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

Jared Gars† Ram Fishman ‡ Avinash Kishore § Yoav Rothler ¶
Patrick Ward‖

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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 evidence that soil testing and targeted fertilizer

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†OECD, France; email jared.gars@oecd.org
‡Tel Aviv University, Israel; email ramf@post.tau.ac.il
§International Food Policy Research Institute, India; email A.Kishore@cgiar.org
¶Tel Aviv University, Israel; email yoavr@post.tau.ac.il
‖Duke Kunshan University, China and International Food Policy Research Institute, USA; email patrick.s.ward@dukekunshan.edu.cn

recommendations increased urea usage but did not lead to more balanced fertilizer application. To rationalize these findings, we model and test the impacts of confidence and trust 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 while trust further impedes the effectiveness of the recommendations.

1 Introduction

The imbalanced use of chemical fertilisers is a major environmental and public health issue in many emerging economies (Vitousek et al., 2009), including in many parts of India. Farmers tend to under apply certain types of fertilizers and typically over apply nitrogen fertilizers, which pollutes water resources, harms soils and entails substantial public expenditure on subsidies with no benefits for crop yields.[1] To address this imbalance, the Government of India launched a Soil Health Card (SHC) program in 2015 that aimed to provide all 140 million farmers in the country with lab-derived soil health information and targeted fertilizer application recommendations on a triennial basis. The goal of the 85 million dollar program is to improve the precision of farmers' fertilizer usage in order to increase yields and profits and reduce pollution. The implicit assumption underlying the program is that farmers misapply fertilizers because they lack scientific information and recommendations that are targeted to their soil attributes.

The SHC program is likely one of the largest informational interventions in the developing world. Information provision experiments are used increasingly in public policy, health, education, and labor economics, but evidence on their impacts remains mixed.[2] In developing countries in particular, the delivery of targeted agricultural information has proved difficult. While traditional extension systems are often thought to be ineffective and costly (Anderson and Feder, 2007), several recent evaluations found novel, ICT based extension approaches to derive substantial impacts on input usage and agricultural practices (Casaburi et al., 2014; Cole and Fernando, 2016). One potential explanation for the lack 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 beliefs, an unanswered question is whether targeted information is sufficient to change input use behavior.

In this paper, we provide experimental evidence on this question and examine whether the introduction of targeted soil health cards that provide soil quality information and input recommendations influences fertilizer usage. We conducted a randomized controlled trial with 864 households in the Indian state of Bihar that was introduced before the gov-

[1]Public expeditures on fertilizer subsidies represent 1% of GDP, by some estimates.

[2]There is a large literature that studies the impacts of information provision on health behavior and outcomes (Bennett et al., 2018; Dupas, 2011; Guiteras et al., 2016), job search (Belot et al., 2019; Fafchamps et al., 2020), education investments (Dizon-Ross, 2019; Jensen, 2010), and increasingly in public policy (Banuri et al., 2019; Hjort et al., 2019; Vivalt and Coville, 2020) under the assumption that lack of information about costs and benefits is a binding constraint on optimal investments and behaviors. See Dupas and Miguel (2017) for a review of this literature in public health and a discussion of the impacts of general and tailored information in health programs.

ernment's SHC program and shared many of its characteristics. Enumerators collected soil samples from treated farmers' fields that were tested in a certified laboratory. Trained field staff provided farmers with the SHCs as well as derived recommendations for the required dosage of various fertilizers for the dominant cropping patterns in the area. Although the recommendations of the SHCs were markedly different from farmers' baseline fertilizer applications, there is little evidence that they encouraged more balanced fertilizer application decisions. We find that, on average, the recommendations increased urea application rates during the *rabi* wheat crop by between 5 and 6 percent and increased the likelihood of applying potash by 8 percentage points, but had no effect on DAP usage.[3] Analysis of heterogeneity in willingness to pay for soil testing and responsiveness to the recommendations amongst treated farmers reveals that the measured effects are driven primarily by farmers with less confidence in their beliefs about optimal fertilizer usage. Further, trust in existing extension services is low amongst farmers and while we find no effect of trust on demand for information, lack of trust further moderates the impact of the recommendations on responsiveness to the soil tests.

Various factors may limit the impacts of informational interventions on agents' choices, and in recent years, a growing literature has explored them in the context of smallholder farmers' cultivation practices and technology adoption. One possibility is that informational gaps are not in fact the binding constraints, but instead other market inefficiencies limit farmers' investments or technology adoption (Jack, 2013). A second class of explanations blame the quality of the information, agent trust in the source of the information, and the manner in which it is disseminated.[4]

A third potential class of explanation, which is less studied in the literature, is focused on the "receivers" of the information and the role of biased beliefs.[5] In this paper, in particular, we examine the possibility that pre-existing beliefs can be too strong to be affected by newly supplied information. It is very common for extension professionals to anecdotally blame such beliefs for the persistence of (what they consider to be) misguided practices

[3]The recommendations were based on existing soil characteristics and encouraged increased fertilizer usage for some farmers and decreased fertilizer usage for others. See section 3.4 for summary statistics of fertilizer recommendations and baseline fertilizer application rates.

[4]For example, in a highly heterogenous environment typical of smallholder farming (Suri, 2011), generic or insufficiently targeted recommendations may be of little use; Extension agents, who are typically charged with delivering information to farmers, are often overtaxed, poorly trained and incentivised (Anderson and Feder, 2007); And sources of information (e.g. lead farmers) may not be incentivised (BenYishay and Mobarak, 2018) to diffuse it or be sub-optimally placed within social networks to reach most farmers (Beaman et al., 2018).

[5]In agriculture, Hanna et al. (2014) point to the difficulty of noticing crucial dimensions of productivity as an impediment to learning from experience or from others. Barham et al. (2018) show that receptiveness to advice sped up GM corn seed adoption amongst farmers in the U.S with low cognitive ability, but slowed adoption amongst farmers with high cognitive ability.

by farmers. We sketch a simple learning model in which we extend the target-input model (Bardhan and Udry, 1999) and allow for farmers to purchase and use a signal conditional on their beliefs, farming ability, and perceptions of the trustworthiness of the signal. In this Bayesian framework, the precision of farmers' beliefs may attenuate the demand for information as well as the impact of the information on input usage. We elicit the precision of farmers' beliefs about optimal input use (i.e., their confidence) using simple visual aids similar to those frequently used in the field to elicit subjective beliefs (Delavande et al., 2011).[6] Using the elicited beliefs and a self-reported measure of confidence, we provide some of the first field evidence that it can indeed reduce both demand for and responsiveness to an informational intervention. The context of the study is highly suitable for such an investigation. Unlike most existing studies, which are concerned with information about the benefits of adopting a new practice or input, the goal of the intervention we study is to adjust the use of a familiar and highly subsidized input. The recommendations therefore mostly incur little costs, and are also highly targeted, ruling out other potential explanations for lack of responsiveness.

This paper contributes to and bridges the literatures on information provision in agriculture on the one hand, and the role of evidence and beliefs on the other.[7] Farmers in developing countries often lack access to timely and reliable information about modern technologies and inputs that are essential to improve agricultural productivity. Traditional methods of disseminating information through extension agents have not produced compelling evidence either on its impact on productivity or on cost effectiveness. A developing literature has shown promising results using digital technologies as a means of information diffusion to encourage technology adoption and deliver targeted information about inputs and practices to farmers.[8] Cole and Fernando (2016) use a Becker-Degroot-Marschak (BDM) mechanism to elicit farmer willingness-to-pay for a voice-based ICT advisory service in Gujarat, India. Interestingly, they find that the farmers had high demand for and self-reported utilization of the service, but that the intervention did not have a statistically significant impact on yields or profits.[9] Two recent papers study the provi-

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

[7]Our methodology is related to a growing literature measuring the impacts of information-provision on beliefs and decision-making more generally, including on energy consumption (Allcott, 2011), college major choice (Wiswall and Zafar, 2015), and attitudes towards immigration and discrimination (Grigorieff et al., 2020; Haaland and Roth, 2019).

[8]See Fabregas et al. (2019) for an overview of the potential of using mobile-phone based services for digital agricultural extension, as well as Palloni et al. (2018) for additional evidence on farmers' WTP for information. Existing studies suggest that there are large gaps between farmers' willingness to pay for information and its social value.

[9]Further, they find that the service increased an aggregate index of inputs recommended by the service

sion of soil tests specifically. Harou et al. (2019) find that plot specific information and vouchers for fertilizer purchase in Tanzania were insufficient to encourage adoption of chemical fertilizers individually, but that their combination did. Their findings suggest that a combination of information and liquidity constraints limited farmers' response to the soil tests on the application of under-used fertilizers. Cole and Sharma (2017) show that farmer understanding is a potential barrier to the efficacy of soil testing. Providing Indian farmers with audio and video supplements that explain soil health cards increased farmer understanding and trust considerably more than in-person delivery alone. While previous studies have highlighted the potential of ICTs to provide more targeted information to farmers, there has been no work to our knowledge that examines how farmers' beliefs, particularly the strength of their beliefs, affect demand and responsiveness to information. Using a randomized information intervention, our results help to explain the attenuated impact of providing farmers with information that have not yet been addressed in previous studies and suggest that identifying and targeting advice to farmers with low confidence and high marginal value of information may produce the highest returns to information diffusion efforts, especially if there are cost constraints.

