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

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Abstract

The imbalanced use of chemical fertilizers in India is widely blamed for low yields, poor soil health, and pollution of water resources. Simultaneously, fertilizer subsidies – especially urea – are a source of large public expenditures. To address the issue, the government of India invested in a large-scale program of targeted soil testing and customized fertilizer recommendations, with the hope that scientific information will lead farmers to optimize their fertilizer mix. We conducted a randomized controlled trial in the Indian state of Bihar in what we believe to be the first evaluation of the effectiveness of the program as currently implemented. We find no evidence that soil testing and targeted fertilizer recommendations had any effect on fertilizer use nor on farmers' willingness to pay for micronutrients. To rationalize these findings, we model and test the impacts of confidence on farmers' willingness to pay for and 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 of fertilizer usage to the recommended application rates.

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1 Introduction

Fertilizer consumption in India increased remarkably during the second half of the 20th century and into the first decade of the 21st century, rising from roughly 66,000 tons in the 1950-1951 agricultural year to more than 26 million tons in 2009-2010 (Mujeri et al., 2012). This large increase in fertilizer use was largely the result of a favorable policy regime in which fertilizers were heavily subsidized. While cereal grain production increased significantly during the same time period, it failed to keep pace with the dramatic increases in fertilizer application, resulting in low and deteriorating fertilizer-use efficiency. Over time, and as a consequence of policy reforms, fertilizer application rates have become increasingly imbalanced.[1] To address these imbalances – and to reduce the large fiscal burden associated with fertilizer subsides – the Government of India launched a massive INR 5.7 billion (USD 85 million) centrally-sponsored Soil Health Card (SHC) Scheme in February 2015 with the aim of providing all 140 million farmers in the country with soil health information and fertilizer application recommendations on a triennial basis.[2] The stated goal of the program is to promote long-term soil health and increase cereals production through more scientific and modern techniques.

Research on technology adoption frequently cites ignorance about proper management of technologies as a potential source of input misallocation. If this source of misallocation is substantial, facilitating learning by relaxing information constraints may be pivotal in moving farmers closer to a private optimum (Foster and Rosenzweig, 2010). However, evidence from information interventions has found mixed behavioral responses to information provision in a variety of domains including agriculture (Cole and Fernando, 2016) and public health (Bennett et al., 2016; Dupas, 2011; Guiteras et al., 2016) as well as in investments in own and children's education (Dizon-Ross, 2019; Wiswall and Zafar, 2015). While there is research on identifying how changes in the source or type of information affect behavior, there is little evidence on the impacts of individual heterogeneity on responsiveness to information interventions.[3] One potential explanation for the lack

[1]Since the early 1950s there has been an imbalance in the application of chemical fertilizers in Indian agriculture, with urea being applied at a disproportionate rate relative to phosphatic and potassic fertilizers. The application ratio varies from year to year, but the imbalance remains significant to this day. In 2012-13, the N:P:K application ratio was 8:3:1, compared to the broad recommended ratio of 4:2:1 (Chanda et al., 2013).

[2] Rather than collecting soil samples directly from every farmer's field, the program collects soil samples on a 2.5 ha basis in irrigated areas and a 10 ha basis in rainfed areas.

[3]As an exception, Dizon-Ross (2019) finds that poorer parents have less accurate beliefs about their children's performance in school and respond more to correct information when making decisions to invest in books for their

of response to information interventions is that individuals do not deem the information useful, even if it is new to them. When farmers are confident in their ability, due to extensive experience with inputs and well-formed beliefs about optimal input usage, an unanswered question is whether targeted information is sufficient to change input use behavior.

In this paper, we provide some of the first empirical evidence on this matter and test the validity of the assumptions underlying India's flagship SHC scheme. The evidence comes from a randomized controlled trial in the Indian state of Bihar that was introduced before – and thus approximated – the government's SHC intervention. Enumerators collected soil samples from treated farmers' fields that were sent to a certified laboratory for testing and analysis. Trained field staff provided farmers with the SHCs, which included the soil test results as well as crop- and season-specific recommendations for the required dosage of different fertilizers and micronutrients for a rice-wheat cropping system, by far the most prevalent cropping system in Bihar. Although the recommendations of the SHCs were markedly different from farmers' baseline fertilizer applications, we find that the SHCs had no effect on fertilizer application decisions.

To rationalize these findings, we designed an experiment to understand the role of confidence on willingness to pay for and responsiveness to the soil quality measures and input recommendations. To motivate our analysis, we extend the target-input model (Bardhan and Udry, 1999; Jovanovic and Nyarko, 1996) and allow for the agent to purchase and use a signal conditional on their contemporary beliefs, farming ability, and perceptions of the trustworthiness of the signal. The initial strength of farmers' beliefs regarding optimal input use (i.e., their confidence) is elicited using simple visual aids similar to those frequently used in the field to elicit subjective beliefs (cf. Delavande et al., 2011b).[4] We use data on treatment farmers for whom we observe input behavior before and after the receipt of the SHCs and explore the heterogeneous impacts of baseline beliefs on demand for and responsiveness to the fertilizer recommendations.

Consistent with findings from the psychology and economics literature, we find that farmers vary in their degree of confidence, and we provide evidence that the dispersion of elicited beliefs measures are internally consistent with relative confidence measures and actual fertilizer application.

children.

[4]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.

We find strong evidence that confidence in initial beliefs reduces the perceived value of information, and that confidence is an important source of heterogeneity in responsiveness to information. Our empirical results suggest that farmers with stronger, or less disperse, beliefs have a lower (stated) willingness to pay for SHCs. The effect size implies that a one standard deviation reduction in dispersion decreases willingness to pay by an average of USD 0.30, or 15 percent of the total price of a SHC.

Furthermore, conditional on fertilizer use adjustment in the direction of the signal, confidence and ability are associated with lower responsiveness to the recommendations provided on the SHCs. A standard deviation decrease in belief dispersion is associated with a five percent decrease in responsiveness, on average. We find that farmers that are literate or have a greater degree of trust in agents from the national extension system are willing to pay more for the SHCs, but we do not find evidence that trust has a significant effect on responsiveness to the recommendations. Thus, low levels of literacy and the perceived credibility of the information are further threats to the efficacy of these types of information interventions.

This paper contributes to two strands of the literature. First, it contributes to the growing literature on the role of information as a constraint to technology adoption by smallholder farmers in developing countries. Cole and Fernando (2018) find that the introduction of a toll-free hotline, through which farmers can ask questions to agricultural experts, significantly increased adoption of more effective pesticides and both cumin and cotton yields among farmers in Gujarat, India. Hanna et al. (2014) show that despite having extensive experience, seaweed farmers in Indonesia are unaware of the optimal size distribution of planted seaweed pods due to their failure to notice. Providing farmers with their potential gains from changing the size and weight of pods led to changes in their planting practices towards the information provided. More closely related to this paper, recent evidence on providing soil tests to farmers has had more mixed results. Using plot level soil tests in Tanzania, Harou et al. (2019) find that plot specific information and vouchers for fertilizer purchase were insufficient to encourage adoption of chemical fertilizers by themselves. However, the combination of both increased the application of fertilizers substantially, from a baseline average of relatively little fertilizer usage. Cole and Sharma (2017) find that providing Indian farmers with audio and video supplements that explain soil health cards performs considerably towards farmer understanding and trust than in-person delivery. Heterogeneity in the strength of farmers' beliefs about optimal input usage may help to explain the attenuated behavioral impact of providing farmers with information, even if it is individualized.

Second, an expanding experimental literature has identified confidence as an important source of heterogeneity in the demand for and usage of information. Existing research focuses primarily on its causes rather than consequences, and is mostly confined to laboratory experiments using binary decisions. Schotter (2003) finds subjects in the lab follow advice of others that only have slightly more experience than themselves. Surprisingly, subjects in their experiment prefer to receive the advice from others rather than get the information directly and make their own choice, presumably due to under-confidence. Eliaz and Schotter (2010) find that agents are willing to pay for information that supports their prior beliefs, or increases the confidence in their decisions, despite the information not having any instrumental value. These experiments suggest there are a number of possible motivations for information demand that are not necessarily linked to its instrumental value but the players' beliefs about their own or others' judgement. With the exception of Hoffman (2016), no studies of demand for information have moved beyond the lab to analyze the impacts of confidence on actual decision making. Hoffman (2016) models and tests the impacts of mis-calibrated self-confidence on demand and usage of direct and subjective signals using a framed field experiment. Contrary to the previously cited research, he finds that experts systematically underpay for information and that this effect is stronger among overconfident individuals. He also documents significant overconfidence among his participants, in line with previous research using incentivized experiments that measure ability and confidence.

This paper bridges the gap between the literature on information interventions and the role of confidence on information demand. To our knowledge, the present study is the first attempt to consider the role of confidence on demand for and use of information within the context of technology adoption. Two recent papers consider other differences across farmers in the search for and usage of advice. Barham et al. (2018) construct an experimental measure of responsiveness to advice and find that it is positively correlated with a survey-based measure of confidence. They find that cognitive ability predicts earlier adoption of GMOs, but that receptiveness to advice actually slows adoption for farmers with high cognitive ability and speeds up adoption for those with low cognitive ability. Their results highlight the importance of differences in receptiveness relative to the ability of farmers in the decision to use available information.

Finally, we make a theoretical and methodological contribution by operationalizing the dispersion of a farmer's subjective probability estimates, interpreted as confidence, within a preexisting model of learning about technology. 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 estimate these parameters directly from farmers' subjective beliefs distribution, elicited using visual aids. This method of belief elicitation, summarized in Delavande et al. (2011b), requires respondents to allocate beans or stones 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).

The remainder of this paper is organized as follows. In Section 2, we provide a model of learning about optimal input usage to explore the role of confidence on information demand and responsiveness and motivate our empirical analysis. In Section 3, we describe the soil testing intervention and data collection and provide summary statistics. In Section 4, we show the impacts of the intervention on fertilizer usage and we test the impacts of confidence on responsiveness to the recommendations. In Section 5, we discuss alternative explanations for the lack of response to the soil testing intervention. Finally, in Section 6, we conclude with a discussion of the implications of our findings for the design of similar information interventions and how to improve the existing soil health card scheme in India.

2 Model

In this section, we build a model of information demand and responsiveness that demonstrates how farmers' confidence in their input use explains a lack of adherence to the soil testing recommendations. The target-input model (Bardhan and Udry, 1999; Foster and Rosenzweig, 1995; Jovanovic and Nyarko, 1996) is frequently used to explain learning about optimal management of a new technology (e.g., through experimentation, observing or learning from others, etc.) and its implications for technology adoption. The model allows the agent to have a period-specific optimal input choice by weighing her various sources of information, including own experimentation and information from her peers (Foster and Rosenzweig, 2010). This process of updating and evaluating the relative importance of own-experimentation and information from peers has frequently been the basis for empirical work on social learning in developing countries (Bandiera and Rasul, 2006; BenYishay and Mobarak, 2018; Conley and Udry, 2010; Foster and Rosenzweig, 1995). In the present application, we allow for decisions to be informed by an external information source (a signal), which is potentially used by the agent (in this case, a farmer) to update beliefs about optimal management strategies prior to taking an action. We will then demonstrate the conditions under which this information would have any value for the agent.

We first present the general model and discuss how farmers update their beliefs in each period. 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 many periods of individual and social experimentation, and thus, it seems reasonable to assume that they have well-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 perception of the reliability of her estimate – that is, her confidence – is a function of the variance of this prior distribution, $\sigma_{\theta_t}^2$. 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. In our framework, farmer's confidence in subjective beliefs at period t is represented by $\rho_{\theta_t} = \frac{1}{\sigma_{\theta_t}^2}$.

The period-specific target input level (θ_t) varies with independent and identically distributed shocks, u_t.[5] 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.[6]

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

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

From this result it is clear that subjective expected output is decreasing in $\sigma_{\theta_t}^2$ and σ_u^2, and therefore

[5] 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.

[6] 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.

increasing in the level of confidence over the target input level (ρ_{θ_t}) as well as in the farmer's ability (ρ_u). The farmer makes input choices to maximize expected profit, conditional on the precision of her subjective beliefs about the target parameter. After applying input level θ_t^* and observing the realized out q_t, the farmer uses equation (1) to deduce the period specific optimal input, θ_t, and updates her beliefs about θ using Bayes' rule:

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

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

In this section we extend the model to analyze the farmer's decision to purchase a signal. 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.

