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

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Abstract

We use a field experiment in Bihar, India to test whether plot-specific fertilizer recommendations affect fertilizer usage and farming practices. We do not find compelling evidence that the information treatment led farmers to substantially change their overall fertilizer application nor their willingness to pay for recommended micronutrients, though there is some evidence that farmers may have altered the timing of their fertilizer application in such a way that improves fertilizer use efficiency. To rationalize the top line results, we model and test the impacts of confidence on farmers' responsiveness to input recommendations and soil quality measures. We find that farmers with less disperse priors (greater confidence) have a lower ex ante willingness to pay for soil testing and lower responsiveness to the fertilizer recommendations. These results suggest that heterogeneity in beliefs may constrain the effectiveness of information provision, even when the information is credible.

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1 Introduction

The imbalanced use of fertilizers is a major economic and environmental concern in emerging economies (FAO, 2019; Vitousek et al., 2009), including in many parts of India (Bora, 2022). In India, farmers tend to under apply certain types of fertilizers and over apply others, which reduces long-term yields and farmer income, harms soil health and pollutes water resources. While soil nutrient management is vital to close the existing yield gap in cultivated crops to meet population and consumption demands (Mueller et al., 2012), governments face the challenge of encouraging yield growth while simultaneously decreasing the environmental impacts of input intensification. Since the over-utilized fertilizers are often subsidized, it also entails substantial public expenditure with little benefit for crop yields.

To address these imbalances, in 2015 the Government of India launched a Soil Health Card (SHC) program that aims 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 the program is 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 experiment based on the model of the SHC program that provided farmers in a random subset of villages with plot-level soil fertility information and customized recommendations on three of the most common macronutrients and their accompanying fertilizers as well as two micronutrients. We find the program to have small but positive effects on urea usage and the adoption of a recommended practice pertaining to the timing of fertilizer application, but no impact on the application of the other two primary macronutrients. We then investigate the reasons, focusing on the role of their prior beliefs.

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] Informational barri-

[1] There is a large literature that studies the impacts of information provision on health behavior and outcomes

ers are thought to be a major likely inhibitor of the adoption of improved farming practices, inputs and technologies by smallholder farmers (Fabregas et al., 2019; Jack, 2013). [2] However, even if information is a binding constraint, various factors may limit the impacts of informational interventions on agents' choices. One class of explanations focus on the quality of the information and the manner in which it is disseminated.[3] Another class of explanations focuses on the recipients of the information and potential biases in learning and information processing (Barham et al., 2018; Hanna et al., 2014).[4]

Our analysis focuses on the possibility - relatively little studied in the agricultural sector - that farmers' baseline confidence can systematically affect responsiveness to externally provided information. We use experimental variation in information provision to assess how farmers respond to new information and identify farmer characteristics that are correlated with responsiveness. Previous research suggests that biases associated with the strength of peoples' priors are important for learning and information responsiveness. In particular, excessive certainty in the accuracy of their prior beliefs (overprecision) (Benjamin, 2019; Moore et al., 2015) can lead to people to neglect advice and scientific information, which can be costly if the information is useful. In the agricultural context, it is very common for extension professionals to anecdotally blame such beliefs for the persistence of (what they consider to be) misguided practices by farmers.

First, we present results from a randomized controlled trial with 864 households across 48 villages in the Indian state of Bihar that was introduced before the government introduced it's national SHC program, though our pilot shared many of the characteristics of the government's

(Bennett et al., 2018; Dupas, 2011; Guiteras et al., 2016), job search (Belot et al., 2019; Fafchamps et al., 2020), education investments (Dizon-Ross, 2019; Jensen, 2010), and increasingly in public policy (Banuri et al., 2019; Hjort et al., 2019; Vivalt and Coville, 2020) 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.

planned program. 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 recommendations for the usage rates of several important fertilizers. In the weeks prior to planting in the 2014-15 *rabi* wheat season, trained field staff provided farmers with SHCs that contained information on tested nutrient levels and the derived recommendations. We surveyed farmers before and after the season about their intended and actual fertilizer usage.[5]

Even though the fertilizer recommendations differed substantially from farmers' self-reported planned fertilizer applications, a comparison of endline fertilizer use between farmers in control and treatment villages yields little evidence of substantial effects of the information intervention. 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) and Tanzania (Harou et al., 2022). We do find some evidence of shifts in the timing of fertilizer applications to fit the recommendations, but changes in total fertilizer application are evident mostly for the lowest cost (and highly subsidized) fertilizer, and are of small relative magnitude. There is also little evidence of shifts in the willingness to pay for micronutrient amendments that are seldom used by the sample farmers but widely recommended by the SHCs due to pre-existing deficiencies in the soil. In explaining why they deviated from the SHC recommendations, farmers mostly refer to their own beliefs, with cost appearing as a secondary factor, and only for the more expensive fertilizers.

This latter observation motivates our empirical investigation of the role that prior beliefs – and especially the strength of those prior beliefs – had in limiting the impact of the SHC recommendations. Our analysis is guided by an extension of the target-input model (Bardhan and Udry, 1999; Foster and Rosenzweig, 1995; Jovanovic and Nyarko, 1996) that allows farmers to purchase and use an external signal about optimal inputs. In this Bayesian framework, the precision of farmers' prior beliefs – which we treat as a measure of one's confidence in prior beliefs – is pre-

[5]During the soil testing process, roughly 7 percent of treatment farmers' samples were not able to be processed due to contamination and were excluded from endline data collection. The project partners decided to exclude farmers in treatment villages that did not receive soil tests. In the following analysis, we account for this attrition using a bounding approach and discuss the implications for our results and policy recommendations.

dicted to attenuate the demand for external information as well as the degree to which they will use the signal to update their beliefs about optimal input usage.

To test the model's predictions, during the baseline survey we elicited from farmers stated willingness to pay for the SHC as well subjective belief distributions about optimal fertilizer usage (Delavande et al., 2011). The method made use of simple visual aids and enabled us to construct probability distributions for the two most widely used chemical fertilizers in our study area. We define confidence as the inverse of the belief distribution's standard deviation.[6] In addition, we include two survey based measures of confidence: farmers' incidence of doubts about agricultural practices and a measure of their farming ability relative to their peers. Consistent with recent work on within-person correlations of behavioral biases (Stango and Zinman, 2020), we show that there is a strong correlation across our confidence measures.

Consistent with the model's prediction, we find that confidence in one's prior beliefs decreases farmer's stated willingness-to-pay for a SHC. Moreover, endline fertilizer use is found to be correlated with both a farmer's pre-season planned use as well as the SHC recommendation, and represented as a weighted average of the two. The weight given to the SHC recommendation is found to be negatively and significantly correlated with their confidence in prior beliefs, including when we control for a battery of other characteristics. We find similar results using two survey based measures of confidence. In short, farmers who are more confident in their beliefs at project baseline place less weight on the SHC in determining their final fertilizer application. In contrast, no such effect is found for self-reported trust in extension agents, even though it is low in general, suggesting priors are a more important determinant than trust of farmers' utilization of external information. While we cannot explicitly test for overconfidence, 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. 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.

[6]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.

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. Recent studies that investigate the effectiveness of various forms of information provision to farmers in developing countries include, but are not limited to: Beaman et al. (2021); BenYishay and Mobarak (2018); Casaburi et al. (2014); Cole and Fernando (2021); Emerick and Dar (2020). A few 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 Gujarat, India, Cole and Sharma (2017) and Cole et al. (2020) investigate the effects of customized soil recommendations through mobile phones. 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. The difference between these results and our own is notable, and may potentially be related to substantial differences in the populations under study, the ease of understanding the SHCs and pre-existing relationship and trust between the Gujarati sample and the NGO that provides the information. Murphy et al. (2017) analyse the effect of plot level soil information and fertilizer recommendations on willingness to pay for inputs using experimental auctions. They find that the information affects farmers' WTP for DAP, and that the effect is stronger when farmers receive a negative recommendation (i.e. to no prioritize DAP). We are not aware of other work that examines how farmers' beliefs – particularly the strength of their beliefs – affect demand for and responsiveness to tailored advice like the SHCs. Our results fill this gap by explaining the attenuated impact of providing farmers with information, and suggest that identifying and targeting advice to farmers with low confidence may produce the highest returns to information diffusion efforts, especially if there are cost constraints.

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., 2020) 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., 2019; Vivalt and Coville, 2020). 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., 2020), as well as variance neglect and asymmetric updating in favor of good news (Vivalt and Coville, 2020).[7] 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, 2019) 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., 2020). We provide the first evidence on information provision and belief updating in the context of agriculture, where large amounts of public and private expenditure are dedicated to reducing information asymmetries with limited results. Further, 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.[8]

Finally, we make a further contribution by operationalizing the dispersion of a farmer's subjective probability estimates, a fundamental parameter in learning models, within an existing technology adoption framework. The model used in this paper is an adaptation of the Bayesian learning-by-doing model popularized by Jovanovic and Nyarko (1996), and adapted to the agricultural context by Foster and Rosenzweig (1995). The model relies on the agent updating the mean and variance of her beliefs over the true value of a parameter, in this case optimal fertilizer input levels. The majority of previous research ignores heterogeneity along this dimension

[7] Vivalt and Coville (2020) 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

[8] Previously cited literature connects prior uncertainty to belief updating, though no studies to our knowledge move beyond the direct effects on beliefs to real-world investment choices.

and assumes common priors across farmers. Our method allows us to quantify these parameters directly from farmers' subjective beliefs distributions. The relatively simple method of belief elicitation we use, summarized in Delavande et al. (2011) and described in section 3 below, requires respondents to allocate tokens across bins to represent probabilities of events occurring. Similar measures have been used to elicit expectations about future earnings and resulting education choices in Mexico (Attanasio and Kaufmann, 2009), expectations of rainfall among Kenyan pastoralists (Lybbert et al., 2007), and expectations about contracting and death from HIV/AIDS in Malawi (Delavande and Kohler, 2009), but this is the first study that has used the information on farmers' subjective beliefs to inform a measure of farmer confidence and operationalize this measure in explaining farm management.

The remainder of this paper is organized as follows. In Section 2, we describe a model of learning about optimal input usage that provides a series of testable hypotheses about the relationship between the strength of farmers' prior beliefs and their responsiveness – or lack thereof – to targeted information. In Section 3, we describe the soil testing intervention and the data collection and provide summary statistics. We estimate the impacts of the intervention on fertilizer usage in Section 4. In Section 5 we investigate the impacts of confidence on responsiveness to the recommendations and discuss demand for the SHCs. Section 6 concludes.

2 Model of information demand and responsiveness

In this section, we present a model of information demand and responsiveness that demonstrates how the strength of farmers' priors over optimal input use explains responsiveness to the soil testing recommendations. The model is an adaptation of the target-input model (Bardhan and Udry, 1999; Foster and Rosenzweig, 1995; Jovanovic and Nyarko, 1996). The model allows the agent to have a period-specific optimal input choice by weighing her sources of information, including own experimentation and information from her peers (Foster and Rosenzweig, 2010). In the present application, we allow for input decisions to be informed by an external signal, and characterize farmers' willingness to pay for the signal and how farmers' update their beliefs in response to the information.

The farmer has knowledge of the production function and the relationship between inputs and profits but does not know a random target parameter – in this case, the optimal level of fertilizer. In the context of soil testing in Bihar, farmers have learned about this parameter over multiple periods of costly individual and social experimentation, and thus, it seems reasonable to assume that they have defined prior beliefs over the parameter. However, variation in shocks, soil quality, farming ability, and confidence prevents all of the uncertainty from being resolved when farmers make planting decisions in the current period.

The farmer's output at time t is defined as q_t, and is declining in the squared distance between actual input use k_t and the optimal input level θ_t:

$$q_t = 1 - (k_t - \theta_t)^2 \tag{1}$$

The target input level, θ_t, is the period-specific level of the input that would maximize total production. The farmer does not know the target level at the time inputs are chosen. Rather, the farmer chooses input level k_t to maximize expected output. The optimal input level at time t is

$$\theta_t = \theta + u_t \tag{2}$$

where $u_t \sim \mathcal{N}(0, \sigma_u^2)$ is an independent and identically distributed shock with known variance. The θ term represents the objective mean optimal input level about which the farmer is learning over time. The farmer does not know θ at time t but has subjective (prior) beliefs about the distribution based on a history of input decisions and realized yields: $\theta \sim \mathcal{N}(\theta_t^*, \sigma_{\theta_t}^2)$. At time t, the farmer's confidence ($\rho_{\theta_t} = \frac{1}{\sigma_{\theta_t}^2}$) is their perception of the reliability of her estimate. For narrow prior distributions (i.e., with a small variance) the farmer is confident in her beliefs about the optimal input level, while for wide prior distributions (i.e., with a large variance), the farmer is less confident.

