world investment choices.

[10]See Delavande (2023) for a recent overview of subjective expectations in agriculture.

[11]65% of farmers cultivated more than one plot at the time of the baseline.

[12]The national program collected samples in 2.5 hectare grids in irrigated areas and 10 hectare grids in rain fed areas.

[13]For control farmers, we randomly selected their comparison plot from their two primary plots and collected data in the midline and endline for the selected plot as well as their second primary plot when relevant.

[14]Survey data at the time of the SHC distribution shows that only 6% of farmers had purchased any inputs for the upcoming season.

[15]Original power calculations preceded endline data analysis. We assumed a test size of 5 percent and 80 percent power. We set sample sizes of 48 villages across 16 blocks, with 18 households per village, consistent with the research design for the original study population. We used ICCs of 0.25, 0.15, and 0.02, corresponding to the observed baseline ICCs for urea, DAP, and MOP use, respectively. Under these assumptions and ICCs, the sample size was sufficient to detect effects of 0.5, 0.4, and 0.25 standard deviations for urea, DAP, and MOP, respectively. These effect sizes are arguably conservative, as they do not account for stratification, which may increase precision.

[16]Many belief elicitation studies provide incentives to participants to encourage truthful responses regarding their beliefs. The use of incentives in these experiments requires an objective measure in which to benchmark the reported beliefs, which would reduce heterogeneity in the way the elicitation question is interpreted. In our context, we are constrained by the non-verifiability of the true optimal application rate, and therefore there is no objective benchmark against which to compare individuals' subjective beliefs and consequently we are unable to elicit beliefs with incentives. Nevertheless, there is currently no systematic evidence that incentives reduce measurement error or improve truthful reporting of beliefs in non-political domains (Haaland et al. 2022). Using a method similar to ours, Delavande et al. (2011) suggest that answers to hypothetical beliefs elicitation experiments such as this are reasonable, and therefore do not require incentives. Recent experimental evidence finds some evidence for hypothetical bias due to risk aversion using non-incentivized beliefs-elicitation methods (Harrison 2016), and we discuss the implications of hypothetical bias and risk aversion in our results.

[17]Prior to initiating the elicitation, enumerators gave farmers a brief introduction to the fundamentals of probability to help them conceptualize the subsequent experiment. Farmers then evaluated a series of five practice questions that tested their comprehension of subjective probabilities and their ability to allocate 20 beans to represent these probabilities.

[18] Local farmers are accustomed to using *katha* rather than hectares in discussing fertilizer amounts. A

katha is a local unit of land area, of which there are about 80 katha per hectare.

[19]Delavande et al. (2011) conduct experiments to test the sensitivity of subjective distributions to a variety of elicitation methods and find that results are generally robust across bin count, predetermined versus self-anchored support, and the number of beans to be allocated. However, accuracy increases by including more bins and beans without a marked increase in the cognitive burden on respondents.

[20]This measure is related to the concept of overplacement, which is a form of overconfidence (Moore and Healy 2008). When performing a task, researchers can measure overplacement by asking respondents to estimate their performance relative to others performing a task. The difference between their subjective estimation and actual performance provides a measure of overplacement. Our measure is intended to capture farmers' confidence in their farming ability, though we do not have a benchmark with which to compare their evaluations relative to actual performance.

[21]For example, respondents may be asked how confident they are about their answers on a series of questions (ranging from not at all to extremely) (Giglio et al. 2021), or to judge their confidence about a particular belief using a scale from 1 to 5 (Armona et al. 2019) or from very unsure to very sure (Roth and Wohlfart 2020).

[22]Note that we do not suggest that the *expectation* of the optimal fertilizer application rate for the rice crop would be a reasonable proxy for the *expectation* for wheat crop. Consequently, we are not suggesting that the *location* of the distributions would be roughly the same – only that the distributions should be roughly the same *shape*.

[23]Subsidies for these two fertilizers have been scaled back in recent years

[24]The measure of trust is a binary question: *I will not trust new information from extension agents until there is clear evidence that it is effective* vs *I will trust new information from extension agents until I have clear evidence that it is not effective.*

[25]To test joint balance, we implement a conventional asymptotic test, and regress the treatment indicator on all the variables included in Table 3 and strata dummies, and with standard errors adjusted for the clustering at the village level, reflecting the clustered nature of our sampling design.

[26]We did not detect differential rates of wheat planting by treatment and therefore restrict the estimation to wheat farmers. Of the 743 farmers interviewed at endline, roughly 84% planted wheat (column 3 in Table 4.)

[27]The SHC instructed farmers to apply half of the recommended urea at the time of sowing and the other half split evenly and applied at the time of the first irrigation (approximately 20-25 days after sowing) and at the time of tillering (concurrent with the second irrigation).

[28]Prices for each fertilizer were obtained from the baseline survey.

[29]The confidence intervals extend from the lower end of the 95% confidence interval of the lower Lee bound to the upper end of the 95% confidence interval of the upper Lee bound.

[30]One possibility for the low impact on overall urea usage is that recommendations for this fertilizer were less uniform in suggesting increases, so that the overall impact may mix positive (negative) effects for those who were recommended to increase (decrease) it. We cannot directly test this possibility, since we did not conduct soil tests for the control group. Naive (and potentially biased) re-estimations of the treatment effect that limits the treated sample to farmers who were recommended to increase urea usage, or to those whose recommended amount was above median, derives a treatment effect which is only slightly larger than the overall treatment effect, cautiously suggesting other factors were responsible for the muted overall impact.

