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

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Abstract

When people hold strong beliefs, is targeted scientific advice sufficient to change input usage? Using a randomized evaluation in Bihar, India we show that plot-level soil testing and tailored input recommendations changed farmers' fertilizer usage and increased the adoption of recommended practices, leading to improved yields. We then 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 (more confident) have a lower willingness to pay for soil testing ex-ante and lower responsiveness to the recommended application rates. 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 many emerging economies (FAO, 2019; Vitousek et al., 2009), including in many parts of India. Farmers tend to under apply certain types of fertilizers and over apply others, which reduces yields and farmer income, harms soil health and pollutes water resources. Since the over-utilized fertilizers are often subsidized, it also entails substantial public expenditure with little benefit for crop yields.

To address this imbalance, 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 experimental implementation of an intervention based on the model of the SHC program. We find the program to have limited effects on farmer choices, and 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. While information provision interventions have become more common in various domains of policy, evidence on their impacts remains mixed, particularly in agricultural contexts (Haaland et al., 2020).[1] Informational barriers 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 lack of 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 preexisting beliefs can be too strong to be affected by externally provided information. 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

[1] There is a large literature that studies the impacts of information provision on health behavior and outcomes (Bennett et al., 2018; Dupas, 2011; Guiteras et al., 2016), job search (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., 2018; 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.

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 SHC program, though it shared many of its characteristics. 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 2014-2015 wheat season, trained field staff provided farmers with SHCs that contained information on tested nutrient levels and the derived recommendations.

Farmers were surveyed before and after the season about their intended and actual fertilizer usage. Even though the recommendations differed substantially from farmers' intended usage, a comparison of endline fertilizer usage between control and treatment farmers yields little evidence of substantial effects. There is some evidence of shifts in the timing of fertilizer applications to fit the recommendations, but changes in total fertilizer amounts are evident mostly for the lowest cost fertilizer, and are of small magnitude. There is also little evidence of shifts in the willingness to pay - elicited using a BDM auction - for fertilizers that are seldom used by the sample farmers but recommended by the SHCs. 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 observation motivates our empirical investigation of the role that prior beliefs had in limiting the impact of the SHC. Our analysis is guided by an extension of the target-input model (Bardhan and Udry, 1999) 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 refer to as confidence, is predicted 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. [5]

Consistent with the model's prediction, we find that confidence decreases farmer's stated willingness-to-pay for a SHC and the probability that they have retained it at endline. Moreover, actual endline fertilizer usage is found to be correlated with both a farmer's pre-season intended usage and 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 confidence: farmers who are, at baseline, more confident of their beliefs, place less weight on the SHC in deciding their final fertilizer usage. 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 determinants 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

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

reduce both demand for and responsiveness to an informational intervention.

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. (2018); 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. (2020) find that plot-specific information or vouchers for fertilizer purchase in Tanzania were insufficient to increase fertilizer adoption on their own, though a combination of both 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. We are not aware of other work that examines how farmers' beliefs, particularly the strength of their beliefs, affect demand 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., 2018) 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, substantial heterogeneity in updating arises due to a variety of individual characteristics and biases. These include numeracy and "taste" for information (Fuster et al., 2018), as well as variance neglect and asymmetric updating in favor of good news (Vivalt and Coville, 2020).[6] 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., 2018). To our knowledge, 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

[6] 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

measures prior uncertainty affect actual investment choices and responsiveness to advice rather than just expectations.

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 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. In Section 3, we describe the soil testing intervention and the data collection and provide summary statistics. We discuss demand for the SHCs in Section 4 and estimate the impacts of the intervention on fertilizer usage in Section 5. In Section 6 we investigate the impacts of confidence on responsiveness to the recommendations. Section 7 concludes.

2 Model

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.[7] The optimal annual input use will be a function of growing conditions (including, 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.[8]

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

[7] 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 the common component to simplify the analysis.

[8] 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.

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 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 $\rho_S = \frac{1}{\sigma^2_S}$ 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:

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

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

$$WTP \equiv \sigma^2_{\theta_1}-\frac{1}{\frac{1}{\sigma^2_{\theta_1}}+\frac{1}{\sigma^2_S}} \tag{8}$$

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

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

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 help 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 most capable testing capacity to carry out the soil testing and recommendations. The study area comprised three districts in Bihar with a predominant rice-wheat cropping system: Bhojpur, Madhubani, and Nawada (Figure 7). 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 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 Data Collection 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 (Figure 7). In the second stage, we 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 strata, we randomly selected 2 villages from which to draw households for treatment and 1 village from which to draw households for a control group. From each of these 48 villages, we randomly selected 18 rice- and wheat-growing households from village rosters prepared by enumerators through door-to-door listing. The sample therefore included 864 farmers, of which 576 are treatment farmers and 288 are control farmers.

Figure 8 illustrates the timeline of the SHC intervention and data collection activities. In April and May of 2014 we conducted a baseline survey that covered both treatment and control 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 risk preferences, self-reported confidence, and subjective beliefs regarding optimal use of two major fertilizers - urea and DAP - for the upcoming 2014 *kharif* rice crop.[9] 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.[10] 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.[11]

Technical delays in conducting all soil tests prevented us from distributing the SHC and associated recommendations prior to the planting of the rice crop. We therefore shifted the experiment to the Rabi season (December-March) of 2014-15, and had fertilization recommendations prepared for the wheat crop, the main crop of this season. Because the baseline survey was focused primarily on rice, in November 2014, prior to distributing the SHCs with soil test results and recommendations to treatment farmers, we carried out a mid-line survey to collect information on cultivation practices and fertilizer application in the wheat crop of the previous *rabi* season (2013-4), 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 mid-line 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* 2015 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).

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.[12] Farmers were asked to allocate beans across bins according to how likely they think

[9] See Ward and Singh (2015) for further discussion on the risk elicitation experiment and estimation of risk preferences using a method similar to Tanaka et al. (2010).

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

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

[12] 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 reduce measurement error or

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 kattha)[13] for the upcoming *kharif* season on their primary rice-growing plot. 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 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 usage while allowing for variation where the majority of application occurs and control for the mean of the subjective beliefs distributions in all regressions.[14]

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

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

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

Figure 1 shows the range of values for urea and DAP application rates (kg per kattha), 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

improve truthful reporting of beliefs in non-political domains (Haaland et al., 2020). 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.

[13] Local farmers are accustomed to use *kattha* rather than hectares in discussing fertilizer amounts. A katha is a local land unit, of which there are about 80 in a hectare.

[14] 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.

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 variance 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 2 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 self-reported measures of relative confidence as well as a question that captures farmer's subjective perception of their own ability. 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 whether farmers have the same or more doubts relative to their peers and a measure of farmers' subjective relative ability assessment, respectively.