The period-specific target input level (θ_t) varies with independent and identically distributed shocks, u_t.[9] The optimal annual input use will be a function of growing conditions (including,

[9]The period-specific shock can be decomposed into village-level (covariate) and individual-level (idiosyncratic) components with respective variances σ_v and σ_i. We assume the shocks are additive and independent and exclude

among other things, the nutrient levels present in the soil) and the ability of the farmers to adjust other inputs to suit growing conditions. To reflect this, we assume that the variance of the optimal input level (σ_u^2) varies across farmers and depends on farmers' ability. Farmer-specific ability is denoted as $\rho_u = \frac{1}{\sigma_u^2}$, where better (higher ability) farmers have a lower variance of shocks to optimal input usage. Ability reflects management capacity, including effective coordination of inputs such as fertilizers, pesticides, labor, irrigation, etc. That is, conditional on aggregate shocks like weather variability and disease pressure, better farmers have a lower variance of transitory shocks to optimal input use.[10]

To simplify the exposition, we normalize output prices to one and assume that the input is costless. Farmers apply the expected optimal target as the input level, so that $k_t = E_t(\theta_t) = \theta_t^*$. Expected output (profit) can be expressed as

$$E_t(q_t) = 1 - E_t[k_t - \theta_t]^2 = 1 - E_t[\theta_t^* - \theta - u_t]^2 = 1 - \sigma_{\theta_t}^2 - \sigma_u^2 \tag{3}$$

From this result it is clear that subjective expected output is decreasing in $\sigma_{\theta_t}^2$ and σ_u^2, and therefore increasing in the level of confidence over the target input level (ρ_{θ_t}) as well as in the farmer's ability (ρ_u). The farmer makes input choices to maximize expected profit, conditional on the precision of her subjective beliefs about the target parameter. After applying input level θ_t^* and observing the realized out q_t, the farmer uses equation (1) to deduce the period specific optimal input, θ_t, and updates her beliefs about θ using Bayes' rule:

$$\theta_{t+1}^* = \theta_t \left(\frac{\rho_u}{\rho_u + \rho_{\theta_t}}\right) + \theta_t^* \left(\frac{\rho_{\theta_t}}{\rho_u + \rho_{\theta_t}}\right) \tag{4}$$

The farmer's updated expectation of the optimal input is a linear combination of her previous expected optimal value (θ_t^*) and the revealed optimum after harvest (θ_t). Specifically, the weight on the prior expectation is proportional to the farmer's confidence in her prior beliefs, while the

the common component to simplify the analysis.

[10] BenYishay and Mobarak (2018) also interpret $1/\sigma_u^2$ as a measure of innate farming ability in a model where farmers are considering the purchase of a signal about new technology. Unlike in the present study, their model assumes farmers do not have previous experience with the technology, and consequently the distribution of priors is not considered in the decision to purchase the signal.

weight on the revealed target is proportional to the farmer's ability. Farmers with better ability (larger ρ_u) place more weight on the revealed optimum (θ_t), and their beliefs move closer to the true value of θ, holding confidence fixed. Conversely, other things equal, farmers with higher confidence in their own subjective beliefs will place more weight on prior beliefs, and thus their posterior beliefs will more closely resemble their prior beliefs. In the extreme, if a farmer were to have absolute confidence in her prior subjective beliefs, then the posterior beliefs will perfectly replicate prior beliefs, such that the farmer learns nothing from additional information.

Similarly, posterior beliefs about the variance of the target parameter are updated according to

$$\sigma^2_{\theta_{t+1}} = \frac{1}{\rho_{\theta_t} + \rho_u} \tag{5}$$

A farmer's confidence at time $t+1$ is determined by her prior level of confidence and her ability. Notice however, that through combining information from the prior subjective beliefs and the revealed information, the farmer's posterior beliefs are more precise than if she were to only rely on one source of information.

2.1 Demand and Responsiveness to Information

In this section we extend the model to analyze the farmer's responsiveness to a signal about input usage. Consider a farmer in time $t = 1$ with beliefs $\mathcal{N}(\theta^*_1, \sigma^2_{\theta_1})$ and ability ρ_u. The farmer's beliefs at time $t = 1$ are updated using the output from the initial planting season ($t = 0$), when her planting decision is made using only initial confidence (ρ_{θ_0}) and ability (ρ_u). Initial confidence and ability are assumed to be randomly chosen from some arbitrary distribution and are independent, conditional on demographics, wealth, and cognitive ability.

When considering the decision to purchase the signal, the farmer applies Bayes's rule to update her beliefs about the variance of θ conditional on her belief of the signal's precision or reliability. Given these beliefs, the variance after purchasing the signal is calculated according to:

$$\tilde{\sigma}^2_{\theta_1} = \frac{1}{\rho_{\theta_1} + \rho_S} \tag{6}$$

where $\rho_S = \frac{1}{\sigma_S^2}$ is the subjective precision of the signal. As before, the updated beliefs are a weighted function of the farmer's prior beliefs and the received signal, with the weight on prior beliefs proportional to the degree of confidence in these beliefs and the weight on the received signal proportional to the perceived precision of the signal. Note again, if confidence in the prior beliefs is high, then these updated beliefs will closely resemble the prior beliefs, other things equal.

We assume that beliefs about the precision of the signal do not change after the signal is revealed and that farmers are myopic in their choice to purchase the signal (i.e. only the expected yields of the following season are included in the expected benefits). Substituting equation (6) into the expected profit equation (3), the farmer will purchase information if and only if $E(\pi|S = 1) - E(\pi|S = 0) > 0$. Farmers' willingness to pay (WTP) for the signal is the difference between expected profit with and without the signal:

$$WTP \equiv E(\tilde{q}_1) - E(q_1) = (1 - \tilde{\sigma}_{\theta_1}^2 - \sigma_u^2) - (1 - \sigma_{\theta_1}^2 - \sigma_u^2) = \sigma_{\theta_1}^2 - \tilde{\sigma}_{\theta_1}^2 \tag{7}$$

Substituting equation (6) for the second term of this difference gives

$$WTP \equiv \sigma_{\theta_1}^2 - \frac{1}{\frac{1}{\sigma_{\theta_1}^2} + \frac{1}{\sigma_S^2}} \tag{8}$$

So long as the distribution of the signal has a finite variance, this difference is always greater than zero, so farmers should be willing to pay some positive price for information, regardless of its perceived precision.

This framework allows us to make the following predictions about how farmers' valuation of soil tests vary based on their beliefs and how their input usage is expected to respond to new information about soil characteristics and recommendations.

Prediction 1: Demand for information is decreasing in farmer confidence

Combining the result from equation 7 with equation 5 yields

$$\sigma_{\theta_1}^2 - \tilde{\sigma}_{\theta_1}^2 = \frac{1}{\rho_{\theta_0} + \rho_u} - \frac{1}{\rho_{\theta_0} + \rho_u + \rho_S} \equiv WTP \tag{9}$$

Taking the first derivative with respect to ρ_{θ_0} gives

$$\frac{\partial WTP}{\partial \rho_{\theta_0}} = \frac{1}{(\rho_{\theta_0} + \rho_u + \rho_s)^2} - \frac{1}{(\rho_{\theta_0} + \rho_u)^2} < 0 \tag{10}$$

For any two farmers with the same ability, the farmer with higher confidence at $t = 1$ will demand less information. We note that $\partial WTP/\partial \rho_u = \partial WTP/\partial \rho_{\theta_0}$. This results from only having two periods, so both ability and *initial* confidence are equally weighted in the calculation of ρ_{θ_1}. In reality, the weight on ρ_u in the calculation of ρ_{θ_t} will be scaled by the number of periods that the farmer has planted, and this equality will only hold in the first period.

Prediction 2: The weight that farmers place on the signal is decreasing in their confidence

We now consider a farmer that is given a signal S, for which the farmer has a prior about its precision, ρ_S. Assuming that a farmer's beliefs about the precision of the signal remain constant, a Bayesian farmer will form a posterior about optimal input usage:

$$\tilde{\theta}_1 = \alpha \cdot S + (1 - \alpha) \cdot \theta_1^* \tag{11}$$

A Bayesian farmer's posterior will be a convex combination of their prior and the recommendation (signal), with weights ($\alpha = \frac{\rho_S}{\rho_S + \rho_{\theta_1}}, 1 - \alpha = \frac{\rho_{\theta_1}}{\rho_S + \rho_{\theta_1}}$) that are proportional to the farmer's confidence and trust in the signal. From this expression, it is clear that the weight that the farmer places on their prior will be increasing in their confidence (ρ_{θ_1}) and the weight they place on the signal will be decreasing in their confidence. Similarly, the weight that farmers place on the signal will be increasing in their trust in the signal (ρ_S). We test these predictions directly in the following empirical analysis.

3 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; June to October) crop, while wheat is the predominant *rabi* (dry, winter season; December-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 to get their soil tested 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.

3.1 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. Withing 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 and collected information on household and farm characteristics and the use of farm inputs for the *kharif* rice crop harvested in 2013. 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. 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 3.1.1 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.[11] Eight graduates from local agricultural universities were selected to serve as extension agents for this study. These agents received a three-day training from experts 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 recommendations in Section 3.1.2.

Technical delays in conducting all soil tests prevented us from distributing the SHC and associated recommendations prior to the planting of the 2014 *kharif* paddy rice crop. We therefore shifted the experiment to the *rabi* season of 2014-15, and had fertilizer recommendations prepared for the wheat crop, the main crop of this season. Because the baseline survey was focused

[11] Slightly more than half of the sample farmers (54%) reported having more than one plot.

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

primarily on rice, in November 2014, prior to distributing the SHCs with soil test results and recommendations to treatment farmers, we carried out a midline survey to collect information on cultivation practices and fertilizer application in the wheat crop of the previous *rabi* season (2013-14), as well as the intended application in the coming season. The great majority of farmers in the study area and in our sample also cultivate wheat during the *rabi* season.

Following the midline survey, SHCs (printed in Hindi) were hand-delivered by the eight field agents to treatment farmers, weeks before the sowing of the wheat crop, when most farmers had yet to purchase fertilizers. The agents were trained in the proper interpretation and explanation of the SHC to farmers. Finally, an endline survey on fertilizer application rates was conducted after the *rabi* 2014-15 wheat harvest (June-July 2015). 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.

An additional follow-up survey was conducted to elicit farmers' WTP for zinc (June-July 2015), following the endline survey. A simplified Becker-DeGroot-Marschak mechanism was implemented, allowing us to compare zinc valuation by farmers whose land is zinc deficient with zinc valuation by those whose land is zinc sufficient (both in the treatment group), as well as zinc valuation by those whose specific land characteristics are undetermined (that is, farmers in the control group).

We note several aspects of the study implementation and their implications for our analysis. First, we opted not to test soils for farmers within control villages, due both to the cost of sampling and testing soils as well as concerns that – since the research design required that they be an un-informed control – not receiving the SHC after testing could diminish their future trust in soil health card programs. Consequently, since we do not know what the fertilizer recommendations *would have been* for farmers in the control villages, we 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, as previously mentioned, the original goal was to provide farmers with recommendations for their paddy rice crop in the *kharif* 2014 season, but as previously mentioned unforeseen technical delays imperiled that original goal and forced us to delay delivery of the SHCs until later in the year, prior to the planting of the *rabi* wheat crop. All of the farmers in our sample have experience growing wheat during the *rabi* season, though roughly 85% do so in any given season, implying that roughly 15% of the farmers in the original sample were ultimately excluded from the final sample due to not satisfying a critical inclusion criteria. Finally, while the original treatment sample consisted of 576 farmers, the research team failed to collect soil samples from 79 of these farmers, due to a combination of technical reasons (samples that were too small or contaminated) and lack of cooperation in a handful of cases. The enumerators 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 Appendix A). The initial sample size provided 80 percent statistical power to identify effects of 0.25âĂŞ0.5 standard deviations in fertilizer application rates, depending on the range of intracluster correlation (ICC) that were in the observed range in the baseline data. Due to the technical delays described above, the sample size decreased in the treatment group following the baseline. Previous findings in Corral et al. (2020) and Harou et al. (2022) These effect sizes fall within the range of positive outcomes found in many studies of education interventions.[13]

3.1.1 Prior belief elicitation

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.[14] Farmers were asked to allocate beans across bins according

[13] 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 of 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 stratification which may increase precision.

[14] The usage of incentives in belief elicitation requires an objective measure in which to benchmark the reported beliefs. In our context, we are constrained by the non-verifiability of the true optimal application rate, and therefore we are unable to elicit beliefs with incentives. Nevertheless, there is not currently systematic evidence that incentives

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. In order to minimize the risk of confusion or idiosyncratic differences in interpretation, we attempted to ensure that all respondents began the experiment with a comparable baseline understanding of probability. 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.

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 *kharif* season on their primary rice-growing plot.[15] The bins of fertilizer application rates were predetermined based on 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 and control for the mean of the subjective beliefs distributions in all regressions.[16]

Eliciting the beliefs distributions entailed two questions for each bin. Before starting, respon-

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. While recent experimental evidence finds some evidence for hypothetical bias due to risk aversion using non-incentivized beliefs-elicitation methods (Harrison, 2016), we present results controlling for risk aversion and discuss the implications of hypothetical bias in our results.

[15]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 in a hectare.

[16]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.

dents 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 urea that results in crop failure. There is no apparent bunching at particular values of the distribution, and most bins have over 15 percent of respondents believing that there is at least some possibility that the corresponding range of fertilizer application will result in the highest yields.

From the sequence of responses, 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 expectation and variance of the farmers' true fertilizer application belief distributions prior to receiving soil testing (θ_1 and $\sigma^2_{\theta_1}$, respectively). We treat farmers' confidence as a measure of dispersion of their prior beliefs ($\rho_{\theta_1} = \frac{1}{\sigma^2_{\theta_1}}$).

Figure 3 shows the relationship between actual fertilizer application rates during the 2014 *kharif* season and the elicited expectations (mean values) of the subjective beliefs distributions for urea and DAP. In general, there is a high correspondence between elicited expectations of optimal fertilizer use and actual behavior: expectations of the beliefs about optimal urea and DAP are nearly the same as actual application rates in the season immediately subsequent to the elicitation of these expectations. This similarity provides credible evidence that the elicitation procedure captured meaningful information about farmers' beliefs.

In addition to subjective beliefs, we asked questions that provide survey based measures of relative confidence. The first question asks: *How often do you have doubts about agricultural practices?* The second question asks: *Given the same soil quality and access to inputs, how would your yields compare to others in your village?* 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 from their incidence of doubts that is equal to one if farmers have considerably fewer doubts relative to their peers. Similarly, using their relative ability responses, we construct a binary measure equal to one if they responded that they would have much higher yields relative to their peers.