Our paper is also related to the literature on the impacts of biased beliefs and confidence on information demand and responsiveness. The implications of overconfidence have been studied in a variety of settings including CEO performance (Malmendier and Tate, 2005), self-control problems (DellaVigna and Malmendier, 2006), and trader behavior (Eyster et al., 2019). In the domain of information demand, the literature tends to find that people overweight their private information relative to information from experts or information conveyed by others' choices (Benjamin, 2019).[10] Increasingly, research on beliefs has included qualitative measures of confidence to test its impact on Bayesian updating (Armona et al., 2017; Roth and Wohlfart, 2019). Most closely related to our paper is Hoffman (2016), who conducts framed field experiments with experts that buy and sell website domain names. The author finds that experts systematically underpay for valuable information and that this effect is stronger among overconfident individuals (us-

by 0.125 sd. Though large, their findings on inputs and agricultural knowledge overall are not significant when accounting for multiple hypothesis testing.

[10]The existing literature using lab experiments suggests that there are a number of possible motivations for information demand that are not necessarily linked to its instrumental value, but rather the players' beliefs about their own or others' judgment. Schotter (2003) show that subjects in the lab follow advice of others that only have slightly more experience than themselves. Surprisingly, subjects preferred 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, but which has no instrumental value. Ambuehl and Li (2018) show that individuals exhibit differences in *responsiveness* to information, due to biases in belief updating when receiving new signals.

ing a measure of overplacement). He also documents significant overconfidence amongst his participants, in line with previous research using incentivized experiments that measure ability and confidence. Traditional beliefs, common in many developing countries, may also affect the strength of agents' priors and their response to information. Bennett et al. (2018) evaluate a program that improves upon existing hygiene education by showing participants in Pakistan evidence of microbes using microscopes. They show that the impact of the intervention is attenuated for individuals with strong beliefs in traditional medicine and argue that this effect is due to the precision of participants priors that hygiene is ineffective. However, no papers to our knowledge have examined how measured confidence affects responsiveness to advice in real-world settings. There is little evidence in particular of the role of confidence on decision making in developing countries, including on entrepreneur behavior, job search, or agricultural investment. We fill this gap and identify substantial hetereogeneity in the strength of farmers' beliefs and its impacts on farmers' investment choices and response to targeted advice. While previous studies on information demand used proxies for confidence, our work advances the literature by using quantitative measures of confidence (prior belief precision about agricultural practices).

Finally, we make a further contribution by operationalizing the dispersion of a farmer's subjective probability estimates, a fundamental parameter in learning models, within an existing technology adoption framework. The model used in this paper is an adaptation of the Bayesian learning-by-doing model popularized by Jovanovic and Nyarko (1996), and adapted to the agricultural context by Foster and Rosenzweig (1995). The model relies on the agent updating the mean and variance of her beliefs over the true value of a parameter, in this case optimal fertilizer input levels. The majority of previous research ignores heterogeneity along this dimension and assumes common priors across farmers. Our method allows us to elicit these parameters directly from farmers' subjective beliefs distribution using visual aids. This method of belief elicitation, summarized in Delavande et al. (2011), 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 present a model of information demand and responsiveness that demonstrates how the strength of farmers' priors over optimal input use explains a lack of adherence to the soil testing recommendations.[11]

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

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

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

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

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

where $u_t \sim \mathcal{N}(0, \sigma_u^2)$ is an independent and identically distributed shock with known

[11]The model is an adaptation of the target-input model (Bardhan and Udry, 1999; Foster and Rosenzweig, 1995; Jovanovic and Nyarko, 1996). The model allows the agent to have a period-specific optimal input choice by weighing her various sources of information, including own experimentation and information from her peers (Foster and Rosenzweig, 2010). 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.

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

The period-specific target input level (θ_t) varies with independent and identically distributed shocks, u_t.[12] 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.[13]

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

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

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

[12]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.

[13]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.

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

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

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

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

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

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 increasing in farmer trust

Conditional on an initial level of confidence, ρ_{θ_0}, WTP is an increasing function of farmer trust, ρ_s.

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

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

Conditional on the initial level of confidence and ability, demand for information is increasing in the subjective precision of the signal (ρ_s).

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

$$\alpha = S - \tilde{\theta}_1 \tag{14}$$

where responsiveness captures the degree to which the posterior of the optimal input value moves towards the signal. The closer that the posterior is to the signal, the more responsive the farmer is to information, conditional on their prior and the signal.

From equation 6, we can rewrite responsiveness (α) as:

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

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

$$\frac{\partial \alpha}{\partial \rho_{\theta_1}} = \frac{\rho_S(\theta_1^* - S)}{(\rho_S + \rho_{\theta_1})^2} \tag{16}$$

If the planned input amount is larger than the recommendation, $\theta_1^* > S$, then

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

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 $\theta_1^* < S$.[14]

[14] Here we consider two cases: when $\theta_1^* > \tilde{\theta}_1 > S$ and $\theta_1^* < \tilde{\theta}_1 < S$. There are also cases in which the posterior "overshoots" the signal (e.g $\theta_1^* < \tilde{\theta}_1 < S$). In this case, it is trivial to show that the difference between the posterior will be declining in the degree of confidence and ability.

Proposition 4: Information responsiveness is increasing in trust in the source

For any signal S, the difference between actual input use after receiving information and planned input use prior to receiving information is increasing in farmer trust in the source of the information.

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

$$\frac{\partial \alpha}{\partial \rho_S} = \frac{\rho_{\theta_1}(S - \theta_1^*)}{(\rho_S + \rho_{\theta_1})^2} \tag{18}$$

If the planned input amount is larger than the recommendation such that $\theta_1^* > S$:

$$\frac{\partial \alpha}{\partial \rho_S} > 0 \tag{19}$$

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

3 Experimental Design and Data

To test the effectiveness of the soil health card scheme in Bihar and the theoretical predictions, we implemented a field experiment in partnership with the Department of Soil Science of Rajendra Agricultural University (RAU) in Samastipur district, Bihar.[15] 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.

3.1 Randomization and Timeline

To select households, we used a multistage sampling approach. In the first stage, we selected three districts with a predominant rice-wheat cropping system from which to sample households: Bhojpur, Madhubani, and Nawada (Figure 1). In the second stage, we selected 16 high-rice-producing blocks (subdistrict administrative units) across the three

[15] RAU is the oldest and most prestigious institution for agricultural research and extension in the state and has the most capable testing capacity to carry out the soil testing and recommendations

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.[16] 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.

Figure 2 illustrates the timeline of the SHC intervention and related data collection activities undertaken during the study. In April-May 2014 we conducted a baseline survey that 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 rice crops harvested during 2012-2013.

During the baseline survey, we elicited risk preferences, self-reported confidence, and subjective beliefs regarding optimal urea and diammonium phosphate (DAP) use on the upcoming rice crop for *kharif* 2014.[17] We also collected information about farmers' past experience with soil testing and their stated willingness-to-pay for soil test. The belief elicitation process and willingness-to-pay are explained in greater detail in Section 3.2 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

[16] 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.

[17] 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).

rather than on a gridded basis.

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,[18] 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.[19]

The SHCs (printed in Hindi) were hand-delivered to individual farmers in November 2014 (prior to planting the *rabi* wheat crop) by the 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. Just prior to receiving the recommendations, treatment farmers were asked about the planned input usage on their two main plots in the upcoming 2014-2015 *rabi* season, as well as their expected yields.

Because the baseline survey was focused primarily on rice rather than wheat, a pre-treatment survey of households was carried out prior to the distribution of the SHCs (November 2014) to collect information on cultivation habits, fertilizer application, and wheat yields from the previous *rabi* season (2013-2014).[20] The endline survey was conducted after the *rabi* 2014-15 wheat harvest (June-July 2015) and collected information on farmers' fertilizer application and production during the 2014-2015 *rabi* season.

3.2 Measurement

3.2.1 Willingness-to-pay for soil tests

During the baseline survey, we collected information about previous experiences with soil testing and farmers' stated demand for soil testing which included both soil health infor-

[18] See section 3.2.4 for a description of the yield response equations

[19] A quintal is equivalent to 100 kg.

[20] The pre-treatment survey was administered to collect data on input usage and yields in the previous *rabi* season as a supplement to the initial baseline survey.

mation and plot specific recommendations for fertilizer application rates. In general, while soil testing was possible in the study area during the baseline survey, the process of collecting samples and bringing them to the lab was prohibitively costly and time consuming for individual farmer. In practice, the market for the service was not developed and existing private and public providers lacked capacity for soil testing to become widespread. Further, there was very little knowledge about soil testing in general or how to have their soil tested. 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. The primary reason for not having their soil tested was that there was no facility available (63 percent), followed by cost and lack of interest. Of the farmers 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).

To collect WTP for the soil tests we use a contingent valuation (CV) method. Policymakers are often interested in how individuals value goods and services that are not traded in the marketplace and these valuations can be measured using survey questions elicit respondents' willingness to pay (Alberini and Kahn, 2006; Cawley, 2008).[21] Prior to collecting the WTP, farmers in both the treatment and control groups were informed about the process of soil testing, how fertilizer recommendations were developed, and how they could interpret the soil tests. After receiving the information, and being told that the research team would collect soil samples and deliver soil health cards to them, farmers were then asked: *How much are you willing to pay to have your soil tested and to be provided with soil health information and fertilizer recommendations?*.