While the subjective beliefs we collected pertained to the kharif season rice crop, as mentioned above, 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). 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 confidence in beliefs for fertilizer application for the *kharif* rice crop is a reasonable, though imperfect, proxy for confidence in beliefs for fertilizer application for the *rabi* wheat crop.[15] Table A1 shows that the dispersion in beliefs for both urea and DAP are positively correlated (Pearson correlation coefficient of 0.38), providing some evidence that confidence is correlated across different fertilizers for the same crop. Further, the dispersion measures are correlated with our survey measures of self-reported relative confidence (i.e., the frequency that farmers have doubts about agricultural practices relative to their peers, or their potential yields compared with neighbors with similar soil quality), suggesting that we are potentially capturing heterogeneity in underlying confidence that should also be applicable across crops and seasons.

[15]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*.

3.2 Summary Statistics and Balance

While the original treatment sample consisted of 576 farmers, soil samples failed to be collected from 79 of these farmers, due to a combination of technical reasons (samples that were too small or contaminated) and lack of cooperation. The partner NGO did not collect endline data from these farmers, feeling reluctant to approach them again without SHCs. This only affected 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).

Table 1 presents comparisons of selected 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.[16] 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.[17]

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 usage and yields, and 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 A2 we examine any remaining attrition stemming from failure to find or interview other farmers at endline. 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 to wheat cultivation, our sample is farther restricted to (the roughly 85% of) farmers that indeed cultivated wheat in the primary plot. In column 2, 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.

3.2.1 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 key macro-nutrients: Nitrogen (N), Phosphorus (P), and Potasium (K)

[16]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*

[17]To test joint balance, we implement a conventional asymptotic test, and regress the treatment dummy on all the variables included in Table 1 and strata dummies, and with standard errors adjusted for the clustered nature of our sampling design.

available in the soil, 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 Bihari soils are widely believed to suffer from sulfur (S) and zinc (Zn) deficiencies, and because both of these micro-nutrients 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 9. 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 fertilizers and micronutrienrs to apply to their *rabi* wheat crop. An English translation of the back side of the SHC is presented in Figure 9.

A complicating factor in the determination of fertilizer application recommendations is that they depend on the target yield of the crop. 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, at least in the case of Bihar, is to calibrate the recommendations to a fixed yield rate (in our case, 4 tonnes per hectare), but to provide farmers with a formula through which they can re-calibrate them in accordance with the yields they expect. To simulate the public program, we followed the same practice. While the field agents explained this to farmers, our assessment is that most farmers could not understand how the re-calibration could be performed, and referred to the basic recommendations (calibrated for 4 t/ha), which we refer to as the un-calibrated recommendations, as the recommended levels of application they should be following. The average baseline yield in our sample was 3 t/ha, 25 percent lower than the target yield used for the un-calibrated recommendations.

Table 2 compares treatment farmers' self-reported planned fertilizer application rates (Columns 2-3) in the 2014-5 wheat season (collected prior to receiving the SHC) with the un-calibrated recommendations (i.e. calibrated uniformly to 4t/ha, Columns 4-5). The average un-calibrated recommendations for the use of urea and DAP were 22 and 46 percent higher, respectively, than their planned application rates. The recommended usage of MOP (potash) was more than six fold larger than planned usage, related to the fact that only 38% of farmers in our sample planned to use MOP at all (Column 1). Figure 3 plots the distribution of the differences between planned and recommended application rates of Urea and DAP. While not all farmers were recommended to increase fertilizer usage, about two thirds of the farmers received (uncalibrated) recommendations that were above the planned levels of both urea and DAP usage, whereas 10% received recommendations that were below the planned levels of both of these fertilizers. Eighty five

[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.

percent of farmers were recommended to increase their usage of DAP, and only 8 were recommended to apply less MOP than they planned.

In Columns 6-7 we report recommendations that are calibrated to farmers' previous season yields. These calibrated recommendations are somewhat lower than planned levels for Urea and DAP, but still higher for MOP.

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

4 Willingness to Pay and Comprehension of the SHCs

In this section, we examine the evidence on farmers' interest in the information contained in the SHC and their grasp of the contents.

4.1 Willingness to Pay for the SHC

Figure 4 displays the distribution of the stated WTP for the SHC, elicited from treatment farmers prior to distributing it. 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 in their beliefs about the optimal rate of fertilizer application should display lower demand for the SHC recommendations.

Table 4 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, ability, and risk aversion. 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. 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.

We also examine whether confidence has an effect on a measure of revealed valuation of the SHC. In the endline survey, we asked farmers whether they had kept the SHC, requested them to produce it for enumerator inspection, and asked if they consulted the SHC when making input choices. We found 95% of farmers to report having kept the SHC and 53% to be able to physically produce it for enumerators to inspect. Estimates reported in Table 5 indicate confidence does not seem to be correlated with farmers stating that they kept the card, but that it is correlated with farmers being able to produce the

[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.

card for inspection (an increase of 3 percentage points per standard deviation increase in urea urea beliefs dispersion). Only 26% of farmers report consulting the SHC, but we do not find a relationship between confidence and stating that they consulted the recommendations. In sum, we only find an effect for the revealed valuation of the SHC, but not the stated behavior.

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., 2018). 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). However, the fact that less confidant farmers had revealed stronger interest in the content of the SHC, including in a phone survey, is reassuring in this regard.

4.2 Farmers' Comprehension of the SHC Content

We now examine indications of whether farmers had understood and noted the recommendations.

In the endline survey, farmers were asked whether they had applied more or less Urea, DAP and MOP that the recommended amount. In Table 2, we cross-tabulate these answers with the difference between the actual rate of application and the (un-calibrated) 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 have had least some sense of the content of the SHC and the recommendation. It also suggests that they mostly referred to the un-calibrated recommendations. A similar decomposition as in Table 2 that is performed with the calibrated recommendations shows a substantially lower correspondence. The saliency of the un-calibrated recommendations is in line with qualitative field observations and the difficulty of calibrating the recommendations numerically, especially given that it is not clear what yields farmers should expect in the beginning of the season.

5 Impacts of the SHC on Fertilizer Application

In this section, we estimate the causal impacts of the SHC distribution on actual fertilizer usage. We begin by estimating the impacts on the application rates of the three main macro-fertilizers, Urea, DAP and MOP, for which application rates were collected in the endline. We then turn to a separate analysis in the case of Zinc, a micro-fertilizer that is hardly used by farmers in the sample. The lack of impact on the usage of Zinc could be related to market prices that exceed farmers' willingness to pay, even conditional on information. To examine this more closely, we therefore collect WTP for Zinc and examine how it is impacted by treatment.