In period 1, prior to planting, the farmer is given a choice to purchase a signal, S. Without seeing the information, the farmer has prior beliefs about the distribution of the signal, σ_S^2. We interpret this variance as the perceived degree of signal reliability, or similarly the degree of trust that the farmer has in the source of information. If she purchases the signal, S is revealed and the farmer updates her beliefs to $\mathcal{N}(\tilde{\theta}_1, \tilde{\sigma}^2_{\theta_1})$ according to

$$\tilde{\theta}_1 = \theta_1^* \left(\frac{\rho_{\theta_1}}{\rho_S + \rho_{\theta_1}} \right) + S \left(\frac{\rho_S}{\rho_S + \rho_{\theta_1}} \right) \tag{6}$$

and uses $\tilde{\theta}_1$. If she does not purchase the signal, she plants using θ_1^* to maximize expected profit.

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

$$\tilde{\sigma}^2_{\theta_1} = \frac{1}{\rho_{\theta_1} + \rho_S} \tag{7}$$

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

We assume that beliefs about the precision of the signal do not change after the signal is revealed and that farmers are myopic in their choice to purchase the signal (i.e. only the expected yields of the following season are included in the expected benefits). Substituting equation (7) 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:

$$WTP \equiv E(\tilde{q}_1) - E(q_1) = (1 - \tilde{\sigma}^2_{\theta_1} - \sigma^2_u) - (1 - \sigma^2_{\theta_1} - \sigma^2_u) = \sigma^2_{\theta_1} - \tilde{\sigma}^2_{\theta_1} \tag{8}$$

Substituting equation (7) for the second term of this difference gives

$$WTP \equiv \sigma^2_{\theta_1} - \frac{1}{\frac{1}{\sigma^2_{\theta_1}} + \frac{1}{\sigma^2_S}} \tag{9}$$

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.

Proposition 1: Demand for information is decreasing in farmer confidence

Conditional on ability, ρ_u, WTP is a decreasing function of initial farmer confidence, ρ_{θ_0} and is therefore decreasing in confidence at time $t = 1$.

Combining the result from equation 8 with equation 5 yields

$$\sigma^2_{\theta_1} - \tilde{\sigma}^2_{\theta_1} = \frac{1}{\rho_{\theta_0} + \rho_u} - \frac{1}{\rho_{\theta_0} + \rho_u + \rho_S} \equiv WTP \tag{10}$$

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

$$\frac{\partial WTP}{\partial \rho_{\theta_0}} = \frac{1}{(\rho_{\theta_0} + \rho_u + \rho_s)^2} - \frac{1}{(\rho_{\theta_0} + \rho_u)^2} < 0 \tag{11}$$

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.

Proposition 2: Demand for information is decreasing in farmer ability

Conditional on an initial level of confidence, ρ_{θ_0}, WTP is a decreasing function of farmer ability, ρ_u.

Taking the first derivative of (10) with respect to ρ_u gives:

$$\frac{\partial WTP}{\partial \rho_u} = \frac{1}{(\rho_{\theta_0} + \rho_u + \rho_s)^2} - \frac{1}{(\rho_{\theta_0} + \rho_u)^2} < 0 \tag{12}$$

Conditional on the initial level of confidence, demand for information is decreasing in farmer ability (ρ_u).

2.2 Responsiveness to Information

We now consider a farmer that is given a signal for free. Upon receiving the signal S, and assuming that a farmer's beliefs about the precision of the signal remain constant, σ_S^2, optimal input usage is updated according to Bayes' rule as given in equation 6:

$$\tilde{\theta}_1 = \theta_1^* \left(\frac{\rho_{\theta_1}}{\rho_S + \rho_{\theta_1}} \right) + S \left(\frac{\rho_S}{\rho_S + \rho_{\theta_1}} \right) \tag{13}$$

Proposition 3: Information responsiveness is decreasing in farmer confidence *For any signal S, the difference between actual input use after receiving information and planned input use prior to receiving information is decreasing in farmer confidence.*

We define the degree of information responsiveness after receiving the signal (α) as

$$\alpha = \frac{\tilde{\theta}_1 - \theta_1^*}{S - \theta_1^*} \tag{14}$$

where responsiveness captures the degree to which the posterior of the optimal input value moves towards the signal as the fraction of the distance between the prior and the signal. For $\theta_1^* > \tilde{\theta}_1 > S$, α increases from zero to one as the posterior approaches the signal (i.e., the farmer responds more to the information).[7]

From equation 6, we can rewrite the numerator of equation (14) as:

$$\tilde{\theta}_1 - \theta_1^* = S \left(\frac{\rho_S}{\rho_S + \rho_{\theta_1}} \right) + \theta_1^* \left(\frac{\rho_{\theta_1}}{\rho_S + \rho_{\theta_1}} \right) - \theta_1^*. \tag{15}$$

[7] We provide further explanation and justification for this measure of responsiveness in Section 3.5.

Taking the derivative of this expression with respect to confidence at time $t = 1$ yields:

$$\frac{\partial}{\partial \rho_{\theta_1}}[\tilde{\theta}_1 - \theta_1^*] = \frac{\rho_S(\theta_1^* - S)}{(\rho_S + \rho_{\theta_1})^2} \tag{16}$$

If the planned input amount is larger than the recommendation, such that $\theta_1^* > S$ and $\partial[\tilde{\theta}_1 - \theta_1^*]/\partial\rho_{\theta_1} > 0$, the denominator of equation (14) is negative and fixed at time t=1, hence

$$\frac{\partial \alpha}{\partial \rho_{\theta_1}} < 0 \tag{17}$$

In other words, the degree of advice utilization is decreasing in farmer confidence. The same result holds when farmers are applying less than the recommended amount, or $\theta_1^* < S$.

Proposition 4: Information responsiveness is decreasing in farmer ability *For any signal S, the difference between actual input use after receiving information and planned input use prior to receiving information is decreasing in farmer ability for a given initial level of confidence.*

As above, taking the derivative of the numerator of equation (14) with respect to ability at time $t = 1$ yields

$$\frac{\partial}{\partial \rho_u}[\tilde{\theta}_1 - \theta_1^*] = \frac{\rho_S(\theta_1^* - S)}{(\rho_S + \rho_{\theta_0} + \rho_u)^2} \tag{18}$$

The weight placed on the signal is decreasing in the farmer's ability, so that

$$\frac{\partial[\tilde{\theta}_1 - \theta_1^*]}{\partial \rho_u} < 0 \tag{19}$$

Advice utilization decreases in ability. If the planned input amount is larger than the recommendation such that $\theta_1^* > S$ and $\partial[\tilde{\theta}_1 - \theta_1^*]/\partial\rho_u > 0$, the denominator of equation (14) is negative and fixed at time $t = 1$, hence

$$\frac{\partial \alpha}{\partial \rho_u} < 0 \tag{20}$$

In other words, the degree of advice utilization is decreasing in farmer ability. The same result holds when farmers are applying less than the recommended amount, or $\theta_1^* < S$.

3 Experimental Design and Data

3.1 Study Area and Randomization

The study was conducted in partnership with the Department of Soil Science of Rajendra Agricultural University (RAU) in Samastipur district, Bihar, the oldest and most prestigious institution for agricultural research and extension in the state. We used a multistage sampling approach to form our survey sample. 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 1). These three districts span two distinct agroecological zones and have varying levels of agrarian dynamism. 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.[8] Within each of these 16 blocks, 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. After eliminating households for which the soil samples were not collected, our treatment group consists of 490 households (89 percent of sampled households) and the control group consists of 284 households (98 percent of sampled households).[9]

3.2 SHC Intervention and Data Collection

Despite India's history of soil testing, the state of Bihar has lagged behind other states such as Gujarat in its soil testing program. Among treatment farmers, only 2 percent reported ever having their soil tested, but 95 percent indicated that they would like to have their soil tested. This suggests a potentially high demand for the service that is not currently being met. Of the farmers

[8] We had originally planned to carry out the intervention during the monsoon rice-growing season (*kharif*). Due to logistical challenges with the pace of soil analysis in the RAU laboratory, we were forced to delay distribution of SHCs until just prior to the wheat-growing season (*rabi*). Limited soil testing capacity remains a major challenge for the successful implementation of the soil testing program all over India, and delays are common. Fortunately, almost all farmers in our study area also grow wheat on more than 90 percent of their gross cultivated area during the *rabi* season.

[9] Eleven percent of households either refused to have their soil tested, did not want to participate in the SHC delivery when enumerators returned with the results, or could not be located during the follow-up.

that expressed the desire to have their soil tested, over half wanted information about how much urea and other fertilizers to use as well as the timing of fertilizer application. Others were concerned only with how much urea to use (17 percent), which other fertilizers to use (26 percent) or when to apply fertilizers (5 percent). Farmers that did not want their soil tested reported that there would be no benefit as the primary reason (37 percent), while others cited a lack of trust in the results (9 percent), that they already know soil health (9 percent), or had some other reason (45 percent).

Figure 2 illustrates the timeline of the SHC intervention and related data collection activities undertaken during the study. We conducted a baseline survey in April-May 2014 prior to collecting soil samples. The baseline survey covered both treatment and control households and collected information on farmer characteristics (such as age, gender, education, caste membership, total landownership), use of inputs (including quantities of applications for different types of fertilizers), and yields for crops harvested during 2012-2013. In order to analyze the underlying reasons for farmers' fertilizer choices and responses to the SHCs, we collected additional data throughout the experiment. During the baseline survey, we administered experiments to treatment and control farmers to elicit risk preferences, self-reported confidence, and subjective beliefs regarding optimal urea and diammonium phosphate (DAP) use on the upcoming rice crop for *kharif* 2014.[10] These latter experiments are explained in greater detail in Section 3.2.1 below.

In May-June 2014, following the baseline survey, we collected soil samples from one plot of every treatment farmer. The plot from which samples were collected was randomly selected from a list of farmers' self-identified two most important plots. Eight graduates from local agricultural universities with farming experience 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. These 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 approximate the intended execution of the central government's SHC program, albeit at an individual household level rather than on a gridded basis (see footnote 2).

[10]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).

The soil samples were sent to RAU for chemical analysis. Using wet chemistry methods, the soil scientists at RAU tested for the levels of key macronutrients (nitrogen, phosphorus, and potash) available in the soil, as well as organic carbon content, electrical conductivity, soil pH value (i.e., whether the soil is alkaline, acidic, or neutral), and the levels of some important secondary- and micronutrients (sulfur, zinc, iron, copper, and manganese). Based on these analyses, and using simple yield response equations (see section 3.4), the 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 crop-wise fertilizer recommendations for the 2014 *kharif* and 2014-15 *rabi* seasons. Recommendations were calibrated for a designated target yield of 40 quintals per hectare for wheat.[11]

The SHCs (printed in Hindi) were hand-delivered to individual farmers in November 2014 (prior to planting the *rabi* wheat crop) by the aforementioned extension agents trained on the proper interpretation and explanation of SHC results and recommendations. 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 information on the recommended quantities of different fertilizers to apply to their various crops. An example of the soil health card (translated into English) is presented in Figure 3.

An additional survey was carried out following the distribution of the SHCs (December 2014-January 2015) to collect information on cultivation habits, fertilizer application, and wheat yields from the previous *rabi* season (2013-2014). A follow-up survey was conducted after the *rabi* 2014-15 wheat harvest (June-July 2015) to collect information on farmers' fertilizer application and production. An additional interaction was conducted to elicit farmers' WTP for zinc (June-July 2015), following the follow-up 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).

[11] A quintal is equivalent to 100 kg.

3.2.1 Measurement of Subjective Belief Distributions

To elicit subjective beliefs about optimal fertilizer application rates, we employed a hypothetical, visually-aided elicitation method. Specifically, farmers were asked to allocate beans across bins according to how likely they think that each fertilizer application rate bin would lead to the highest yields on their primary agricultural plot. Delavande et al. (2011a) argue 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), our elicitation procedure is constrained by the non-verifiability of the true value of the random variable, and therefore we are unable to elicit beliefs with incentives. Nevertheless, we present results controlling for risk aversion and discuss the implications of hypothetical bias in our results.[12]

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

After participants were comfortable representing probabilities with the beans, they were asked to allocate 20 beans to represent their subjective beliefs regarding the optimal urea and DAP application rates (in kg per katha) for the upcoming *kharif* season on their primary rice-growing plot.[13] 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

[12] Harrison (2016) argues that, for empirically plausible levels of risk aversion, the most important features of the latent subjective beliefs distribution can be elicited without needed calibration for risk attitudes.

[13] A katha is a unit of land commonly used throughout South Asia, with 1 acre approximately equivalent to 32 katha.

distribution of urea application rates. Both supports have wide tails, and the bins are not of equal size. 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.[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. For each bin, respondents were asked:

> Do you think that this range of total urea (or 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 repeating these questions for each bin, respondents were allowed to reconsider their choices and re-allocate beans accordingly, using the entire support and all beans.