[31]To test for the degree of updating in response to new information, subjects' posteriors can be represented by the convex combination $Posterior_i = \alpha * Signal_i + (1-\alpha) * Prior_i$, where α is the weight on the signal and $(1-\alpha)$ is the weight on the prior. In our context, the signal is represented by the information in the SHC, the posterior by the endline fertilizer application, and the prior by the pre-season planned usage. Rearranging this combination yields the primary estimating equation.

[32]In general, the α parameter is estimated by interacting $(SHC_i - Plan_i)$ with a treatment indicator while controlling for $(SHC_i - Plan_i)$ to account for spurious reasons that subjects may revise their usage in the direction of the signal regardless of whether they were shown the information. In previous studies on belief updating, the magnitude of the estimated spurious revision tends to be less than 0.10 percentage points (Cavallo et al. 2017; Cullen and Perez-Truglia 2022; Fuster et al. 2022).

[33]For example, if a farmer planned to use 200 kg/ha, but actually applied 300 kg/ha after receiving a recommendation to apply 300 kg/ha, the slope would be 1.

[34]The model developed in the online supplementary appendix (equation 11) shows that the weight that a farmer places on the signal (α) will be decreasing in their confidence, or increasing in the dispersion of their priors ($\sigma^2_{\theta_1}$).

[35]We only conduct this exercise for urea and DAP as we did not collect beliefs for MOP.

[36]We perform the inverse hyperbolic sine transformation to reduce the influence of the rightward skew. We report the same regressions using levels of WTP in Table C9 in the online supplementary appendix.

[37]We report the same regressions using levels of WTP in Table C10 in the online supplementary appendix.

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Table 1: Correlations Across Measures of Farmer Confidence

	(1) SD Urea	(2) SD Urea	(3) SD Urea	(4) SD Urea	(5) SD DAP	(6) SD DAP	(7) SD DAP
Less yields	0.075***					0.048**	
	(0.023)					(0.018)	
More doubts		0.039**					0.059***
		(0.017)					(0.0100)
CV Urea			2.70***				
			(0.095)				
SD DAP				0.49***			
				(0.065)			
CV DAP					0.88***		
					(0.036)		
Constant	0.57***	0.58***	-0.36***	0.43***	-0.20***	0.36***	0.35***
	(0.055)	(0.053)	(0.033)	(0.059)	(0.028)	(0.032)	(0.031)
Observations	853	849	862	853	853	844	841
R^2	0.336	0.322	0.917	0.408	0.772	0.357	0.373
Mean dep. var	0.42	0.41	0.42	0.42	0.34	0.34	0.34

* Significant at 10 percent level; ** Significant at 5 percent level; *** Significant at 1 percent level.
Notes: Dependent variables include the standard deviations of farmers' beliefs over urea application rates (columns 1-3) and the standard deviations of farmers' beliefs over DAP application rates (columns 4-5). *Less confident* (*yields*) is a binary indicator equal to 1 if farmers in the baseline survey did not respond that they would get much higher yields than their peers given the same soil quality and access to resources. *Less confident* (*doubts*) is a binary indicator equal to 1 if farmers in the baseline survey did not respond that they have much fewer doubts than their peers about farmings practices. *CV* is the coefficient of variation of farmers' beliefs. Controls include the mean of the farmer's distributions of subjective beliefs and village fixed effects. Standard errors (adjusted for clustering at the village level) in parentheses.

Table 2: Planned Fertilizer Application for the 2014-15 *Rabi* Season vs. Recommended Fertilizer Application from SHC (Based on 4 t/ha Target Yield)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Planned					Recommendation					Rec> Plan
Fertilizer (kg/ha)	Y/N	Mean	SD	Min	Max	Y/N	Mean	SD	Min	Max	Share
Urea	0.97	205.8	83.5	39.5	553.3	1.00	244.6	27.1	127.3	316.8	0.71
DAP	0.97	115.0	33.9	39.5	217.4	1.00	164.8	35.2	99.7	240.0	0.85
MOP	0.37	36.3	18.8	19.8	158.1	1.00	81.6	20.2	34.1	122.5	0.98
N	376					389					

Notes: Columns 1-5 report a binary indicator for whether farmers in treatment villages planned to use the indicated fertilizer in the 2014-15 *Rabi* wheat season, along with the mean, standard deviation, minimum, and maximum of the planned application rates prior to receiving the soil health card. The values in columns 2-5 are reported for farmers than plan to use a positive amount of the indicated fertilizer. Columns 6-10 report a binary indicator for whether farmers in treatment villages were recommended to use the indicated fertilizer in the 2014-15 *Rabi* wheat season, along with the mean, standard deviation, minimum, and maximum of the recommended application rates prior to receiving the SHC. Column 11 reports the share of farmers that were recommended to apply more of the fertilizer than they had planned to apply. The sample includes only those farmers that had their soil tests successfully processed and delivered. All values reported in kilograms per hectare (kg/ha).