5.1 Urea, DAP, MOP.

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

$$y_{i1} = \alpha_0 + \alpha_1 T_i + X_{i0}^{'}\gamma + \mu_b + \nu_e + \epsilon_{i1} \tag{12}$$

where y_{i1} is the endline measure for the outcome of interest for farmer i, T_i is a binary treatment indicator indicating receipt of a SHC, and X_{i0} 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, 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.

Our primary outcomes are the application rates of the three major macro fertilizers: Urea, DAP and MOP, measured in kg per hectare. While Urea and DAP are used by most farmers, MOP is often not used at all. We therefore also estimate impacts on a binary indicator of MOP usage. In addition, we examine effects on the practice, recommended in the SHC (see Figure 9), of applying half of the overall amount of Urea during sowing. Unlike other SHC recommendations, this practice did not necessitate changes in overall fertilizer application rate, but only in its temporal distribution.

We report the estimated impacts in Table 3. In addition to the point estimates, we report 95% confidence intervals as well as Lee bounds. Overall, we find little evidence that SHCs had a strong impact on fertilizer application levels. [20] The point estimate on Urea usage is significant, but the size of the effect (10 KG/Ha) is less than 5% of the mean level of usage. Other point estimates are not significant and also of modest size (roughly 5% and 10% of mean levels of DAP and MOP usage, respectively). The probability of using MOP is positively affected, with a larger proportional impact (15%) that is marginally insignificant. However, the Lee intervals [21] of all four impacts include zero.

An additional indication of the modest size of the estimated effects is obtained by comparing them to the potential (simulated) impact of the SHCs that would have occurred if all treatment farmers followed the (un-calibrated) recommendations to the letter. [22] We report these hypothetical estimates in the bottom row of Table 3. 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 roughly 10% of its potential.

In contrast, we find stronger evidence of an effect of the SHC on the suggested 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.

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

[21] 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.

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

5.2 Zinc

The SHC also provided recommendations on the use of Zinc. While Zinc deficiency is widespread in the area, few farmers use it. If costs, or another binding constraint unrelated to beliefs limits the usage of Zinc, then the low impact the the SHCs have had on Zinc usage may not in fact reflect a lack of effect on farmers' beliefs.

In order to examine this issue, 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.[23] We then set out to examine whether revealed WTP for Zinc was affected by the SHC and its content. While we are aware that conducting a BDM for goods available in local markets requires caution in interpretation, we believe the results can still be informative for the purposes of understanding whether the SHC impact farmers' beliefs about the value of using the fertilizer.

Prior to conducting 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, with one practice round entailing a real bidding process (essentially open-ended contingent valuation) with an actual transaction of money for a good of a relatively lower value than zinc (a 250 g pack of lentils). In the actual zinc valuation exercise, 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: a random sample of control farmers who did not receive a SHC ("No SHC", n=80), the sample of treatment farmers whose SHC indicated zinc sufficiency ("Sufficient", n=182) and the sample of treatment farmers whose SHC indicated zinc deficiency ("Deficient", n=163). The latter group was further randomly divided into two sub-groups, "Deficient, Not Shown" (n=81) and "Deficient, Shown" (n=82). 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. Due to logistical constraints, the control group (group 1) included half of the farmers in each control villages in Bhojpur and Nawada districts, but did not include any farmers in Madhubani district.

A comparison of WTP between the "No SHC" group and the rest of the sample estimates the causal effect that the SHC distribution has had on WTP. A comparison of the WTP between the "Sufficient" and "Deficient" groups is not experimental, but could provide suggestive indications of whether signals of deficiency and the associated recommendation increase WTP for a fertilizer. A comparison of the WTP between the "Deficient, Shown" and "Deficient, Not Shown" estimates the causal effect of making the content of the SHC salient to farmers prior to revealing the WTP.

[23]The BDM mechanism is widely used in experimental economics as an incentive-compatible procedure for eliciting the WTP for a good or a service. In a BDM, each subject submits an offer price to purchase the good. Afterwards, a binding sale price is randomly drawn from a distribution of prices ranging from a very low value to a price greater than the anticipated maximum possible WTP among bidders. Any bidder who submits a bid greater than the sale price receives a unit of the good and pays an amount equal to the sale price. If the bid is lower than the sale price, the bidder gets nothing. The dominant strategy for the bidder is to truthfully reveal his or her preferences.

The mean WTP elicited in each of the four sub-groups is reported in Figure 5 (we report the mean WTP separately in Madhubani and the other two districts because we only have a "No SHC" group in the other two districts). The WTP is very similar across all three sub-groups of SHC recipients, and slightly lower in the "No SHC" group. However, none of the comparisons mentioned above yields differences that are close to being statistically significant. Overall, these comparisons suggest that the SHC's Zinc information had very little effect on farmers' valuation of it.

5.3 Self Reported Reasons for Not Following the SHCs

A 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 A3 presents the full breakdown). High costs (high prices or liquidity constraints) were mentioned as a reason for applying less than recommended 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. (2020), 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 practice. This is true for farmers applying both more or less than the recommendations. Sixty six percent of the farmers who reported having used more than the recommended amount of urea and 58 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. Similar responses were observed for DAP and MOP. Substantial proportions of farmers also claimed using less fertilizers would reduce yields (30%, 52% and 50% for Urea, DAP and MOP, respectively). These results motivate the next phase of the analysis, which examines to what degree the level of confidence displayed by farmers was indeed correlated with their demand for and responsiveness to the SHCs.

6 Confidence and Responsiveness to the SHCs Among Treated Farmers

The model developed in section 3.1.1 predicts (equation 11) that a Bayesian farmer's updated belief about the optimal input application rate to be a convex combination of her prior belief and the information revealed in the SHC. The weight on the prior belief is predicted to be proportional to the confidence level in the prior, while the weight on the new information from the SHC is predicted to be proportional to the confidence level in the SHC.

We formally estimate this relation by regressing the observed endline application rate on the planned application rate (self-reported in the mid line survey prior to receiving the SHC and representing the prior) and the SHC recommendation:

$$y_{i1} = \beta_0 + \beta_1 SHC_i + \beta_2 Prior_i + X_{i0}^{'}\gamma + \nu_e + u_i. \tag{13}$$

where y_{i1} is farmer i's endline fertilizer application rate, SHC_i is the recommendation shown on the SHC, and $Prior_i$ is the planned fertilizer usage stated prior to receiving the SHC. As before, nu_e are enumerator fixed effects, and X_{i0} are controls. that include access to credit, plot size, risk aversion, experience, literacy, and age Standard errors are clustered at the village level. We interpret β_1 to reflect the average confidence placed by farmers in their priors, and β_2 to reflect the average confidence placed by farmers in the information revealed by the SHC. More precisely, based on equation 11, the ratio between β_1 and β_2 reflects that average relative confidence farmers place in their own prior and in the SHC.