Figures 6 and 6 give the range of values available for urea and DAP, respectively, and the proportion of total beans (or total probability) allocated to each bin. The figures show that at least some farmers consider the whole support to be plausible for both fertilizers and they are relatively uniform, though slightly right-skewed. The skewness may be attributed to local beliefs over 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 20 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 estimate the first and second moments for each individuals' subjective beliefs assuming a stepwise uniform distribution (Attanasio and Augsburg, 2016). The expectation and variance of the elicited beliefs are used as proxies for the corresponding expectation and variance of the farmers' true beliefs distribution prior to receiving soil testing $(\theta_1, \sigma^2_{\theta_1})$. Table 1 reports the summary statistics for the moments of the subjective beliefs distributions for urea and DAP.

[14]Delavande et al. (2011a) 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.

3.3 Self-Reported Confidence and Trust

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 trust in agricultural extension agents. The first question asks:

> How often do you have doubts about agricultural practices?

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, which we use as a proxy for a farmer's confidence in their farming abilities.

To have a measure of farmer trust in agricultural extension agents, we asked a binary measure of respondent trust in the information provided by agricultural extension agents. Trust in extension agents is a proxy for beliefs about the efficacy of agricultural extension services and the information provided. Lower trust should therefore provide information on farmers' perception of the reliability of signals from extension agents. Referring back to equation 7, we treat farmers' relative confidence as a measure of the precision of their prior beliefs (ρ_{θ_1}) and their trust response as a binary measure of the subjective precision of the signal (ρ_S).

While we elicited subjective beliefs over optimal fertilizer rates for the rice crop for *kharif* 2014, logistical constraints delayed the preparation of SHCs until after the sowing for the *kharif* 2014 season. Due to the timing of the experiment discussed in the previous section, we use these subjective beliefs in the analysis of fertilizer usage during the winter *rabi* (wheat) season of 2014/2015. Empirical overconfidence experiments find within-agent confidence correlations between 0.50 and 0.60 across tasks (Klayman et al., 1999). Given the similarity in experimental tasks in the present study, we believe confidence in beliefs for fertilizer application during the *kharif* season is a reasonable, though imperfect, proxy for confidence in beliefs for fertilizer application in the *rabi* season. Table 2 provides evidence that dispersion in beliefs for both urea and DAP are positively correlated (Pearson correlation coefficient of 0.38), suggesting that confidence is correlated across different fertilizers for the same crop. The dispersion measures are also correlated with survey measures of relative confidence described above, suggesting that our dispersion measures are capturing meaningful heterogeneity in respondents that may also be applicable across crops[15]

Additionally, from the baseline survey, over 92 percent of farmers planned to use urea in *kharif* 2014, while only 75 percent planned to use DAP. Lower rates of DAP usage may be indicative of a lack of experience with the fertilizer on rice crops. Farmers have more experience with urea and DAP in the *rabi* wheat season, with only 1 percent of farmers in the sample not applying both fertilizers.

3.4 Ability

In the theoretical model developed in section 2, ability reflects farmers' managerial capabilities and their capacity to limit the impacts of shocks. As a result, ability results in faster convergence of beliefs to the optimum and, consequently, higher yields. Based on this reasoning, we construct a measure of ability using the simple, linear yield response equation used by the soil scientists at RAU as the basis for the soil recommendations. The equation relates the target yield and available levels of nitrogen in the soil to calculate a recommendation for urea application at the plot-level. These equations are customized to each district based on some underlying basic soil characteristics. The recommended urea application (in quintals per hectare) :

$$S_{U,i} = (Y^* \times 4.06 - N_i \times 0.23)/46.08$$

where $S_{U,i}$ is the recommended level (or signal) for urea (U) specific to farmer i, Y^* is the target yield (in quintals per hectare), and N_i is the nitrogen available in the soil. From this equation, we calculate the yield that the farmer *should* have obtained in *rabi* 2013 by replacing $S_{U,i}$ with the actual level of urea applied and solving for Y_i^*. This "target", Y_i^*, therefore, would then be the yield that farmer i *should* have obtained, assuming the specified yield response parameters. Using this value, we calculate the difference between realized wheat yields during *rabi* 2013 ($Y_{13,i}$) and $Y_{13,i}^*$. Farmers are categorized as "high" ability if their difference falls within the bottom quartile of the distribution of $Y_{13}^* - Y_{13}$, and are categorized as "low" ability if their difference in the top quartile of the distribution of $Y_{13}^* - Y_{13}$. The middle fifty percent of farmers are classified as "medium" ability. The resulting categories provide a measure of ability across farmers that allows us to control for

[15] Note that we do not utilize subjective assessments of the *location* of these beliefs distributions (e.g., the means), but rely on assessments of the *shape* of the distributions (e.g., the variance).

relative differences in innate farming ability and test the comparative statics from the model on the relationship between ability and responsiveness to the SHCs.

3.5 Responsiveness to Information

Information responsiveness (α), described in Section 2.2, is proxied by a measure of advice taking commonly used in the Judgment-Advisor System (JAS) literature.[16] In this literature, advice utilization of a "judge", $\alpha = \frac{E-B}{S-B} \in (-\infty, \infty)$, is the ratio of two differences: that between the endline (E) and baseline (B) estimates, and that between the recommendation (S) and the baseline estimate. In our context, we take the fertilizer application rates during *rabi* 2013-14 to represent baseline estimates in the calculation of responsiveness and fertilizer application rates during *rabi* 2014-15 to represent the endline estimates after having received the plot-level fertilizer recommendations (S) in the form of SHCs.[17]

This measure of advice utilization is appealing because it provides a simple way of capturing the degree to which the signal recipient moved from her initial estimate to her final estimate as a function of the recommendation, but it has a number of drawbacks. First, the formula is undefined when the baseline estimate equals the recommendation. None of the sample households applied urea or DAP at the same rate as the recommendation, so this does not affect our sample. Second, in the event that the signal recipient moves in the opposite direction from the recommendation, the advice utilization measure becomes negative, and the interpretation of magnitude of these values becomes ambiguous. Similarly, if the judge overshoots the recommendation, the measure is strictly larger than one. These undefined or "out of range" values are generally dropped in the JAS literature. However, the majority of JAS studies are confined to lab experiments where the proportion of problematic observations is less than 5 percent. The nature of farming in rural India implies that the proportion of "out of range" values in our sample is large relative to the literature (above 50 percent for urea and 30 percent for DAP). Moving in the opposite direction or overshooting the advice may be due to a variety of reasons including season specific constraints (credit, labor, etc), biased learning, or shocks (e.g. pests, health). In the analysis that follows,

[16] See Bonaccio and Dalal (2006) for an overview of this literature and a detailed description of various measures of advice utilization.

[17] Ideally, we would have preferred to use the experimentally-elicited priors as our baseline measure, but since the priors were elicited with respect to the *kharif* rice crop and we measure responsiveness following signals provided for the *rabi* wheat crop, we were unable to do so.

we exclude these problematic observations for two reasons. One, we do not have an otherwise defensible strategy to sufficiently explain why farmers move in the opposite direction or overshoot in responses to advice due to data limitations. Second, our model makes predictions about marginal changes in responsiveness in the direction (i.e., the adjustment from prior to posterior is an increase or decrease consistent with the recommendation, though of a different magnitude) of the advice.

3.6 Summary Statistics

Table 3 presents summary statistics from the baseline survey and examines the balance between the treatment and control groups. In our sample, 90 percent of the respondents were male, and their average age was 46 years. Nearly 40 percent of respondents were illiterate. The summary statistics reported in Table 3 show that the randomization process resulted in a balanced sample in terms of farmer characteristics, productivity, beliefs, and fertilizer application.

Summary statistics for the dependent and explanatory variables used to test the impacts of confidence on demand for and responsiveness to information are reported in Table 4. Of the 470 treated households, 30 households are excluded from the analysis because of missing values for baseline urea application rates and 72 households are excluded because they did not plant wheat in either the *rabi* 2013 or *rabi* 2014 season. Consequently, we only report summary statistics for the remaining 369 households. From this sample, 87 percent of household heads are male and 62 percent are able to read and/or write. Household sizes are quite large, with over 8 members per household on average. Notably, the percentage of farmers with less than 10 years of experience with planting wheat is less than 20 percent; that is, a large majority of households have had substantial farming experience with which to form beliefs about optimal input management. The average size of tested plots was 0.19 hectares (0.47 acres). Only a quarter of households own an irrigation pump. Those without an irrigation pump rely on renting one (73 percent) or water from a nearby canal (2 percent). Credit access is low in Bihar, as shown in our sample. Nine percent of farmers applied for or had access to credit during the *rabi* 2013 season. In terms of confidence and trust, only 4.5 percent of farmers have a little more doubts than others and 38 percent said they have the same amount, suggesting that confidence in farming techniques is pertinent for rural Bihar. Sixty nine percent of farmers responded that they would not trust extension agents until there is clear evidence that the information is effective.

3.7 Soil Test Results and Recommendations

The recommended doses of different fertilizers are partly determined on the basis of available concentrations of different nutrients as found in the chemical analysis of soil samples, but are also conditioned by a target yield that is specific to a particular crop. One way to think about the recommendations is that they provide advice on the application of nutrients required to achieve a target yield, once the availability of nutrients in the soil is taken into consideration. The basic recommended dose was based on a target wheat yield of 4 metric tons per hectare. With this target yield, the recommended dose of urea varied from 232 to 297 kg per hectare while baseline application rates varied widely (mean of 210 kg, standard deviation of 86 kg). For phosphate (DAP), the recommended application varied from 100 to 240 kg per hectare, and for potash, from 34 to 122 kg per hectare. In our sample, 137 farmers received a recommendation to apply 20 kg per hectare of sulfur, and 180 farmers received a recommendation to apply zinc at the rate of 25 kg per hectare. 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.

While the recommendations provided by RAU assumed a target yield of 4 metric tons per hectare, in reality, farmers' "target" yields vary because of budgetary considerations and other factors constraining productivity. The average yield at baseline was 25 percent lower than the target yield used as the basis for recommendations (3.03 metric tons per hectare). We therefore also calculate recommendations that were re-calibrated on the basis of farmers' self-reported wheat yields. These recommendations were not provided to farmers, but provide information on the inputs farmers could use to obtain yields similar to what they might reasonably establish as a target given their soil characteristics.

Table 5 compares the recommendations with data on actual fertilizer use from the baseline survey. Calibrated results show that more than 80 percent of farmers in our sample apply more than the recommended dose of urea for their level of yields. We also find that overapplication of DAP is common, with more than 75 percent of farmers applying more than the recommended dose. During the 2013-2014 *rabi* season, urea and DAP application was higher than the calibrated recommendations by 72 and 36 percent, respectively. Farmers generally applied less potash than the recommended dose, with average applications 69 percent less than the calibrated recommendations. While RAU scientists recommended that most farmers in our sample apply potash to their wheat crop at an average rate of 43 kg/ha, only 143 treatment farmers applied potash to wheat.

It is widely argued that the high subsidy on urea could be one of the reasons for its excessive use. We note, however, that although DAP is not as heavily subsidized as it once was (and as urea presently is), a significant number of farmers were found to have applied excessive amounts of DAP. In fact, DAP is not only costly, but when applied in excess, it gets fixed into the soil and is not available to plants. The application of secondary nutrients and micronutrients was found to be very rare among sample farmers. For example, one in four soil samples were found deficient in zinc and sulfur, but few farmers had applied zinc or sulfur in the previous season.

In Figures 6 and 6, we compare the densities between fertilizer usage in *rabi* 2013 and recommended fertilizer application rates for *rabi* 2014 for treatment farmers (using 4 metric tons per hectare as target). Urea usage during *rabi* 2013-14 was more widely dispersed than the recommended values, as over 25 percent of farmers have baseline application rates below the tenth percentile of the recommended value. Additionally, the spread of the recommended urea density demonstrates substantial heterogeneity in nitrogen levels in soil across households in the region. Similarly, DAP application rates are more disperse than the recommendations, though baseline DAP application rates are higher than the recommendations.

The difference between the baseline fertilizer application rates and the recommendations are presented in Figures 6 and 7. The figures suggest that a large proportion of treatment farmers (42 percent) apply urea at a rate within 50 kg per hectare of the recommended rate, but many treatment farmers are far from the optimal value, and may stand to benefit from revising their fertilizer application behavior. The divergence between the target and actual behavior may be due to a variety of factors including season specific constraints, lower yield targets, and a lack of knowledge about optimal management of inputs. Data on treatment farmers' farm management across the *kharif* rice seasons (e.g., 2013-2015) suggests that application rates stay relatively stable over time.

4 Empirical Strategy

In this section, we first test whether the SHCs affected fertilizer use and, in particular, whether there are heterogeneous responses based on farmer confidence. Second, we test the predictions of the model introduced in Section 2; specifically, whether confidence in one's prior subjective beliefs affects responsiveness to the information intervention.