Table 3: Summary Statistics and Statistical Balance Across Experimental Arms (Baseline)

Variable	(1) Control Mean/(SE)	(2) Treatment Mean/(SE)	(3) No Test Mean/(SE)	(1)-(2) Pairwise t-test P-value	(1)-(3) Pairwise t-test P-value	(2)-(3) Pairwise t-test P-value
Age	46	45	45	.19	.52	.62
	(.88)	(.73)	(1.7)			
Female	.052	.085	.13	.039**	.049**	.22
	(.013)	(.014)	(.043)			
Literate	.65	.69	.58	.44	.64	.17
	(.049)	(.029)	(.044)			
Trust	.31	.31	.29	.87	.86	.9
	(.03)	(.022)	(.061)			
Clay	.74	.76	.8	.62	.79	.59
	(.039)	(.035)	(.079)			
Slope (flat)	.91	.92	.95	.81	.53	.34
	(.021)	(.021)	(.025)			
WTP	1.6	1.6	1.8	.99	.53	.97
	(.25)	(.17)	(.36)			
Mean urea beliefs (kg/ha)	208	207	203	.94	.34	.29
	(15)	(8.4)	(12)			
Mean DAP beliefs (kg/ha)	103	103	91	.89	.26	.31
	(6)	(4.3)	(7.4)			
2013 *Kharif* apply urea	.98	.96	.95	.19	.17	.86
	(.012)	(.009)	(.03)			
2013 *Kharif* apply DAP	.97	.96	.94	.3	.42	.98
	(.018)	(.011)	(.029)			
2013 *Kharif* urea (kg/ha)	215	210	219	.6	.68	1
	(17)	(12)	(15)			
2013 *Kharif* DAP (kg/ha)	104	108	99	.26	.65	.2
	(4.9)	(4.1)	(6.9)			
F-test of joint significance (F-stat)				1.5	.97	1.6
Number of observations	288	497	79	785	367	576
Number of clusters	16	31	21	47	37	32

* Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level.
Notes: Column 1 reports average self-reported measures of age, gender, literacy, trust, soil type, elicited beliefs, average fertilizer use collected during the baseline survey for farmers in the control group. All plot level characteristics are for the experimental plot only. Standard errors are reported in parentheses. Columns 2 and 3 are analogous to column 1 but include the treatment sample that had their soil tested (column 2) and those for which the soil test was contaminated or could not be processed (column 3). Fertilizer application rates are reported in kilograms per hectare. The p-values in columns 4-6 are for tests of the null hypothesis that mean values across the indicated treatment arms are equal. Standard errors for the differences are adjusted for the clustered nature of treatment assignment (at the village) level. Balance tests include block fixed effects to account for randomization stratified at the block level. The p-value for the asymptotic F-test of the null hypothesis that observations are jointly orthogonal across groups is estimated using OLS, with treatment assignment as the dependent variable, all baseline covariates as independent variables, block fixed effects, and standard errors adjusted for the clustered nature of treatment assignment.

Table 4: Sample Attrition and Wheat Production.

	(1) Attrition	(2) Attrition	(3) Plant wheat
Treatment	-0.14***	-0.0088	-0.015
	[-0.21,-0.059]	[-0.048,0.030]	[-0.075,0.044]
Observations	864	785	735
Adjusted R^2	0.106	0.034	0.029
Mean dep. var	0.85	0.94	0.84
Sample	BL	BL (no-test excl.)	EL

* Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level.

Notes: This table reports results on attrition in different samples of our study. For all columns, we run the following regression: $Y_{ivb} = \beta_0 + \beta_1 SHC_i + \alpha_b + \epsilon_{ivb}$, for farmer i, in village v in block b. In columns 1 and 2, Y_{ivb} is a binary indicator that indicates if the farmer is surveyed in the endline survey. In column 3, Y_{ivb} is a binary indicator that indicates if the farmer planted wheat in the 2015 $Rabi$ season. We include strata fixed effects and cluster standard errors at the village level. At the bottom of the table, we report the mean of the outcome for the sample under consideration. In Column 1, we use the full sample of 864 farmers who participated in the baseline survey. In Column 2, we limit the sample to all control farmers and treatment farmers that received soil tests (we exclude treatment farmers for which we did not collect data in the endline due to contaminated soil tests). In column 3, we limit the sample to the 735 farmers that were interviewed in the endline. Standard errors in parentheses.

Table 5: Effects of SHC on Fertilizer Application Rates, and Practice Adoption in *Rabi* 2015

	(1)	(2)	(3)	(4)	(5)
	Urea	DAP	MOP	MOP=1	Urea sowing=.5
SHC	10.2**	-6.45	2.02	0.073	0.092**
	[0.60,19.9]	[-16.6,3.69]	[-1.27,5.30]	[-0.020,0.17]	[0.0040,0.18]
Observations	621	621	621	621	621
Adjusted R^2	0.357	0.216	0.498	0.575	0.066
Mean dep. var.	217.3	115.9	17.6	0.46	0.20
Lee Bounds (95 CI)	[-5.42,31.40]	[-15.91,3.72]	[-5.60,3.92]	[-0.09,0.10]	[0.03,0.20]
Benchmark	25.64	39.19	64.61	0.65	0.87

* Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level.
Notes: The dependent variable in columns 1-3 are endline fertilizer application rates (kg/ha). In column 4, the dependent variable is a binary indicator that takes a value of 1 if the farmer applied any MOP during the season and 0 otherwise. In column 5, the dependent variable is a binary indicator that takes a value of 1 if the farmer applied half of the total amount of urea during sowing and 0 otherwise. All regressions include the dependent variable at baseline, and enumerator and block (strata) fixed effects. We report 95% confidence intervals using standard errors adjusted for clustering at the village level in brackets. At the bottom of the table, we report the mean of the outcome for the control group and report the 95% confidence intervals of the Lee bounds for the independent variable to take into account potential selection into the sample, compared to the original study sample of 864 farmers. The reported benchmark values are the coefficients from the treatment effects estimation (Equation (1)), in which the outcome variable for treatment farmers is replaced with the recommendations provided on the SHC. Outcomes and baseline values are winsorized at the 95th percentile where applicable.