The subjective beliefs we collected pertained to the *kharif* season rice crop, as mentioned above, but technical delays in the preparation of SHCs forced us to focus our experiment on the subsequent *rabi* season wheat crop. While we have not measured the strength of farmers priors for the wheat crop, we rely on measures of these priors for the rice crop as a proxy for the strength of the wheat crop priors. Empirical confidence experiments find that within-agent confidence tends to be highly correlated across tasks (Klayman et al., 1999) and that empirical measures of overconfidence exhibit positive correlation within person (Stango and Zinman, 2020). Given the similarity in experimental tasks in the present study, and that nearly all farmers in our sample have more than ten years of experience with both 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.[17] Table 1 shows that the dispersion (SD) in beliefs for both urea and DAP are highly positively correlated, providing some evidence that confidence is correlated across different fertilizers for the same crop. Further, the dispersion measures (precision of one's expectations) are correlated with our survey measures confidence based on relative performance (i.e., the frequency that farmers have doubts about agricultural practices relative to their peers, or their potential yields compared with

[17] 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*.

neighbors with similar soil quality), suggesting that we are capturing heterogeneity in underlying confidence. The positive

3.1.2 Soil Tests and Recommendations

The soil samples that were collected 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). Because Bihar soils are widely believed to suffer from sulfur (S) and zinc (Zn) deficiencies, and because both of these micronutrients are considered to be important for soil health and crop yields, we included this additional information in the laboratory analysis and SHCs.[18]

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 some threshold level) and provided recommendations for the application of macro fertilizers including urea (the main source of N), DAP (the main source of P), MOP (the main source of K), and micro fertilizers including Sulphur and zinc.

Urea and DAP are very commonly used by farmers in the area (all farmers in our sample made use of them), while MOP is less commonly used (40% of the farmers in our sample made use of it at baseline). While all three fertilizers are subsidized by the government, urea is the most heavily subsidized, costing around Rs. 5 / kg, with DAP and MOP costing around 8 and 5 times more per kg, respectively (subsidies for these two fertilizers have been scaled back in recent years).

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 few micronutrients (Zn and S) to apply to their *rabi* wheat crop.

[18] In addition to all of the above, the national program also provides information on the availability of iron (Fe), copper (Cu), manganese (Mn), and boron (Bo) in the soil.

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. One way to think about these recommendations is that they represent the nutrient requirements of crops attaining a certain level of yield. Calibrating the recommendations is therefore challenging. The typical practice in Bihar is to calibrate the recommendations to a fixed yield rate (in our specific case, 4 tonnes per hectare). To simulate the public program, we followed the same practice. 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. Although it is possible that farmers could have perceived the target yield to be unattainable and attempted to re-calibrate the recommendations based on their own experiences and perceptions of their own yield potential, we maintain the assumption that they view the SHC as an authoritative source on appropriate fertilizer application rates.

Table 2 compares treatment farmers' self-reported planned fertilizer application rates (Columns 1-5) in the 2014-5 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 (potash) 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). Over 70% and 80% of farmers received a recommendation to increase their use of urea or DAP, respectively, while all farmers were told to increase their use of MOP (Column 11). Figure 5 plots the distribution of these differences between planned and recommended application rates of urea and DAP.

In addition to the major fertilizers, the application of micro-nutrients was found to be very rare among sample farmers. Although one in four soil samples were deemed to be deficient in zinc and sulfur, few farmers reported having applied zinc or sulfur in the previous season.[19]

[19] Once applied, zinc remains available to crops for up to three cropping seasons, though marginal returns on the application of zinc are higher if it is first applied to the rice crop in a rice-wheat cropping system.

3.2 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 60%-70% of the sample are literate. The average stated willingness to pay for a SHC was about USD 1.5. Trust in existing extension services is low amongst farmers as 60% of farmers report not trusting information from extension agents until there is evidence that it is effective.[20] While treated and control farmers were mostly similar statistically, treated farmers were a little more likely to be female (9 vs 5 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 that treatment is jointly orthogonal to all baseline variables (p-values reported at the bottom of the table).[21]

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 and less likely to be literate. 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 Appendix A).

In Table 4 we examine any remaining attrition stemming from failure to find or interview other farmers at endline. Column 1 shows that overall, 10 percent of households could not be matched to the endline data due to such difficulties. Column 1 shows, however, that attrition does not differ across control and treatment farmers. Since the SHC we distributed were specific

[20] 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*

[21] 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.

to wheat cultivation, our sample is farther restricted to (the roughly 85% of) farmers that indeed cultivated wheat in the primary plot. In column 3, we show that the likelihood of cultivating wheat also did not differ across control and treatment farmers. Our final sample for estimating effects on wheat cultivators consists of 613 farmers.

4 Impacts of the SHC on Fertilizer Application

In this section, we first estimate the causal impacts of the SHC distribution on fertilizer use in Section 4.1. We begin by estimating the impacts on fertilizer application rates in the 2014-15 *rabi* season for the three main macro-fertilizers: Urea, DAP and MOP, as well as the timing of urea application. We discuss the results and potential reasons for the muted impact of the intervention in Section 4.2. Finally, in Section 4.3, we report an analysis of the intervention on demand for zinc, a micronutrient that is rarely used by farmers in the sample.

4.1 Urea, DAP, MOP

To estimate the effects of SHC distribution on endline applications of the three macro-fertilizers and the timing of urea application, we estimate the following regression:

$$y_{iv} = \alpha_0 + \alpha_1 T_v + X_{iv}^{'}\gamma + \mu_b + \nu_e + \epsilon_{iv} \tag{12}$$

where y_{iv} is the endline measure for the outcome of interest for farmer i 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 treated plot). We also include block (strata) fixed effects (μ_b) and enumerator fixed effects (ν_e) in the regression, and adjust standard errors for the clustered nature of the intervention (at the village level – the unit of randomization). As discussed above, the sample includes all farmers who planted wheat in the target plot at endline, and we report Lee bounds for our estimates in order to account for failure to collect soil samples and endline data from some of the treatment farmers.[22]

Our primary outcomes are the application rates of the three major macro fertilizers: urea, DAP and MOP, measured in kg per hectare. This allows us to measure the effect of the information treatment on fertilizer use along the intensive margin. While urea and DAP are used by all farmers, only about 30% of sampled farmers applied MOP on their wheat crop. We therefore also estimate impacts on a binary indicator of MOP use to capture the effect of the information treatment on MOP use along the extensive margin. In addition, we examine effects on the practice, recommended on the SHC, of applying half of the overall amount of urea during sowing to improve fertilizer use efficiency. Unlike other SHC recommendations, this practice did not necessitate changes in overall fertilizer application rate, but only in its temporal distribution.

Table 5 presents estimates of treatment effects on the intensive margin of fertilizer use, the extensive margin of MOP use, and practice adoption. In addition to the point estimates, we report 95% confidence intervals as well as the 95% confidence intervals of the Lee bounds. Overall, we find evidence that SHCs had a small impact on fertilizer application levels.[23] The point estimate on urea use is significant at the 5% level and suggests an increase of 10 kg/ha or about 5% of the mean level of urea use among farmers in the control group. For the remaining fertilizers, the point estimates are of only a modest size (roughly 5% and 10% of mean levels of DAP and MOP usage, respectively), and are not significant. There is a positive effect on the probability of farmers using MOP, with a larger proportional impact (15%) that is marginally insignificant. However, it should be noted that the Lee intervals of all four impacts include zero.[24]

At the bottom row of Table 5, we report the the potential impact of the SHCs that would have occurred if all treatment farmers followed the recommendations to the letter.[25] For urea usage, the estimated effect is 40% of the potential effect (10 kg/ha relative to about 25 kg/ha). For all other indicators, the effect is lower than 10% of its potential. Thus, the estimated impacts are relatively modest to what would have been possible under full compliance to the recommendations.

[22]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.)

[23]We note that the results are insensitive to the inclusion or omission of the controls or the enumerator fixed effects.

[24]Defined to 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.

[25]To simulate these impacts, we replace each treated farmer's application with the (un-calibrated) recommended level and then re-estimate the regression.

In contrast, we do 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 share of farmers in the treatment group that followed this practice increased by 7 percentage points (p.p.) relative to the control farmers, a 33% increase over a control mean of 20 p.p. This effect is significant, and even the lower lee bound is positive and significant.

4.2 Discussion

These results provide evidence that farmers respond partially to the recommended quantities on the intensive margin. The effect appears to be strongest for urea, and less so for MOP. Our findings are consistent with previous interventions that provided soil tests and recommendations to farmers and 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). We further reiterate that the average estimated treatment effects suffer from differential attrition and are not robust to Lee bounds corrections. There is, however, strong evidence that farmers adjust the timing of their urea application in line with the information on the Soil Health Cards. Taken together, SHCs can be succesful at delivering information to farmers, though further analysis is needed to identify why farmers respond to certain pieces of information and not others.

Further, we note that the treatment effects on the intensive margin combine farmers that received recommendations to increase usage with those that were recommended to decrease usage and therefore may understate impacts of the intervention. Due to the experimental design, we cannot provide causal evidence on heterogeneity in updating based on the direction of farmers' recommendation. However, in Section 5, we investigate how responsive treatment farmers were to the recommendations and document farmer characteristics that are correlated with how much individual farmers update in response to information.

4.2.1 Farmers' Comprehension of the SHC Content

One explanation for the muted treatment effect is that farmers may not have understood or taken note of the recommendations. A lack of understanding has been argued to be a inhibitor on the cards as has been found in other areas in India (Cole and Sharma, 2017). 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. If they could correctly recall the amounts on the card, then their answers to this question should be reflected in their reported application rates relative to the recommendations. In Table 6, we cross-tabulate their answers with the difference between the actual rate of application and the recommendation in the SHC. 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 decent grasp of the recommendations. This is less clear-cut for DAP and MOP, but most farmers under-applied these fertilizers and have also correctly indicated this (indicated by line 5 in the table). This suggests that farmers had at least some sense of the content of the SHC and the recommendations. It also suggests that they mostly referred to the un-calibrated recommendations when making reference to the cards.

4.2.2 Self-Reported Reasons for Not Following the SHCs

A second potential explanation for the stronger evidence we find for increases in urea usage in comparison to DAP and MOP may be related to their costs. As noted above, while urea continues to be highly subsidized in Bihar, subsidies in 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. This hypothesis is consistent with farmers' self-reported reasons for applying more or less than the recommended levels, summarized in Figure 6 (Table 7 presents the full breakdown). High costs (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. Hardly any farmers cited low costs as a reason for applying more than the recommendation.

These results are consistent with those found by Harou et al. (2022), who show that plot-specific soil tests increased fertilizer usage from low baseline adoption in Tanzania only when accompanied by vouchers for purchase. In our case, the SHCs may have increased the usage of low cost urea but did not appear to have substantial impacts on the much more expensive (about 8 times more expensive than urea) DAP, and only a marginal effect on MOP (which is 4-5 times more expensive than urea). These results highlight the potential downside of providing information that targets multiple inputs when farmers face different costs across inputs, with the net effect being a farther increase in the overall imbalance of the fertilizer mix, which is skewed towards urea to begin with.

And yet, the clearly dominant factor cited by farmers for not complying with the recommendations was their confidence in the accuracy of their own practices. This is true for 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 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 change their behavior from previous seasons based on 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. These results motivate our analysis in Section 5, which examines to what degree the level of confidence displayed by farmers was indeed correlated with their demand for and responsiveness to the SHCs.

4.3 Willingness-to-pay for Zinc

The SHC also provided information on levels of zinc in the soil as well as recommendations on zinc amendments. While zinc deficiency is common in the area, few farmers use it. In our sample, 38 percent of farmers were zinc deficient, though only 15 percent planned to apply zinc in the 2014 *rabi* season. To examine both whether the soil health card affected demand for zinc and how demand was correlated with the contents of the SHC, we elicited farmers' willingness to pay (WTP) for zinc using a simplified Becker-DeGroot-Marschak (BDM) valuation elicitation exercise following the conclusion of the endline survey (Becker et al., 1964).[26] See Appendix B

[26]The BDM mechanism is a widely used incentive-compatible procedure for eliciting the WTP for a good or a service (Berry et al., 2020). In a BDM, each subject submits their bid to purchase the good. Afterwards, a random sale price is drawn from a distribution of prices ranging from a very low value to a price greater than the anticipated maximum possible WTP among bidders. If the random price is less than or equal to their bid, the subject receives a

for further details on the implementation and sample.

In Figure 7, we report the mean WTP elicited across various subgroups and 95% confidence intervals to determine whether the SHC affected farmers' willingness to pay for zinc. We report the mean WTP separately in the district of Madhubani, where there is no control group. Panel (a) compares farmers in Nawada and Bhojpur that received the SHC (N=165) to control farmers (N=67) in the districts of Nawada and Madhubani. The SHC group pools treatment farmers that received an SHC that showed that their soil was deficient in zinc (N=57) as well as those that were not deficient (N=108). WTP is higher in the treatment group, though the difference is not statistically significant. In Panel (b), we then disaggregate the treatment group into (1) farmers that had zinc deficiency and received a reminder of the contents prior to the elicitation, (2) farmers that had zinc deficiency and did not receive a reminder of the contents prior to the elicitation, and (3) those that were zinc sufficient. Mean WTP is higher amongst treatment farmers that were zinc deficient (mean=42.9) and that were zinc sufficient (mean = 40.7) relative to the control (mean = 37.5), though none of the differences are statistically significant. Panel (c) shows the comparison in Madhubani (with no control group), where mean WTP is higher on average than in the other two districts, though none of the differences are statistically significant. Overall, these comparisons suggest that the SHC's zinc information had very little effect on farmers' valuation of it.

5 Responsiveness to the SHCs Among Treated Farmers

We now turn to how farmers incorporate the recommendations in their fertilizer usage. To study how farmers update, we follow a similar strategy to what has been used recently in survey experiments in a variety of contexts.[27] In our context, rather than estimating learning using an elicited posterior belief, we observe the actual input decision of the farmer (y_{iv}) and take it to represent their mean of their posterior belief distribution. Similarly, their planned input usage, elicited

unit of the good and pays the random price rather than their bid. If the random price is greater than their bid, the participant is unable to purchase the good. The dominant strategy for the bidder is to truthfully reveal his or her preferences and therefore the BDM is incentive-compatible.