4.1 Did the SHCs Influence Farmers' Fertilizer Use?

The randomized design of the intervention allows us to estimate the causal impacts of the delivery of SHCs through a comparison of mean fertilizer use between the treatment and control groups. Because we had control over who received the SHC, there are no concerns about sample selection, nor do we have reason to believe that any farmers from control villages would have inadvertently received information on soil health or fertilizer recommendations from treated farmers. We estimate the impacts of the receipt of the soil health card on the sample of farmers that planted wheat in both the baseline and endline.[18] Our outcome variable of interest is the log of the respective fertilizer use at endline. We use the following estimating equation to study effects on fertilizer use:

$$F_{ivbe} = \beta_0 + \beta_1 T_{iv} + X_i^{'}\gamma + \mu_b + \nu_e + \epsilon_{ivbe} \quad (21)$$

where F is the log of fertilizer application rates measured in kg per hectare by farmer i from a village in block b, T_iv is a treatment indicator. We include block (strata) fixed effects μ_b and enumerator fixed effects ν_e. The latter effects are included because farmers may have felt obligated to adhere to the SHC recommendation, and self-reported fertilizer use could have been sensitive to the identity of the enumerator, who also distributed the SHC. In some specification, we include X_i a vector of individual and household characteristics including gender, age, literacy, landholding size, size of the treated plot, and baseline fertilizer usage to increase precision.[19]Finally, we adjust our standard errors e_{ivbe} for the clustered nature of the intervention (at the village level) in all estimations.

[18]Table 2 in the appendix provides evidence that there was no differential selection out of wheat production in the treatment group. The results are robust to including households that grew other crops (lentils, vegetables, etc.).

[19]Including baseline values of the outcome variable increases the power of the estimator relative to difference-in-differences estimators when auto-correlation is low and and allows for differences in the measurement of baseline variables (McKenzie, 2012).

Table 6 reports the results from estimating equation (21), using the application rates of the three major fertilizers (urea, DAP, and potash) and an indicator for potash application used by local farmers in the wheat season as the dependent variables in a series of regressions. In these regressions we use the full experimental sample and the outcome variables are in logs. Therefore the samples vary across specification based on whether farmers applied any of the respective fertilizer in the endline. As shown in Section 3.7, the recommendations for urea and DAP may be higher or lower than farmers' status-quo application rates, but given the random assignment of treatment and control villages, it seems plausible to maintain the assumption that there are no systematic patterns of these differences. Therefore we can only distinguish whether the treatment had a differential impact on total fertilizer use and cannot determine whether treatment farmers adjusted fertilizer use in the direction of the recommendation.

Across the regressions, the treatment effects are of a generally small magnitude, representing between 2 and 6 percent of the average level of fertilizer application in the control group, and further are not statistically significant at conventional levels. The estimates remain insignificant when control variables, including baseline application rates, are included to increase precision. Interpreting the signs of the treatment effects as responses to the SHC information treatment depends on whether the farmers considered the 4 metric ton per hectare target yield or if they re-calibrated the recommendations based on their own subjective target yield. If farmers were responsive to the recommendations based on the 4 metric ton per hectare target yield, then we should expect to see increased application of all three fertilizers. If, on the other hand, farmers re-calibrated the recommendations to a more attainable yield target, then we should expect to see reductions in urea and DAP application and a smaller increase in potash application.

We find scant evidence that the information treatment increased the average urea application (95 percent CI: -0.02, 0.10). These results suggest that receipt of a SHC had no systematic effect on farmers' subsequent urea application, and we can rule out positive or negative effects larger than 10 percent. But the lack of a systematic effect also signals continued over-application of urea relative to the efficient level required to achieve the attained yields. A similar narrative applies to application of DAP: we fail to find convincing statistical evidence that receipt of SHC recommendations systematically affected DAP application (95 percent CI: -0.14, 0.03). Indeed, while the SHCs on average recommended an increase in DAP application to achieve a 4 metric ton per hectare target yield, the negative point estimate on the treatment effect is consistent with the opposite behavior. When it comes to potash, the point estimate is consistent with what would be expected if the SHC produced the appropriate response, though again there is rather weak statistical evidence that this effect is systematic (95 percent CI: -0.09, 0.16). Since the majority of farmers did not apply potash at all, we also estimated a linear probability model to test for the effect of SHC receipt on a binary indicator of potash use (columns 7 and 8), but we do not find strong evidence that the SHC increased the use of potash in the sample.

4.2 Heterogeneity in Treatment Effects

One explanation for why there may not be evidence of a systematic response to the SHC is that farmers update their beliefs about the appropriate fertilizer application rates in different ways, due to, among other factors, their degree of confidence in their initial beliefs. In this section we look at heterogeneity in the SHC treatment effect by the level of farmers' confidence. We expect treatment farmers with higher levels of confidence to behave as if they were control farmers and not respond to treatment while less confident farmers are more likely to change their behavior. To test this prediction, our outcome variable of interest is the level of fertilizer usage in the endline. Our regression equation is:

$$F_{ibve} = \beta_0 + \beta_1 T_{iv} + \beta_2 T_{iv} C_i + \beta_3 C_i + X_i^{'} \gamma + \mu_b + \nu_e + \epsilon_{ivbe} \tag{22}$$

where F is the log of fertilizer application rates measured in kg per hectare by farmer i from a village in block b, $T_i v$ is a treatment indicator. Across different estimations, we include two different measures of confidence (C_i): if farmers have more doubts and the coefficient of variation the farmers' elicited beliefs. We include block (strata) fixed effects μ_b and enumerator fixed effects ν_e. Where noted, we include X_i vector of individual and household characteristics including gender, age, literacy, landholding size, size of the treated plot, and baseline fertilizer usage to increase precision. Finally, we adjust our standard errors e_{ivbe} for the clustered nature of the intervention (at the village level) in all estimations.

Table 7 reports results that interact the treatment dummy with measures of confidence. Given the lack of treatment effects on average, we might expect that only less confident farmers would be likely to change their input usage in response to new information. The theoretical predictions seem strongly borne out by the results: less confident farmers applied more urea overall but their input usage declines relatively more as an impact of the treatment. Farmers with one standard deviation higher dispersion in beliefs (less confident) decrease their urea usage by 11 percent relative to control farmers. Similar effects emerge for DAP and potash application rates, though we do not find strong evidence for a comparable effect on the likelihood of applying potash (column 3).

Thus, while the results in Table 6 suggest that the SHC treatment was not successful overall, the results in Table 7 suggest that the subset of less confident farmers were somewhat receptive to the information and lowered their input usage in response to the recommendations. This is contrary to what would be expected if farmers were basing fertilizer application decisions based on the recommendations calibrated to a 4 metric ton per hectare yield target, but are consistent with what would be expected if farmers were re-calibrating the recommendations based on what they perceive to be more attainable yields. Further, the impacts are of a relatively large magnitude and suggest that identifying and targeting farmers who are open to new information may increase the returns to soil testing. In this estimation, we are unable to control for farmer ability because we can only calculate it for those households in the treatment group whose soil characteristics we know. However, the successful randomization implies that our treatment and control samples are observationally similar in expectation, which should allay concerns that this effect is driven by differences in farmers ability or other unobservables.

4.3 Demand for Information

We now turn to examining whether treatment farmers' subjective beliefs and farming ability influence their demand for soil testing. Because soil tests and willingness to pay for soil tests were only collected for farmers in the treatment, we restrict the sample to treatment farmers for the remaining analysis. The theoretical model developed in section 2 predicts that willingness to pay for a signal is decreasing in both confidence and ability. To test the comparative statics of ability and confidence on demand for soil testing recommendations empirically, we use farmer i's stated willingness to pay for soil testing elicited during the baseline survey (WTP_i) as our dependent variable. We estimate a Tobit model to account for left-censoring in the stated valuations (thirty percent of the sample state a willingness to pay of zero). The ability measure (A_i) used in the following estimations classifies households into high, medium, and low ability based on the difference between the realized yield in *rabi* 2013 and the yield they should have achieved given their observed fertilizer application. We include a binary measure of trust in extension agents (Tr_i) to control for perceived signal accuracy and the age and literacy of the household head to account for initial beliefs (I_i).

Specifically, we estimate the following equation, where i indexes households, v indexes villages, and $k \in \{1, 2, 3\}$ indexes the confidence measures:

$$WTP_{iv} = \beta_0 + \beta_1 C_{iv}^k + \beta_2 A_{iv} + \beta_3 Tr_{iv} + \beta_4 I_{iv} + X_{iv}^{'} \gamma + \tau_v + e_{iv} \tag{23}$$

where the βs and γ are coefficients to be estimated and τ_v is a vector of village fixed effects.

Tables 8 and 9 provide the Tobit coefficient estimates for the latent WTP given in equation 23. The coefficients of interest are β_1 and β_2, which capture the effects of confidence and ability on WTP, respectively. Consistent with model predictions, farmers that are less confident about their agricultural decisions have a higher WTP than the most confident farmers, which is consistent with the model's prediction ($\beta_1 < 0$). We find that farmers with more doubts relative to their peers (i.e. they are less confident in their decisions) have a higher WTP for the SHCs. Moving from having fewer doubts to having above average doubts increases WTP by USD 0.45 (p-value= 0.04), which is slightly less than one third of a standard deviation increase in WTP.[20] Further, columns 2 and 3 demonstrate that WTP is increasing in both measures of dispersion (urea) as predicted by the model, where a standard deviation decrease in dispersion (0.19) decreases willingness to pay by an average of USD 0.30, or 15 percent of the total price of a SHC (p-value < 0.01). These results are robust to the inclusion of baseline characteristics, as shown in columns 4 through 6, and quantitatively similar to those using measures of dispersion for DAP in Table 9. These results suggest that less confident farmers in Bihar may be aware of their potential knowledge gaps and may demand information about decisions they make regularly, even after controlling for individual levels of experience.

Farmer trust in extension services is positively correlated with WTP across the models (p-value = 0.04) implying that subjective perceptions about the credibility of the source of the signal may be

[20] For comparison purposes, at the time of the survey, the price of SHCs was slightly above USD 2.00.

important in farmer decisions to purchase or utilize soil testing and/or fertilizer recommendations, though the effect is not large. Nevertheless, this has important implications, as extension agents are a primary source of 'official' advice on inputs, technologies, and practices, and are likely to continue to be the primary channel through which the government distributes SHCs under the national program. Literacy increases demand for the SHCs by USD 0.27 (p-value $= 0.03$) as farmers that are unable to read may anticipate interpreting the cards incorrectly. The impacts of ability are jointly statistically insignificant across specification (p-value ≥ 0.49) but the coefficients are in the direction predicted by the model. In summary, the result that less confident farmers have a higher WTP is robust across all estimations, consistent with the theoretical model, and implies that both the survey-elicited response and the dispersion of beliefs capture underlying heterogeneity in individual confidence. Further, literacy may act as a barrier to adoption of SHCs, as illiterate farmers have a lower WTP for SHCs in the baseline survey.

4.3.1 Usage of Information

We now turn to the relationship between confidence and responsiveness to the SHCs as predicted by the model. Our dependent variable is the advice utilization measure (α) described in Section 3.5. We include input responsiveness for both urea (α_U) and DAP (α_D) as they are the primary fertilizers used by farmers in the sample during the *rabi* season. As discussed in Section 3.2, all treatment farmers received input recommendations provided by the SHCs that included plot specific application rates of urea and DAP, and various of micronutrients including zinc. In the construction of the dependent variable, the baseline inputs are the fertilizer application rates in *rabi* 2013 and the endline inputs are the fertilizer application rates in *rabi* 2014. The signal (S) is the recommended value of fertilizer application displayed on the SHC based on the yield response estimates from the soil scientists at RAU.

To test the comparative statics of ability and confidence on responsiveness to soil testing recommendations, we estimate the following equation using OLS:

$$\alpha_{ijv} = \beta_0 + \beta_1 C^k_{ijv} + \beta_2 A_{ijv} + \beta_3 Tr_{ijv} + \beta_4 I_{ijv} + X'_{ijv}\gamma + \tau_v + u_{ijv}. \tag{24}$$

where the responsiveness are fertilizer-specific $j \in \{U, D\}$ and indexed by confidence measures

$k \in \{1, 2, 3\}$, and, as before, the βs and γ are coefficients to be estimated. The coefficients of interest are β_1 and β_2, which capture the effects of confidence and ability on input responsiveness to the SHC recommendations, respectively.