Table 6: Effects of SHC on Yields and Costs in *Rabi* 2015

	(1) Yield	(2) Cost
SHC	1.94**	-197.3
	[0.044,3.84]	[-623.7,229.0]
Observations	621	621
Adjusted R^2	0.269	0.201
Mean dep. var.	18.3	5810.2
Lee Bounds (95 CI)	[0.68,4.49]	[-604.84,242.63]

* Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level.
Notes: The dependent variable in column 1 is wheat yields on the experimental plot in quintals per hectare. In column 2, the dependent variable is the sum of per hectare total expenditures on the urea, DAP, and MOP. All regressions include the dependent variable at baseline, and enumerator and block (strata) fixed effects. We report 95% confidence intervals using standard errors adjusted for clustering at the village level in brackets. At the bottom of the table, we report the mean of the outcome for the control group and report the 95% confidence intervals of the Lee bounds for the independent variable to take into account potential selection into the sample, compared to the original study sample of 864 farmers. Outcomes and baseline values are winsorized at the 95th percentile.

Table 7: Actual vs. Recommended Fertilizer Application by Farmers who Self-Reported Over- or Under-Application

	(1)	(2)	(3)	(4)	(5)	(6)
	Actual minus Recommended (KG/Ha)					
	Urea		DAP		MOP	
Self-Reported to Apply:	Diff.	N	Diff.	N	Diff.	N
More than recommended	19.60	118	-3.42	42	-52.25	12
Less than recommended	-67.44	85	-63.12	135	-69.15	230
Recommended amount	-21.44	93	-45.40	119	-45.34	54
No SHC for reference	-36.61	93	-63.41	93	-65.98	93
Full sample	-22.67	389	-51.32	389	-64.56	389

Notes: Difference between endline fertilizer use and the recommended application, disaggregated by farmers' self-reported quantities of fertilizer applied relative to the amount on the SHC. *No SHC for reference* includes farmers that reported that they no longer had the SHC or did not consult the SHC during the endline survey. The sample includes only those farmers from treatment villages that had their soil tests successfully processed and delivered. All values reported in kilograms per hectare (kg/ha). *Actual* denotes fertilizer application rates during the 2014-15 *Rabi* season. *Recommended* denotes the derived fertilizer application rate recommendation from soil tests based on a target yield of 4 t/ha. The self-reported evaluations of how much they applied relative to the recommendations on the SHC were elicited during the endline survey.

Table 8: Self-Reported Rationales for Over- and Under-applying Fertilizers Relative to Recommended Application

	(1)	(2)	(3)	(4)	(5)	(6)
	Urea		DAP		MOP	
	Freq.	Percent	Freq.	Percent	Freq.	Percent
Why used more than recommended?						
Fertilizer cost is low	5	4	0	0	0	0
Using less will reduce yields	42	32	25	54	6	55
Believe usual amount is the right amount	86	65	21	46	5	45
Why used less than recommended?						
Fertilizer cost is high	7	6	61	35	84	31
Does not have enough money	8	7	7	4	9	3
Yields would not increase by using more	7	6	4	2	10	4
Returns would not increase by using more	4	3	6	3	5	2
Using more would damage the crop	6	5	7	4	9	3
Believe usual amount is the right amount	71	61	84	49	141	51
Fertilizer is not available	5	4	1	1	8	3
Other	8	7	3	2	9	3

Notes: This table reports the reasons that farmers stated in the endline survey why they used more or less than the indicated fertilizers in the 2014-15 *Rabi* wheat season. Farmers were asked how much fertilizer they used in comparison with the recommendations (more than, less than, or recommended amount). Farmers who reported having applied more or less of the recommended amount were then asked why they did so. Both the frequency and the share are reported for each indicated fertilizer. DAP = diammonium phosphate.

Table 9: Urea Responsiveness: Weight Placed on Signal by Confidence Level

	(1) (EL-Plan)	(2) (EL-Plan)	(3) (EL-Plan)	(4) (EL-Plan)	(5) (EL-Plan)	(6) (EL-Plan)
(SHC - Plan)	0.50***	0.49***	0.63***	0.63***	0.74***	0.72***
	(0.15)	(0.15)	(0.11)	(0.12)	(0.090)	(0.094)
SD Urea × (SHC - Plan)	0.71**	0.71**				
	(0.29)	(0.30)				
Less confident (yields)=1 × (SHC - Plan)			0.21***	0.19**		
			(0.072)	(0.071)		
Less confident (doubts)=1 × (SHC - Plan)					0.28**	0.29**
					(0.11)	(0.12)
Observations	388	387	388	387	388	387
R^2	0.483	0.499	0.480	0.495	0.483	0.500
Mean dep. var.	23.0	23.1	23.0	23.1	23.0	23.1
Mean dispersion	0.40	0.40	0.74	0.74	0.16	0.16
SD dispersion	0.19	0.19	0.44	0.44	0.36	0.36
Controls	No	Yes	No	Yes	No	Yes

* Significant at 10 percent level; ** Significant at 5 percent level; *** Significant at 1 percent level.
Notes: Dependent variable is the adjustment in farmers' urea application rate, measured as endline urea application rates (EL) minus planned application rates (Plan). The primary explanatory variable is the difference between the received signal (SHC) and farmers' planned application rates (Plan), with and without interactions with three measures of confidence: the standard deviation of the distribution of subjective beliefs about optimal urea application (*SD Urea*), a binary indicator equal to 1 if farmers in the baseline survey did not respond that they would get much higher yields than their peers given the same soil quality and access to resources (*Less confident* (*yields*)), and a binary indicator equal to 1 if farmers in the baseline survey did not respond that they have much fewer doubts than their peers about farmings practices (*Less confident* (*doubts*)). *SHC* is the recommended application rate of urea shown on the SHC (kg/ha). *Plan* is the planned fertilizer application rate for the 2015 Rabi season, which was elicited prior to receiving the SHC (kg/ha). All regressions control for the mean of farmers' belief distribution. Where indicated, the regressions control for farmer characteristics (age, literacy, trust, experience), wealth characteristics (credit access, IHS of house value, if the farmer owns a cow) and plot characteristics (if the farmer owns the plot, slope, and if the soil is clay). Standard errors (adjusted for clustering at the village level) in parentheses. Fertilizer application rates are winsorized at the 95th percentile.