[27]Examples include belief updating about house prices (Fuster et al., 2020), salaries (Cullen and Perez-Truglia, 2022), and inflation (Cavallo et al., 2017; Coibion et al., 2018).

prior to receiving the SHC, is taken as the mean of their prior belief distribution. In a model of Bayesian learning, as shown in Appendix 2, a Bayesian farmer's updated mean of their posterior belief about the optimal input application rate is a convex combination of the mean of her prior belief and the information revealed in the SHC (signal).[28]

Figure 9 illustrates the degree to which farmers updated their endline fertilizer application after receiving the fertilizer recommendations via the SHC (Posterior - Prior) as a function of the difference between their planned fertilizer application rates and the recommendations (Signal - Prior).[29] The former reflects an adjustment from prior to posterior beliefs, while the latter reflects the deviation in the information from the prior – a measure of how "surprising" the information might have been. We report the estimated coefficient α from the equation $\mathit{Posterior}_i - \mathit{Prior}_i = \alpha(\mathit{SHC}_i - \mathit{Prior}_i)$, where α is a parameter that represents farmers' responsiveness, or the weight placed on the signal, SHC_i is the recommended fertilizer application rate, and $Prior_i$ and $Posterior_i$ are the means of farmer i's respective belief distributions represented by their planned fertilizer usage and their endline fertilizer usage.[30] The y-axis plots the revision in usage (the difference between the posterior and their prior) and the x-axis plots the difference between the recommendation and their prior. We report binned scatter plots with a linear regression fit line of the estimated relationship for urea, DAP, and MOP (both including and excluding farmers that use any MOP).[31]

Panel (a) in Figure 9 depicts the responsiveness in urea in urea application for all farmers in the treatment group that planted wheat. If farmers fully reacted to the signal provided on the SHC (placed all weight on the signal), the coefficient would be 1. If farmers did not respond at all to the signal, the coefficient would be equal to zero. The relationship for urea appears to be linear (with an estimated slope of 0.64) and is highly significant ($p < 0.01$), meaning that a per-

[28]The convex conmbination can be expressed as: $\mathit{Posterior}_i = \alpha * \mathit{SHC}_i + (1-\alpha) * \mathit{Prior}_i$, where α is the weight on the signal and $(1-\alpha)$ is the weight on the prior.

[29]Treatment farmers' planned input usage was elicited using a survey just prior to receiving their SHC card and corresponding recommendations.

[30]In a Bayesian learning model, this relationship assumes that the priors and the signals are normally distributed and that the variance of the prior and signal are independent of their respective means.

[31]In general, the α parameter is estimated by interacting $(\mathit{SHC}_i - \mathit{Prior}_i)$ with a treatment indicator while controlling for $(\mathit{SHC}_i - \mathit{Prior}_i)$ to account for spurious reasons that subjects may revise their beliefs in the direction of the signal regardless of whether they were shown the information. In previous studies, 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., 2020).

centage point increase in the gap between the recommendations and farmers' planned fertilizer application rate is associated with a 0.68 percentage point increase in the gap between farmers' endline application rate and their planned application rate. Further, the plotted relationship suggests that there is not a large asymmetry in updating for positive and negative signals, though the relationship appears to be slightly less steep for recommendations that are more than 100 kg/ha larger than their planned usage (the dashed line). Panel (b) in Figure 9 shows that although farmers that received a recommendation to *decrease* their DAP did so on average, there is less evidence that the treatment induced the majority of farmers who received a recommendation to increase their DAP to increase their DAP application. Farmers' response to the MOP recommendation was both linear (slope=0.51) and highly significant ($p < 0.01$), similar to that of urea (Panel (c)). When we consider the subset of farmers that actually applied MOP (N=141), the responsiveness was higher (slope=0.62) and those that received a recommendation to decrease MOP usage did so (Panel (d) in Figure 9). Nearly half of farmers increased their MOP usage relative to their planned application rate when they received a recommendation to increase MOP.

Next, we next study heterogeneity in updating and the role of confidence on responsiveness. The model developed in Section 2 shows (equation 11) that the weight that a farmer places on the signal ($\alpha = \frac{\rho_S}{\rho_S + \rho_{\theta_1}}$) will be decreasing in their confidence, or increasing in the dispersion of their priors ($\rho_{\theta_1} = \frac{1}{\sigma^2_{\theta_1}}$). In order to test the model predictions, we estimate the following regression, where β captures spurious reversion to the signal and $Confidence_i$ is one of three measures of farmer i's confidence: the standard deviation of the elicited beliefs distribution, a dummy that is equal to 1 if farmers reported have much less doubts than their peers about input usage, and a dummy that is equal to 1 if farmers reported that they would have much higher yields relative to their peers if they cultivated on the same plot with equal access to inputs.[32]

$$Posterior_i - Prior_i = \gamma + \alpha(SHC_i - Prior_i) \cdot Confidence_i + \beta(SHC_i - Prior_i) + X_{i0}^{'}\gamma + \nu_e + u_i., \quad (13)$$

$Posterior_i$ is farmer i's endline fertilizer application rate (y_{1iv}), SHC_i is the recommendation shown on the SHC, and $Prior_i$ is the planned fertilizer usage stated prior to receiving the SHC

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

(y_{0iv}). As before, ν_e are enumerator fixed effects, and X_{i0} are controls that include access to credit, plot size, experience, literacy, and age. Standard errors are clustered at the village level

Table 9 reports the differences in responsiveness in urea application by measures of confidence. Using a model of Bayesian updating, less confident farmers, should place more weight on the SHC recommendation. This is confirmed in column 2. A one standard deviation increase in belief dispersion increases the weight that farmers place on the SHC signal by 14 percentage points. Moving from the bottom quartile to the top quartile of the dispersion of farmers' priors increases the weight on the recommendation by more than 23 percentage points. In columns 3 and 4, we report similar results using the the interactions with survey based measures of confidence. Farmers that respond that they would get much higher yields than others given the same inputs have a 17 percentage point less weight on the recommendations and those that report having much less doubts than their peers about input usage place 22 percentage points less weight on the recommendations. The results broadly confirm the model's prediction that more confident farmers place less weight on the signal.

Table 10 reports the differences in responsiveness in DAP application by measures of confidence. We find a similar pattern of estimates as for urea, but the interaction effects, while sizable and in the expected direction, are imprecisely estimated. The estimates suggest that confidence might have played a role in the overall low level of responsiveness of DAP usage to the SHC recommendation, but are inconclusive.

We also assess the extent of heterogeneity in farmers' responsiveness to the SHC across a number of other farmer characteristics including trust, WTP for soil tests, literacy, credit constraints, and wealth for urea (Appendix Tables C1 and C2). We do not find a meaningful effect of baseline trust on responsiveness, though as we show below, trust seems to be correlated with demand for information. It should be noted however that our measure of trust was collected in the baseline survey and may have changed between when it was collected and when farmers received their soil test. Given these caveats, we cannot rule out that trust has an impact on information responsiveness, but we do not find strong evidence for its effect in this context. Further, female farmers place more weight on the urea recommendations. While we don't find an effect of prior credit access, wealthier farmers place a significantly higher weight on the recommendations, suggesting that resource constraints may restrict responsiveness even for a highly subsidized fertilizer. Finally, for DAP, farmers with access to credit in the baseline tend to respond less to the recommendations.

In short, when presented with new soil quality information and recommendations, farmers update their input usage in a Bayesian manner, by revising their input usage towards the recommendations they receive and do so more when they are are less confident. This is true using both elicited measures of prior uncertainty as well as survey based measures of confidence. This updating is particularly strong for urea, and not significant for DAP, which may reflect a higher willingness to experiment with urea due to lower costs, or it may be easier to change the dosing of urea relative to DAP depending on what was available in the market.

5.1 Demand for the SHC

Figure 10 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 section 3.1.1 predicts that farmers with greater confidence should display lower demand for the SHC recommendations.

Table 11 reports regressions of stated WTP on confidence, trust, and literacy. In Columns 1 and 2, confidence is measured through the standard deviation 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 ability. The results indicate that higher levels of dispersion in beliefs on the optimal level of urea or DAP (lower levels of confidence) are both associated with increased WTP for the SHC. A one standard deviation increase in urea beliefs dispersion (0.17) is associated with an increase of $0.32 in WTP, or roughly 20% of the price of the mean WTP. Similarly, a one standard deviation increase in DAP beliefs dispersion (0.19) is associated with an increase in WTP of 0.41. We find similar results in Table 12 using survey based measures of confidence. Farmers that respond that they would get much higher yields than others given the same inputs have a WTP that is 40% lower than the mean WTP and those that report having much less doubts than their peers about input usage have a WTP that is 53% lower than the mean WTP. Not surprisingly, literacy is also found to be positively correlated with WTP, with an effect comparable to that of one standard deviation in urea belief dispersion. However, we do not find evidence that trust is correlated with higher WTP.

Overall, these results lend support to the predictions of the 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., 2020). 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).

6 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 fertilizer use that fall far well short of the potential impacts that would have occurred if farmers fully complied with the SHC recommendations, even for the lowest cost fertilizer (urea). 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. There was, however, a relatively large effect on the likelihood of applying half of the total urea at sowing, which was a practice recommended on the SHC and which improves fertilizer use efficiency.

We further document significant heterogeneity in beliefs about optimal fertilizer application levels prior to receiving the SHC information. Consistent with Bayesian updating in the target input model, 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. 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 may produce the largest returns to the program's investment, especially if there are cost constraints to providing information.

References

Anderson, J. R. and G. Feder (2007). Agricultural extension. *Handbook of agricultural economics 3*, 2343–2378.

Armantier, O., S. Nelson, G. Topa, W. Van der Klaauw, and B. Zafar (2016). The price is right: Updating inflation expectations in a randomized price information experiment. *Review of Economics and Statistics 98*(3), 503–523.

Armona, L., A. Fuster, and B. Zafar (2019). Home price expectations and behaviour: Evidence from a randomized information experiment. *The Review of Economic Studies 86*(4), 1371–1410.

Attanasio, O. and B. Augsburg (2016). Subjective expectations and income processes in rural india. *Economica 83*(331), 416–442.

Attanasio, O. and K. Kaufmann (2009). Educational choices, subjective expectations, and credit constraints. Technical report, National Bureau of Economic Research.

Banuri, S., S. Dercon, and V. Gauri (2019). Biased policy professionals. *The World Bank Economic Review 33*(2), 310–327.

Bardhan, P. and C. Udry (1999). *Development Microeconomics*. Oxford University Press.

Barham, B. L., J.-P. Chavas, D. Fitz, and L. Schechter (2018). Receptiveness to advice, cognitive ability, and technology adoption. *Journal of Economic Behavior & Organization 149*, 239–268.

Beaman, L., A. BenYishay, J. Magruder, and A. M. Mobarak (2021). Can network theory-based targeting increase technology adoption? Technical Report 6.

Becker, G. M., M. H. DeGroot, and J. Marschak (1964). Measuring utility by a single-response sequential method. *Behavioral science 9*(3), 226–232.

Belot, M., P. Kircher, and P. Muller (2019). Providing advice to jobseekers at low cost: An experimental study on online advice. *The review of economic studies 86*(4), 1411–1447.

Benjamin, D. J. (2019). Errors in probabilistic reasoning and judgment biases. In *Handbook of Behavioral Economics: Applications and Foundations 1*, Volume 2, pp. 69–186. Elsevier.

Bennett, D., A. Naqvi, and W.-P. Schmidt (2018). Learning, hygiene and traditional medicine. *The Economic Journal 128*(612), F545–F574.

BenYishay, A. and A. M. Mobarak (2018). Social learning and incentives for experimentation and communication. *The Review of Economic Studies 86*(3), 976–1009.

Berry, J., G. Fischer, and R. Guiteras (2020). Eliciting and utilizing willingness to pay: Evidence from field trials in northern ghana. *Journal of Political Economy 128*(4), 1436–1473.

Bora, K. (2022). Spatial patterns of fertilizer use and imbalances: Evidence from rice cultivation in india. *Environmental Challenges*, 100452.

Casaburi, L., M. Kremer, S. Mullainathan, and R. Ramrattan (2014). Harnessing ict to increase agricultural production: Evidence from kenya. *Harvard University*.

Cavallo, A., G. Cruces, and R. Perez-Truglia (2017). Inflation expectations, learning, and supermarket prices: Evidence from survey experiments. *American Economic Journal: Macroeconomics 9*(3), 1–35.

Coibion, O., Y. Gorodnichenko, and S. Kumar (2018). How do firms form their expectations? new survey evidence. *American Economic Review 108*(9), 2671–2713.

Cole, S., T. Harigaya, G. Killeen, and A. Krishna (2020). Using satellites and phones to evaluate and promote agricultural technology adoption: Evidence from smallholder farms in india. Technical report, Working Paper.

Cole, S. and G. Sharma (2017). The promise and challenges of implementing ict in indian agriculture.

Cole, S. A. and A. N. Fernando (2021). Mobileizing agricultural advice technology adoption diffusion and sustainability. *The Economic Journal 131*(633), 192–219.

Corral, C., X. Giné, A. Mahajan, and E. Seira (2020). Autonomy and specificity in agricultural technology adoption: Evidence from mexico.

Cullen, Z. and R. Perez-Truglia (2022). How much does your boss make? the effects of salary comparisons. *Journal of Political Economy 130*(3), 766–822.

De Quidt, J., J. Haushofer, and C. Roth (2018). Measuring and bounding experimenter demand. *American Economic Review 108*(11), 3266–3302.

Delavande, A., X. Giné, and D. McKenzie (2011). Eliciting probabilistic expectations with visual aids in developing countries: How sensitive are answers to variations in elicitation design? *Journal of Applied Econometrics 26*(3), 479–497.

Delavande, A. and H.-P. Kohler (2009). Subjective expectations in the context of HIV/AIDS in Malawi. *Demographic Research 20*, 817–874.

Dizon-Ross, R. (2019). Parents' beliefs about their children's academic ability: Implications for educational investments. *American Economic Review 109*(8), 2728–65.