Table 10 reports regression results for urea responsiveness, with standard errors adjusted for clustering at the village level, both with and without individual and household characteristics. We provide results for the subsample of observations for which the farmer responds in the direction of the recommendation and does not overshoot the recommendation, or $\alpha \in [0, 1]$. Less confident farmers, categorized using both their incidence of relative doubts and the dispersion of their subjective beliefs, are more responsive to urea recommendations provided in SHCs. The advice utilization measure (α) can be interpreted as a percentage movement towards the recommendation, so that farmers with similar or more doubts than their peers move 14 percent closer (p value = 0.08) to the recommended urea rate than those with fewer doubts. Responsiveness is increasing in the dispersion of farmers' beliefs, such that a standard deviation increase in the coefficient of variation in beliefs (0.19) is associated with a 5.4 percent increase (p-value = 0.03) in responsiveness, with a similar value of 6.3 percent using the standard deviation (p-value = 0.01). The results are robust to the inclusion of numerous baseline characteristics (columns 4-6) with the exception of the coefficient on relative doubts which becomes insignificant at conventional levels (p-value = 0.10). Table 11 reports regression results for DAP responsiveness, with standard errors clustered by village, both with and without individual and household characteristics. The impacts of confidence on responsiveness are not significant for farmers' relative doubts, though responsiveness is increasing in the measures of dispersion.

The results on farmer ability confirm the predictions of the model for urea, as more able farmers respond less to the urea target on the SHCs. Relative to low ability farmers, high ability farmers are between 28 percent and 36 percent further from the recommendation. The coefficients for medium ability farmers are negative and insignificant, but the coefficients on medium and high ability farmers are jointly significant across all specification (p-values from 0.001 to 0.019). These results are negative for DAP responsiveness but insignificant with the exception of column 4. Surprisingly, after controlling for confidence and ability, farmers with less than five years of experience respond less to the SHCs. An extension of the theory that includes farmers' full history of learning suggests that more periods of learning will increase accuracy and expected yields. However, those with little experience may rely more on rules of thumb, own experimentation or social networks rather than scientifically-derived recommendations during early periods.

We therefore see that, at least among treatment farmers, farmers that are less confident about their agricultural decisions (using three separate measures of confidence) have a higher willingness to pay for soil testing and recommendations, consistent with model predictions. We interpret these results to suggest that less confident farmers in Bihar demand information outside of their own experience or the information to which they typically have access. Further, when provided with recommendations from the soil tests, less confident farmers were more likely to adjust their input use in the direction of the recommendation (once re-calibrated based on more attainable yields) and are more responsive to both the urea and DAP recommendations as predicted by the model.

5 Alternative Explanations

In this section we provide alternative explanations into the reasons behind the lack of response to the SHC intervention. In the first part of this section, we report farmers' own explanations for why they over- or underapplied different fertilizers relative to the recommended doses. This self-reporting generally points toward an adherence to traditional fertilizer use, reflecting a lack of confidence in the information contained in the SHCs. We then explore two further explanations for the lack of response. The first is that farmers simply did not understand the contents of the SHC; we should not expect farmers to change their behavior on the basis of recommendations that they do not understand. The second is that farmers did in fact internalize recommendations, and the information did alter their preferred fertilizer mix, but other factors (such as cost, lack of access to credit, insufficient liquidity, or lack of timely availability of specific fertilizers) prevented them from acting on these changed preferences by shifting their actual application. The results from farmers' self-reported explanations provide additional evidence that farmers' confidence in their own input decisions largely explain the lack of response to the soil health card intervention, and we discuss the implications for future soil testing interventions in the following section.

5.1 Self-Reported Explanations

In the endline survey, we asked farmers whether they had retained the SHCs that were distributed prior to the *rabi* season, and whether they had consulted them in making fertilizer application decisions. While 93 percent of farmers claimed to have kept the SHCs, only 56 percent were able to locate the SHCs and show them to enumerators, and only 25 percent reported having consulted the SHCs.

We then asked farmers to report how much of different fertilizers they had applied relative to the recommendation: the recommended amount, more than the recommended amount, or less than the recommended amount. Farmers that self reported having applied more or less than the recommended amount were then asked why they did so. The results, presented in Table 13, suggest that trust in their own input choices over the recommendations is a crucial factor, with most farmers indicating a belief that their preferred amount was the correct amount and that the scientific recommendations were incorrect. For example, 66 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. We observed similar trends for DAP and potash. A similar proportion of farmers that reported having used more than the recommended amount of fertilizers said they believed yields would be reduced if they applied less.

Farmers that reported having applied less than the recommended amount also cited fertilizer cost as a factor, especially for DAP and potash, which are not as heavily subsidized as urea, and hence considerably more expensive. Liquidity constraints thus appear to be a barrier to more balanced fertilizer application. For example, 38 percent of farmers that used less than the recommended amount of DAP and potash said they did so because they did not have enough money or because these fertilizers were too expensive. Interestingly, despite the high urea subsidy often being blamed for the overapplication of urea, only 3 percent of farmers who applied more than the recommended dose of urea said they did so because it was inexpensive.

5.2 Did Farmers Understand the SHC?

A comparison of their subjective beliefs about whether they had used more or less than the recommended dose of a given fertilizer with the actual difference shows no significant correlation, suggesting that farmers exhibited a poor awareness of the recommendations or their current application rates. Only 40 percent of the farmers who overapplied urea (that is, those farmers whose self-reported application was more than the recommended dose from the SHC) believed that they had used more than the recommended dose. Similarly, of the farmers who overapplied DAP and potash, only 16 percent and 4 percent, respectively, believed that they had used more of these fertilizers than recommended by the SHCs. In contrast, the results seem to suggest that farmers are more prone to believe they have underapplied these fertilizers.

We carried out a telephone survey among treatment farmers in the course of the 2014-15 *rabi* season, not long after the SHCs were distributed, in order to further examine whether farmers understood the SHC recommendations issued to them. Treatment farmers were asked if they remembered whether their SHC recommended the use of some fertilizers that are less common in the study area, namely potash, zinc, and sulfur. These took the form of simple yes/no questions. The results of the phone survey show a very weak correlation between the actual recommendations and those recalled by the farmers. On average, 74-78 percent of farmers with nutrient-deficient soil correctly stated that the SHC recommended applying the relevant fertilizers. However, 67-68 percent of farmers with nutrient-sufficient soil wrongly stated that the SHC recommended applying more of the relevant fertilizers.

In sum, these results support the notion that farmers generally have a bias toward assuming that the SHCs recommended using more fertilizers and that farmers are unable to recall the information in the SHC. However, we also found that this gap can be rectified substantially by repeating the SHC information in a more salient context.

To assess whether trust in the quality of this information can explain these results, we also asked farmers in the Madhubani district (a largely zinc-deficient region) to report their own assessment of the zinc status of their soils. The results, reported in Table 15, show that even though, as we saw above, most farmers were clearly aware of the SHC indication, it seems that they preferred to ignore it: 96 percent of the farmers with zinc-sufficient soil according to the SHC recommendations believed their soils to be zinc deficient, and only 2 percent of those with zinc-sufficient soil believed their soils to be zinc sufficient. In other words, even when they are aware of the SHC contents, farmers seem to adhere to their own beliefs about the condition of their soils, a belief that tends to assume deficiency of micronutrients.

5.3 Revealed Preferences for Zinc

To gain further insight into the reasons behind farmers' seeming lack of responsiveness to the SHC, we implemented a simplified Becker-DeGroot-Marschak (BDM) valuation elicitation exercise following the conclusion of the endline survey.[21] The exercise was conducted in order to reveal farmers' WTP for fertilizers they are underusing (specifically zinc) and to determine whether the information obtained from the SHC affected this WTP. That is, we are interested in whether farmers whose SHC indicated zinc deficiency and recommended application of zinc were willing to pay more for zinc than farmers whose SHC indicated that their soils were zinc sufficient or who did not know the status of their soil health. This distinction is important because the lack of SHC impact on farmers' actual fertilizer application can be interpreted as indicating that the information did not affect their preferences or, alternatively, that it did affect preferences but that other factors, such as costs, prevented farmers from acting on them. If both groups have a low WTP and there is no impact of the information, then we cannot differentiate between these explanations. If both groups have a high WTP, then we can rule out liquidity constraints as the main determinant of the lack of adherence to the recommendations in the case of zinc and assume that the information had no effect on the farmers' preferences. Finally, if the zinc-deficient group has a higher WTP, then we can conclude that the information was effective in encouraging zinc usage amongst farmers.

Before administering the BDM exercises, we randomly allocated farmers with zinc-deficient soils into two groups. The protocol informed all farmers of the potential impact of zinc deficiency for crops and the expected gains from application of zinc to deficient soils. This information was conveyed in very general terms, without explicit reference to the farmers' actual conditions.

[21] 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.

However, farmers in the first group (group 1) were also shown their SHCs and reminded of their zinc deficiency and the scientific recommendation to apply zinc in their fields. Farmers in the second group (group 2) received no such reminder. Among farmers in the treatment group whose soil was determined to be zinc sufficient (that is, their SHC indicated no deficiency and no need to apply zinc), half were randomly selected to take part in the valuation exercise as well (group 3). A fourth group (group 4) consisted of control farmers, for whom no soil testing was conducted. Farmers in this group were notified by agents that there was no information on whether they needed zinc or not. Due to logistical constraints, the BDM exercises in Madhubani district included only farmers from the first three groups, whereas those in Bhojpur and Nawada districts included farmers from the control group as well. Half of the farmers in each control village in Bhojpur and Nawada were randomly selected to be part of the fourth group.

A comparison between groups 1 and 2 sheds light on the lower bound value that farmers place on nutrient deficiency information contained in the SHCs. A comparison of groups 1 and 2 with group 3 sheds light on the value of information indicating deficiency vis-à-vis sufficiency, while a comparison of the composite group consisting of groups 1, 2, and 3 with group 4 provides evidence on the impact of having SHC-based information at all. However, we stress that only the comparison of group 1 with group 2 yields a proper counterfactual, because farmers in other groups have or potentially have different soil characteristics that might be correlated with other attributes affecting the WTP.

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.

Table 16 reports the revealed WTP for zinc for the different groups in the BDM exercises. Treatment farmers were willing to pay 41.2 Rs/kg on average, regardless of whether their soils were determined to be zinc deficient (groups 1 and 2) or zinc sufficient (group 3). Statistical tests of sample mean WTPs in Table 17 indicate there are no significant differences between the WTPs in any of the intergroup comparisons. Also, estimates of differences between the groups, based on a linear regression of WTP on group dummy variables reported in Table 17, are small and statistically insignificant. The WTP for zinc in Madhubani (which is generally a zinc-deficient region) is higher than in Bhojpur or Nawada (generally zinc-sufficient regions) – INR 42.8 per kg versus INR 41 per kg, respectively – but even that difference is not statistically significant. Thus, farmers in all groups have a positive willingness to pay for zinc, regardless of the information provided in the soil health card. From this we conclude that liquidity constraints are not the primary determinant of the lack of adherence to the SHC, at least in the case of zinc.

6 Discussion and Conclusions

The government of India recently launched an ambitious program of providing SHCs based on individualized soil tests to promote balanced use of fertilizers in agriculture throughout India. The program is expected to deliver more than 145 million SHCs covering all plots and farmers in India, with farmers expected to receive a new SHC every three years. To evaluate the feasibility of this program and test its potential effectiveness, we conducted a randomized controlled trial in three districts of Bihar in which we mimicked the operational approach of the government's SHC program. Our experimental approach enabled us to test whether farmers would change their fertilizer use pattern after receiving fertilization recommendations based on soil tests from their own farm plots.

Our results suggest that farmers largely ignore the soil test results and fertilizer use recommendations contained in the SHCs. The impact of the SHCs on fertilizer application was insignificant, both for farmers who applied more than the recommended dose of fertilizers and for those who applied less. Thus, even farmers who could have saved money on fertilizers by following scientific recommendations and applying less did not do so. Contrary to a prevailing narrative in policy circles, this suggests that neither credit nor liquidity constraints are a major reason for not attending to the scientific recommendations, and points toward informational factors as the primary culprit.

To explain the adherence to own-beliefs, we have outlined a theoretical model of demand and usage of information about optimal input application that allows for farmer heterogeneity in subjective beliefs and the degree of confidence in those beliefs. The model makes clear and unambiguous predictions about the effect of farmer ability and confidence on the demand for and the responsiveness to an external information signal. Specifically, the model predicts that farmers who are more confident in their beliefs about proper input use are less likely to demand additional information, and even in the case where such information is provided free of charge, such farmers are less likely to respond to the generated signal. Similar, more skillful farmers are less likely to be willing to pay even a modest sum for information, and would be less likely to respond to information provided.

Empirically, we test the predictions of this model in the context of a soil testing and fertilizer recommendation intervention in the state of Bihar, in northern India. We measure farmers' subjective beliefs about appropriate fertilizer application rates using a visually-aided beliefs elicitation mechanism. This experimental mechanism allows us to empirically estimate farmers' prior mass functions of appropriate urea and DAP application rates, from which moments can be estimated assuming a stepwise uniform distribution of beliefs. We combine measures of confidence with farming ability with observed input use both before and after the information intervention. Farmers exhibit significant heterogeneity in beliefs about optimal applications of urea and DAP and we find that belief dispersion is correlated with other measures of self-confidence. Positive correlation across dispersion measures and various measures of confidence is congruent with research that finds within person confidence correlated across domains (Klayman et al., 1999) and suggests that the various confidence measures are internally consistent and reflect actual heterogeneity in individual characteristics.