This approach is similar to that of Hjort et al. (2019), who estimate a model of belief updating in which a subject's posterior is a weighted combination of their prior and the new information. In our context, rather than estimating the effect on an elicited posterior, we observe the actual input decision of the farmer and take it to represent their posterior belief.

Table 6 presents the estimates of regression 13 for each of the three macro fertilizers targeted by the SHCs. Because endline and planned fertilizer usage might both be influenced by similar farmer attributes, we present estimates of regressions with and without controls. For both Urea and MOP, endline application rates are significantly correlated with both the priors and the SHC. Both coefficients are similarly sized, suggesting farmers have, on average, similar levels of confidence in both their prior and the SHC. Farmers have somewhat larger levels of confidence in the SHC for Urea. For DAP, we find no significant correlation between endline application rates and the information in the SHC. The results do not change significantly when controls are included in the regressions. Overall, the pattern of the result is consistent with the treatment effects estimated above on the application rates of the three fertilizers. Effects were found to be strongest for Urea, followed by MOP (on the extensive margin), and largely absent for DAP.

In order to further test the model predictions, i.e. that β_1 ($\beta 2$) is positively (negatively) related to the level of confidence a farmer has in her prior, we add interaction terms between the SHC recommendation and the prior and a farmer's belief dispersion with regard to the fertilizer in question SD (which is anti-correlated with confidence, by definition) to regression 13: [24]

$$y_{i1} = \beta_0 + \beta_1 SHC_i + \beta_2 Prior_i + \kappa_1 SHC_i \cdot SD_i + \kappa_2 Prior_i \cdot SD_i + X_{i0}^{'}\gamma + \nu_e + u_i. \tag{14}$$

Our model predicts that if an individual is less confident (has higher dispersion of beliefs SD) they will place more weight on the signal from the SHC and correspondingly less weight on their prior, holding everything else constant. As a result, we would expect κ_1 to be positive AND $kappa_2$ to be negative.

We also conduct a similar excercise which interacts the SHC recommendation with an indicator of trust in extension workers, instead of the Urea belief dispersion. If trust is a factor which influences the degree to which farmers will rely on the SHC information, the coefficient on this interaction terms would also be

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

expected to be positive.

Table 7 reports the related estimates in the case of Urea. The results in Columns 1 and 2 confirm the model's prediction. Farmers with lower level of confidence in their beliefs about Urea (higher $SDUrea$) place more weight on the SHC recommendation, and less weight on their prior. The two interaction coefficients are very similar in magnitude and of opposite sign. A one standard deviation increase in belief dispersion increases the weight that farmers place on the SHC signal by 12 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 19 percentage points.

In columns 3 and 4, we report similar results on the interaction of the priors and the recommendation with baseline trust in extension workers. The coefficients on the interaction between trust and the signal are small and insignificant. We do not find evidence that trust affects the weight farmers place in the SHC recommendations. It should be noted however that our measure of trust was collected in the baseline survey and may have been 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.

Table 8 reports similar results in the case of DAP. 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.

As discussed previously, one potential explanation for the lack of response is that DAP is costly relative to urea. More than 80% of treatment farmers received recommendations to apply more DAP than they planned to apply in the upcoming season, but this would have significantly increased their inputs costs. Farmers may also have attempted to substitute Urea for DAP.

7 Conclusion

In this paper, we investigate how the strength with which agents hold beliefs and their trust in the information source affect the responsiveness to scientifically derived advice. We conducted 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 farmer fertilizer usage that fall far short of the potential impacts that would have occurred if farmers fully complied with the SHC recommendations, even for the lowest cost fertilizer. With our most conservative specification, we are not able to reject the null hypothesis of zero change in total amount used of any of the fertilizers we examine. Significant and robust effects are only found for the timing of fertilizer application.

To rationalize these findings, we develop a model in which farmers have beliefs about optimal fertilizer usage and update them based on their own experience and external signals. We empirically document significant heterogeneity in beliefs about optimal fertilizer application levels prior to receiving the SHC information. Consistent with the model's predictions, 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 recommendation. 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. When designing information interventions, identifying and targeting low confidence and high marginal value of information respondents may produce the highest returns to the program's investment, especially if there are cost constraints to providing information, such as in the case of testing soils in a laboratory.

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 (2018). Can network theory-based targeting increase technology adoption? Technical report, National Bureau of Economic Research.

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.

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

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). âĂŸmobileâĂŹizing 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.

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 (2018). 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 (2020). Designing information provision experiments.

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., N. Amuri, M. Madajewicz, C. Magomba, H. Michelson, K. Tschirhart, J. Semoka, and C. Palm (2020). When does information make a difference? a field experiment with farm-specific soil information in tanzania. Working paper.

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.

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.

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

Tanaka, T., C. F. Camerer, and Q. Nguyen (2010). Risk and time preferences: Linking experimental and household survey data from Vietnam. *The American Economic Review 100*(1), 557.

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?

Ward, P. S. and V. Singh (2015). Using field experiments to elicit risk and ambiguity preferences: Behavioural factors and the adoption of new agricultural technologies in rural india. *The Journal of Development Studies 51*(6), 707–724.

Table 1: Summary statistics and Balance Across Treatment Arms

Variable	(1) Control Mean/SE	(2) Treatment Mean/SE	(3) No Test Mean/SE	(1)-(2)	T-test P-value (1)-(3)	(2)-(3)
Age	46	45	45	.31	.54	.99
	(.88)	(.73)	(1.7)			
Female	.052	.085	.13	.094*	.11	.35
	(.013)	(.014)	(.043)			
Literacy	.65	.69	.58	.45	.32	.085*
	(.049)	(.029)	(.044)			
Trust	.31	.31	.29	.82	.83	.7
	(.03)	(.022)	(.061)			
Clay/loam soil	.74	.76	.8	.69	.49	.59
	(.039)	(.035)	(.079)			
Slope (flat)	.91	.92	.95	.88	.28	.34
	(.021)	(.021)	(.025)			
WTP for soil test (USD)	1.6	1.6	1.8	.98	.79	.7
	(.25)	(.17)	(.36)			
Mean urea beliefs	208	207	203	.96	.79	.73
	(15)	(8.4)	(12)			
Mean DAP beliefs	103	103	91	.98	.2	.11
	(6)	(4.3)	(7.4)			
Kharif 2013 urea	223	213	213	.7	.67	.95
	(21)	(16)	(16)			
Kharif 2013 DAP	102	106	95	.57	.38	.067*
	(5.8)	(4.8)	(8.6)			
Rabi yield 2014 (q/ha)	27	27	26	.74	.92	.59
	(1.3)	(.99)	(.35)			
N	288	497	79			
Clusters	16	31	21			
F-test of joint significance (F-stat)				1.1	.81	1.2
F-test, number of observations				785	367	576