Figure 9 shows the distribution of the willingness to pay for soil health cards. On one extreme, 30 percent of farmers answered that they were not willing to pay any money for soil tests. Further, a total of 72 percent of the farmers had a willingness to pay of less than $2 which was the price of soil testing using the available public service at the time of the

[21] Contingent valuation methods are commonly applied in both environmental and health economics. For an overview of the methods and process of WTP elicitation see (Alberini and Kahn, 2006). These methods are also criticized due to the fact that stated preferences are often inferior to observing revealed preferences or eliciting WTP using incentivized methods such as a Becker-DeGroot-Marschak (BDM) mechanism. Due to the relative lack of availability and knowledge about soil testing, we opted for the CV method due to concerns about the ability to elicit non-zero values of WTP using other incentive compatible techniques.

intervention. The distribution of willingness to pay shown in Figure 9 indicates that while some farmers see little value in information about soil quality, a substantial fraction of them value it a lot.

3.2.2 Trust

To have a measure of farmer trust in information provided by agricultural extension agents (ρ_S), 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 and should therefore provide information on farmers' perception of the reliability of signals from extension agents. Specifically, we asked farmers to choose between two options:

> I will not trust new information from KVK (extension) agents until there is clear evidence that it is effective.
> I will trust new information from KVK (extension) agents until there is clear evidence that it is not effective.

3.2.3 Confidence measures

To elicit subjective beliefs about optimal fertilizer application rates, we employed a hypothetical, visually-aided elicitation method. Farmers' beliefs were collected in the initial baseline survey regarding their beliefs about optimal fertilizer application rates (urea and DAP) in the upcoming 2014 *kharif* rice season. To elicit the beliefs, 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.[22]

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

[22] Delavande et al. (2011) 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.

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.[23] The bins of fertilizer application rates were predetermined based on conversations with farmers and extension agents in the region. The DAP support consists of 5 bins spread over the empirical distribution of DAP while the urea support consists of 7 bins spread over the empirical distribution of urea application rates. We chose varying bin sizes in order to cover the whole empirical support of fertilizer usage while allowing for variation where the majority of application occurs and control for the mean of the subjective beliefs distributions in all regressions.[24]

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.

Figure 4 shows 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 except the highest fertilization rates. The slight skewness may be attributed to local beliefs over the amount of urea that results in crop failure. There is no apparent bunching at

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

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

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 calculate 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 $(\theta_1, \sigma^2_{\theta_1})$, and treat farmers' confidence as a measure of the precision of their prior beliefs ($\rho_{\theta_1} = \frac{1}{\sigma^2_{\theta_1}}$). Figure 5 shows the relationship between actual fertilizer application rates during the 2014 *kharif* season relative to the elicited expectations of the subjective beliefs distributions for urea and DAP. In general, the expectations of the beliefs about optimal urea and DAP are nearly the same as actual application rates in the following season. This similarity provides further evidence that the elicitation procedure captured meaningful information about farmers' beliefs.

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 1 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 below, suggesting that we are capturing meaningful heterogeneity in respondents that may also be applicable across crops.

In addition to subjective beliefs, we asked questions that provide self-reported measures of relative confidence as well as a question that captures farmer's subjective perception of their ability. 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.

The second question asks:

> Given the same soil quality and access to inputs, how would your yields compares to others in your village?

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 farmers' subjective relative ability.

3.2.4 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 conditional on soil characteristics. 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. Recall that the subjective beliefs distributions were collected for farmers beliefs about optimal fertilizer application rates for the *kharif* rice season. Thus, the measure of ability that we use in the following analysis is based on performance on their rice crop. The equation below relates the target rice 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) is calculated using the following equation :

$$S_{U,i} = (Y^* \times 4.06 - N_i \times 0.23)/46.08 \tag{20}$$

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

3.3 Summary Statistics and Balance

Of the 864 original sample households, a subset of the treatment households from the initial baseline survey (61 out of 558) did not have their soil samples tested due to contamination or errors in the processing of the soil tests. In the followup surveys, treatment farmers for whom soil testing could not be performed were excluded from the data collection. The resulting experimental sample includes 497 treatment households (89 percent of the original sampled households) and the control group consists of 306 households.

Table 2 presents selected summary statistics measured at baseline for control farmers, treatment farmers that received tests and treatment farmers that did not receive soil tests as well as balance tests for attrition. Columns 1 and 2 report the baseline means of demographic characteristics and fertilizer application for the control and treatment groups, respectively. The average farmer was overwhelmingly male and 45 years old. Nearly 40 percent of respondents were illiterate. Column 4 shows the p-values for the null hypotheses of equality of means between the treatment (with tests) and the control and between the treatment with tests and without tests. The table shows that there is good balance between the treatment and control groups. Out of the pairwise tests, we find the treatment sample that had their soil tested had a slightly higher share of female headed households (9 percent vs 5 percent). While these differences are not pivotal for the interpretation of our results, we report results that control for observed covariates in the analysis to account for lack of balance. The estimates of the treatment effect are robust to such inclusion, with little differences in the point estimates or standard errors. Attrition between the treatment and control group is analyzed at the bottom of Table 2. Overall, 10% of households could not be matched to the endline data due to difficulties in locating the households. The null of equality among treatment and control is not rejected at conventional levels.

Further, the differences between the subset of farmers for whom the soil testing was not possible and the remaining treatment group are not statistically significant with the exception of literacy and plot size. The subsample of treatment farmers without soil tests had slightly lower literacy levels (57 percent 69 percent) and lower plot sizes (.43 hectares vs .6 hectares). Conversations with the soil testing lab suggested that difficulties in the soil tests were primarily due to too little soil being collected or due to contamination and were likely random. Because we find some differences across these two baseline characteristics, we use the bounding approach of Lee (2009) to construct upper and lower bounds for the treatment effect. In our context, attrition is due to difficulties in processing soil tests for farmers, which is likely random but may be correlated with unobserved variables. To analyze the robustness of our treatment effects to attrition, we construct the bounds by trimming either the top or the bottom of the distribution of fertilizer usage for the treatment groups by the relative difference in attrition rates between treatment and control. We discuss the process further in Appendix A and present results in Table A3.

Throughout this paper, unless otherwise noted, the analysis is restricted to the large majority of households that were present in the endline and that planted wheat during the 2014/2015 *rabi* wheat season. Given that the analysis relies on fertilizer application on wheat crops, we limit the sample to these households and report the balance tests in Table 3. As in the full baseline sample, the evidence in Table 3 shows that the treatment did not result in differential selection out of planting wheat in the treatment and control groups and that there is balance across the covariates. The share of farmers planting wheat was roughly 85 percent in both the treatment and control, resulting in a final sample of 677 farmers.

3.4 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.[25] 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.

[25]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).

Table 4 compares the recommendations with data on actual fertilizer use from the baseline survey. For urea and DAP, the average recommendation was 16 and 20 percent higher than baseline application rates, respectively. The recommendation for MOP (potash) was substantially higher, though only 29 percent of farmers applied MOP in the 2014 *rabi* season. Based on these target yields, more than 70 percent of farmers in our sample applied less than the recommended dose of urea provided on the soil health cards in the baseline survey and 84 percent applied less than the DAP recommendation. 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 149 treatment farmers applied potash to wheat. 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.

The difference between the baseline fertilizer application rates in *rabi* 2014 and the recommendations are presented in Figure 6. 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.

Due to the fact that soil tests were only collected for treatment farmers, we do not have the associated values for control farmers. To overcome this challenge in estimating the treatment effects on responsiveness, we use the fertilizer recommendations for treatment farmers to predict the values for control farmers. To do so, we regress the urea recommendations on baseline yields and measures of soil quality including the slope, soil type, erosion and their interactions as well as block level fixed effects. These controls explain 72 percent of the variation in the recommended urea application rates. Figure 8 plots the relationship between the predicted values and actual urea application rates for the treated sample. Roughly 90 percent of the predicted recommendations are within 5 kilograms per hectare of the actual recommendations which represents less than a 3 percent difference. A comparison of the average predicted urea application recommendations in Table 2 shows that they are 3.6 percent higher in the control group, though the difference is not significant.

4 Results

In this section, first we provide evidence about the impacts of farmers' beliefs on demand for soil testing. Second, we present the results of the soil health card intervention and document limited impacts of the treatment on fertilizer usage and other input usage. We then test whether the strength of farmers' subjective beliefs affects responsiveness to the soil health cards.

4.1 Do beliefs affect demand for information on input usage?

How do farmers' beliefs affect demand for soil testing and recommendations? The answer is important both for understanding the targeting of information interventions and for the optimal pricing and profitability of private soil testing. Figure 10 plots the non-parametric relationship between farmers' stated willingness to pay for soil health cards relative to the coefficient of variation in prior beliefs about optimal fertilizer usage. The WTP is increasing in the dispersion in beliefs about urea application rates (Panel A), meaning that farmers with less strong priors about optimal input usage have a higher WTP for the soil health cards. WTP increases from \$1.5 for farmers with the strongest priors and to \$2.4 for those with the weakest priors. The same relationship is observed for the dispersion in farmers' beliefs about DAP application rates (Panel B).

