Imperfect information and learning: Evidence from cotton cultivation in Pakistan

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Abstract

Information problems are pervasive in developing economies and can hinder productivity growth. This paper studies how much rural producers in developing countries can learn from their own cultivation experience, i.e. learning by doing, to redress important information gaps about imperfectly known input technologies. First, I build a theoretical model which links learning by doing in one period to improved input choices in the next period, and show that this can be impeded by uncertainty about what is being observed due to noisy cultivation signals and by uncertainty about what to infer about market varieties due to imperfect variety integrity. Second, I apply this framework to cotton farmers in Pakistan, where farmers have imperfect information prior to cultivation about the extent to which their seeds have pest resistant biotechnology. The results suggest that farmers are unable to learn by doing about this aspect of their seeds due to a high degree of noise in cultivation signals. The paper highlights the potential difficulties in parsing out and processing information from cultivation experience alone and therefore of learning by doing by rural producers in a development context.

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1 Introduction

Economic development is a process characterized by potentially severe and persistent information failures for both private and public agents. Given the salience of agricultural production in developing countries, the information failures faced by farmers are particularly important to understand. This paper contributes to the literature on how producers in developing countries learn to adapt and use technology, with a focus on learning from own cultivation experience (learning by doing) about imperfectly known seed-embodied technologies.

Seed technologies arise out of crossing or lab-based genetic engineering and can improve resistance to pests, reduction of spoilage, or nutrient profile. Developing countries account for the majority of genetically modified seed use in the world in terms of acreage (ISAAA, 2017), but much of these technologies originate from non-local expertise and are imported and back-crossed with poor regulatory standards (FAO, 2009). Coupled with the problem that one cannot deduce the attributes of a seed by physical inspection, this can create significant difficulties for farmers in selecting and cultivating seeds with the desired qualities.

In this paper I investigate whether, in the presence of imperfect information, farmers can discover the "hidden" attributes of their seeds from cultivation outcomes and use this to make improved input choices. Although farmers may learn about input quality from extension services or social networks, learning from own experience is important to understand because external information provision is rare and often expensive in developing countries, while heterogeneity in growing conditions can mute social learning (Foster and Rosenzweig, 2010).

I first provide a theoretical model in which a farmer, using an input of a specific variety, can learn from cultivation experience about a hidden attribute of this input and subsequently make improved input variety choices in the next period. I highlight that learning in this adverse information context can be impeded by two core challenges: noisy cultivation signals on the field and imperfect variety integrity in the market. Noisy cultivation signals will create uncertainty about the extent to which what is observed on the field is useful for learning about underlying attribute levels, while imperfect variety integrity will create uncertainty about whether what is inferred from the field is useful for learning about variety quality on the market and for making input choices accordingly.

The model shows that when uncertainty created by both noisy cultivation signals and imperfect variety integrity is limited, a farmer with high (low) levels of the desired attribute will discover this through cultivation experience and be motivated to repurchase the same variety (switch varieties) next season. By contrast, when either type of uncertainty is high, the underlying attribute level will exert no effect on subsequent variety choices. In addition, I model how such a learning and switching process can translate into improvements in average input quality consumed between two periods and into monetary gains for farmers, and, conversely, how lack of learning by doing can lead to substantial losses.

I then use this model to derive a specification which tests empirically for learning by doing by examining the effect of the ex-ante unknown attribute level on variety choices in the next season, and I apply it to a dataset on cotton cultivation in Pakistan. Pakistan is the fourth largest grower and exporter of raw cotton in the world, making cotton central to the country's economic development, but farmers have limited information about the pest resistance technology of the varieties they purchase. *Bacillus thuringiensis* (Bt) cotton, which is a genetically modified crop first patented and commercialized by US-based Monsanto in 1996 to be toxic to bollworm pests, is the most popular type of cotton in Pakistan. However, it was introduced in the country haphazardly, through unlicensed borrowing of the original Monsanto Bt variety and trial-and-error mixing with local varieties (Spielman et al, 2017); there are now many "Bt" varieties in Pakistan with different degrees of effective expression of the Bt trait (Spielman et al, 2015). As a result of haphazard technology adoption and weak regulatory capacities, the Pakistani government has failed to ensure that cotton varieties are accurately labeled or standardized in the market, and seeds are often sold without appropriate packaging or labelling. Most cotton farmers rely on the seller to tell them what the variety is and whether it effectively expresses the Bt trait, without being able to verify this information. To the extent that expression of the Bt trait reduces crop damage, missing knowledge about this key trait is an impediment to productivity.