Notes: This table reports the balance checks for farmer and soil characteristics and fertilizer usage for the 864 farmers in our study sample at baseline. 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. 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 of equal means across the indicated treatment arms. 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. Asterisks denote test significance: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 2: Actual vs. Recommended Application by 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	23.19	118	-2.48	42	-52.25	12
Less than recommended	-67.44	85	-63.12	135	-68.93	230
Recommended amount	-21.16	93	-43.70	119	-43.87	54
No SHC for reference	-36.61	93	-61.66	93	-65.75	93
Full sample	-21.51	389	-50.28	389	-64.18	389

Notes: This table reports the difference between endline fertilizer usage and the recommendation printed on the SHC, disaggregated by farmers' self-reports of how much the applied relative to the amount on the card The sample includes only treatment farmers that had their soil tests processed and delivered. All values reported in kilograms per hectare (kg/ha). EL denotes fertilizer application rates during the 2014/2015 *rabi* season. Recommendation denotes the derived recommended fertilizer application rate from soil tests for a rabi wheat yield of 4 tons per hectare. The self-reported evaluations of how much they applied relative to the recommendations on the SHC were asked during the endline survey.

Table 3: Treatment Effects on Fertilizer Application Rates

	(1) Urea	(2) DAP	(3) MOP	(4) MOP=1	(5) 50% at Sowing
SHC	10.0**	-6.52	1.91	0.071	0.092**
	[0.39,19.7]	[-16.9,3.84]	[-1.32,5.13]	[-0.019,0.16]	[0.0028,0.18]
Observations	627	627	627	627	627
Adjusted R^2	0.358	0.209	0.501	0.577	0.066
Mean dep. var.	217.6	115.8	17.4	0.46	0.20
Lee Bounds (95 CI)	[-5.21,32.08]	[-16.21,3.58]	[-5.90,3.65]	[-0.10,0.09]	[0.03,0.20]
Full SHC Compliance	25.69	39.23	64.73	0.66	0.87

Notes: This table reports the effects of the treatment on usage of fertilizers by farmers that planted wheat on their largest plot in the 2015 *rabi* wheat season. 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 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 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 dummy that takes value 1 if the farmer applied any MOP during the season. In column 5, the dependent variable is a dummy that takes value 1 if the farmer applied half of the total amount of urea during sowing. * Significant at 10 percent level; ** Significant at 5 percent level; *** Significant at 1 percent level.

Table 4: Effects of confidence on willingness to pay for SHCs

	(1) WTP	(2) WTP	(3) WTP	(4) WTP
SD Urea	1.79***	1.68***		
	(0.43)	(0.44)		
Trust	0.050	0.049	0.067	0.060
	(0.14)	(0.14)	(0.12)	(0.12)
Literacy	0.39***	0.31**	0.42***	0.30**
	(0.11)	(0.12)	(0.12)	(0.13)
SD DAP			2.90***	2.95***
			(0.51)	(0.51)
Constant	1.87***	1.91***	1.60***	1.75***
	(0.40)	(0.40)	(0.38)	(0.40)
Controls	No	Yes	No	Yes
Observations	862	862	853	853
Adjusted R^2	0.301	0.313	0.316	0.334
Mean dep. var	1.65	1.65	1.66	1.66

Note: This table reports correlations between measures on belief dispersion and stated WTP for soil testing in the baseline survey. The 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 of urea and DAP beliefs are measures of farmer confidence calculated from their subjective beliefs distributions. 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 and 4 include ability, household size, house value, whether the household owned the tested plot, whether the household owned an irrigation pump, whether the household had access to credit during *rabi* 2013. * Significant at 10 percent level; ** Significant at 5 percent level; *** Significant at 1 percent level.

Table 5: Effects of confidence on keeping SHC and trust

	(1) Kept shc	(2) Show shc	(3) Consult shc
SD Urea	0.027	0.079*	-0.13
	(0.13)	(0.045)	(0.12)
Literacy	0.014	0.028	0.091**
	(0.053)	(0.025)	(0.044)
Trust	-0.0046	0.023	-0.019
	(0.048)	(0.020)	(0.042)
Observations	464	464	464
Mean dep. var	0.95	0.53	0.26

Note: This table reports results on the effect of farmers characteristics on outcomes related farmer's perceived value of the information. The sample in columns 1 and 2 includes treatment farmers that were present in the online survey. The sample in column 3 includes a random subset of treatment farmers that were contacted fur a supplementary phone survey during the 2015 *rabi* season. The dependent variable in column 1 is equal to one if farmers reported that they kept the SHC. The dependent variable in column 2 is equal to one if farmers actually showed the SHC to enumerators. The dependent variable in column 3 is equal to one if farmers correctly answered the level of zinc in their soil (High/Medium/Low) that was reported in the SHC. The SD of urea and DAP beliefs are measures of farmer confidence calculated from their subjective beliefs distributions. 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 include ability, household size, house value, whether the household owned the tested plot, whether the household owned an irrigation pump, whether the household had access to credit during *rabi* 2013. * Significant at 10 percent level; ** Significant at 5 percent level; *** Significant at 1 percent level.

Table 6: Correlations of Observed Applications with Recommendations and 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

Notes: This table reports the results from a regression of endline fertilizer application rates on the recommendation and farmers' planned application rates. The dependent variables are endline fertilizer application rates (kg/ha). SHC rec is the recommended application rate shown on the SHC. Prior is the planned fertilizer application rate in the 2014 rabi season which was asked prior to receiving the SHC. Controls include age, literacy, 2013 *kharif* yields, trust, CRRA, and plot size. Regressions include enumerator fixed effects and robust standard errors clustered at the village level are in parentheses.

Table 7: Effects of confidence and trust on Urea application

	(1) Urea	(2) Urea	(3) Urea	(4) Urea
SHC Rec	0.022	0.036	0.30	0.24
	(0.21)	(0.21)	(0.20)	(0.23)
Prior	0.56***	0.53***	0.27***	0.28***
	(0.12)	(0.12)	(0.071)	(0.075)
SHC Rec × SD Urea	0.68**	0.61**		
	(0.29)	(0.29)		
Prior × SD Urea	-0.74**	-0.64**		
	(0.30)	(0.30)		
SHC Rec × Trust			-0.064	0.074
			(0.066)	(0.40)
Prior × Trust			0.0094	-0.0058
			(0.082)	(0.086)
Controls	No	Yes	No	Yes
Observations	388	388	388	388
Mean dep. var	221.8	221.8	221.8	221.8

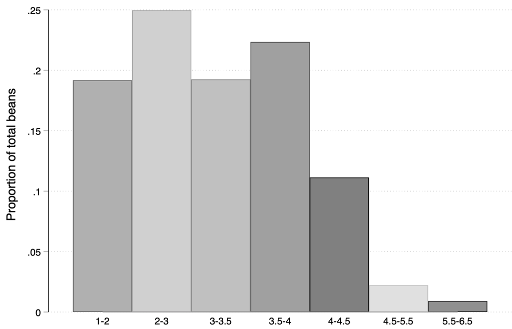
Notes: This table reports the results from a regression of endline urea application rates on the recommendation and farmers' planned application rates and their interactions with confidence and trust. The dependent variables are endline urea application rates. SHC rec is the recommended urea application rate shown on the SHC. Prior is the planned urea application rate in the 2014 rabi season which was asked prior to receiving the SHC. SD is the standard deviation of the elicited beliefs distribution for the indicated fertilizer. Trust is a binary variable equal to one if respondents trust information from extension agents. Controls include the mean of the beliefs distribution, age, credit access, plot size,literacy, 2013 *kharif* yields and plot size. Regressions include enumerator fixed effect and robust standard errors clustered at the village level are in parentheses.