If farmers place less weight on their priors, then WTP should be larger for less confident farmers. Similarly, if farmers value accurate information, WTP should be larger the more informative the signal is perceived to be. To test the impacts of confidence and trust on willingness to pay for fertilizer recommendations, we estimate farmers' stated willingness to pay for soil testing elicited during the baseline survey using OLS as follows :

$$WTP_{iv} = \alpha + \beta_1 Confidence_{iv} + \beta_2 Trust_{iv} + X_{iv}^{'}\gamma + \tau_v + e_{iv} \tag{21}$$

where WTP_{iv} is the stated willingness-to-pay for soil tests by farmer i in village v. In the following estimations we use the standard deviation of the beliefs distributions (controlling for the mean) as the measure of confidence ($Confidence_{iv}$). We include a binary measure of trust in extension agents ($Trust_{iv}$) to control for perceived signal accuracy. As controls, we including ability ($Ability_{iv}$) which 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. Further, baseline beliefs may be correlated with numerous factors that influence demand, including prior farming experience, age, socio-economic status, and cognitive ability. To control for these omitted factors which can confound the impact of baseline beliefs on information demand, we include a vector of farmer characteristics including the age, education, and literacy of the household head as well as measures of household wealth. Further, we include controls for household risk aversion, as well as household wealth and access to credit. In all regressions we report standard errors clustered at the village level and include village fixed effects (τ_v).

Table 5 presents the OLS results for WTP for soil tests. We find that on average, farmers with more disperse priors about optimal urea application rates have higher WTP than the more confident farmers. Column 1 demonstrates that WTP is increasing in the standard deviation of beliefs about optimal urea. A standard deviation increase in dispersion (0.17) is associated with a rise in willingness to pay by an average of \$0.34, or 17 percent of the price of a SHC at the time of testing.[26] These results are robust to the inclusion of baseline characteristics including wealth, ability, and risk aversion, as shown in column 2 and similar to those using measures of dispersion of beliefs about DAP (columns 3 and 4). Overall, these results demonstrate that less confident farmers in Bihar may be aware of their potential knowledge gaps and demand information about decisions they make regularly, even after controlling for individual levels of experience, ability, and trust in the source of information.

Farmer trust in extension services is positively correlated with WTP across the models but is not significant at conventional levels Thus, the subjective informativeness of the SHC does not appear to affect farmers' demand *ex-ante*. However, literacy increases demand for the SHCs by between \$0.58 and \$0.73. Farmers that are unable to read may anticipate interpreting the cards incorrectly, suggesting that literacy may be important in farmer decisions to purchase or utilize soil testing and/or fertilizer recommendations. This has important implications, as extension agents are a primary source of 'official' advice on inputs, technologies, and practices, and will have to allocate additional effort to communicating the value of soil tests to illiterate farmers. While we cannot rule out experimenter demand effects due to the hypothetical nature of the willingness to pay (De Quidt et al., 2018), which may be worsened if the effects are correlated with confidence, the estimates are quantitatively similar with and without enumerator fixed effects. Further, the results using actual investment choices in the following section suggest that confidence and trust

[26] For comparison purposes, at the time of the survey, the price of SHCs from existing facilities was slightly above \$2.00 though there was little availability. The average WTP amongst treatment farmers was \$1.61. Additionally, we can compare the mean WTP in our study with the results other papers that elicit WTP for information amongst farmers using incentivized measures. Those studies tend to find similar valuations in a variety of contexts: \$2 for a 9-month interactive extension advice in Gujarat (Cole and Fernando, 2016), 2 GhC/month for nutrition based agricultural information in Ghana (Palloni et al., 2018)

lowers responsiveness to the SHC.

Taken together, these estimates are consistent with the theoretical model and highlight economically significant heterogeneity in farmers' beliefs on demand for information. While this result follows from a standard model of belief updating, recent empirical evidence on information demand finds that agents may also vary in their taste for information, in which case farmers with higher belief precision could potentially demand information regardless of whether they plan to use it (Fuster et al., 2018). We do not find evidence that this is the case in our context. Further, we find that literacy may act as a barrier to adoption of SHCs, as illiterate farmers have a lower WTP for SHCs in the baseline survey. These findings provide further justification for using complementary low-cost information dissemination methods in contexts with a high share of illiterate farmers, including audio and video supplements, that reinforce information provided on soil health cards (Cole and Sharma, 2017).

4.2 Impacts of SHCs

We estimate the intention-to-treat (ITT) effects of receiving the soil health card on endline fertilizer using an ANCOVA specification.[27] Our main specification uses the endline data and controls for the baseline value of the outcome of interest when available. We estimate the treatment effects for the full experimental sample, as well as for farmers that only planted wheat in the endline.[28]

We estimate the treatment effects using the following specification:

$$y_{ivb} = \beta_0 + \beta_1 T_{ivb} + \beta_2 y_{ivb0} + X'_{ivb0}\gamma + \mu_b + \epsilon_{ivb} \tag{22}$$

where y_{ivb} is the outcome of interest on the treated plot at endline. Our primary outcomes are fertilizer application rates measured in kg per hectare by farmer i from a village v in block b. We estimate the treatment effects separately for the three fertilizers on the SHC: urea, DAP, and MOP, as well as an indicator for if the farmer applied MOP. We also estimate the impact of the soil health cards on yields (quintals/ha) and trust. T_{iv} is a binary treatment indicator indicating receipt of the SHC, y_{ivb0} is the values of the outcome at baseline. Where indicated, we include X_ivb0 a vector of individual and household baseline

[27] 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 allows for differences in the measurement of baseline variables (McKenzie, 2012).

[28] Table 2 shows a comparison of means for whether households planted wheat in the endline by treatment group. T-tests of the difference in means shows that there was no differential selection out of wheat production in the treatment group.

characteristics including gender, age, literacy, landholding size, and size of the treated plot, to increase precision and control for any baseline imbalances. In all regressions we include are block (strata) fixed effects (μ_b) and report standard errors clustered at the village level (the unit of randomization).

4.2.1 Fertilizer response to targeted fertilizer recommendations

Table 6 shows the main estimates of the impact of soil health cards on average fertilizer usage amongst farmers that planted wheat in the endline. As discussed in Section 3.4, the recommendations for urea and DAP may be higher or lower than farmers' baseline application rates (Figure 6) but in general, they tend to be higher, especially for DAP.

Focusing on the impacts on urea usage, column 1 shows that treatment farmers applied 12.7 kg more urea per hectare on their plots and the difference is significant. This implies a 6 percent increase in urea application rates in the treatment group relative to the control group. However, adding controls reduces the treatment effect by half and it becomes insignificant. In contrast, columns 3 and 4 show that the treatment led to declines in DAP usage by roughly 5 percent but the effect is not significant. Similarly, while the likelihood of potash (MOP) application increased by 8 percentage points relative to the control mean there was no significant impact of the treatment on total MOP usage. 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. However, on average the estimates suggest that the soil recommendations induced a relatively small increase in urea application rates and a marginal increase on the likelihood of using potash fertilizers.

Appendix Table A2 reports the intention-to-treat effects for the full experimental sample. The coefficients for the treatment effect on urea usage are twice as large than for the sample of farmers that planted wheat, and are significant with and without controls. The coefficients for the treatment effect on DAP and MOP usage are small in magnitude and insignificant across the estimations, with the exception of the likelihood of applying MOP which increased by 8 percentage points amongst farmers that received the soil health card.

Taken together, we find a slight increase in fertilizer usage due to the soil health card intervention on average but the intervention did not have a significant impact on application rates of the other recommended fertilizer inputs. This effect may be partially driven by the fact that because these recommendations were tailored to individual farmers, some farmers received recommendations that were below and some received recommendations that were above their normal fertilizer application rates. Amongst treatment farmers, 65 percent received recommendations that were above both planned urea and DAP usage, and 10 percent received recommendations below both planned urea and DAP usage (Figure

7). 85 percent of farmers received a recommendation to use more DAP, which amounted to 62 kg per hectare more than their planned usage. Only 8 treatment farmers were recommended to apply less MOP than they planned, and nearly half of the treatment farmers did not report plans to apply MOP. Thus, it is unlikely that this effect is driven purely by the treatment inducing comparable increases and decreases in fertilizer usage.

A second explanation for the attenuated effect of the treatment on DAP and MOP usage is related to the costs of fertilizers. While urea continues to be highly subsidized in Bihar, subsidies in DAP and MOP declined in the years prior to the intervention. When farmers were asked why they did not adapt their input usage to the recommendations, the majority in all cases stated that they believed the usual amount that they use is correct. However, the secondary reason for applying less than the recommended amounts of DAP and MOP were monetary. Roughly 40 and 36 percent of farmers cited cost as an impediment to DAP and MOP usage, respectively.

These results complement those found by Harou et al. (2019), who show that plot-specific soil tests increased fertilizer usage from low baseline adoption in Tanzania only when accompanied by vouchers for purchase. In our case, the soil health cards increased urea usage which is relatively cost free, but had no effect on DAP (a more costly fertilizer) and a marginal effect on MOP. These results highlight the potentially negative effects of providing information that targets multiple inputs when farmers face different costs across the inputs and have to trade off the perceived benefits of the information with costs of input usage.

4.2.2 SHC impacts on yields and trust

The soil health cards specifically targeted fertilizer usage with the goal of improving more balanced fertilizer usage rather than increased yields. Given that the overall treatment effect suggests an average increase in urea application with little change in other fertilizer inputs, the treatment may have increased yields for treatment farmers if yields respond only to urea application. Table 7 reports the effects of the treatment on endline wheat yields in the 2014 *rabi* season using the ANCOVA regression specified above. Columns 1 and 2 show that the treatment had no significant impact on wheat yields. The coefficient suggests a 6 percent decrease in wheat yields, though the effect is imprecisely estimated, including when controls for inputs and wealth are included. While it is reassuring that yields did not decrease significantly due to the receipt of the SHC, the previous results suggest that they may have worsened fertilizer imbalances which can lower yields in the long run while also leading to increased groundwater contamination.