Dupas, P. (2011). Do teenagers respond to HIV risk information? Evidence from a field experiment in Kenya. *American Economic Journal: Applied Economics*.

Emerick, K. and M. H. Dar (2020). Farmer field days and demonstrator selection for increasing technology adoption. *Review of Economics and Statistics*, 1–41.

Fabregas, R., M. Kremer, and F. Schilbach (2019). Realizing the potential of digital development: The case of agricultural advice. *Science 366*(6471).

Fafchamps, M., S. Caria, G. Abebe, S. Quinn, P. Falco, and S. Franklin (2020). Anonymity or distance? job search and labour market exclusion in a growing african city. *Review of Economic Studies*.

FAO (2019). *The international Code of Conduct for the sustainable use and management of fertilizers*. Food & Agriculture Org.

Foster, A. D. and M. R. Rosenzweig (1995). Learning by doing and learning from others: Human capital and technical change in agriculture. *Journal of Political Economy*, 1176–1209.

Foster, A. D. and M. R. Rosenzweig (2010). Microeconomics of technology adoption. *Annual Review of Economics 2*.

Fuster, A., R. Perez-Truglia, M. Wiederholt, and B. Zafar (2020). Expectations with endogenous information acquisition: An experimental investigation. *Review of Economics and Statistics*, 1–54.

Guiteras, R. P., D. I. Levine, S. P. Luby, T. H. Polley, K. K. e Jannat, and L. Unicomb (2016). Disgust, shame, and soapy water: Tests of novel interventions to promote safe water and hygiene. *Journal of the Association of Environmental and Resource Economists 3*(2), 321–359.

Haaland, I., C. Roth, and J. Wohlfart (2022). Designing information provision experiments. *Journal of Economic Literature*.

Hanna, R., S. Mullainathan, and J. Schwartzstein (2014). Learning through noticing: Theory and evidence from a field experiment. *The Quarterly Journal of Economics 129*(3), 1311–1353.

Harou, A. P., M. Madajewicz, H. Michelson, C. A. Palm, N. Amuri, C. Magomba, J. M. Semoka, K. Tschirhart, and R. Weil (2022). The joint effects of information and financing constraints on technology adoption: Evidence from a field experiment in rural tanzania. *Journal of Development Economics 155*, 102707.

Harrison, G. W. (2016). Hypothetical surveys or incentivized scoring rules for eliciting subjective belief distributions? Technical report, Center for the Economic Analysis of Risk.

Hjort, J., D. Moreira, G. Rao, and J. F. Santini (2019). How research affects policy: Experimental evidence from 2,150 brazilian municipalities. Technical report, National Bureau of Economic Research.

Jack, B. K. (2013). Market inefficiencies and the adoption of agricultural technologies in developing countries.

Jensen, R. (2010). The (perceived) returns to education and the demand for schooling. *The Quarterly Journal of Economics 125*(2), 515–548.

Jovanovic, B. and Y. Nyarko (1996). Learning by doing and the choice of technology. *Econometrica*, 1299–1310.

Klayman, J., J. B. Soll, C. González-Vallejo, and S. Barlas (1999). Overconfidence: It depends on how, what, and whom you ask. *Organizational Behavior and Human Decision Processes 79*(3), 216–247.

Lee, D. S. (2009). Training, wages, and sample selection: Estimating sharp bounds on treatment effects. *The Review of Economic Studies 76*(3), 1071–1102.

Lybbert, T. J., C. B. Barrett, J. G. McPeak, and W. K. Luseno (2007). Bayesian herders: Updating of rainfall beliefs in response to external forecasts. *World Development 35*(3), 480–497.

Magruder, J. R. (2018). An assessment of experimental evidence on agricultural technology adoption in developing countries. *Annual Review of Resource Economics 10*, 299–316.

Moore, D. A. and P. J. Healy (2008). The trouble with overconfidence. *Psychological Review 115*(2), 502.

Moore, D. A., E. R. Tenney, and U. Haran (2015). Overprecision in judgment. *The Wiley Blackwell handbook of judgment and decision making 2*, 182–209.

Mueller, N. D., J. S. Gerber, M. Johnston, D. K. Ray, N. Ramankutty, and J. A. Foley (2012). Closing yield gaps through nutrient and water management. *Nature 490*(7419), 254–257.

Murphy, D. M., D. Roobroeck, D. R. Lee, and J. Thies (2017). Underground knowledge: Estimating the impacts of soil information transfers through experimental auctions. *American Journal of Agricultural Economics*.

Roth, C. and J. Wohlfart (2019). How do expectations about the macroeconomy affect personal expectations and behavior? *Review of Economics and Statistics*, 1–45.

Roth, C. and J. Wohlfart (2020). How do expectations about the macroeconomy affect personal expectations and behavior? *Review of Economics and Statistics 102*(4), 731–748.

Stango, V. and J. Zinman (2020). We are all behavioral, more or less: A taxonomy of consumer decision making. Technical report, National Bureau of Economic Research.

Suri, T. (2011). Selection and comparative advantage in technology adoption. *Econometrica 79*(1), 159–209.

Vitousek, P. M., R. Naylor, T. Crews, M. B. David, L. Drinkwater, E. Holland, P. Johnes, J. Katzenberger, L. A. Martinelli, P. Matson, et al. (2009). Nutrient imbalances in agricultural development. *Science 324*(5934), 1519–1520.

Vivalt, E. and A. Coville (2020). How do policymakers update their beliefs?

Table 1: Correlations across alternative measures of farmer confidence

	(1) Sd Urea	(2) Sd Urea	(3) Sd Urea	(4) Sd DAP	(5) Sd DAP
Much higher yields	-0.062***			-0.063***	
	(0.022)			(0.014)	
Much less doubts		-0.083***			-0.066***
		(0.023)			(0.019)
SD DAP			0.69***		
			(0.054)		
Constant	0.44***	0.50***	0.20***	0.36***	0.41***
	(0.035)	(0.033)	(0.033)	(0.019)	(0.021)
Observations	864	864	864	864	864
R^2	0.022	0.029	0.279	0.040	0.034
Mean dep. var	0.41	0.41	0.41	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). *"Much higher yields"* is a binary indicator equal to 1 if farmers in the baseline survey responded that they would get much higher yields than their peers given the same soil quality and access to resources. *"Much less doubts"* is a binary indicator equal to 1 if farmers in the baseline survey responded that they have much fewer doubts than their peers about farmings practices. Controls include the mean of the farmer's distributions of subjective beliefs. Standard errors (adjusted for clustering at the village level) in parentheses.

Table 2: Planned fertilizer application for *rabi* 2014-15 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	%
Urea	1.0	199.4	89.6	0.0	553.3	1.0	244.6	27.1	127.3	316.8	70
DAP	1.0	112.0	38.1	0.0	217.4	1.0	164.8	35.2	99.7	240.0	80
MOP	0.4	13.2	20.8	0.0	158.1	1.0	81.6	20.2	34.1	122.5	100
N			388					389			

Notes: Columns 1-5 report a binary variable 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. Columns 6-10 report a binary variable 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

Variable	(1) Control Mean/SE	(2) Treatment Mean/SE	(3) No Test Mean/SE	T-test P-value (1)-(2)	(1)-(3)	(2)-(3)
Age	46	45	45	0.31	0.54	0.99
	(0.88)	(0.73)	(1.70)			
Female	0.05	0.09	0.13	0.09*	0.11	0.35
	(0.01)	(0.01)	(0.04)			
Literacy	0.65	0.69	0.58	0.45	0.32	0.09*
	(0.05)	(0.03)	(0.04)			
Trust	0.31	0.31	0.29	0.82	0.83	0.70
	(0.03)	(0.02)	(0.06)			
Clay/loam soil	0.74	0.76	0.80	0.69	0.49	0.59
	(0.04)	(0.04)	(0.08)			
Slope (flat)	0.91	0.92	0.95	0.88	0.28	0.34
	(0.02)	(0.02)	(0.03)			
WTP for soil test (USD)	1.60	1.60	1.8	0.98	0.79	0.70
	(0.25)	(0.17)	(.36)			
Mean urea beliefs	208	207	203	0.96	0.79	0.73
	(15)	(8.4)	(12)			
Mean diammonium phosphate (DAP) beliefs	103	103	91	0.98	0.20	0.11
	(6)	(4.3)	(7.4)			
Kharif 2013 urea	223	213	213	0.70	0.67	0.95
	(21)	(16)	(16)			
Kharif 2013 DAP	102	106	95	0.57	0.38	0.07*
	(5.8)	(4.8)	(8.6)			
Rabi yield 2014 (q/ha)	27	27	26	0.74	0.92	0.59
	(1.30)	(0.99)	(.35)			
N	288	497	79			
Clusters	16	31	21			
F-test of joint significance (p-value)				0.39	0.64	0.34
F-test, number of observations				785	367	576

* 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 and realized paddy yields in 2013 for farmers in the control group. 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	-0.12***	-0.0088	-0.015
	[-0.20,-0.045]	[-0.048,0.030]	[-0.075,0.044]
Observations	864	785	743
Adjusted R^2	0.105	0.034	0.031
Mean dep. var	0.86	0.94	0.84

This table reports results on attrition in different samples of our study. For all columns, we run the following regression: $Y_{ivb} = \beta_0 + \beta_1 SHC_i + \alpha_b + \epsilon_{ivb}$, where i corresponds to a farmer, Y is the outcome of interest. We include randomization strata fixed effects and compute robust standard errors. At the bottom of the table, we report the mean of the outcome for the control group, the omitted category in our regression. In Column 1, we use the sample of 864 farmers who participated in the baseline survey and were not part of the treatment group that was excluded due to contaminated soil tests. The outcome is a dummy that takes value of 1 for farmers that were interviewed during the endline survey. In Column 2, we limit the sample to the 735 farmers that were interviewed in the endline and the outcome is a dummy that takes value 1 for farmers who planted wheat on their tested plot. Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Effect of SHC on fertilizer application rates in *rabi* 2014-15

	(1) Urea	(2) DAP	(3) MOP	(4) MOP=1	(5) Urea sowing=.5
SHC	10.3**	-6.33	2.02	0.075	0.092**
	[0.69,20.0]	[-16.7,4.01]	[-1.27,5.30]	[-0.018,0.17]	[0.0040,0.18]
Observations	621	621	621	621	621
Adjusted R^2	0.358	0.213	0.498	0.575	0.066
Mean dep. var.	217.3	115.9	17.6	0.46	0.20
Lee Bounds - Full (95 CI)	[-5.62,31.60]	[-16.06,3.73]	[-5.64,3.92]	[-0.09,0.10]	[0.03,0.20]
Benchmark	25.68	39.21	64.72	0.65	0.87

* Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level.
Notes: All columns report the estimates from a regression of endline fertilizer application rates on receipt of the SHC as well as 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 Lee bounds for the independent variable to take into account potential selection into the sample that planted wheat compared to the original study sample of 864 farmers. The dependent variable in columns 1-3 are endline fertilizer application rates (kg/ha). In column 4, the dependent variable is a binary variable 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 variable that takes a value of 1 if the farmer applied half of the total amount of urea during sowing and 0 otherwise.

Table 6: 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	23.24	118	-2.67	42	-55.73	12
Less than recommended	-67.44	85	-63.02	135	-68.86	230
Recommended amount	-21.40	93	-43.99	119	-44.12	54
No SHC for reference	-36.61	93	-61.66	93	-65.75	93
Full sample	-21.56	389	-50.36	389	-64.28	389

Notes: Difference between endline fertilizer use and the recommended application, disaggregated by farmers' self-reports of how much fertilizer they actually applied relative to the amount on the SHC. 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. "Recommendation" denotes the derived fertilizer application rate recommendation from soil tests based on a target yield of 4 tons per hectare. The self-reported evaluations of how much they applied relative to the recommendations on the SHC were elicited during the endline survey.

Table 7: Self-Reported Rationales for Over- and Under-applying Fertilizers Relative to Recommended Application

	Urea		DAP		Potash	
Reason for over-/under-application of fertilizers	Freq.	Percent	Freq.	Percent	Freq.	Percent
Why used more than recommended?						
Fertilizer cost is low	5	2	0	0	0	0
Using less will reduce yields	46	30	27	52	7	50
Believe the usual amount is the right amount	101	66	25	48	7	50
Why used less than recommended?						
Fertilizer cost is high	7	5	62	31	86	27
Does not have enough money	9	7	14	7	27	9
Yields would not increase by using more	8	6	4	2	10	3
Returns would not increase by using more	4	3	12	6	7	2
Using more would damage the crop	7	5	8	4	13	4
Believe usual amount is the right amount	76	58	92	46	152	48
Fertilizer is not available	9	7	1	1	10	3
Other	11	8	5	2	12	4

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 2015 *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 8: Correlations of observed fertilizer application with SHC recommendations and planned fertilizer application (priors)

	(1) Urea	(2) Urea	(3) DAP	(4) DAP	(5) MOP	(6) MOP
SHC Rec	0.42**	0.40**	-0.052	-0.050	0.21***	0.21***
	(0.18)	(0.17)	(0.10)	(0.10)	(0.064)	(0.063)
Prior	0.28***	0.28***	0.095	0.095	0.22***	0.22***
	(0.079)	(0.077)	(0.078)	(0.078)	(0.070)	(0.070)
Controls	No	Yes	No	Yes	No	Yes
Observations	388	388	388	388	388	388
Mean dep. var	221.8	221.8	113.5	113.5	17.0	17.0
$\beta 1 + \beta 2 = 1$	0.1	0.1	0.0	0.0	0.0	0.0

* Significant at 10 percent level; ** Significant at 5 percent level; *** Significant at 1 percent level.
Notes: Dependent variables are endline fertilizer application rates (kg/ha). "SHC Rec" is the recommended application rate shown on the SHC. "Prior" is the self-reported planned fertilizer application rate in the 2014-15 rabi season, which was elicited prior to receiving the SHC. Controls include age, literacy, 2013 *kharif* yields, trust, CRRA, plot size, and enumerator fixed effects. Standard errors (adjusted for clustering at the village level) in parentheses.