Consistent with the model's predictions, our empirical results suggest that farmers with stronger, or less disperse, beliefs have a lower (stated) willingness to pay for SHCs and recommendations. Furthermore, conditional on fertilizer use adjustment in the direction of the signal, confidence and ability are associated with lower responsiveness to the recommendations provided on the SHCs, even after adjusting for baseline wealth and agricultural characteristics. Additionally, we find that farmers that have a greater degree of trust in agents from the national extension system are willing to pay more for the SHCs, but we do not find evidence that trust has a significant effect on responsiveness to the recommendations. While the lack of a significant response to the SHCs is observed only among the sample for which the response was in the direction of the signal (i.e., the adjustment from baseline to endline was an increase or decrease consistent with the recommendation, though of a different magnitude), and this sample is only a portion of the entire baseline sample, the large p-value associated with this estimate suggests that this non-result is not simply the result of insufficient power.

Our findings relate to a larger literature in both developing and developed countries that identifies subjective beliefs as predictive of behavior in a variety of settings including insecticide treated mosquito nets (Tarozzi et al., 2011), college choice (Wiswall and Zafar, 2015), and investment decisions in children's education (Dizon-Ross, 2019). Additionally, we provide further evidence in the support of research on the role of confidence in demand and usage of information (Hoffman, 2016) and highlight a source of observed heterogeneity that can undermine the efficacy of information interventions (Bennett et al., 2016; BenYishay and Mobarak, 2018). Though, there are a number of limitations of the analysis that we have noted.

In order to explore additional reasons behind the lack of responsiveness, we undertook a series of exercises, including a BDM valuation elicitation exercise (in order to assess farmers' WTP for zinc) and short quizzes to test farmers' knowledge of the contents of the SHCs. Many farmers believed that changing their fertilizer according to the SHC recommendations could lead to yield losses. Moreover, farmers also struggled to internalize the soil test results and recommendations despite receiving the SHC in their native language and having its contents explained to them in one-to-one sessions by trained personnel. The inability to recall the contents of the SHC could reflect lack of interest or difficulty in absorbing information of this kind. Together, these exercises confirm that most farmers trusted their own practices more than the recommendations and therefore were not willing to change their existing practices.

From a policy perspective, our results have significant implications for information interventions such as India's 'Soil Health Card' scheme. Using the recommendations calibrated using the 4 metric tons per hectare target yield, the least confident farmers applied 37 kg/ha less urea than the recommended rate at baseline while the remaining farmers applied 23 kg/ha less urea on average.[22] Further, using the status-quo calibrated yields reveals that less confident farmers apply urea at a rate 33 kg/ha higher than necessary for their current yields. The remaining farmers apply urea at a rate of 19 kg/ha higher than the status-quo calibrated recommendations. Taken

[22] Here we refer to the least confident farmers as those that are in the 75th percentile of the distribution of the coefficient of variation of their beliefs about optimal urea usage. Farmers with low belief dispersion (smaller CV) are confident while those with high belief dispersion (large CV) and less confident.

together, this suggests that less confident farmers in Bihar both are most likely to respond and stand to benefit the most from targeted soil test recommendations either (1) when the goal is to increase urea usage and yields (2) or when the goal is to limit urea usage while maintaining current practices. Thus, pilot surveys that assess whether confidence, and therefore responsiveness to information, is correlated with a higher marginal value of the information can be helpful to determine the potential value of similar intervention interventions. Further, if there are cost constraints to providing information, such as in the case of testing soils in a laboratory, identifying and targeting low confidence/high marginal value of information respondents may produce the highest returns to the program's invesment.

In the case of fertilizer application in India, in addition to targeting less confident farmers, our results suggest that the existing program potentially requires several modifications to become effective. First, we suggest rigorously testing different ways to inspire farmers' trust in the soil test results and fertilizer use recommendations. For example, making local input dealers a part of the soil testing program may help win farmers' trust because farmers often seek input dealers' advice on farming practices and technologies. Second, since many farmers struggle to understand and remember the information in the SHC, follow-up visits by trained extension agents to discuss the SHC results and recommendations may help increase compliance. Third, as previous research in this area has shown (Ward and Singh 2015), farmers are often risk averse. Farmers may benefit from some form of risk management that allows them to cover or transfer downside risks arising from altering their fertilizer application, which may encourage greater compliance with the scientific recommendations. We recommend using a series of randomized controlled trials to test a number of different approaches to making SHCs more effective tools for the promotion of balanced fertilizer use in Indian agriculture. Evidence generated from such experiments will help improve the soil testing program not only in India but also potentially in other parts of the world where imbalanced use of fertilizer is a serious problem.

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Table 1: Fertilizer Belief Distributions (Kg/Katha)

	Urea	DAP
Mean	2.91	1.55
	(1.12)	(0.65)
Std. Dev.	0.48	0.33
	(0.24)	(0.14)
Coefficient of variation	0.23	0.27
	(0.20)	(0.19)

Table 2: 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

Table 3: Summary statistics across treatment groups at baseline

Variable	N	(1) Control Mean/SE	N	(2) Treat Mean/SE	T-test P-value (1)-(2)
Urea kg.	204	43.99	427	40.25	0.11
		(1.96)		(1.34)	
DAP kg.	223	25.60	457	25.45	0.93
		(1.29)		(0.95)	
MOP kg.	221	2.11	458	2.99	0.07*
		(0.30)		(0.30)	
Apply MOP	221	0.30	458	0.31	0.81
		(0.03)		(0.02)	
CV Urea	259	0.24	458	0.23	0.34
		(0.01)		(0.01)	
More doubts	255	0.43	455	0.43	0.93
		(0.03)		(0.02)	
Literate	245	0.58	458	0.61	0.38
		(0.03)		(0.02)	
Age	243	45.07	456	45.84	0.42
		(0.78)		(0.56)	
Female	245	0.08	458	0.10	0.47
		(0.02)		(0.01)	
Plot 1 size (ha)	244	0.20	456	0.20	0.59
		(0.01)		(0.01)	
Plot 1 yield (kg/ha)	241	2626.13	432	2701.10	0.25
		(49.15)		(40.58)	

This table presents the mean and standard error of the mean (in parentheses) for several characteristics of households across treatment groups. The same consists of all households that were present at the baseline. Column (5) shows the p-value from testing whether the mean is equal across all treatment groups (H0 := mean is equal across groups). DAP is diammonium phosphate. Standard errors are clustered village for the test of equality * $p < 0.10$

Table 4: Summary Statistics - Treatment Subsample

Variable	Mean	Std. Dev.	Min.	Max.	N
Dependent Variables					
WTP SHC (USD)	1.61	1.76	0	10	356
α_U	0.51	0.28	0	0.99	124
α_D	0.43	0.29	0	1	249
Ind. Variables					
Farmer has same/more doubts	0.44	0.5	0	1	363
CV urea	0.22	0.19	0.03	0.65	369
SD urea	0.49	0.25	0.14	1.27	369
CV DAP	0.28	0.19	0.06	0.70	366
SD DAP	0.33	0.14	0.14	0.75	366
Not trust extension	0.69	0.46	0	1	369
Medium ability	0.5	0.5	0	1	369
High ability	0.25	0.43	0	1	369
Experience (10 years)	0.14	0.35	0	1	369
Experience (5 years)	0.05	0.21	0	1	369
Controls					
Age	46.94	14.43	15	80	369
Male	0.87	0.34	0	1	369
Can read or write	0.62	0.49	0	1	369
Years educ.	6.56	5.89	0	18	369
HH members	8.62	4.66	1	38	369
IHS House value	11.03	4.55	0	16.12	369
IHS Savings	2.28	4.27	0	13.59	369
Own cattle	0.26	0.44	0	1	369
Own plot	0.83	0.37	0	1	369
Plotsize (ha)	0.19	0.14	0.03	0.8	369
Own irrigation pump	0.25	0.43	0	1	369
Remember tested plot	0.78	0.42	0	1	369
Credit *rabi* 13	0.09	0.28	0	1	368

The sample includes treatment households. $\alpha = \frac{E-B}{S-B}$ is the measure of information responsiveness for the indicated fertilizer. CV is the coefficient of variation of the beliefs distribution. SD is the standard deviation of the beliefs distribution. Lack of trust equals one if farmers report not trusting extension agents. Experience (10 years) equals one if farmers have between 5 and 10 years farming experience. Experience (5 years) equals one if farmers have 5 or less years farming experience. IHS is the inverse hyperbolic sine of the reported value. House and savings values reported in Rupees/1000. Remember tested plot equals one if the farmer could recall which plot was tested during the endline survey. Credit *rabi* 13 equals one if farmers received credit in the the 2013 *rabi* season.

Table 5: Status-Quo Calibrated Recommendations and Target Yield (4 T/Ha) Recommendations

	Fertilizer		
Variable	Urea	DAP	Potash
Average baseline application	210.8	136.1	13.2
Target yield recommendations (4 T/ha)			
Average recommendation	245	164.6	81.5
Average difference	-33.6	-28.5	-68.3
Average absolute difference	75.9	46.9	68.6
Status-quo calibrated recommendations			
Average recommendation	122.9	100.4	43.1
Average difference	87.9	35.7	-29.9
Average absolute difference	104.8	53	32.7

Source: Authors' calculations. All values in kg/ha

Table 6: Effects of the SHC on fertilizer application rates.

	(1) Urea	(2) Urea	(3) DAP	(4) DAP	(5) MOP	(6) MOP	(7) MOP=1	(8) MOP=1
SHC	0.043	0.028	-0.058	-0.052	0.033	0.047	0.060	0.015
	(0.031)	(0.038)	(0.045)	(0.048)	(0.065)	(0.069)	(0.039)	(0.041)
Literate		-0.055		0.016		-0.00032		-0.0052
		(0.046)		(0.040)		(0.087)		(0.047)
Age		-0.0016		0.0017		-0.00091		-0.0011
		(0.0016)		(0.0014)		(0.0042)		(0.0014)
Female		0.0083		-0.032		-0.070		-0.0069
		(0.050)		(0.048)		(0.11)		(0.056)
Plot 1 size (ha)		0.18		0.033		-0.12		0.037
		(0.13)		(0.12)		(0.22)		(0.12)
Block FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Enumerator FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	617	567	621	594	287	274	681	618
Adjusted R^2	0.218	0.214	0.186	0.180	0.154	0.139	0.483	0.459
Mean dep. var	5.25	5.25	119.9	120.3	3.63	3.65	0.42	0.50

Notes: Dependent variables in columns 1-6 are endline fertilizer application rates in logs (kg/ha). Dependent variable in columns 7 & 8 is binary variable equal to 1 if the farmer used MOP. All columns report the estimates from a regression of the respective fertilizer application rate on receipt of the soil health card treatment, block fixed effects, and enumerator fixed effects. Standard errors adjusted for clustering at the village level in parentheses. * Significant at 10 percent level; ** Significant at 5 percent level; *** Significant at 1 percent level.

Table 7: Heterogenous effect of the SHCs by confidence

	(1) Urea	(2) Urea	(3) DAP	(4) DAP	(5) MOP	(6) MOP	(7) MOP=1	(8) MOP=1
SHC	0.14***	0.064**	0.015	-0.019	0.17*	0.12*	0.12**	0.11***
	(0.051)	(0.029)	(0.053)	(0.050)	(0.085)	(0.061)	(0.051)	(0.038)
SHC*CV Urea	-0.44**		-0.32**		-0.49*		-0.24	
	(0.20)		(0.16)		(0.28)		(0.15)	
CV Urea	0.16***		0.059**		0.39*		0.085	
	(0.06)		(0.03)		(0.22)		(0.086)	
SHC*More doubts		-0.034*		-0.082		-0.19**		-0.11*
		(0.019)		(0.050)		(0.083)		(0.061)
More doubts		0.032		0.052		0.26***		0.067
		(0.064)		(0.036)		(0.066)		(0.044)
Block FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Enumerator FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	616	607	620	611	287	281	678	671
Adjusted R^2	0.225	0.222	0.195	0.183	0.157	0.160	0.490	0.481
Mean dep. var	5.25	5.25	4.73	4.73	3.63	3.65	0.42	0.41

Notes: Dependent variables in columns 1-6 are endline fertilizer application rates in logs (kg/ha). Dependent variable in columns 7 & 8 is binary variable equal to 1 if the farmer used MOP. Estimations include controls for age, literacy, gender, plot size, block fixed effects, and enumerator fixed effects. Standard errors adjusted for clustering at the village level in parentheses. * Significant at 10 percent level; ** Significant at 5 percent level; *** Significant at 1 percent level.