One potential downside of the lack of improved yields is that the credibility of information from extension agents may decline due to perceived inconsistency of the information that was provided. While the extension agents that delivered the soil tests clearly explained to farmers the need for more balanced fertilizer usage, the estimated effect of the SHC suggests that farmers may have adjusted fertilizer usage, particularly urea, to increase their yields. In columns 3-6, we find evidence that the SHC treatment actually makes farmers less likely to trust information provided by extension agents. In particular, the SHC reduces a binary measure of trust in extension agents by 11 percentage points, a 30 percent decrease in trust, amongst the overall experimental sample. When we restrict the sample to farmers that planted wheat, the effect is even larger. The SHC reduces trust amongst these farmers by 14 percentage points. Rather than increasing the credibility in extension agents and the government in general, farmers place less faith in new information after the provision of scientific information. This is particularly concerning given the results in the following section which show that trust in the credibility of information is a significant determinant of responsiveness to the SHC recommendation. Extension agents, and governments in general, frequently face a tradeoff between conveying new information that updates previous recommendations about agricultural practices and possibly losing credibility as a result of inconsistent messaging. One way proposed in the literature to improve the credibility of information is through the use of scientifically based recommendations or demonstrations, such as using microscopes to demonstrate the existence of disease causing microbes (Bennett et al., 2018). However, these results suggest that when communicated through an existing institution with low initial trust, inconsistency in messaging or a lack of verifiable results can have an adverse effect on credibility.

4.3 Differential responsiveness to soil health cards

This section examines the role of confidence and trust on responsiveness to the soil health card recommendations. We interact treatment status with the dispersion of baseline beliefs and trust to test whether they lower responsiveness to the SHC and to estimate the relative magnitude of the effects. A negatively signed interaction between receipt of the SHC and prior belief dispersion is evidence that farmers with more confidence farmers place relatively less weight on their planned input usage and move closer to the recommendation. Confidence may be correlated with farmer ability and other characteristics that influence initial beliefs and learning including age and education. We control for these factors which threaten to confound the interaction between the treatment and prior beliefs and to isolate the impact of confidence on responsiveness to the SHC recommendations.

Our measure of responsiveness (α) is the absolute difference between the predicted recommendation and farmers' endline fertilizer application.[29] This measure captures the degree to which farmers move their input usage towards the information provided in the soil health card. To test the impacts of confidence on responsiveness to the SHC, we estimate the following equations for farmers that planted wheat using OLS to estimate :

$$\alpha_{ivb} = \beta_0 + \beta_1 T_{ivb} + \beta_2 Confidence_{ivb} + \beta_3 T_{ivb} * Confidence_{ivb} + \beta_4 Trust_{ivb} + \tau_b + u_{ivb}. \quad (23)$$

$$\alpha_{ivb} = \beta_0 + \beta_1 T_{ivb} + \beta_2 Trust_{ivb} + \beta_3 T_{ivb} * Trust_{ivb} + \beta_4 Confidence_{ivb} + \tau_b + u_{ivb}. \quad (24)$$

where (α_{ivb}) is the responsiveness to the SHC urea recommendation for farmer i in village v, confidence ($Confidence_{ivb}$) is measured as the standard deviation of the beliefs distributions and ($Trust_{iv}$) is a binary measure of trust in extension agents. To test for heterogeneity in responsiveness to the test, we include interactions between the treatment, confidence, and trust as well as a triple interaction between the three. We include individual and household characteristics including wealth, ability, and risk aversion, as well as block fixed effects, and standard errors are clustered at the village level. The sample includes all treatment farmers that planted wheat in *rabi* 2014.

Table 8 reports regression results for the differential effects of the SHC on responsiveness by confidence and trust. The effect of the treatment on responsiveness is negative (column 1), meaning that treatment farmers' endline urea application was closer to the recommendation, though the effect is not significant. Column 2 includes the interaction between the SHC treatment and the standard deviation of farmers' priors. Farmers in the control group with low levels of confidence are further away from recommendation. However, less confident farmers in the treatment group are substantially more responsive to the SHC recommendation for urea usage. The interaction between confidence and treatment (column 2) implies that a standard deviation increase in belief dispersion increases responsiveness by 8 percentage points, or 11 percent. Similarly, control farmers that report trusting advice from extension agents prior to seeing evidence of its effectiveness are 16 percent further away from than urea recommendations. But when provided with information, farmers that trust advice from extension agents are 25 percent more responsive. In column 4, we include the triple interaction between confidence, trust, and the treatment to test whether confidence limits responsiveness to the SHC even amongst farmers that have a high amount of trust in advice from extension agents. The effect of confidence on responsiveness is substantially larger for farmers with high trust than with low trust. Comparing the differential effect of confidence between low trust and high trust

[29] See Section 3.4 for details on the predicted fertilizer recommendation rates

farmers implies that farmers with a standard deviation lower confidence are 26 percent more responsive to the signal. Taken together, these findings indicate that confidence further moderates responsiveness to information even amongst farmers with higher levels of trust in the source of the information. These effects support the argument that information interventions may be less effective when the beneficiaries do not trust the source of the information or have low trust in institutions in general. These magnitudes are quite large and suggest that a subset of farmers may be delaying their implementation or adoption of advice to wait and see how effective the advice is, akin to strategically delaying technology adoption (Bandiera and Rasul, 2006).

Overall, we see that farmers that are less confident about their agricultural decisions have a higher willingness to pay for soil testing and recommendations. 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 and are more responsive to the urea recommendations as predicted by the model. In addition to confidence, farmers trust in advice from the source of the information, extension agents, does not affect demand for information. But when provided with information and making actual investment choices, lack of trust diminishes responsiveness.

4.4 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 9, 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. Sixty six percent of the farmers who reported having used more than the recommended amount of urea and 58 percent of those who used less than the recommended amount of urea said they did so because they did not want to change their behavior from previous seasons. We observe 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 Conclusions

In this paper, we investigate how the strength with which agents hold beliefs and their trust in the information source affect the responsiveness to scientifically derived advice. To do so, we evaluate a randomized controlled trial in three districts of Bihar that provided soil health cards (SHCs) to farmers based on individualized soil tests to promote balanced use of fertilizers. Though not identical in the implementation, the provision of soil tests closely mirrored the operational approach of a large scale government soil testing program in India that intended to provide 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 wide spread soil testing in Bihar, 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 on average, farmers largely ignore the soil test results and fertilizer use recommendations contained in the SHCs. The impact of the SHCs on urea application was small (around a 6 percent increase) and marginally significant but had no effect on DAP. Due to the high subsidy rate of urea in this region, these findings suggest that credit or liquidity constraints are not likely a major reason for not attending to the scientific recommendations with respect to urea and points toward informational factors or behavioral biases as the primary culprit. However, the lack of response to the DAP and MOP recommendations may be at least partially due to other factors including either liquidity constraints, crowding out effect of the urea recommendations, or a combination of both.

To rationalize these finding, we document significant heterogeneity in beliefs about optimal applications of urea and DAP prior to receiving information. Consistent with the model's predictions, we show that confidence is associated with lower demand for SHCs and lower responsiveness to the recommendations provided on the SHCs. 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 and are more responsive to the urea (but not DAP) recommendations. Further, we show that farmers that have a greater degree of trust in advice provided by agents from the national extension system are substantially more responsive to the recommendations.

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., 2014), 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., 2018).

From a policy perspective, our results highlight potential heterogeneity in who is most likely to respond to expert information, with implications for interventions such as India's 'Soil Health Card' scheme. There have been few studies that consider how people vary in their responsiveness to information, especially based on measurable characteristics. Taken together, the results suggest 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. With respect to policy, it is important to consider this heterogeneity because policymakers may have cost constraints and face difficult identifying beneficiaries who have both a high value of information and are likely to respond. Our results show that 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 information 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 investment.

Appendix A. Robustness to Attrition

Attrition in the study comes primarily from soil tests in the treatment group that could not be processed (due to contamination or insufficient sample size) or from being unable to locate households in the endline survey. Appendix Table 3 provides attrition rates by treatment group for the experimental sample. Recall that we eliminated households from the endline that did not have their soil tested. As a result, 11 percent of the original treatment sample is not present in the endline survey due to testing, while another 10 percent of the remaining sample is not present in the endline due to not being able to followup in the endline (11 percent in control and 7 percent in treatment).

To examine how robust our results are to attrition, we use the bounding approach of (Lee, 2009) to construct upper and lower bounds for the treatment effect. We construct the bounds by trimming either the top or the bottom of the distribution of fertilizer application rates for the treatment groups by the relative difference in attrition rates between treatment and control. To examine the impact of attrition on our results, we estimate the bounds of the ITT effect for the full sample of farmers without limiting to those that do not plant wheat in the endline. Table A3 shows the results of estimating these Lee bounds which can be compared directly with Table A2. Column 1 provides the trimmed estimates for endline urea application rates which correspond to columns 2 in Table A2. The estimates of the treatment effect lie between the bounds estimated in column 1 using OLS. The parameter estimates are much closer to the upper bounds than the lower bounds. In this case, the lower bounds would occur only if treatment farmers that apply low amounts of urea attrit. However, in Table 2, a comparison of variables that were correlated with attrition suggest that only literacy and plot size are statistically different from the remaining treatment group. A regression of fertilizer application rates on baseline characteristics in the control group suggest that literacy has no impact on fertilizer application rates. Larger plot sizes tend to have higher fertilizer application rates, though the effect is not significant at the 10 percent level.