Table 9: Urea responsiveness: weight placed on signal by confidence level

	(1) (Post-Prior)	(2) (Post-Prior)	(3) (Post-Prior)	(4) (Post-Prior)
(SHC - Prior)	0.64***	0.42***	0.74***	0.86***
	(0.067)	(0.12)	(0.070)	(0.11)
(SHC - Prior) $\times$ SD Urea		0.69**		
		(0.31)		
Much higher yields=1 $\times$ (SHC - Prior)			-0.17*	
			(0.087)	
Much less doubts=1 $\times$ (SHC - Prior)				-0.21*
				(0.12)
Controls	Yes	Yes	Yes	Yes
Observations	388	388	388	388
R^2	0.358	0.381	0.379	0.379

* Significant at 10 percent level; ** Significant at 5 percent level; *** Significant at 1 percent level.
Notes: Dependent variable is the update in farmers' subjective belief regarding optimal urea application rate, measured as actual endline urea application rates (Post) minus planned application rates (Prior). The primary explanatory variable is the difference between the received signal (SHC) and farmers' planned application rates (Prior), 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 reported have much fewer doubts than their peers about input usage ("Much less doubts"), and a binary indicator that is equal to 1 if farmers reported that they would have much higher yields relative to their peers if they cultivated on the same plot with equal access to inputs ("Much higher yields"). "SHC" is the recommended application rate of urea shown on the SHC (kg/ha). "Prior" is the planned fertilizer application rate for the 2014-15 rabi season, which was elicited prior to receiving the SHC (kg/ha). The regressions control for the mean of farmers' belief distribution, age, literacy, 2013 *kharif* rice yields, trust, plot size, and enumerator fixed effects. Standard errors (adjusted for clustering at the village level) in parentheses.

Table 10: DAP responsiveness: weight placed on signal by confidence level

	(1) (Post-Prior)	(2) (Post-Prior)	(3) (Post-Prior)	(4) (Post-Prior)
(SHC - Prior)	0.49***	0.40***	0.58***	0.64***
	(0.071)	(0.14)	(0.089)	(0.097)
(SHC - Prior) × SD DAP		0.37		
		(0.40)		
Much higher yields=1 × (SHC - Prior)			-0.17	
			(0.13)	
Much less doubts=1 × (SHC - Prior)				-0.14
				(0.12)
Controls	Yes	Yes	Yes	Yes
Observations	388	388	388	388
R^2	0.221	0.246	0.246	0.245

* Significant at 10 percent level; ** Significant at 5 percent level; *** Significant at 1 percent level.
Notes: Dependent variable is the update in farmers' subjective belief regarding optimal DAP application rate, measured as actual endline DAP application rates (Post) minus planned application rates (Prior). The primary explanatory variable is the difference between the received signal (SHC) and farmers' planned application rates (Prior), 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 reported have much fewer doubts than their peers about input usage ("Much less doubts"), and a binary indicator that is equal to 1 if farmers reported that they would have much higher yields relative to their peers if they cultivated on the same plot with equal access to inputs ("Much higher yields"). "SHC" is the recommended application rate of DAP shown on the SHC (kg/ha). "Prior" is the planned fertilizer application rate for the 2014-15 rabi season, which was elicited prior to receiving the SHC (kg/ha). The regressions control for the mean of farmers' belief distribution, age, literacy, 2013 *kharif* rice yields, trust, plot size, and enumerator fixed effects. Standard errors (adjusted for clustering at the village level) in parentheses.

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	1.00**	0.84**	1.79***	1.68***		
	(0.39)	(0.40)	(0.43)	(0.44)		
SD DAP	2.31***	2.46***			2.87***	2.92***
	(0.52)	(0.52)			(0.51)	(0.51)
Trust	0.053	0.053	0.049	0.046	0.092	0.086
	(0.13)	(0.13)	(0.14)	(0.14)	(0.13)	(0.13)
Literacy	0.43***	0.33***	0.39***	0.31**	0.43***	0.32**
	(0.12)	(0.12)	(0.11)	(0.12)	(0.12)	(0.12)
Constant	1.35***	1.41***	1.87***	1.92***	1.60***	1.67***
	(0.45)	(0.43)	(0.40)	(0.40)	(0.37)	(0.39)
Controls	No	Yes	No	Yes	No	Yes
Observations	864	864	864	864	864	864
Adjusted R^2	0.328	0.343	0.302	0.313	0.322	0.339
Mean dep. var	1.65	1.65	1.65	1.65	1.65	1.65

* Significant at 10 percent level; ** Significant at 5 percent level; *** Significant at 1 percent level.
Note: Dependent variable is 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. 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 tested plot, whether the household owned an irrigation pump, 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
Much higher yields	-0.68***	-0.67***		
	(0.11)	(0.10)		
Much less doubts			-0.87***	-0.81***
			(0.20)	(0.20)
Constant	2.74***	2.81***	3.08***	3.09***
	(0.12)	(0.23)	(0.16)	(0.25)
Controls	No	Yes	No	Yes
Observations	864	864	864	864
Adjusted R^2	0.295	0.310	0.297	0.310
Mean dep. var	1.65	1.65	1.65	1.65

* Significant at 10 percent level; ** Significant at 5 percent level; *** Significant at 1 percent level.
Note: Dependent variable is stated willingness to pay for soil testing and recommendations ($US). The measures of confidence include a binary indicator equal to 1 if farmers reported they would have much fewer doubts than their peers about input usage (*"Much less yields"*) and 0 otherwise, and a second binary indicator equal to 1 if farmers reported that they would have much higher yields relative to their peers if they cultivated on the same plot with equal access to inputs (*"Much higher yields"*). 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 tested plot, whether the household owned an irrigation pump, and whether the household had access to credit during *rabi* 2013.

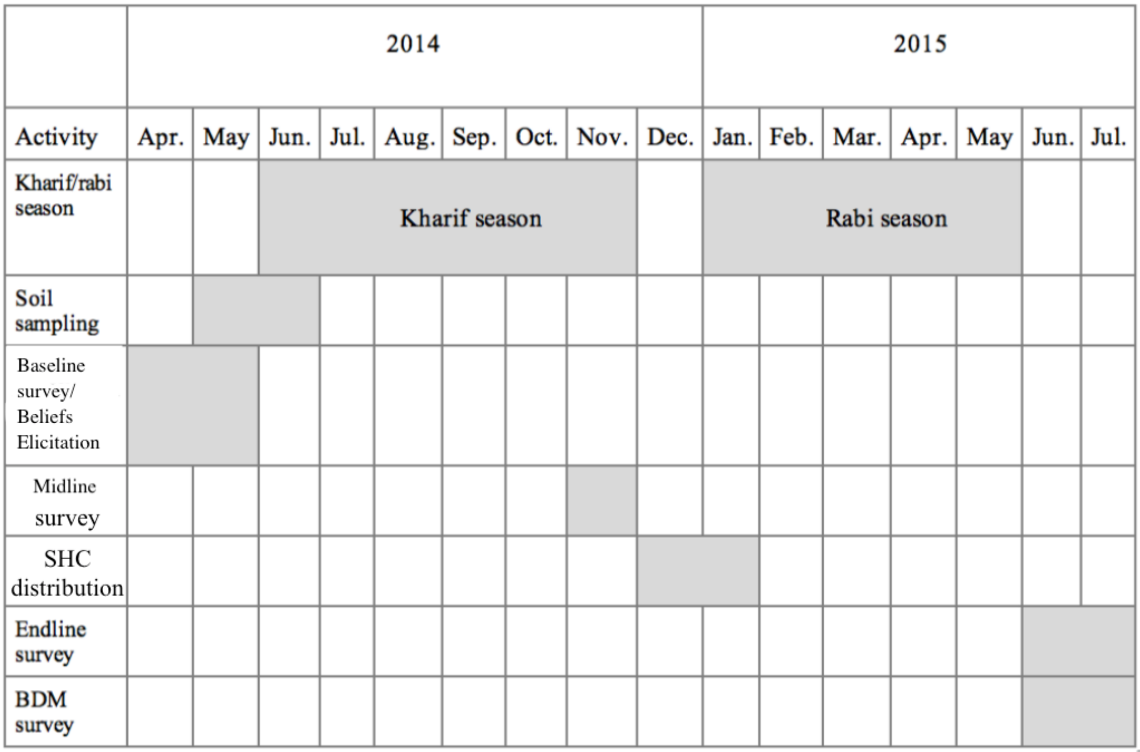
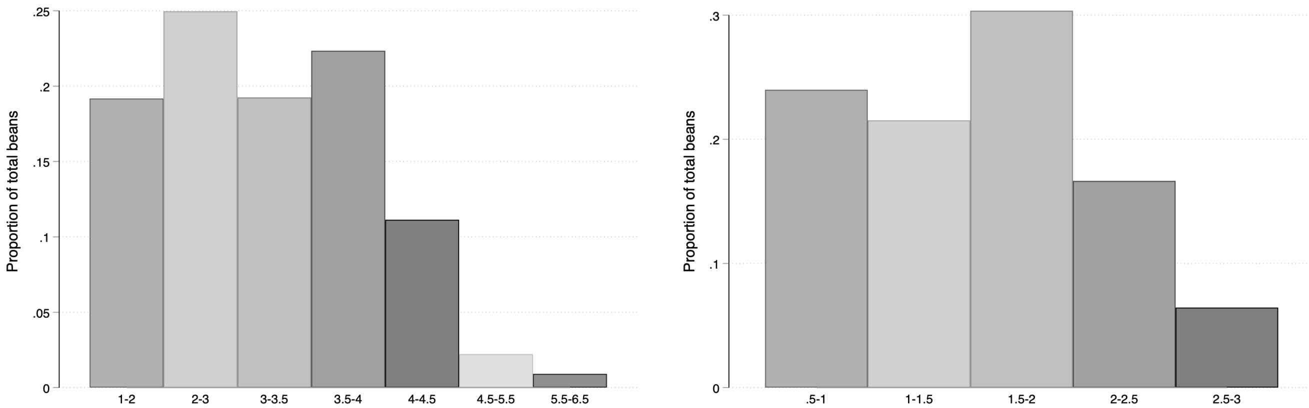


Figure 1: Timeline of Data Collection

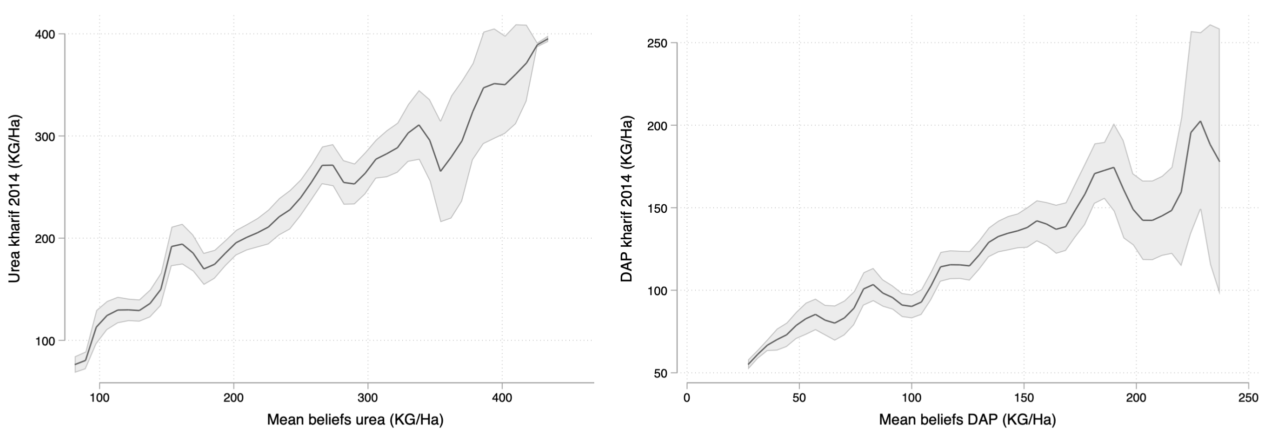
Figure 2: Proportion of Total Beans Allocated to Fertilizer Ranges (kg/katha)



(a) Urea (b) DAP

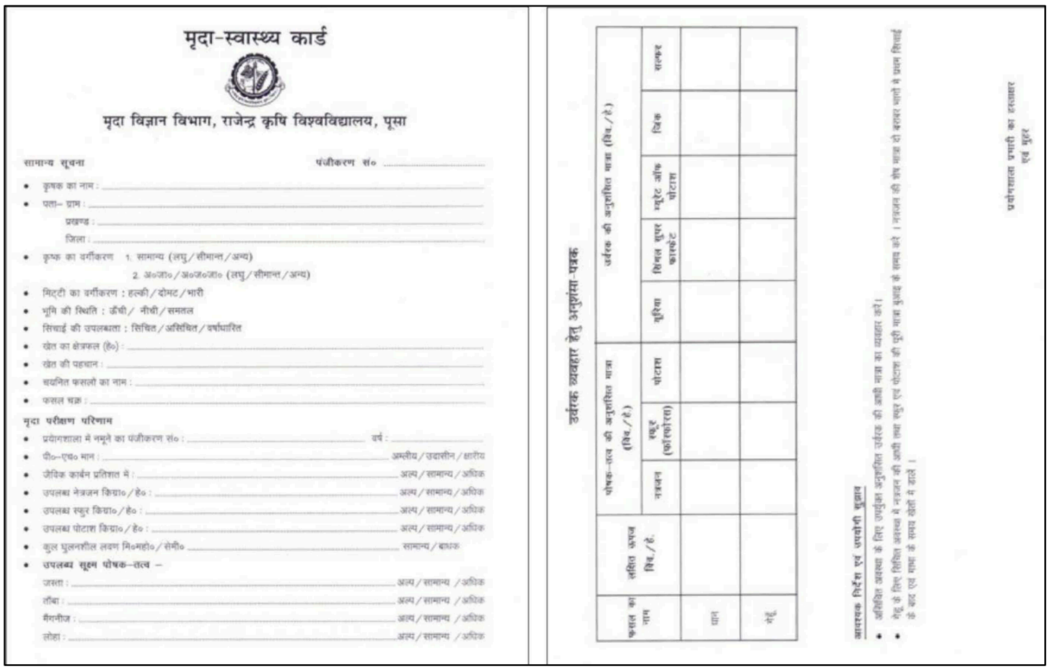
Notes: This figure presents the total proportion of beans allocated to each of the fertilizer application ranges shown to farmers during the belief elicitation exercise in kg/katha.