In testing for learning from own experience, the input quality information must be inaccessible to the farmer so that there is space for learning and discovery, but accessible to the researcher to allow them to verify whether the right information was learned. This opportunity is provided by the unique structure of the dataset I use, the Pakistan Cotton Survey (PCS). Using a representative sample of cotton-producing households in Pakistan, the PCS survey team tested the level of the Bt protein in individual farmers' plots in 2013 and only revealed the results to them two years later, enabling me to use farmer behavior and decisions between 2013 and 2014 to study whether farmers learned from cultivation about information that was unavailable to them ex-ante.

The results show that the actual pest resistance of a seed of a given variety employed in season t by a farmer does not predict the probability of seeking the variety in $t+1$; farmers with lower levels of Bt are not more likely to switch varieties next season.[1] Additional results suggest that this is because Bt expression does not predict the farmer's perceptions (post-cultivation) about whether their crop exhibited satisfactory resistance to bollworm pests. In contrast, these perceptions do predict variety choices, with farmers who rate pest resistance performance as lower being more likely to seek different varieties the following season.

The results are consistent with an interpretation that farmers are unable to learn about the expression of the Bt trait in their seeds and that this is due to a high degree of noise in cultivation signals. Farmers seem to be unable to distinguish the extent to which biophysical characteristics versus other factors drive pest resistance performance, even as they are willing to make choices about varieties despite imperfect variety integrity. I discuss why the observational nature of the data and measurement issues related to seed technologies, despite placing reasonable limits on inference, are unlikely to be driving the results. Most importantly, the distribution of seed Bt level seems to contain a strong element of randomness due to the information problem; it is uncorrelated with observable farmer characteristics and beliefs, making it highly unlikely that unobserved heterogeneity is driving the findings.

The lack of learning which the results lend support to can lead to large productivity losses. Building on the theoretical model, I show how these losses can be estimated in the short run

[1]For brevity, the paper will sometimes use "Bt level" or "Bt content" to refer to the level of expression of the Bt trait, measured as the production of endotoxins which are toxic to pests when ingested.

(between two periods) using calibration of parameters from the data and from the empirical analysis. For more back-of-the-envelope long-run projections, I use the documented effects in the literature of Bt on crop damage abatement to estimate that failing to learn about Bt content and to purchase seeds with maximum Bt effectiveness can result in long term losses of up to 170 million USD, or 12.5% of the value of Pakistan's cotton industry in 2013-2014.

This study contributes to three related strands of literature. First it sheds light, theoretically and empirically, on how rural producers may learn about input quality under imperfect information. The relevant literature has more commonly studied learning from external sources, typically from extension services (Murphy, 2017; Emerick and Dar, 2019; Maertens et al, 2021) or social networks (Munshi, 2004; Conley and Udry, 2010; Crane-Droesch, 2017). On learning from own experience, the paper is distinct from the setup in Foster and Rosenzweig (1995) and Hanna et al (2014).[2] Closest to this paper is Bold et al (2017), which finds that Ugandan maize farmers have trouble learning about fertilizer effectiveness due to noisy yield signals. However, the authors do this by calibrating a learning model to outcomes from researcher-managed experimental plots to simulate what farmers would or would not learn. I also find that noisy signals can make learning from cultivation experience very difficult, but I test for this by applying theory directly to farmer behavior. Moreover, unlike these studies, this paper brings to the forefront the issue of imperfect variety integrity on the market.