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Figure 1: Location of Sample Districts in Bihar, India

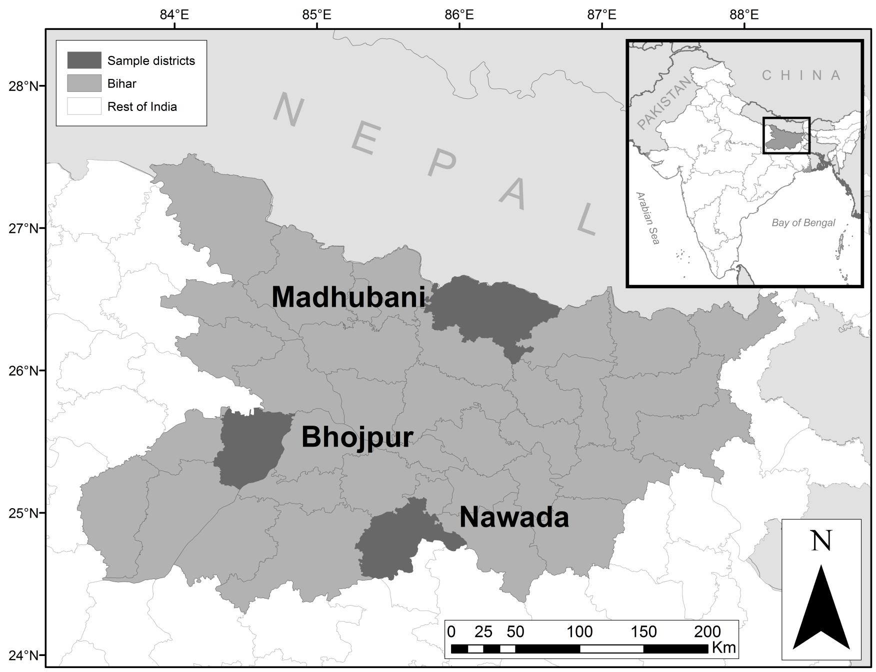


Figure 2: Timeline of Data Collection

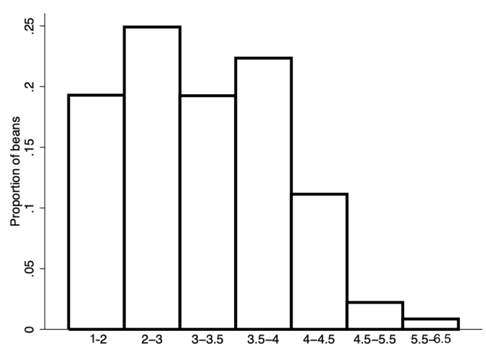
	2014									2015						
Activity	Apr.	May.	Jun.	Jul.	Aug.	Sept.	Oct.	Nov.	Dec.	Jan.	Feb.	Mar.	Apr.	May	Jun.	Jul.
Growing Season			Kharif Season							Rabi season						
Soil Sampling																
Pre-Baseline/Beliefs Elicitation																
SHC distribution/survey																
Baseline survey (pre-rabi)																
Endline survey																
BDM survey																

Figure 3: Example: Soil Health Card (Translated)

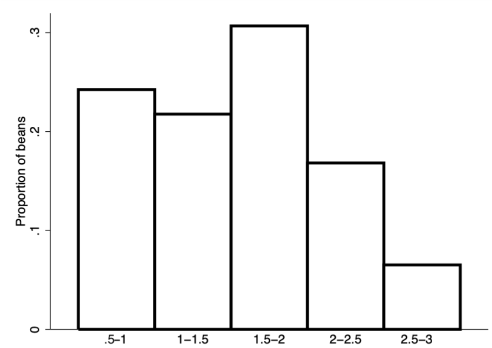
Crop name	Target Yield (quintal/ha.)	Recommended amount of nutrients (Kg/Ha.)			Recommended amount of fertilizer (Kg/Ha.)				
		Nitrogen	Phosphorus	Potassium	Urea	DAP	MOP	Zinc	Sulphur
Paddy/Rice									
Wheat	40q/ha	257.6	15.48	166.5	215	181.9	98.6	.8	27.45

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

Figure 4: Percentage of Beans Allocated to Fertilizer Ranges (Kg/Kattha)



(a) Urea



(b) DAP

Table 1: Correlations Across Confidence Measures

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

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

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

Table 2: Descriptive Characteristics and Balance Across Treatment Arms

	(1) Control		(2) Treatment		(3) No Test		T-test P-value	
Variable	N/[Clusters]	Mean/SE	N/[Clusters]	Mean/SE	N/[Clusters]	Mean/SE	(2)-(1)	(2)-(3)
Age	306	46	497	45	61	44	.24	.6
	[17]	(.84)	[31]	(.73)	[20]	(1.8)		
Female	306	.052	497	.085	61	.15	.088*	.23
	[17]	(.012)	[31]	(.014)	[20]	(.052)		
Literacy	306	.65	497	.69	61	.57	.44	.068*
	[17]	(.046)	[31]	(.029)	[20]	(.056)		
Trust	306	.31	497	.31	61	.28	.89	.66
	[17]	(.029)	[31]	(.021)	[20]	(.077)		
Mean Urea	306	3	494	3	61	3	.87	.73
	[17]	(.12)	[31]	(.072)	[20]	(.17)		
SD Urea	306	.44	494	.4	61	.39	.13	.62
	[17]	(.02)	[31]	(.014)	[20]	(.031)		
Mean DAP	301	1.5	490	1.6	61	1.5	.92	.31
	[17]	(.075)	[31]	(.045)	[20]	(.1)		
SD DAP	301	.28	490	.26	61	.26	.39	.95
	[17]	(.015)	[31]	(.011)	[20]	(.02)		
WTP for soil test (USD)	306	1.7	493	1.6	61	1.5	.87	.57
	[17]	(.24)	[31]	(.17)	[20]	(.36)		
Plot size (ha)	306	.57	497	.6	61	.43	.68	.064*
	[17]	(.05)	[31]	(.065)	[20]	(.067)		
Kharif Urea (kg/kattha)	302	3.1	465	3.1	59	3.1	.9	.91
	[17]	(.17)	[31]	(.14)	[20]	(.15)		
Kharif DAP (kg/kattha)	297	1.5	457	1.6	58	1.6	.17	.55
	[17]	(.069)	[31]	(.051)	[20]	(.11)		
Predicted Urea rec.	306	243	491	245	60	246	.84	.75
	[17]	(5.6)	[31]	(2.9)	[20]	(5.9)		
Predicted DAP rec.	306	158	491	165	60	173	.55	.42
	[17]	(11)	[31]	(5.9)	[20]	(11)		
Attrition	306	.89	497	.93				
	[17]	(.058)	[31]	(.016)				
Plant wheat endline	306	.8	497	.87				
	[17]	(.055)	[31]	(.019)				

Author's calculations from baseline data. The unit of observation is the household head for individual specific characteristics and the household for household level characteristics. The sample consists of all households that were present at the baseline. Differences in the number of observations across these variables are explained by missing entries during the data collection. Fertilizer application rates are reported in kilograms per hectare. The p-values in column 5 are for tests of the null of equal means across treatment arms (robust to intra-village correlation). DAP is diammonium phosphate. Asterisks denote test significance: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 3: Summary statistics across treatment groups at baseline for households that planted wheat.

Variable	(1) Control N/[Clusters]	(1) Control Mean/SE	(2) Treatment N/[Clusters]	(2) Treatment Mean/SE	T-test P-value (2)-(1)
Age	245	47	432	45	.26
	[52]	(1)	[86]	(.74)	
Female	245	.053	432	.081	.15
	[52]	(.012)	[86]	(.015)	
Literacy	245	.63	432	.69	.28
	[52]	(.044)	[86]	(.026)	
Trust	245	.31	432	.31	.99
	[52]	(.029)	[86]	(.023)	
Mean Urea	245	3	431	3.1	.51
	[52]	(.11)	[86]	(.069)	
SD Urea	245	.43	431	.4	.17
	[52]	(.018)	[86]	(.013)	
Mean DAP	240	1.6	427	1.6	.86
	[50]	(.075)	[85]	(.039)	
SD DAP	240	.27	427	.26	.46
	[50]	(.013)	[85]	(.009)	
WTP for soil test (USD)	245	1.5	430	1.6	.65
	[52]	(.19)	[86]	(.15)	
Plot size (ha)	245	.59	432	.6	.82
	[52]	(.044)	[86]	(.068)	
Kharif Urea (kg/kattha)	242	3	405	3.1	.64
	[52]	(.18)	[85]	(.13)	
Kharif DAP (kg/kattha)	237	1.5	397	1.6	.33
	[50]	(.069)	[83]	(.051)	
Predicted Urea rec.	245	243	426	244	.91
	[52]	(5.4)	[86]	(2.3)	
Predicted DAP rec.	245	160	426	164	.74
	[52]	(10)	[86]	(4.9)	