Table 10: DAP Responsiveness: Weight Placed on Signal by Confidence Level

	(1) (EL-Plan)	(2) (EL-Plan)	(3) (EL-Plan)	(4) (EL-Plan)	(5) (EL-Plan)	(6) (EL-Plan)
(SHC - Plan)	0.56***	0.56***	0.60***	0.59***	0.69***	0.68***
	(0.14)	(0.14)	(0.13)	(0.14)	(0.093)	(0.097)
SD DAP × (SHC - Plan)	0.43	0.43				
	(0.37)	(0.37)				
Less confident (yields)=1 × (SHC - Plan)			0.15	0.16		
			(0.13)	(0.13)		
Less confident (doubts)=1 × (SHC - Plan)					0.13	0.16
					(0.11)	(0.11)
Observations	383	383	388	387	388	387
R^2	0.495	0.495	0.487	0.495	0.487	0.496
Mean dep. var.	1.61	1.61	1.51	1.58	1.51	1.58
Mean interaction	0.33	0.33	0.74	0.74	0.16	0.16
SD dispersion	0.14	0.14	0.44	0.44	0.36	0.36
Controls	No	Yes	No	Yes	No	Yes

* Significant at 10 percent level; ** Significant at 5 percent level; *** Significant at 1 percent level.
Notes: Dependent variable is the adjustment in farmers' DAP application rate, measured as endline DAP application rates (EL) minus planned application rates (Plan). The primary explanatory variable is the difference between the received signal (SHC) and farmers' planned application rates (Plan), with and without interactions with three measures of confidence: the standard deviation of the distribution of subjective beliefs about optimal DAP application (*SD DAP*), a binary indicator equal to 1 if farmers in the baseline survey did not respond that they would get much higher yields than their peers given the same soil quality and access to resources (*Less confident (yields)*), and a binary indicator equal to 1 if farmers in the baseline survey did not respond that they have much fewer doubts than their peers about farmings practices (*Less confident (doubts)*). *SHC* is the recommended application rate of DAP shown on the SHC (kg/ha). *Plan* is the planned fertilizer application rate for the 2015 Rabi season, which was elicited prior to receiving the SHC (kg/ha). All regressions control for the mean of farmers' belief distribution. Where indicated, the regressions control for farmer characteristics (age, literacy, trust, experience), wealth characteristics (credit access, IHS of house value, if the farmer owns a cow) and plot characteristics (if the farmer owns the plot, slope, and if the soil is clay). Standard errors (adjusted for clustering at the village level) in parentheses. Fertilizer application rates are winsorized at the 95th percentile.

Table 11: Effects of Confidence on Willingness to Pay for SHCs

	(1) WTP	(2) WTP	(3) WTP	(4) WTP	(5) WTP	(6) WTP
SD Urea	0.51***	0.45**	0.82***	0.78***		
	(0.19)	(0.19)	(0.20)	(0.20)		
SD DAP	0.88***	0.94***			1.16***	1.18***
	(0.25)	(0.24)			(0.23)	(0.23)
Trust	0.11*	0.10*	0.11*	0.11*	0.13**	0.12**
	(0.058)	(0.058)	(0.061)	(0.062)	(0.059)	(0.059)
Literate	0.26***	0.22***	0.25***	0.21***	0.26***	0.21***
	(0.059)	(0.061)	(0.057)	(0.059)	(0.062)	(0.063)
Constant	0.83***	0.86***	1.02***	1.03***	1.00***	1.03***
	(0.22)	(0.22)	(0.19)	(0.20)	(0.17)	(0.19)
Controls	No	Yes	No	Yes	No	Yes
Observations	853	853	862	862	853	853
Adjusted R^2	0.381	0.395	0.372	0.384	0.374	0.389
Mean dep. var	1.01	1.01	1.01	1.01	1.01	1.01

* Significant at 10 percent level; ** Significant at 5 percent level; *** Significant at 1 percent level.
Note: Dependent variable is the inverse hyperbolic sine of the stated willingness to pay for soil testing and recommendations ($US). The sample includes all farmers that were present in the baseline survey. The *SD Urea* and *SD DAP* terms reflect the standard deviations of the distributions of subjective beliefs over optimal fertilizer application rates, and are measures of farmers' confidence. *Trust* is a binary indicator equal to 1 if farmers' reported that they trust information from extension agents. *Literate* is a binary indicator equal to 1 if farmers' are able to read. Standard errors (adjusted for clustering at the village level) in parentheses. All regressions contain village fixed effects and controls for age and gender and the mean of farmers' beliefs distributions. Additional control variables in columns 2, 4, and 6 include ability, household size, house value, whether the household owned the experimental plot, and whether the household had access to credit during *Rabi* 2013.