Table 8: Effects of confidence and trust on DAP application

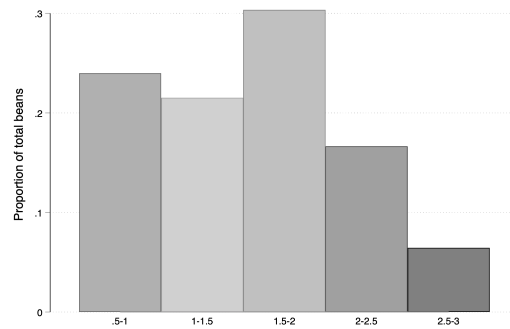
	(1) DAP	(2) DAP	(3) DAP	(4) DAP
SHC Rec	0.050	0.044	-0.13	-0.15
	(0.12)	(0.12)	(0.10)	(0.10)
Prior	0.34**	0.34**	0.17**	0.16**
	(0.16)	(0.16)	(0.065)	(0.065)
SHC Rec × SD DAP	0.33	0.33		
	(0.26)	(0.26)		
Prior × SD DAP	-0.45	-0.48		
	(0.39)	(0.41)		
SHC Rec × Trust			0.019	0.043
			(0.048)	(0.089)
Prior × Trust			-0.017	0.0031
			(0.071)	(0.088)
Controls	No	Yes	No	Yes
Observations	384	384	384	384
Mean dep. var	113.6	113.6	113.6	113.6

Notes: This table reports the results from a regression of endline DAP application rates on the recommendation and farmers' planned DAP application rates and their interactions with confidence and trust. The dependent variables are endline DAP application rates. Rec is the recommended DAP application rate shown on the SHC. Prior is the planned fertilizer application rate in the 2014 rabi season which was asked prior to receiving the SHC. SD is the standard deviation of the elicited beliefs distribution for the indicated fertilizer. Trust is a binary variable equal to one if respondents trust information from extension agents. Controls include the mean of the beliefs distribution, age, credit access, plot size,literacy, 2013 *kharif* yields and plot size. Regressions include enumerator fixed effect and robust standard errors clustered at the village level are in parentheses.

Figure 1: Percentage of Beans Allocated to Fertilizer Ranges (Kg/Kattha)

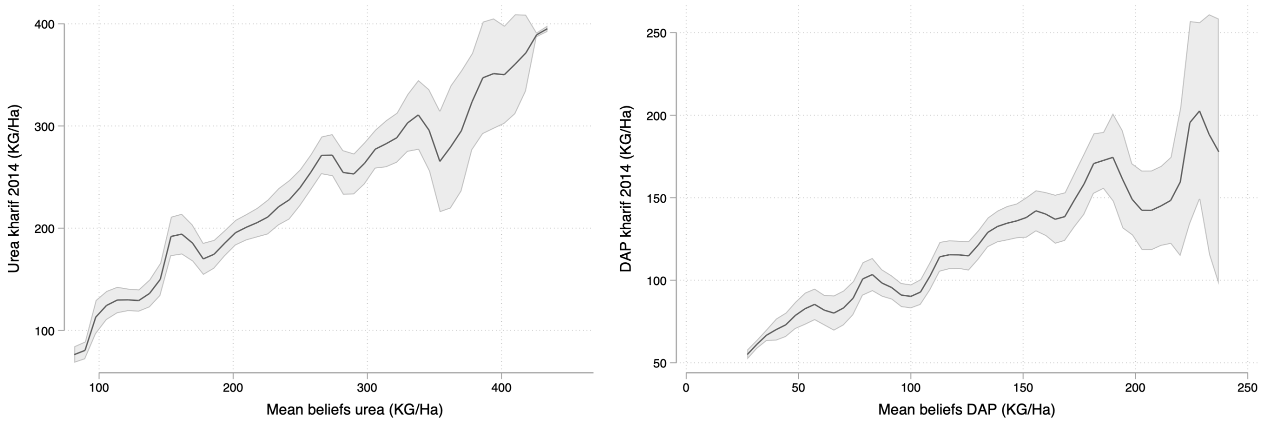


(a) Urea



(b) DAP

Figure 2: Fertilizer application relative to mean of beliefs about optimal fertilizer application

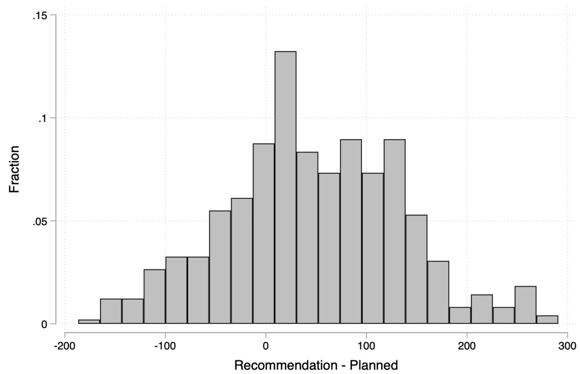


(a) Urea

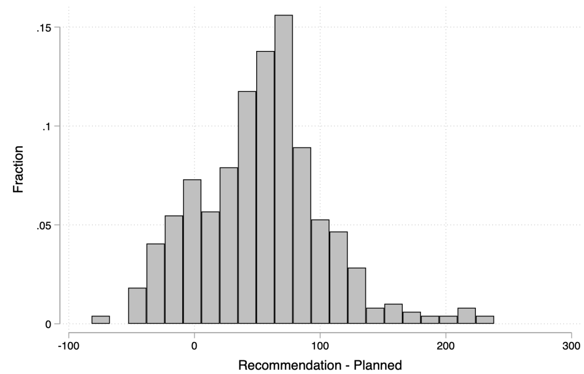
(b) DAP

Notes: Authors' calculations. 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/kattha) are plotted using a locally polynomial smoothing regression with an Epanechnikov kernel (bandwidth = 0.12). The 95% confidence intervals account for clustering by village.