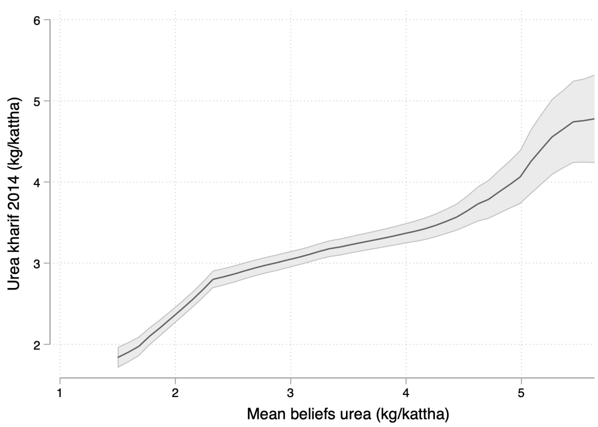
Author's calculations from baseline data. The unit of observation is the household head for individual specific characteristics and the household for household level characteristics. The sample consists of all households that were present at the baseline and andline and planted wheat in the 2014 *rabi* season. Differences in the number of observations across these variables are explained by missing entries during the data collection. Fertilizer application rates are reported in kilograms per hectare. The p-values in column 5 are for tests of the null of equal means across treatment arms (robust to intra-village correlation). DAP is diammonium phosphate. Asterisks denote test significance: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 4: Summary statistics of recommendations - Target yield (4T/Ha)

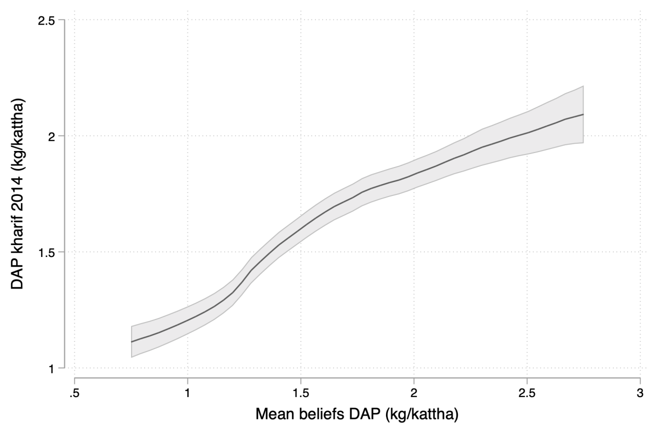
	Mean	Std. Dev.
BL urea	207.0	85.5
Recommendation Urea	243.5	28.1
BL DAP	116.8	33.7
Recommendation DAP	165.5	35.1
BL MOP	35.5	17.4
Recommendation MOP	82.4	19.8
Observations	488	

The sample includes only treatment farmers that had their soil tests processed and delivered. All values reported in kilograms per hectare (kg/ha). BL denotes fertilizer application rates in baseline. Rec denotes recommended fertilizer application rate from soil tests.

Figure 5: Fertilizer application relative to mean of beliefs about optimal fertilizer application



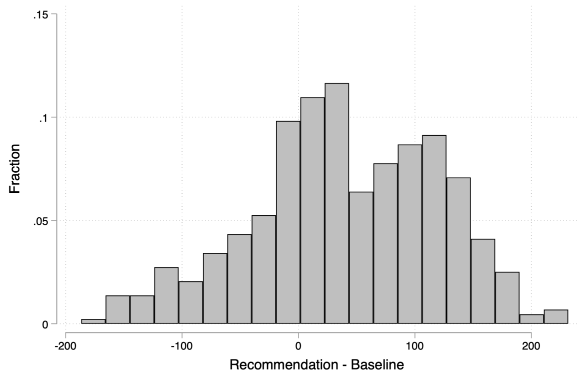
(a) Urea



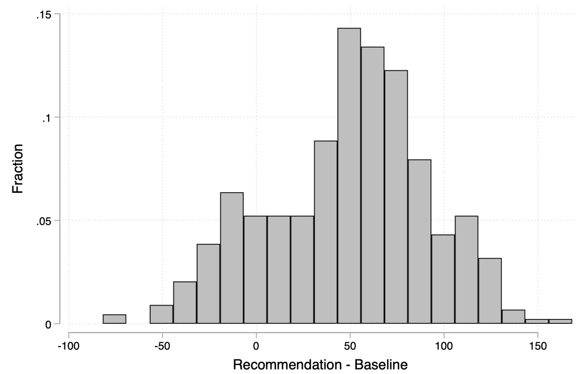
(b) DAP

Notes: Authors' calculations. The X-axis shows the mean of the elicited beliefs distribution of optimal fertilizer application rates for each farmer. Fertilizer application rates in kharif 2014 (kg/kattha) are plotted using a locally polynomial smoothing regression with an Epanechnikov kernel (bandwidth = 0.12). The 95% confidence intervals account for clustering by village.

Figure 6: Density of Difference Between Baseline Fertilizer Application Rates and Recommendation (Kg/Ha)

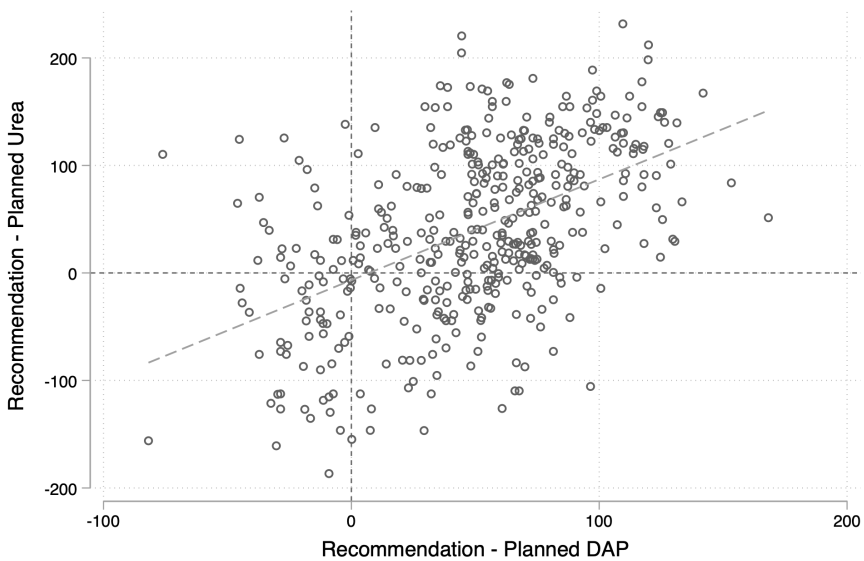


(a) Urea (All blocks)



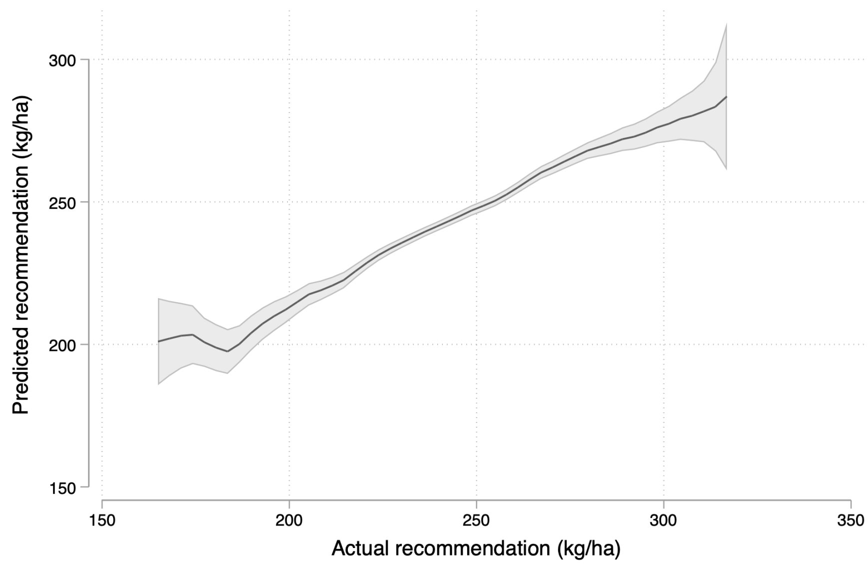
(b) DAP (All blocks)

Figure 7: Joint density of differences between SHC recommendations and baseline fertilizer applications rates (Kg/Ha)



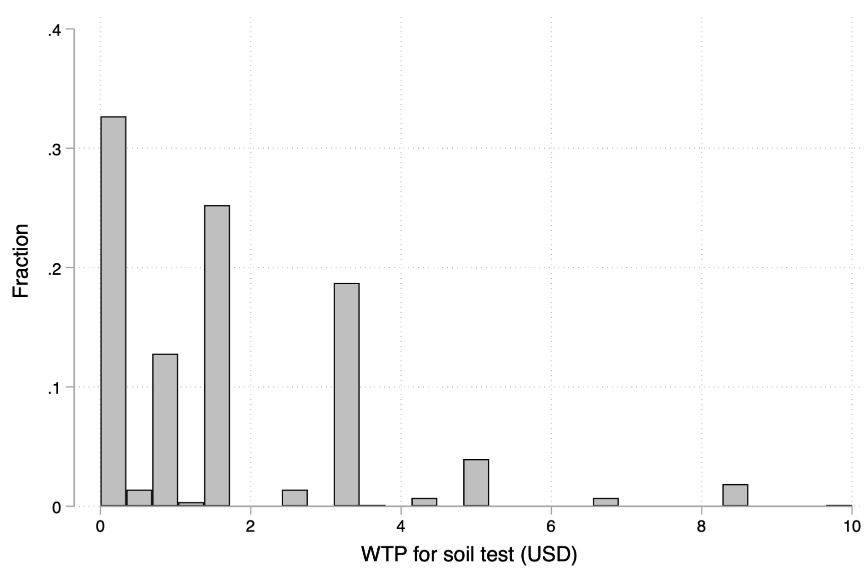
The sample includes only treatment farmers that had their soil tests processed and delivered. All values reported in kilograms per hectare (kg/ha). Planned urea and DAP denote farmers reported planned fertilizer application rates in 2014 *rabi*. Recommendation denotes recommended fertilizer application rate from soil tests.