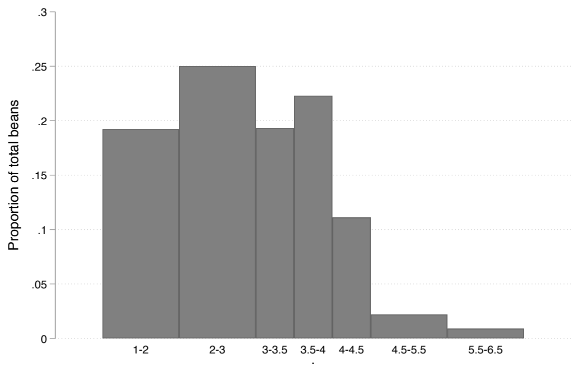
Table 12: Effects of Confidence on Willingness to Pay for SHCs

	(1) WTP	(2) WTP	(3) WTP	(4) WTP
Less confident (yields)	0.35***	0.34***		
	(0.048)	(0.047)		
Less confident (doubts)			0.38***	0.36***
			(0.066)	(0.065)
Trust	0.095	0.087	0.20***	0.19***
	(0.061)	(0.063)	(0.061)	(0.063)
Literate	0.24***	0.20***	0.23***	0.19***
	(0.062)	(0.063)	(0.061)	(0.062)
Constant	1.12***	1.15***	1.22***	1.25***
	(0.077)	(0.10)	(0.068)	(0.11)
Controls	No	Yes	No	Yes
Observations	863	863	863	863
Adjusted R^2	0.375	0.388	0.367	0.380
Mean dep. var	1.00	1.00	1.00	1.00

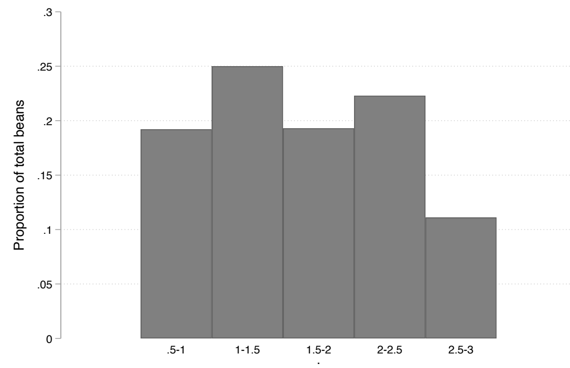
* Significant at 10 percent level; ** Significant at 5 percent level; *** Significant at 1 percent level.
Note: Dependent variable is the inverse hyperbolic sine of the stated willingness to pay for soil testing and recommendations ($US). The measures of confidence include a binary indicator equal to 1 if farmers in the baseline survey did not respond that they would get much higher yields than their peers given the same soil quality and access to resources (*Less confident* (*yields*)), and a binary indicator equal to 1 if farmers in the baseline survey did not respond that they have much fewer doubts than their peers about farmings practices (*Less confident* (*doubts*)). *Trust* is a binary indicator equal to 1 if farmers' reported that they trust information from extension agents. *Literate* is a binary indicator equal to 1 if farmers' are able to read. The sample includes all farmers that were present at the time of the the baseline survey. Standard errors (adjusted for clustering at the village level) in parentheses. All regressions contain village fixed effects, literacy, a measure of trust, and controls for age and gender. Additional control variables in columns 2 and 4 include household size, house value, whether the household owned the experimental plot, and whether the household had access to credit during *Rabi* 2013.

	2014									2015						
Activity	Apr.	May	Jun.	Jul.	Aug.	Sep.	Oct.	Nov.	Dec.	Jan.	Feb.	Mar.	Apr.	May	Jun.	Jul.
Kharif/Rabi Season			Kharif season							Rabi Season						
Soil sampling																
Baseline survey /Beliefs elicitation																
Midline survey																
SHC distribution																
Endline survey																

Figure 1: Timeline of Data Collection



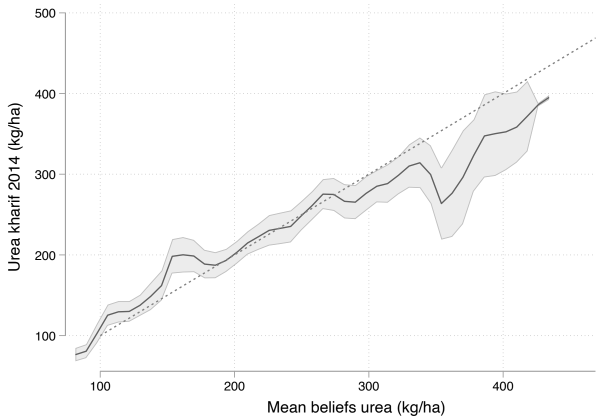
(a) Urea



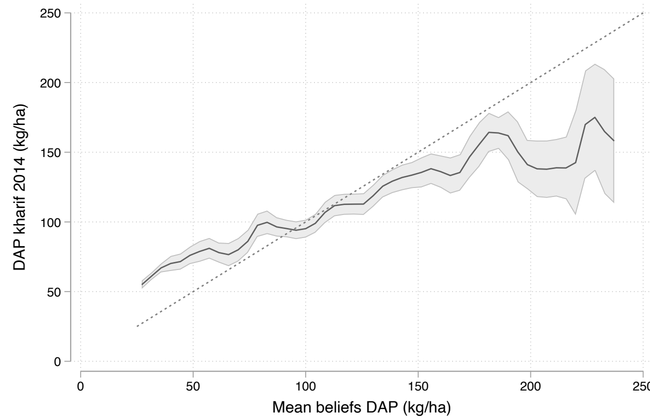
(b) DAP

Figure 2: Proportion of Total Beans Allocated to Fertilizer Ranges (kg/katha)

Notes: This figure presents the total proportion of beans allocated to each of the fertilizer application ranges shown to farmers during the belief elicitation exercise in kg/katha.