Figure 3: Density of Difference Between Baseline Fertilizer Application Rates and Recommendation (Kg/Ha)

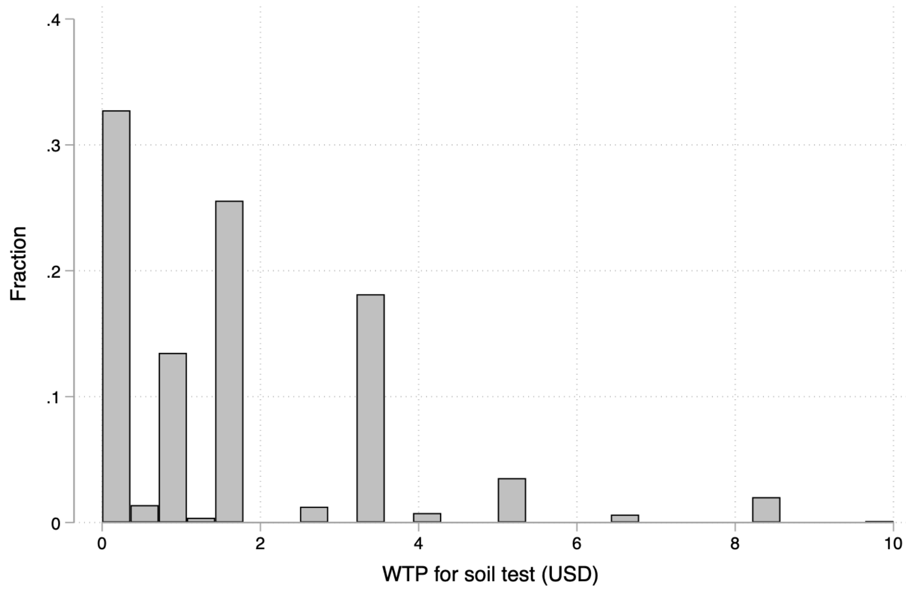


(a) Urea (All blocks)



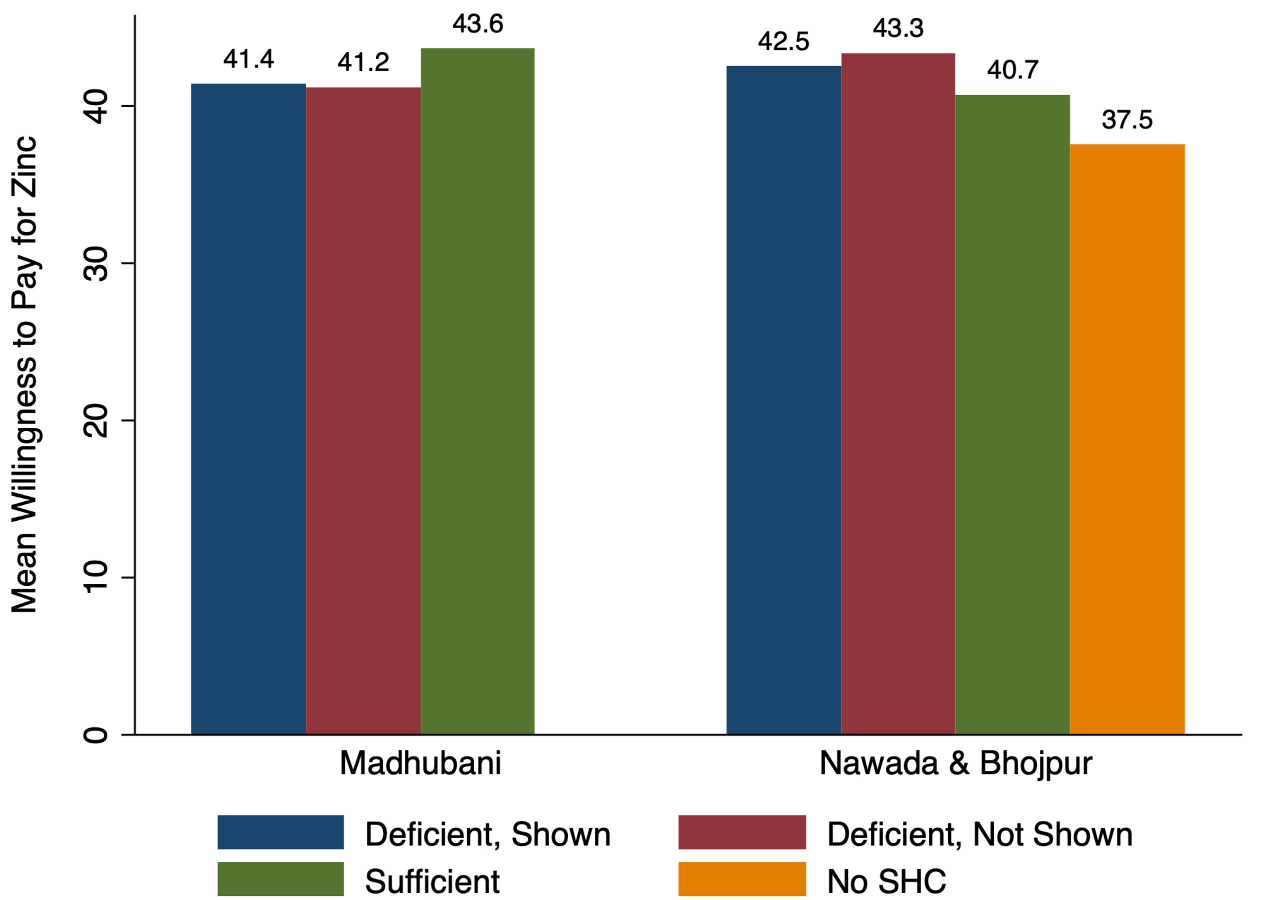
(b) DAP (All blocks)