Figure 8: Predicted urea recommendations relative to actual urea recommendations (Kg/Ha)



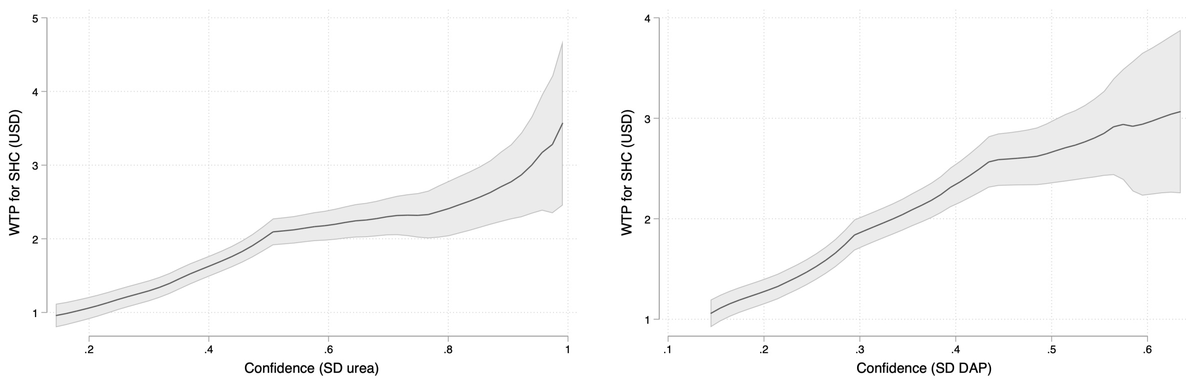
Notes: Predicted urea recommendations are plotted relative to actual fertilizer recommendations using a locally polynomial smoothing regression with an Epanechnikov kernel (bandwidth = 0.12). The 95% confidence intervals account for clustering by village;

Figure 9: Willingness to pay for soil health cards.



Notes: Authors' calculations. Stated WTP is reported in US dollars; SHC = soil health card; WTP = willingness to pay.

Figure 10: Willingness to pay for SHC



(a) Urea (b) DAP

Notes: Stated WTP is plotted using a locally polynomial smoothing regression with an Epanechnikov kernel (bandwidth = 0.12). The 95% confidence intervals account for clustering by village; CV = Coefficient of variation; SHC = soil health card; WTP = willingness to pay.

Table 5: Effects of confidence on willingness to pay for SHCs

	(1) WTP	(2) WTP	(3) WTP	(4) WTP
SD Urea	2.53***	2.49***		
	(0.52)	(0.52)		
SD DAP			4.58***	4.66***
			(0.98)	(0.96)
Trust	0.25	0.26	0.27	0.29
	(0.20)	(0.20)	(0.18)	(0.18)
Literacy	0.73***	0.59***	0.72***	0.58***
	(0.20)	(0.19)	(0.22)	(0.20)
Constant	1.18**	1.19**	1.12**	1.29**
	(0.52)	(0.47)	(0.53)	(0.59)
Observations	731	731	722	722
Adjusted R^2				
Mean dep. var	1.66	1.66	1.67	1.67

Note: Dependent variable is stated willingess to pay for soil testing and recommendations ($US). The sample includes all farmers that were present in the endline survey. The SD of urea and DAP beliefs are measures of farmer confidence calculated from their subjective beliefs distributions. Standard errors (adjusted for clustering at the village level) in parentheses. All regressions contain village fixed effects and controls for age and gender. Additional control variables in columns 2 and 4 include ability, household size, CRRA, whether the household head remembered which plot was tested, house value, whether the household owned cattle, whether the household owned the tested plot, whether the household owned an irrigation pump, whether the household had access to credit during *rabi* 2013. * Significant at 10 percent level; ** Significant at 5 percent level; *** Significant at 1 percent level.

Table 6: Impacts of the SHC treatment on fertilizer application rates for farmers that planted wheat

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Urea	Urea	DAP	DAP	MOP	MOP	MOP=1	MOP=1
SHC	12.7**	5.40	-6.61	-8.40	2.63	0.56	0.078*	0.050
	(5.62)	(8.33)	(5.04)	(6.03)	(1.67)	(1.80)	(0.045)	(0.046)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Observations	650	650	650	650	650	650	650	650
Adjusted R^2	0.278	0.278	0.211	0.214	0.463	0.464	0.556	0.554
Mean dep. var	205.6	205.6	118.9	118.9	18.3	18.3	0.45	0.45

Notes: Dependent variables in columns 1-6 are endline fertilizer application rates (kg/ha). All columns report the estimates from a regression of the endline fertilizer application rates on receipt of the soil health card treatment, baseline outcome variables, 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: Impacts of the SHC on yields and trust.

	(1) Yield	(2) Yield	(3) Trust	(4) Trust	(5) Trust	(6) Trust
SHC	-0.24	-0.29	-0.11**	-0.11*	-0.14***	-0.13**
	(0.29)	(0.33)	(0.044)	(0.057)	(0.047)	(0.060)
Block FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes
Observations	650	650	735	735	650	650
Adjusted R^2	0.068	0.089	0.141	0.152	0.157	0.166
Mean dep. var	3.81	3.81	0.41	0.41	0.45	0.45

Notes: The dependent variable in columns 1 & 2 are the endline yields measured in quintals per hectare. The dependent variable in columns 3-6 is a binary measure of endline trust in extension services. All columns report the estimates from a regression of the dependent variables onr eceipt of the soil health card treatment and block fixed effects. Controls are included where indicated. 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: Impacts of the SHC treatment on urea responsiveness

	(1)	(2)	(3)	(4)
SHC	-5.56	16.9	0.21	2.01
	(5.16)	(11.8)	(5.75)	(14.4)
SD Urea		45.0**		12.1
		(21.0)		(25.0)
SHC × SD Urea		-52.1**		-3.63
		(25.0)		(31.8)
Trust=1			12.9*	-30.6*
			(7.38)	(15.6)
SHC × Trust=1			-19.4**	38.1*
			(9.15)	(19.5)
Trust=1 × SD Urea				88.9*
				(44.6)
SHC × Trust=1 × SD Urea				-121.3**
				(52.4)
Constant	77.0***	67.2***	73.2***	68.0***
	(4.03)	(14.7)	(3.99)	(11.7)
Observations	650	650	650	650
Adjusted R^2	0.097	0.101	0.099	0.107
Mean dep. var	77.4	77.4	77.4	77.4

Notes: The dependent variable is the absolute difference between the predicted recommendation and farmers' endline fertilizer application. All columns report the estimates from a regression of the dependent variables on receipt of the soil health card treatment and block 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 9: 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 A1: Endline fertilizer application rates by whether farmers received recommendations above or below their planned fertilizer usage

	(1) Urea	(2) DAP	(3) MOP
Low rec. urea	-84.9***		
	(15.5)		
Low rec. DAP		-41.7***	
		(11.3)	
Low rec. MOP			-87.1***
			(11.2)
Village FE	Yes	Yes	Yes
Observations	391	393	148
Adjusted R^2	0.316	0.243	0.424
Mean dep. var	215.2	111.2	29.5

Notes: This table reports the the impacts of receiving a signal (recommendation) that is lower than planned fertilizer usage in the rabi season on the difference between endline fertilizer application rates and planned application rates prior to receiving the SHC (kg/ha). The sample includes only treatment farmers that reported their planned input usage in the survey prior to receiving the soil health card. Column 1 reports the results for urea, column 2 for DAP, and column 3 for MOP. All columns include a control for the planned fertilizer usage, village 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 A2: Impacts the SHC treatment on fertilizer application rates - Full sample

	(1) Urea	(2) Urea	(3) DAP	(4) DAP	(5) MOP	(6) MOP	(7) MOP=1	(8) MOP=1
SHC	23.5***	16.2*	2.38	-1.82	2.12	0.34	0.067*	0.041
	(7.11)	(8.78)	(5.43)	(6.58)	(1.53)	(1.67)	(0.040)	(0.044)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Observations	735	735	735	735	735	735	735	735
Adjusted R^2	0.135	0.138	0.115	0.112	0.438	0.438	0.501	0.500
Mean dep. var	181.3	181.3	105.5	105.5	16.1	16.1	0.40	0.40

Notes: This table includes the full experimental sample including households that planted crops other than wheat in the 2014 *rabi* season (lentils, vegetables, etc.). Dependent variables in columns 1-6 are endline fertilizer application rates (kg/ha). All columns report the estimates from a regression of the endline fertilizer application rates 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 A3: Impacts the SHC treatment on fertilizer application rates - Lee bounds

	(1)	(2)	(3)	(4)
	Urea	DAP	MOP	MOP=1
Lower bound	1.64	-9.80*	-1.57	-0.010
	(9.45)	(5.12)	(1.82)	(0.040)
Ubber bound	18.5**	0.10	1.69	0.037
	(8.67)	(4.89)	(2.01)	(0.042)
Observations	864	864	864	864
Adjusted R^2				

Notes: All estimations includes block fixed effects. Standard errors in parentheses, clustered at the village level.