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



(a) Urea (b) DAP

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 locally polynomial smoothing regression with an Epanechnikov kernel (bandwidth = 0.12). The 95% confidence intervals account for clustering by village.



मृदा-स्वास्थ्य कार्ड

मृदा विज्ञान विभाग, राजेन्द्र कृषि विश्वविद्यालय, पूसा

सामान्य सूचना — पंजीकरण सं०

- कृषक का नाम :
- पता– ग्राम :
  प्रखण्ड :
  जिला :
- कृषक का वर्गीकरण 1. सामान्य (लघु/सीमान्त/अन्य)
  2. अ०जा०/अ०ज०जा० (लघु/सीमान्त/अन्य)
- मिट्टी का वर्गीकरण : हल्की/दोमट/भारी
- भूमि की स्थिति : ऊँची/ नीची/समतल
- सिंचाई की उपलब्धता : सिंचित/असिंचित/वर्षाधारित
- खेत का क्षेत्रफल (हे०) :
- खेत की पहचान :
- चयनित फसलों का नाम :
- फसल चक्र :

मृदा परीक्षण परिणाम

- प्रयोगशाला में नमूने का पंजीकरण सं० : वर्ष :
- पी०-एच० मान : अम्लीय/उदासीन/क्षारीय
- जैविक कार्बन प्रतिशत में : अल्प/सामान्य/अधिक
- उपलब्ध नेत्रजन किग्रा०/हे० : अल्प/सामान्य/अधिक
- उपलब्ध स्फुर किग्रा०/हे० : अल्प/सामान्य/अधिक
- उपलब्ध पोटाश किग्रा०/हे० : अल्प/सामान्य/अधिक
- कुल घुलनशील लवण मि०म्हो०/सेमी० सामान्य/बाधक
- उपलब्ध सूक्ष्म पोषक-तत्व –
  जस्ता : अल्प/सामान्य /अधिक
  ताँबा : अल्प/सामान्य /अधिक
  मैंगनीज : अल्प/सामान्य /अधिक
  लोहा : अल्प/सामान्य /अधिक

उर्वरक व्यवहार हेतु अनुशंसा-पत्रक

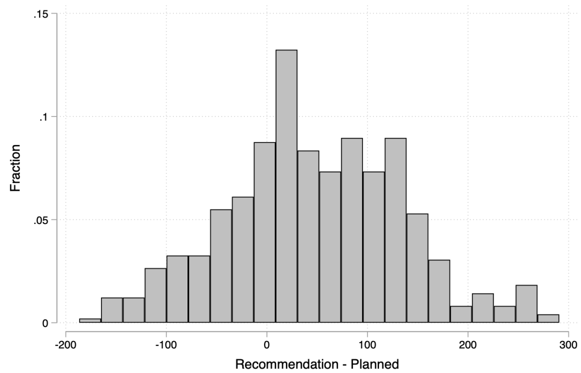
फसल का नाम	लक्षित उपज क्वि./है.	पोषक-तत्व की अनुशंसित मात्रा (कि./है.)			उर्वरक की अनुशंसित मात्रा (कि./है.)				
		नत्रजन	स्फुर (फॉस्फोरस)	पोटास	यूरिया	सिंगल सुपर फास्फेट	म्यूरेट ऑफ पोटाश	जिंक	सल्फर
धान									
गेहूँ									

आवश्यक निर्देश एवं उपयोगी सुझाव

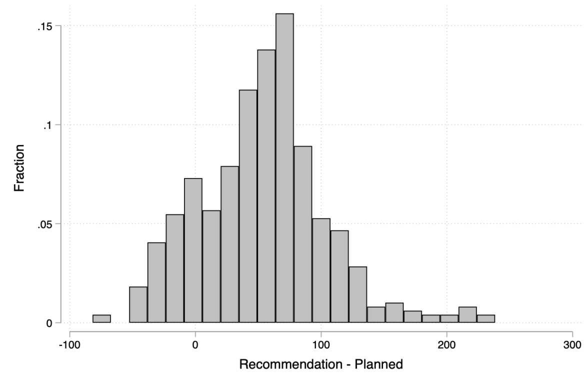
प्रयोगशाला प्रभारी का हस्ताक्षर एवं मुहर

Figure 4: Example SHC (Hindi)

Figure 5: Density of Difference Between Baseline Fertilizer Application Rates and Recommendation (kg/ha)

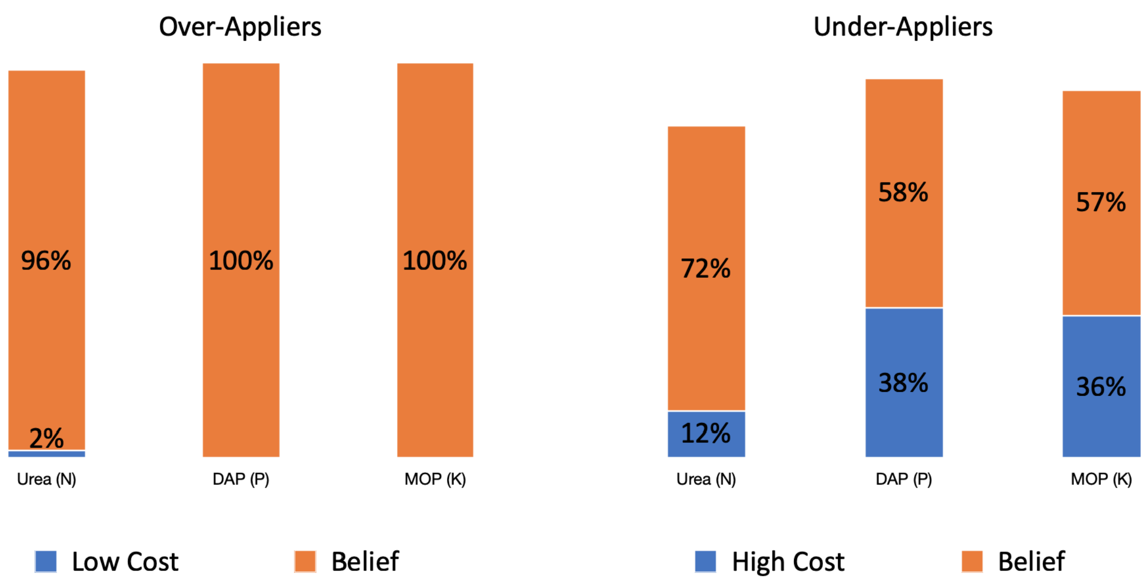


(a) Urea (All blocks)

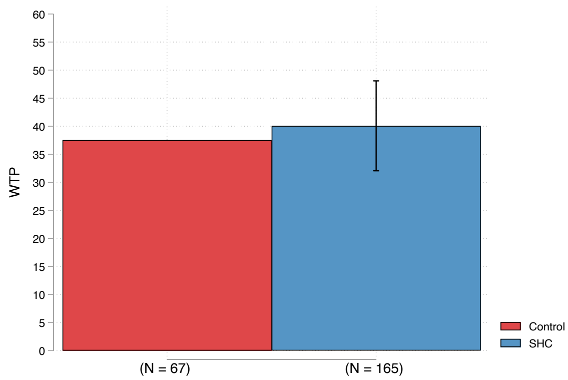


(b) DAP (All blocks)

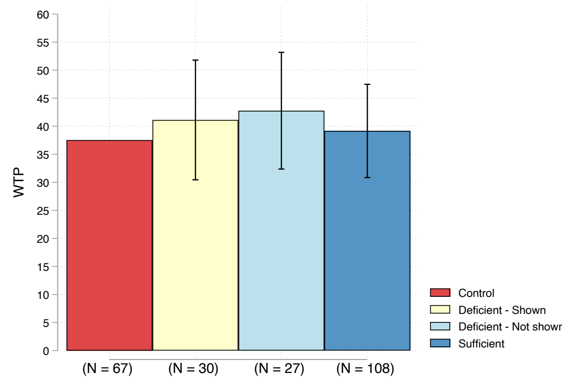
Figure 6: Self-Reported Reasons for Under- or Over-Applying Fertilizers



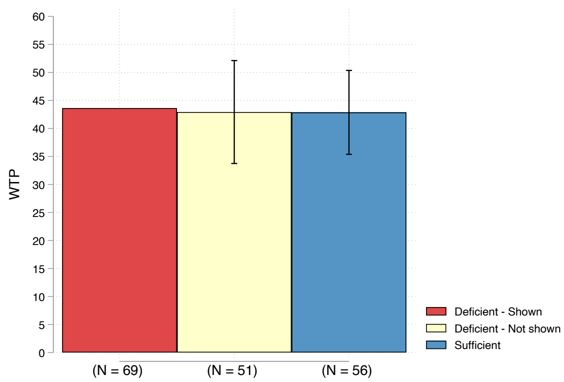
Notes: Fraction of treated farmers who have reported cost related issues and belief related issues as reasons for over (left) or under (right) applying fertilizers in relation to the SHC recommendations. Responses were categorized according to whether they were cost or belief related. See Table 7.



(a) Control vs SHC - Nawada and Bhojpur



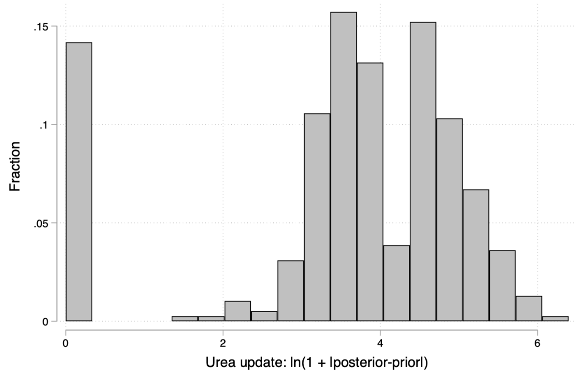
(b) Nawada and Bhojpur



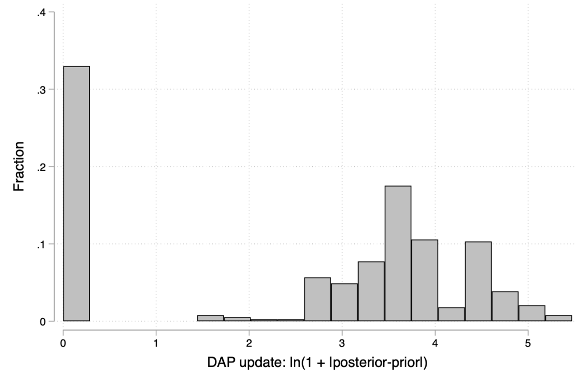
(c) Madhubani

Figure 7: BDM Elicited Willingness to Pay for zinc

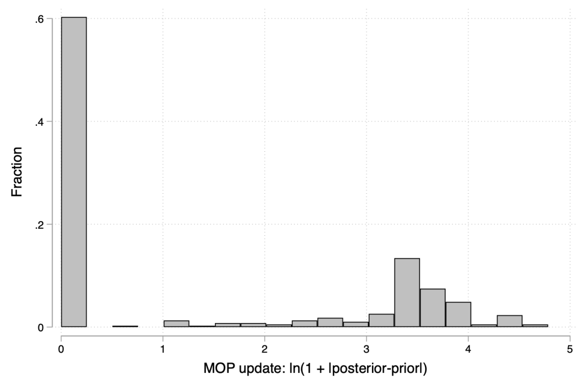
This figure reports the coefficients of a regression of farmers' WTP for 1kg packages of zinc sulphate elicited through a BDM mechanism on treatment status (Panel A) and on sub-samples (defined in the text). In Panel (a), the sample includes farmers in two districts (Nawada and Bhojpur) and the coefficient is the causal effect of treatment on WTP. In Panel (b), the sample includes farmers in Nawada and Bhojpur and the excluded category is the control group. In Panel (c), the sample includes farmers in Madhubani and the excluded category is zinc deficient farmers that were shown the SHC prior to bidding. WTP is reported separately in Madhubani district because the control or "No SHC" sample excluded Madhubani district. The regressions include controls for age, credit access, plot size,literacy, irrigation usage, and plot size. We also include block fixed effects and robust standard errors clustered at the village level are in parentheses. All coefficients are insignificant.