Table 8: Effects of confidence on willingness to pay for SHCs

	(1) WTP	(2) WTP	(3) WTP	(4) WTP	(5) WTP	(6) WTP
Same/More doubts	0.567**			0.481*		
	(0.270)			(0.260)		
CV Urea		1.442*			1.510**	
		(0.833)			(0.734)	
SD Urea			1.608***			1.578***
			(0.567)			(0.487)
Medium Ability	−0.0589	−0.0613	0.00755	−0.177	−0.177	−0.0969
	(0.290)	(0.263)	(0.267)	(0.280)	(0.264)	(0.277)
High ability	−0.215	−0.0701	−0.00386	−0.401	−0.289	−0.214
	(0.405)	(0.367)	(0.373)	(0.390)	(0.356)	(0.363)
Trust	0.336*	0.355*	0.346*	0.330*	0.350*	0.338*
	(0.202)	(0.200)	(0.200)	(0.194)	(0.201)	(0.203)
Exp. 5 years	−0.806*	−0.893*	−0.839*	−0.540	−0.636	−0.598
	(0.461)	(0.465)	(0.470)	(0.532)	(0.557)	(0.549)
Literacy	0.344**	0.356**	0.362**	0.317*	0.323*	0.329**
	(0.154)	(0.156)	(0.152)	(0.164)	(0.165)	(0.160)
Constant	0.516	0.240	−0.478	−0.813	−1.305	−1.899**
	(0.777)	(0.860)	(0.933)	(0.789)	(0.818)	(0.849)
Observations	351	351	351	351	351	351
Controls	*N*	*N*	*N*	*Y*	*Y*	*Y*

Note: Dependent variable is stated willingess to pay for soil testing and recommendations ($US). The sample includes treatment farmers that applied urea during the 2013 kharif season. The CV and SD of urea beliefs are measures of farmer confidence based on the coefficient of variation and standard deviation of their subjective beliefs distributions. Same/more doubts about agricultural practices is a measure of farmer confidence based on self reported incidence of doubts. Standard errors (adjusted for clustering at the village level) in parentheses. All regressions contain village fixed effects and controls for age and gender. Additional control variables in columns 3-4 include household size, CRRA, whether the household head remembered which plot was tested, house value, household savings, whether the household owned cattle, whether the household owned the tested plot, baseline seed type, 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 9: Effects of confidence on willingness to pay for SHCs - continued

	(1) WTP	(2) WTP	(3) WTP	(4) WTP
CV DAP	1.159*		1.383***	
	(0.627)		(0.514)	
SD DAP		1.906*		2.163**
		(0.978)		(0.880)
Medium Ability	−0.0516	−0.0200	−0.139	−0.117
	(0.272)	(0.272)	(0.249)	(0.250)
High ability	−0.0549	−0.0432	−0.266	−0.265
	(0.363)	(0.362)	(0.315)	(0.311)
Trust	0.308	0.297	0.326*	0.318*
	(0.200)	(0.204)	(0.188)	(0.191)
Exp. 5 years	−0.896**	−0.885*	−0.765	−0.728
	(0.437)	(0.464)	(0.520)	(0.530)
Literacy	0.300**	0.310**	0.275*	0.291*
	(0.140)	(0.143)	(0.144)	(0.148)
Constant	0.659	0.177	−0.919	−1.427
	(0.809)	(0.838)	(0.808)	(0.879)
Observations	351	351	351	351
Controls	*N*	*N*	*Y*	*Y*

Note: Dependent variable is stated willingess to pay for soil testing and recommendations ($US). The sample includes treatment farmers that applied urea during the 2013 kharif season. The CV and SD of DAP beliefs are measures of farmer confidence based on the coefficient of variation and standard deviation of their subjective beliefs distributions. Same/more doubts about agricultural practices is a measure of farmer confidence based on self reported incidence of doubts. Standard errors (adjusted for clustering at the village level) in parentheses. All regressions contain village fixed effects and controls for age and gender. Additional control variables in columns 3-4 include household size, CRRA, whether the household head remembered which plot was tested, house value, household savings, whether the household owned cattle, whether the household owned the tested plot, baseline seed type, 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 10: Urea Responsiveness for Observations with $\alpha_U \in [0, 1]$

	(1)	(2)	(3)	(4)	(5)	(6)
Same/more doubts	0.141*			0.167*		
	(0.0767)			(0.0872)		
CV Urea		0.300**			0.279**	
		(0.117)			(0.132)	
SD Urea			0.261***			0.281**
			(0.0878)			(0.108)
Medium Ability	−0.0660	−0.0570	−0.0376	−0.136	−0.0877	−0.0550
	(0.0994)	(0.0932)	(0.0914)	(0.104)	(0.0939)	(0.0968)
High ability	−0.336***	−0.311**	−0.289**	−0.366***	−0.316***	−0.282***
	(0.115)	(0.119)	(0.118)	(0.107)	(0.0965)	(0.0934)
Trust	0.0396	0.0377	0.0392	0.0288	0.0235	0.0259
	(0.0510)	(0.0522)	(0.0510)	(0.0587)	(0.0591)	(0.0554)
Exp. 5 years	−0.246*	−0.295**	−0.311**	−0.292	−0.331*	−0.367*
	(0.144)	(0.120)	(0.119)	(0.178)	(0.181)	(0.183)
Constant	0.439	0.358	0.230	0.551	0.642*	0.543
	(0.274)	(0.261)	(0.269)	(0.328)	(0.341)	(0.324)
Observations	122	124	124	122	124	124
R-squared	0.401	0.394	0.401	0.532	0.511	0.521
FE	*Y*	*Y*	*Y*	*Y*	*Y*	*Y*
Controls	*N*	*N*	*N*	*Y*	*Y*	*Y*

Note: Dependent variable is urea responsiveness (α_U). The sample includes treatment farmers for which $\alpha_U \in [0, 1]$. The CV of urea beliefs are measures of farmer confidence based on the coefficient of variation of their subjective beliefs distributions. More doubts about agricultural practices is a measure of farmer confidence based on self reported incidence of doubts. Standard errors (adjusted for clustering at the village level) in parentheses. All regressions contain village fixed effects and controls for age and gender. Additional control variables in columns 4 - 6 include household size, CRRA, whether the household head remembered which plot was tested (=1), house value, household savings, whether the household owned cattle (=1), whether the household owned the tested plot (=1), baseline seed type, whether the household owned an irrigation pump (=1), 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 11: DAP Responsiveness for Observations with $\alpha_D \in [0, 1]$

	(1)	(2)	(3)	(4)	(5)	(6)
Same/more doubts	0.0156			0.0237		
	(0.0468)			(0.0491)		
CV DAP		0.295**			0.281*	
		(0.136)			(0.144)	
SD DAP			0.280			0.265*
			(0.191)			(0.135)
Medium Ability	−0.0539	−0.0407	−0.0363	−0.0615	−0.0436	−0.0384
	(0.0582)	(0.0618)	(0.0597)	(0.0511)	(0.0549)	(0.0521)
High ability	−0.132	−0.0606	−0.0573	−0.138*	−0.0638	−0.0588
	(0.0895)	(0.0986)	(0.0979)	(0.0744)	(0.0922)	(0.0902)
Trust	−0.0156	−0.0262	−0.0310	0.00689	−0.00644	−0.0106
	(0.0366)	(0.0362)	(0.0356)	(0.0371)	(0.0372)	(0.0364)
Exp. 5 years	−0.164	−0.196*	−0.200**	−0.180	−0.189*	−0.196*
	(0.106)	(0.107)	(0.0951)	(0.128)	(0.106)	(0.0993)
Constant	0.451**	0.393**	0.368*	0.192	0.0735	0.0594
	(0.165)	(0.174)	(0.201)	(0.215)	(0.239)	(0.253)
Observations	243	247	247	243	247	247
R-squared	0.311	0.342	0.361	0.507	0.566	0.572
FE	*Y*	*Y*	*Y*	*Y*	*Y*	*Y*
Controls	*N*	*N*	*N*	*Y*	*Y*	*Y*

Note: Dependent variable is DAP responsiveness (α_D). The sample includes treatment farmers for which $\alpha_D \in [0, 1]$. The CV of DAP beliefs are measures of farmer confidence based on the coefficient of variation of their subjective beliefs distributions. More doubts about agricultural practices is a measure of farmer confidence based on self reported incidence of doubts. Standard errors (adjusted for clustering at the village level) in parentheses. All regressions contain village fixed effects and controls for age and gender. Additional control variables in columns 4 - 6 include household size, CRRA, whether the household head remembered which plot was tested , house value, household savings, whether the household owned cattle, whether the household owned the tested plot, baseline seed type, 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 12: Urea Responsiveness for Observations with $\alpha_U \in [0,1]$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CV Urea (Tri)	0.240**				0.221*			
	(0.104)				(0.123)			
SD Urea (Tri)		0.293***				0.298***		
		(0.0740)				(0.0947)		
CV Urea (LogN)			0.133*				0.115*	
			(0.0791)				(0.0649)	
SD Urea (LogN)				0.0801*				0.0734
				(0.0446)				(0.0525)
Medium Ability	−0.0655	−0.0420	−0.0652	−0.0578	−0.0960	−0.0621	−0.1000	−0.0937
	(0.0921)	(0.0895)	(0.0946)	(0.0970)	(0.0926)	(0.0932)	(0.0947)	(0.0969)
High ability	−0.321***	−0.293**	−0.328***	−0.325***	−0.327***	−0.287***	−0.337***	−0.332***
	(0.116)	(0.117)	(0.116)	(0.116)	(0.0965)	(0.0920)	(0.0978)	(0.0987)
Trust	0.0383	0.0435	0.0388	0.0417	0.0235	0.0303	0.0236	0.0289
	(0.0531)	(0.0510)	(0.0545)	(0.0541)	(0.0605)	(0.0566)	(0.0618)	(0.0603)
Exp. 5 years	−0.293**	−0.291**	−0.295**	−0.297**	−0.329*	−0.344*	−0.336*	−0.339*
	(0.120)	(0.119)	(0.126)	(0.128)	(0.178)	(0.178)	(0.176)	(0.177)
Constant	0.397	0.233	0.443	0.413	0.673*	0.556	0.696**	0.669*
	(0.258)	(0.249)	(0.265)	(0.273)	(0.342)	(0.329)	(0.336)	(0.340)
Observations	124	124	124	124	124	124	124	124
R-squared	0.395	0.413	0.388	0.391	0.511	0.529	0.504	0.507
FE	*Y*	*Y*	*Y*	*Y*	*Y*	*Y*	*Y*	*Y*
Controls	*N*	*N*	*N*	*N*	*N*	*N*	*N*	*N*

Note: Dependent variable is urea responsiveness (α_U). The sample includes treatment farmers for which $\alpha_U \in [0,1]$. The CV and SD of urea beliefs are measures of farmer confidence based on the coefficient of variation and standard deviation of their subjective beliefs distributions. The CV and SD parameters are generated by fitting the subjective beliefs to the triangular and log-normal distributions. Standard errors (adjusted for clustering at the village level) in parentheses. All regressions contain village fixed effects and controls for age and gender. Additional control variables in columns 4 - 6 include household size, CRRA, whether the household head remembered which plot was tested, house value, household savings, whether the household owned cattle, whether the household owned the tested plot, baseline seed type, 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 13: Self-Reported Rationales for Over- and Underapplying Fertilizers Relative to Recommended Application

	Urea		DAP		Potash	
Reason for over/underapplication 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

Source: Authors' calculations. 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. DAP = diammonium phosphate.

Table 14: Correspondence Between Farmers' Memory of SHC and Actual SHC Recommendations (Percent)

Actual SHC	Farmer's memory of SHC		
Recommendations	Zinc deficient	Zinc sufficient	Don't know
Zinc deficient	81	3	16
Zinc sufficient	8	69	23

Source: Authors' calculations. Reported numbers are percentages.

Table 15: Correspondence Between Farmers' Self-Reported Knowledge of Zinc Status and Actual Status Based on Soil Analysis

SHC	Farmer's knowledge		
Recommendations	Zinc deficient	Zinc sufficient	Don't know
Zinc deficient	94	0	6
Zinc sufficient	96	2	2

Source: Authors' calculations. Reported numbers are percentages.

Table 16: Characterization of Subsample Groups for Zinc BDM

Group	Detail	# farmers	Madhubani (Rs/kg)	Bhojpur & Nawada (Rs/kg)	Mean WTP (Rs/kg)	Std. dev. (Rs/kg)
Group 1	Zinc deficient, shown SHC	82	42.5	41.8	42.3	21.2
Group 2	Zinc deficient, not shown SHC	81	41.2	44.4	42.2	21
Group 3	Zinc sufficient	176	43.7	40.4	41.7	20.3
Group 4	Control farmers	67	-	37.5	37.5	26.7
Total		406	42.8	41	41.2	21.7

Source: Authors' calculations. BDM = Becker-DeGroot-Marschak (BDM) valuation elicitation exercise; Rs = rupees; SHC = soil health card; WTP = willingness to pay.