Second, the paper contributes to the broader literature on learning by doing. Past studies have highlighted that, while some elements of how technology operates can be readily transmitted (e.g. through a blueprint or certification), circumstantial sensitivity can generate tacitness about how to best adapt the technology to local circumstances, and this may only be uncovered through learning by doing on the job (Bardhan and Udry, 1999; Khan, 2010). In the cotton seed market in Pakistan, however, the stealth acquistion of the Bt trait and the subsequent difficulties of regulating these varieties (Herring, 2007) have meant that farmers not only face the challenge of learning how to apply the imported technology locally, but *also*

[2] The former uses previous area cultivated to proxy for experience, and does not examine switching choice as relates to past seed quality. The latter studies a traditional technology that is in theory easy to learn about (size) but that is not noticed due to lack of awareness of its effect on yield, along with attention constraints.

of uncovering information that is not inherently tacit and can, in better regulated markets, be transmitted (Bt certification). Therefore, in developing countries the scope for learning by doing may extend to settings where even non-tacit types of information are missing.

Third, the paper provides insights on consumer learning when goods' attributes are not easily observed. It tests whether key attributes of an important commodity, seed, can be evaluated by the consumer (farmer) after use, in which case this commodity is an experience good (Girard and Dion, 2010); if these attributes are not revealed even after use, the commodity may be a credence good (ibid). Few studies address the problem in developing countries of potential credence goods and no empirical paper focuses on seed-embodied technologies. The potential problem of credence input goods may also spill into other markets; this can point to the possibility that missing information in developing countries is often not strategically hidden but unknown, with corrective strategies needing to operate accordingly.[3]

The paper is organized as follows. Section 2 builds a model of learning from cultivation experience and shows the relationship between uncertainty, learning, farmer behavior, and market outcomes. Section 3 provides background to the information problem in the Pakistani cotton seed market. Section 4 describes and discusses the relevant dataset. Section 5 outlines the econometric methodology as informed by the theoretical model and applied to the dataset. Section 6 presents the results and discusses the findings, and Section 7 presents the robustness checks. The last section summarizes and concludes.

2 Theoretical model

2.1 Setup

Suppose farmer i at time t purchases an input of a specific variety. Let x_{it} refer to the level of an attribute in this input, where profit is $\pi = \pi(x_{it})$ and, accounting for input price, $\pi' > 0$. The farmer cannot directly observe this attribute (level) in the input they purchased

[3]For example, in rural financial markets, if a borrowing farmer faces persistent difficulty in evaluating the quality of a key input and expected profitability, then mechanisms to overcome principal-agent problems will still not give the lender the relevant information about the suitability of the borrower.

but rather receives an imperfect signal of it, $\tilde{x}_{it}$, once the crop is cultivated:

$$\tilde{x}_{it} = x_{it} + e_{it}; \qquad e_{it} \sim N(0, \sigma_e^2) \tag{2.1}$$

The source of uncertainty which generates the error term e is that the farmer observes a performance dimension during cultivation which x_{it} affects but which other observed and unobserved variables also affect; the farmer is therefore unable to perfectly deduce input quality from cultivation outcomes.[4] If the unobserved sources of variation are random, then by observing crop performance the farmer will receive a signal of x_{it}, $\tilde{x}_{it}$, which is compounded by a random error term as described in Equation (2.1). For simplicity, I assume the farmer knows the distribution of the error term.

The underlying attribute level x_{it} on which the signal is generated is itself randomly drawn from the distribution:

$$x_{it} = x^* + \mu_{it}; \qquad \mu_{it} \sim N(0, \sigma_\mu^2) \tag{2.2}$$

The x^* refers to the average level of the attribute in the population of the variety purchased by the farmer. The error term μ therefore reflects the presence of less than perfect variety integrity in the market, so that two farmers purchasing the same variety of the input will not be purchasing inputs with exactly the same attribute level. I assume that the farmer knows the distribution of the error term σ_μ^2, and that this is uncorrelated with σ_e^2 as the two sources of uncertainty are fundamentally distinct.

Combining Equations (2.1) and (2.2), the signal the farmer receives, $\tilde{x}_{it}$, will be a function of the average level of the attribute for that variety, x^*, compounded by uncertainty around what is observed from crop performance and uncertainty around within-variety differences:

$$\tilde{x}_{it} = x^* + e_{it} + \mu_{it} \tag{2.3}$$

[4]For example, if x_{it} is the effectiveness of Bt expression of the seed, the relevant performance may be crop damage, observable confounders may include pesticide use if it can be accurately measured, and the unobserved confounders may include random (and difficult to observe) bollworm pressure.