(a) Urea



(b) DAP

Figure 3: Fertilizer application relative to mean of beliefs about optimal fertilizer application

Notes: The X-axis shows the mean of the elicited beliefs distribution of optimal fertilizer application rates for each farmer. Fertilizer application rates in *Kharif* 2014 (kg/katha) are plotted using a local polynomial smoothing regression with an Epanechnikov kernel (bandwidth = 0.12). The 95% confidence intervals account for clustering by village. The dotted line is a 45-degree line.

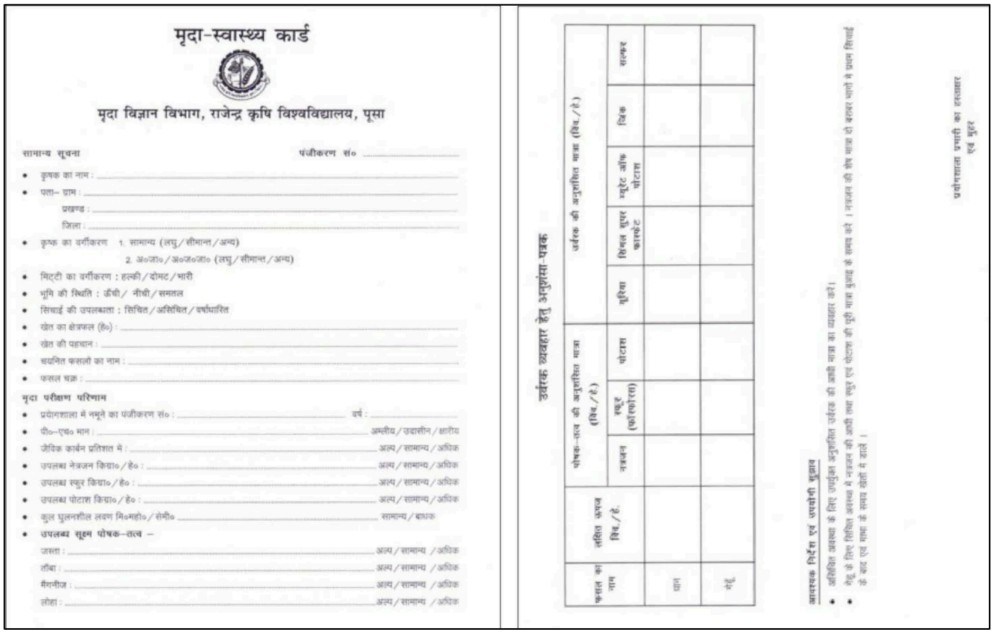


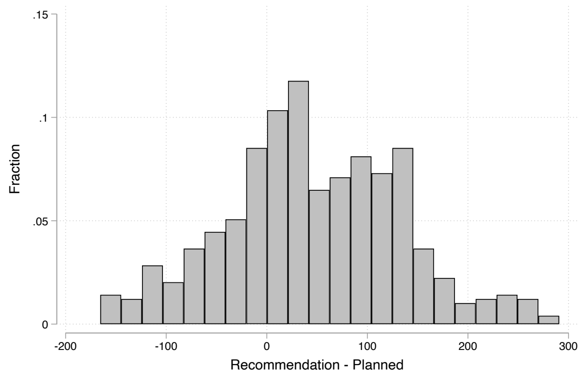
Figure 4: Example SHC (Hindi)

Crop name	Target Yield (quintal/ha.)	Recommended amount of nutrients (Kg/Ha.)			Recommended amount of fertilizer (Kg/Ha.)				
		Nitrogen	Phosphorus	Potassium	Urea	DAP	MOP	Zinc	Sulphur
Paddy/Rice									
Wheat	40q/ha	257.6	15.48	166.5	215	181.9	98.6	.8	27.45

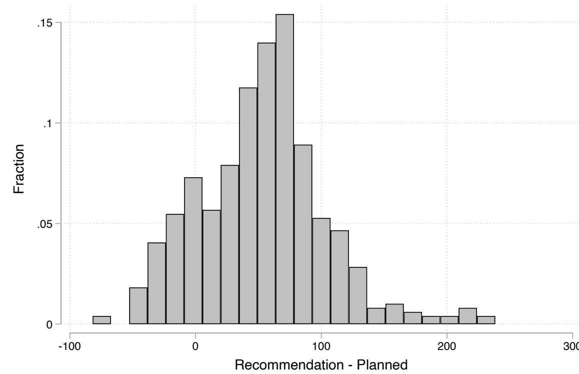
Important information and useful tips:

- For unirrigated situation, treat with half the recommended amount of fertilizer.
- For wheat, use half of nitrogen and full amount of phosphorus and potassium during time of sowing. Divide the remaining nitrogen into two equal parts and apply it during first irrigation and tillering

Figure 5: Example SHC (English)