Figure 4: Willingness to Pay for SHC



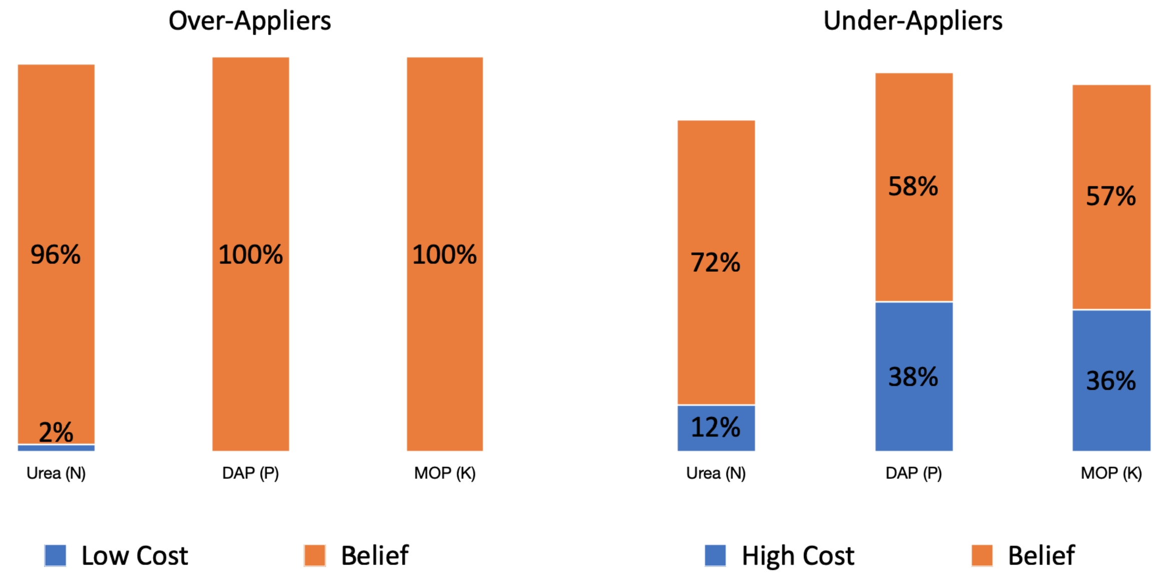
This figure shows the distribution of stated willingness to pay (WTP) for soil testing and the SHC for all farmers in the baseline.

Figure 5: BDM Elicited Willingness to Pay for Zinc



Mean Willingness to Pay for Zinc elicited through a BDM mechanism in four sub-samples. See text for details. WTP is reported separately in Madhubani district and the two other districts in the sample because the "No SHC" sample excluded Madhubani district.

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



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 A3.

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. Appendix Table 1 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 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. Table **??** shows the results of estimating these Lee bounds which can be compared directly with Table **??**. The estimates of the treatment effects for urea lie in between the bounds estimated in column 1 using OLS. The parameter estimates are much 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 attrit. However, in Table 1, 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.. Table **??** reports the bounds for the yield estimates in Table **??**.

Figure 7: Location of Sample Districts in Bihar, India

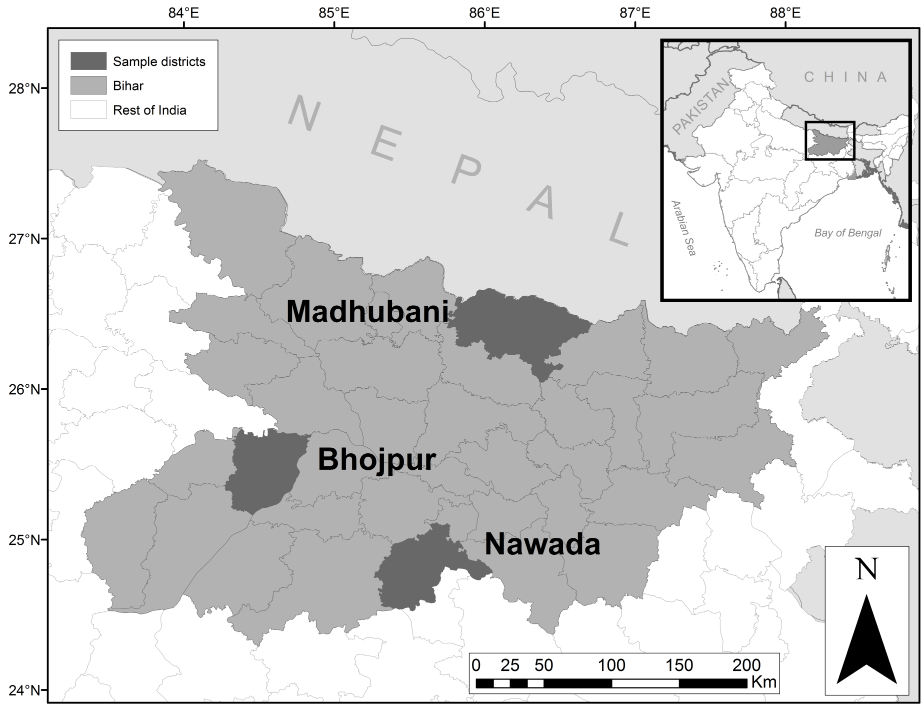


Figure 8: Timeline of Data Collection

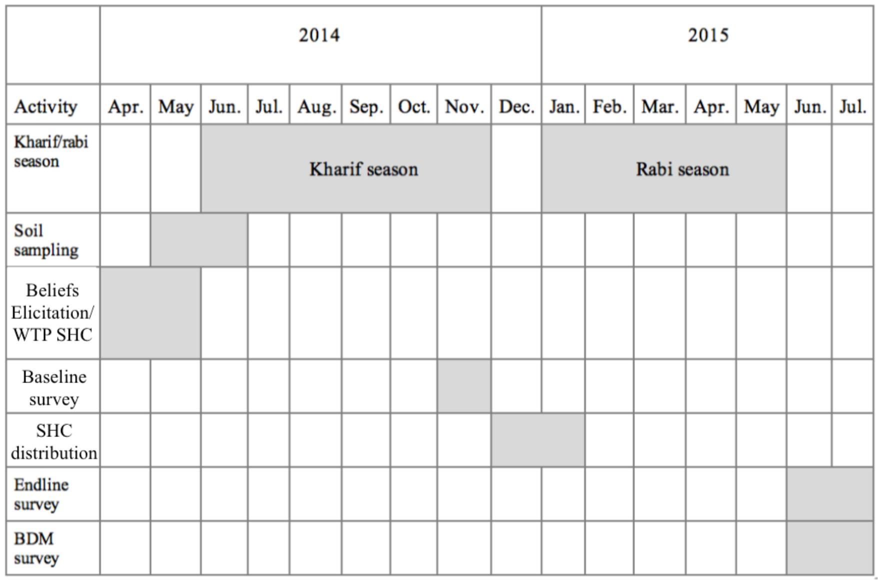


Figure 9: Example: SHC (Translated)

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

Important information and useful tips:

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

Table A1: Correlations Across Confidence Measures

Variables	CV Urea	CV DAP	Same/lower yields	Same/more doubts
CV Urea	1.000			
CV DAP	0.353***	1.000		
Same/lower yields	0.273***	0.147***	1.000	
Same/more doubts	0.140***	0.070**	0.469***	1.000

*** p<0.01 ** p<0.05 * p<0.10

Notes: This table reports correlations between measures of confidence elicited during the initial baseline survey. The coefficients of variations are calculated by dividing the mean by the standard deviation of the subjective belief distributions of Urea and DAP.

Table A2: 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			

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 803 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 A3: 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.