(a) Urea



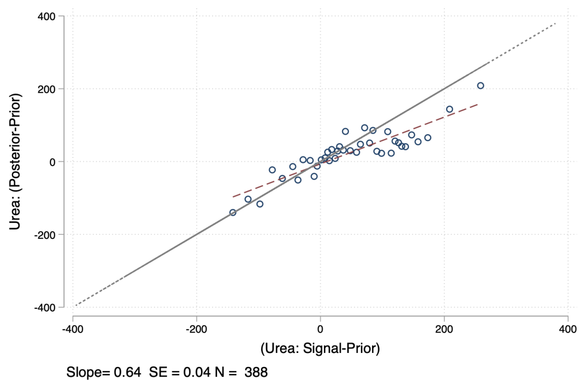
(b) DAP



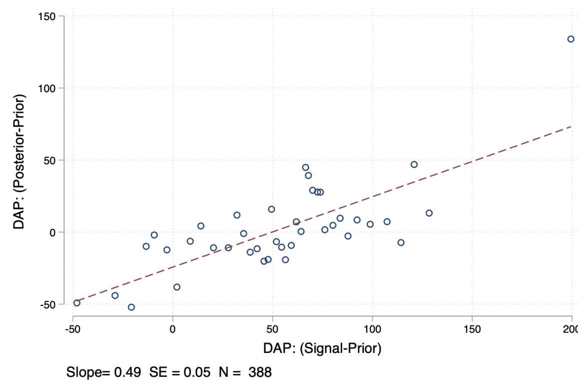
(c) MOP

Figure 8: Distribution of Belief Updating of Fertilizer Application Rates

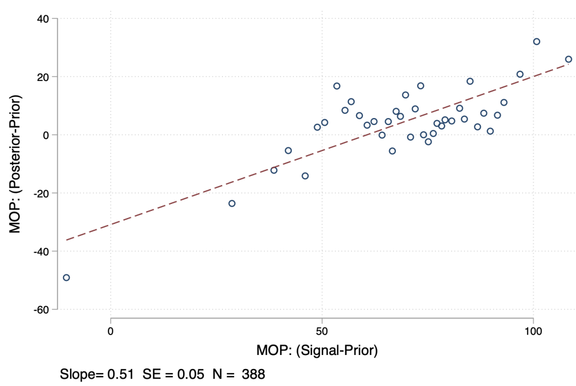
This figure presents the the degree of updating ($ln(1 + |posterior - prior|)$) between planned fertilizer usage in *rabi* 2014 prior to the receipt of the SHC and actual fertilizer application rates in *rabi* 2014 measured at endline. The sample includes farmers that planted wheat in the *rabi* 2014 season. The fraction at zero represents farmers that do not update between their planned usage and actual usage. The corresponding shares of farmers that do not update at all are 14 percent and 33 percent, respectively.



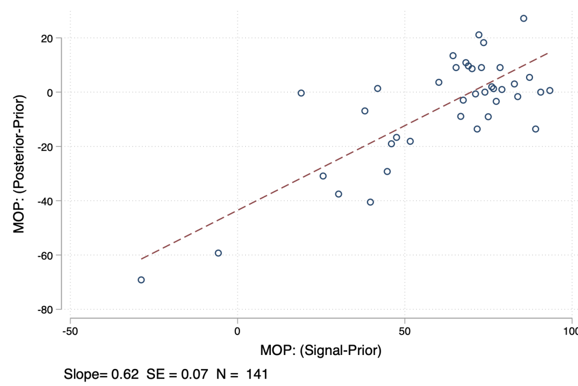
(a) Urea



(b) DAP



(c) MOP



(d) MOP (Planned>0

Figure 9: Responsiveness of Fertilizer Application Rates

Responsiveness is estimated by regressing endline fertilizer usage on the predicted recommendation, control variables, and block fixed effects. Standard errors are clustered at the village level. The slope and robust standard errors for each treatment condition are reported in the figures. Panel (a) shows 20 equal-sized bins of the mean residualized values of endline application rates and the predicted recommendations for urea by treatment condition. Panels (b) and (c) shows statistics for DAP and MOP by treatment condition.

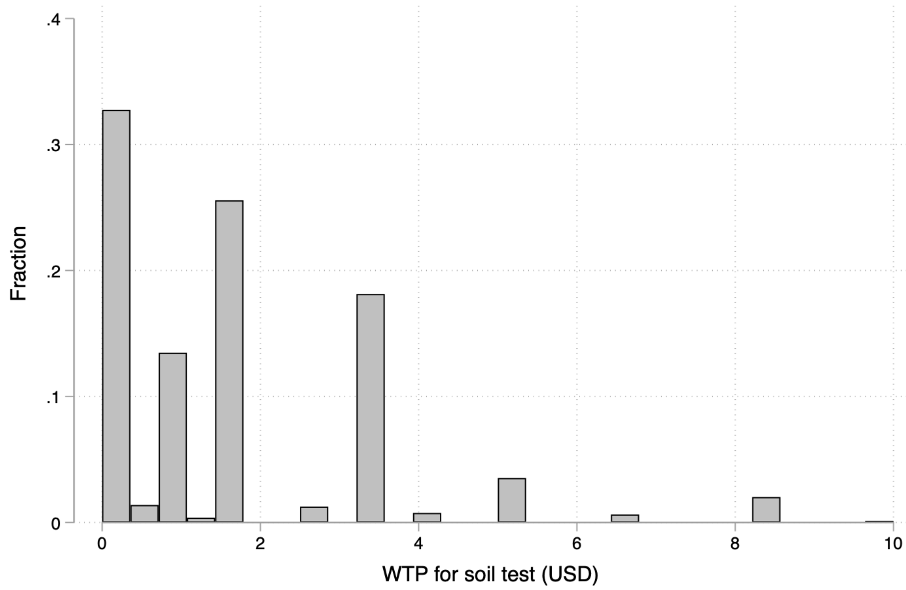


Figure 10: Willingness to Pay for SHC
This figure shows the distribution of stated willingness to pay (WTP) for soil testing and the SHC for all farmers in the baseline.

Appendix A Robustness to Attrition

Attrition in the study comes primarily from soil tests in the treatment group that could not be processed (due to contamination or insufficient sample size) or from being unable to locate households in the endline survey. Table 4 provides attrition rates by treatment group for the experimental sample. We eliminated treatment households from the endline that did not have their soil tested due to concerns from the project partners about lowering trust for the institution. As a result, 11 percent of the original treatment sample is not present in the endline survey due to testing, while another 10 percent of the remaining sample is not present in the endline due to not being able to followup in the endline (11 percent in control and 7 percent in treatment).

To examine how robust our results are to attrition, we use the bounding approach of (Lee, 2009) to construct upper and lower bounds for the treatment effect. We construct the bounds by trimming either the top or the bottom of the distribution of fertilizer application rates for the treatment groups by the relative difference in attrition rates between treatment and control. To examine the impact of attrition on our fertilizer application results, we estimate the bounds of the ITT effect for the full sample of farmers without limiting to those that do not plant wheat in the endline. Lee bounds of the treatment effects on fertilizer application rates are provided in square brackets in Table 5. The estimates of the treatment effects for urea lie in between the bounds estimated in column 1 using OLS. The parameter estimates are closer to the upper bounds than the lower bounds. In this case, the lower bounds would occur only if treatment farmers that apply low amounts of urea attrited. However, in Table 3, a comparison of variables that were correlated with attrition suggest that only the gender of the household head is statistically different from the remaining treatment group. A regression of fertilizer application rates on baseline characteristics in the control group suggest that gender has no impact on fertilizer application rates.

Appendix B Zinc

Prior to initiating the BDM, we informed all farmers, in general terms, of the potential impact of zinc deficiency for crops and the expected gains from application of zinc to deficient soils. After explaining the way the valuation elicitation exercise would be implemented, we conducted two practice rounds. One practice round entailed a real bidding process (essentially open-ended contingent valuation) without an actual transaction of money for a good of a relatively lower value than zinc (a 250 g pack of lentils). The second practice round included the drawing of a random price, which determined whether they did or did not actually purchase the good. In the actual zinc valuation, farmers were offered 1 kg packs of zinc sulfate ($ZnSO_4$) fertilizer. The binding sale price (which was randomly drawn) ranged from INR 10 to INR 60 (the prevailing market rate) for a 1 kg pack. A farmer with a stated WTP above the randomly selected price was then bound to purchase the packet of zinc sulfate, with an option to purchase a quantity up to the recommended dose for his or her tested plot at the random sale price.

The exercise was administered to four groups of farmers in the districts of Nawada and Bhojpur: a random sample of control farmers who did not receive a SHC ("No SHC", n=67), the treatment farmers whose SHC indicated zinc sufficiency ("Sufficient", n=108), the treatment farmers whose SHC indicated zinc deficiency ("Deficient", n=57). The latter group was further randomly divided into two sub-groups, "Deficient, Not Shown" (n=30) and "Deficient, Shown" (n=27). Farmers in group "Deficient, Shown" were shown their SHC and reminded that it had indicated zinc deficiency. The purpose of this was to make the SHC content immediately salient to some of the farmers prior to eliciting their WTP for zinc. The protocol informed all farmers of the potential impact of zinc deficiency for crops and the expected gains from application of zinc to deficient soils. This information was conveyed in very general terms, without explicit reference to the farmers' actual conditions. Due to logistical constraints, the control group ("No SHC") included half of the farmers in each control villages in Bhojpur and Nawada districts, but did not include any farmers in Madhubani district. The BDM exercise was also conducted in the Madhubani district, but the results that we show do not have a relevant control group for comparison. A comparison of WTP between the "No SHC" group and the rest of the sample estimates the causal effect that the SHC distribution had on WTP (in Bhojpur and Nawada). Because the soil health card did not recommend zinc for all treatment farmers, we further analyze the WTP between the "Sufficient" and "Deficient" groups and between the "Deficient, Shown" and "Deficient, Not Shown" farmers. While the comparisons are not experimental, they can provide suggestive evidence of whether signals of deficiency and the salience of the associated recommendation affect WTP for a micronutrient.

Table B1 shows that the treatment and control farmers included in this sub-experiment were balanced in terms of the baseline characteristics (Madhubani excluded). By chance, the treatment farmers were slightly more likely to have a mix of clay and loam soil. We control for this slight imbalance in the soil type in our estimation.

Table B1: Summary Statistics and Balance Across Treatment Arms - BDM sample

Variable	(1) SHC Mean/SE	(2) Control Mean/SE	T-test P-value (1)-(2)
Age	48	46	.39
	(2)	(1.4)	
Female	.03	.048	.51
	(.02)	(.02)	
Literacy	.66	.78	.24
	(.083)	(.044)	
Trust	.27	.28	.71
	(.036)	(.026)	
Clay/loam soil	.7	.84	.097*
	(.079)	(.031)	
Slope (flat)	.9	.93	.42
	(.03)	(.022)	
WTP for soil test (USD)	2	2.1	.78
	(.28)	(.26)	
Mean Urea	249	234	.23
	(12)	(6.9)	
Mean DAP	112	112	.83
	(7.4)	(6.9)	
SD Urea	.43	.43	.84
	(.028)	(.022)	
SD DAP	.36	.35	.77
	(.023)	(.019)	
Rabi yield 2014 (q/ha)	28	27	.74
	(1.4)	(1.5)	
Transplant date (z-score)	.71	.6	.73
	(.14)	(.11)	
N	67	165	
Clusters	9	17	
F-test of joint significance (p-value)			.15
F-test, number of observations			232

* Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level.
Notes: This table reports the balance checks for farmer and soil characteristics and fertilizer usage for the subsample of 232 farmers in that participated in the BDM zinc valuation at endline. This sample excludes farmers from Madhubani where control farmers did not participate in the BDM valuation. Column 1 reports average self-reported measures of age, gender, literacy, trust, soil type, elicited beliefs, average fertilizer usage and realized paddy yields in 2013 for farmers in the control group. Standard errors are reported in parentheses. Column 2 is analogous to column 1 but includes the treatment sample. Fertilizer application rates are reported in kilograms per hectare. The p-values in columns 3 are for tests of the null of equal means across the treatment and control. Standard errors for the differences are clustered at the treatment assignment (village) level. Individual balance tests include block fixed effects to account for randomization stratified at the block level. The p-value for the asymptotic F -tests 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 clustered at the treatment assignment level. DAP is diammonium phosphate.

Appendix C Heterogeneous responses to SHC

Table C1: Weighting of priors and recommendation on Urea application by farmer characteristics

	(1) Trust	(2) WTP	(3) Age	(4) Literate	(5) Female	(6) Experience	(7) IHS(houseval)	(8) Credit
(SHC - Prior)	0.69***	0.63***	0.69***	0.64***	0.73***	0.68***	0.34**	0.69***
	(0.071)	(0.073)	(0.11)	(0.070)	(0.070)	(0.073)	(0.15)	(0.068)
(SHC - Prior) × Char.	-0.015	0.039*	-0.000072	0.068	-0.43***	0.17	0.033**	0.084
	(0.087)	(0.019)	(0.0027)	(0.087)	(0.13)	(0.18)	(0.012)	(0.33)
Observations	388	388	388	388	388	388	388	388
Mean Characteristic	0.30	1.67	45.0	0.69	0.088	0.046	11.1	0.046

* Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level.
Notes: The dependent variables are endline urea application rates (kg/ha). Rec is the recommended application rate shown on the SHC. Prior is the planned fertilizer application rate in the 2015 rabi season which was asked prior to receiving the SHC. We include the following farmer characteristics as interactions: Irrigation hours, Age, Literate=1, Female=1, Years of experience wheat farming=1 if less than 5, CRRA, stated WTP for soil tests, access to credit=1, and the inverse hyperbolic sign of the value of the farmer's house. Regressions include enumerator fixed effects and robust standard errors clustered at the village level are in parentheses.

Table C2: Weighting of priors and recommendation on DAP application by farmer characteristics

	(1) Trust	(2) WTP	(3) Age	(4) Literate	(5) Female	(6) Experience	(7) IHS(houseval)	(8) Credit
(SHC - Prior)	0.54***	0.53***	0.68***	0.53***	0.56***	0.54***	0.43**	0.55***
	(0.077)	(0.097)	(0.17)	(0.13)	(0.074)	(0.076)	(0.17)	(0.073)
(SHC - Prior) × Char.	-0.0095	0.0018	-0.0033	0.0029	-0.30	-0.12	0.012	-0.47**
	(0.086)	(0.027)	(0.0036)	(0.15)	(0.27)	(0.20)	(0.013)	(0.22)
Observations	388	388	388	388	388	388	388	388
Mean Characteristic	0.30	1.67	45.0	0.69	0.088	0.046	11.1	0.046

* Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level.
Notes: The dependent variables are endline DAP application rates (kg/ha). Rec is the recommended application rate shown on the SHC. BL is the planned fertilizer application rate in the 2015 rabi season which was asked prior to receiving the SHCs. We include the following farmer characteristics as interactions: age, Literate=1, Female=1, Years of experience wheat farming, CRRA, stated WTP for soil tests, access to credit=1, and the inverse hyperbolic sign of the value of the farmer's house. Regressions include enumerator fixed effects and robust standard errors clustered at the village level are in parentheses.