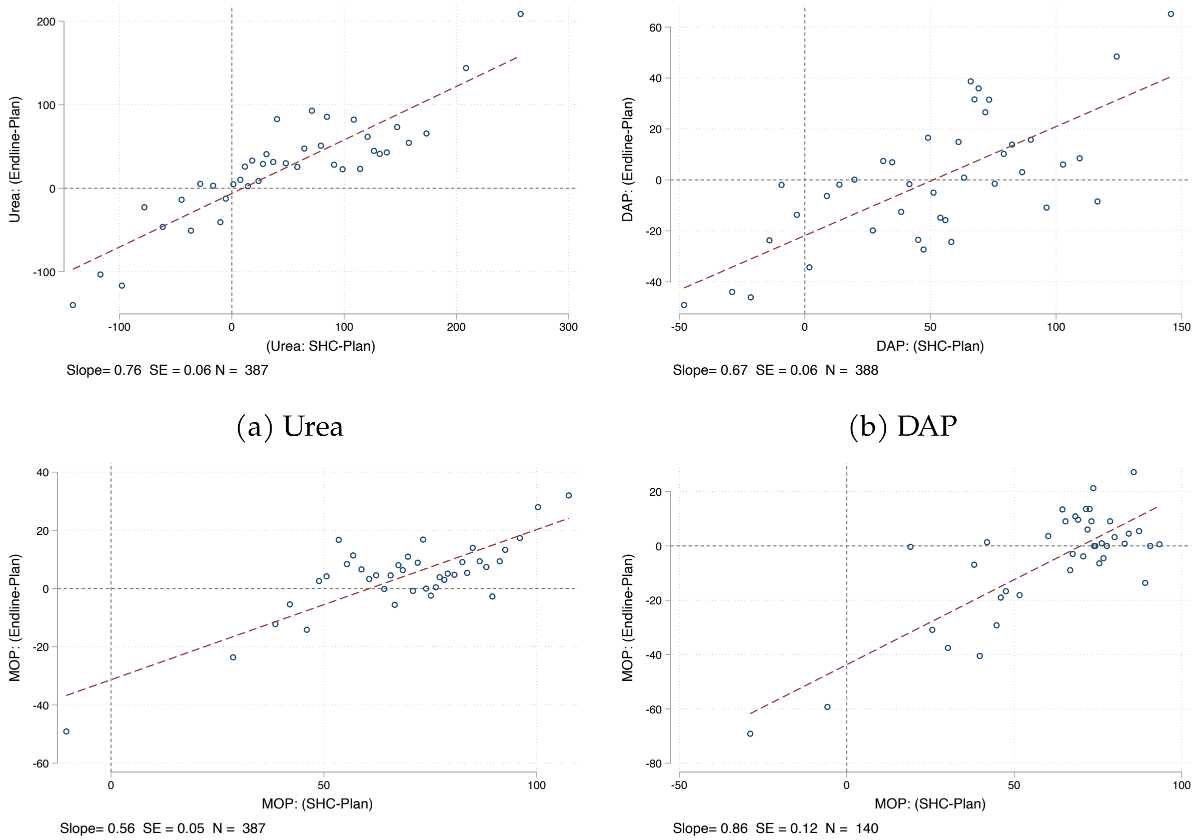


(a) Urea (All blocks)



(b) DAP (All blocks)

Figure 6: Density of difference between planned fertilizer application rates (Rabi 2014-15) and recommendation (kg/ha)



(a) Urea

(b) DAP

(c) MOP

(d) MOP (Planned>0)

Figure 7: Responsiveness of Fertilizer Application Rates

Notes: Responsiveness rates are estimated by the regression: $Posterior_i - Endline_i = \alpha(SHC_i - Plan_i) + \epsilon_i$, where α represents farmers' responsiveness. The graphs show binned scatter plots with a linear regression fit line based on 40 bins of the estimated relationship for urea (Panel a), DAP (Panel b), and MOP (both including (Panel c) and excluding farmers that do not use any MOP (Panel d)). The slopes (dashed line) and standard errors are based on a linear regression of the adjustment (endline application rate minus the planned application rate) on the signal gap (recommendation minus the planned application rate).

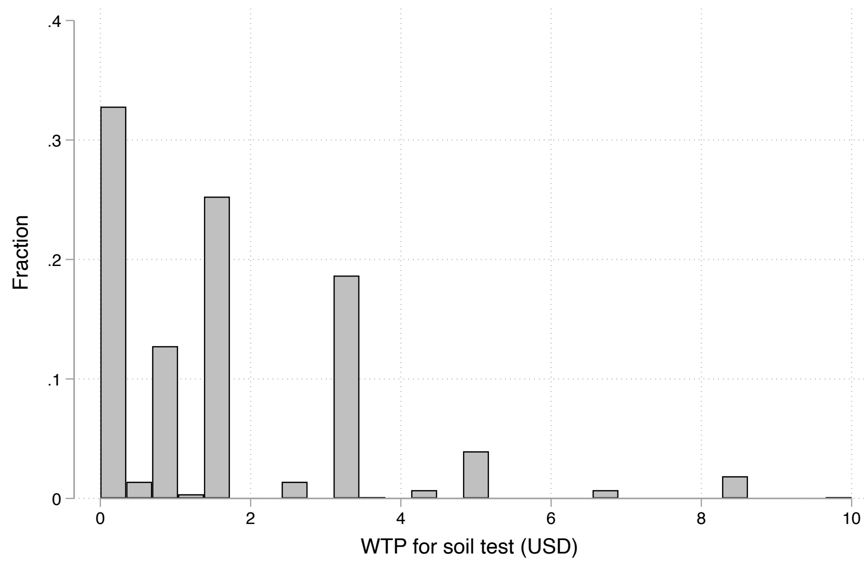


Figure 8: Willingness to Pay for SHC

Notes: This figure shows the distribution of stated willingness to pay (WTP) for soil testing and the SHC for all farmers in the baseline.