Table 17: Comparison of WTP Between Subsample Groups from BDM

T-tests of WTP	Detail	Diff. in WTP	p-value
Group 1 vs. group 2	Value farmers place in information on deficiency contained in the SHC	0.096	0.987
Group (1 + 2) vs. group 3	Value of information on deficiency vis-a-vis sufficiency	0.476	0.831
Group (1 + 2 + 3) vs. group 4	Value of having any information at all	-4.424	0.126

Source: Authors' calculations. Column (4) shows the p-values for t-tests of whether the difference in WTP between the noted group equals 0. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. BDM = Becker-DeGroot-Marschak valuation elicitation exercise; Rs = rupees; SHC = soil health card; WTP = willingness to pay.

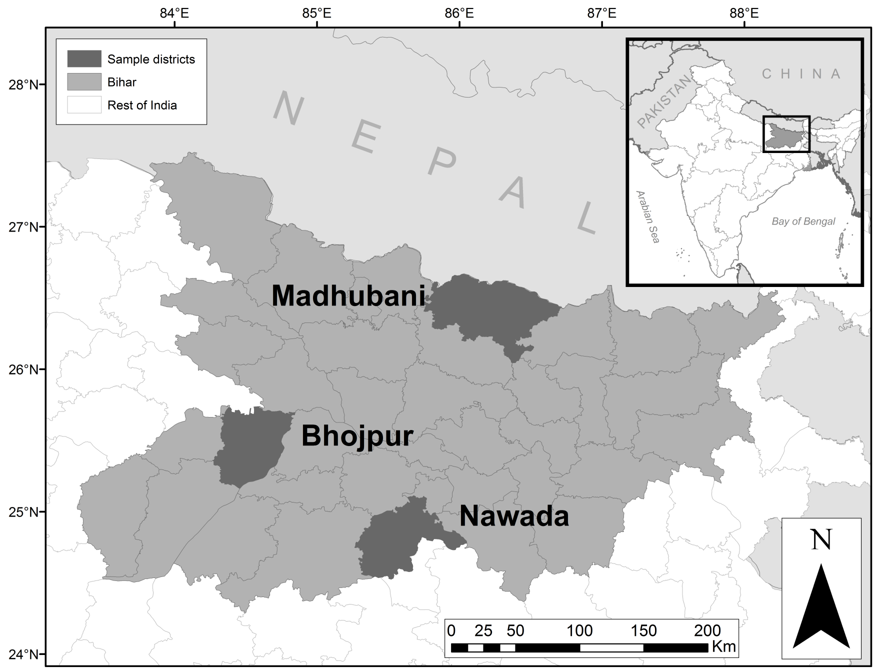

Figure 1: Location of Sample Districts in Bihar, India

	2014									2015						
Activity	Apr.	May	Jun.	Jul.	Aug.	Sep.	Oct.	Nov.	Dec.	Jan.	Feb.	Mar.	Apr.	May	Jun.	Jul.
Kharif/rabi season					Kharif season							Rabi season				
Soil sampling																
Baseline survey/ Beliefs Elicitation																
SHC distribution																
Pre-rabi survey																
Endline survey																
BDM survey																

Figure 2: Timeline of Data Collection

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

Important information and useful tips:

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

Figure 3: Example: Soil Health Card (Translated)

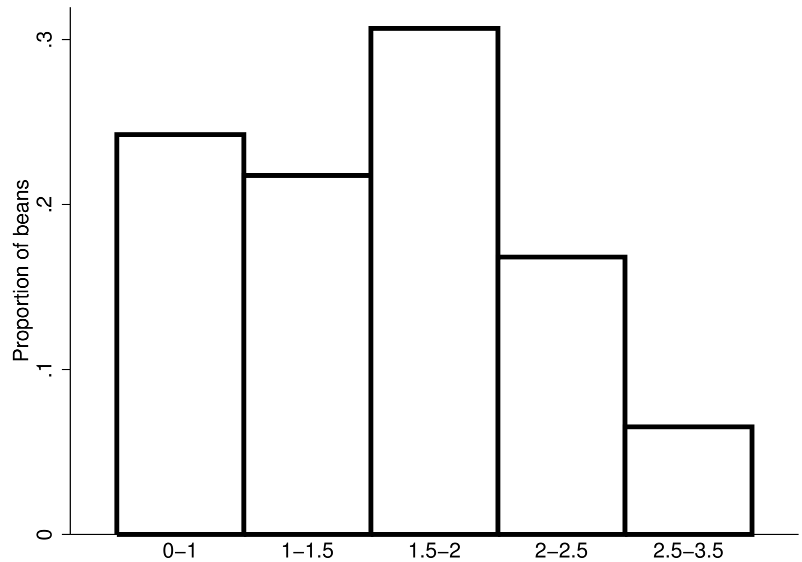

Figure 4: Percentage of Beans Allocated to DAP Ranges (Kg/Katha)

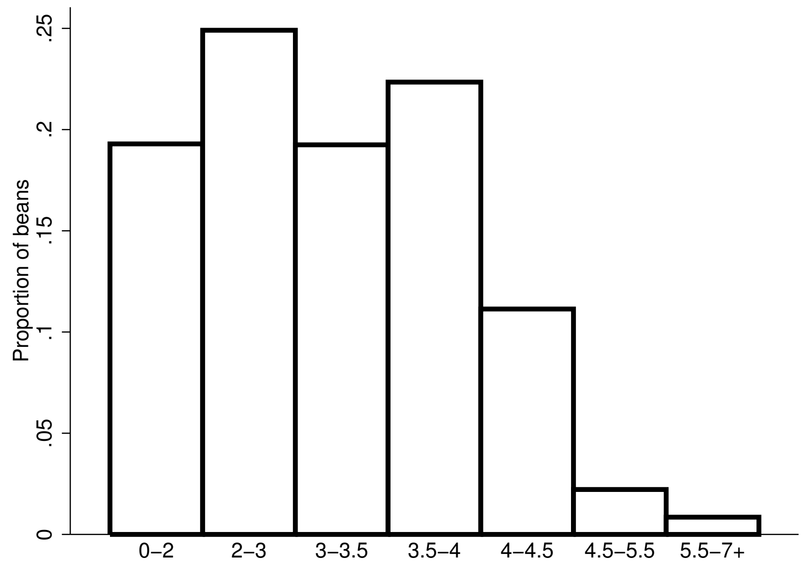

Figure 5: Percentage of Beans Allocated to Urea Ranges (Kg/Katha)

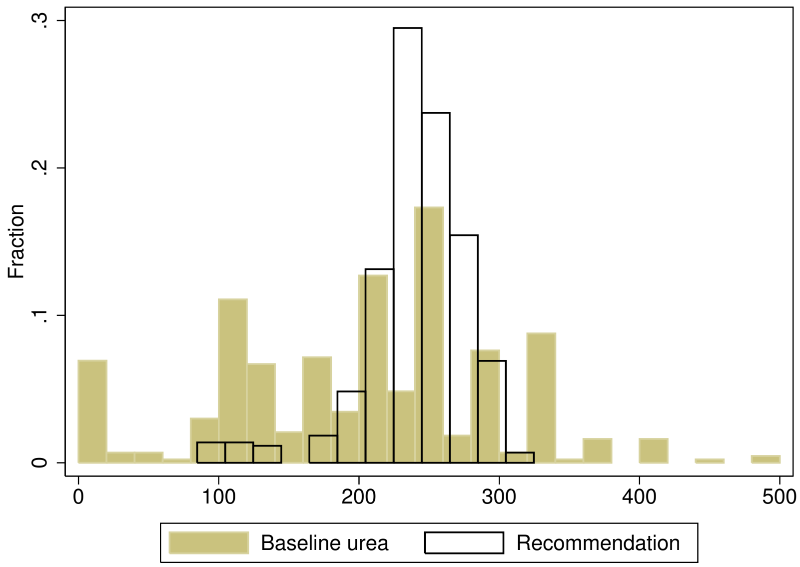

Figure 6: Densities of Baseline Urea and SHC Recommendations (Kg/Ha).

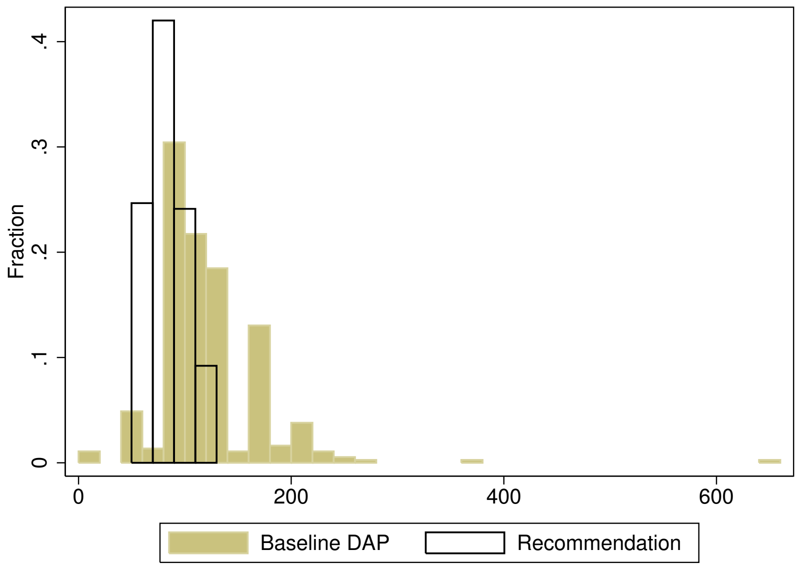

Figure 7: Densities of Baseline DAP and SHC Recommendations (Kg/Ha).

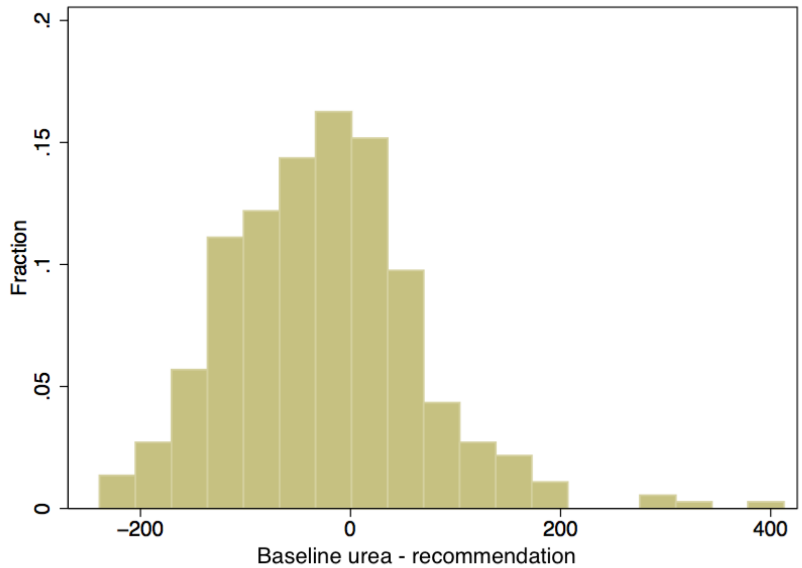

Figure 8: Density of Difference Between Baseline Urea Application Rates and Recommendation (Kg/Ha).

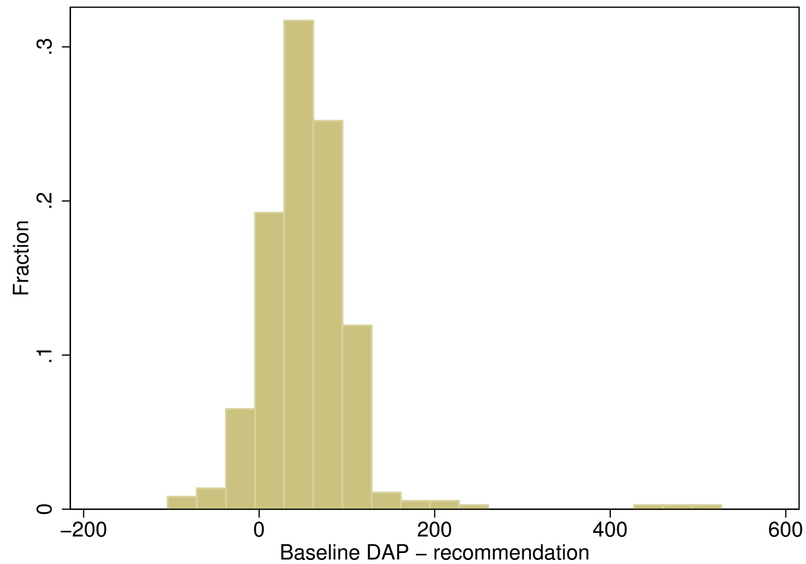

Figure 9: Density of Difference Between Baseline DAP Application Rates and Recommendation (Kg/Ha).