The signal is therefore distributed as follows:

$$\tilde{x}_{it} \sim N(x^*, \sigma_e^2 + \sigma_\mu^2) \tag{2.4}$$

The farmer does not know what x^*, the average level of the attribute for that variety, is; they only have a *belief* about it. The farmer can be uncertain about their own belief, and so farmer i's belief at time t is that x^* is distributed as follows:

$$x^* \sim N(x_{it}^*, \nu_{it}^2) \tag{2.5}$$

Since Equation (2.5) describes a belief distribution, both the center (what the farmer thinks x^* most likely is) and the variance of this belief (how certain they feel about this) can change over time depending on what is learned in previous periods.

2.2 Learning

Learning in this context is the process by which the farmer uses the signal $\tilde{x}_{it}$ to update their belief about x^*. Therefore, it encompasses first learning about the specific input used and then learning about the market (variety quality). Similar to other models on farmer learning by doing, I assume farmers learn through a Bayesian updating process.[5] To see how this learning occurs between two periods, let there only be one prior belief, at t_0, and one posterior belief after one round of harvest, at t_1. The prior is that x^* is distributed as follows:

$$x^* \sim N(x_{i0}^*, \nu_{i0}^2) \tag{2.6}$$

After cultivation, the farmer observes the signal $\tilde{x}_{i1}$. With Bayesian learning, the farmer

[5]The model draws on the target input framework in Foster and Rosenzweig (1995) and Bardhan and Udry (1999), but adjusts the profit function, sources of uncertainty, and subsequent farmer choices. Other adaptations of the target input framework include Bold et al (2017), where farmers learn about whether their input crosses a critical threshold; Vasilaky and Leonard (2016), where farmers learn socially and this is affected by the strength of social ties; and Ma and Shi (2015) where learning and myopia impact technology adoption.

will use this signal to update their belief from the above prior to the following posterior:

$$x^* \sim N(x^*_{i1}, \nu^2_{i1}) \tag{2.7}$$

Appendix A shows that the posterior center and variance of belief are respectively:

$$x^*_{i1} = \frac{\tilde{x}_{i1}\nu^2_{i0} + x^*_{i0}(\sigma^2_e + \sigma^2_\mu)}{\nu^2_{i0} + \sigma^2_e + \sigma^2_\mu} \tag{2.8}$$

$$\nu^2_{i1} = \frac{(\sigma^2_e + \sigma^2_\mu)\nu^2_{i0}}{\nu^2_{i0} + \sigma^2_e + \sigma^2_\mu} \tag{2.9}$$

To see how the farmer's beliefs have changed, we subtract the prior from the posterior:

$$x^*_{i1} - x^*_{i0} = \frac{(\tilde{x}_{i1} - x^*_{i0})\nu^2_{i0}}{\nu^2_{i0} + \sigma^2_e + \sigma^2_\mu} \tag{2.10}$$

$$\nu^2_{i1} - \nu^2_{i0} = -\frac{(\nu^2_{i0})^2}{\nu^2_{i0} + \sigma^2_e + \sigma^2_\mu} \tag{2.11}$$

When $\tilde{x}_{i1} > x^*_{i0}$, the farmer's belief about the average attribute level for that variety is updated upward and vice versa, while precision (inverse of variance) about their belief can only increase. However, the effect of the signal on updating shrinks as uncertainty increases:

$$lim_{\sigma^2_i \to \infty} \frac{\partial(x^*_{i1} - x^*_{i0})}{\partial \tilde{x}_{i1}} = lim_{\sigma^2_i \to \infty} \frac{\nu^2_{i0}}{\nu^2_{i0} + \sigma^2_e + \sigma^2_\mu} = 0 \qquad i \in \{e, \mu\} \tag{2.12}$$

The interpretation is different depending on the source of uncertainty. If $\sigma^2_e \to \infty$, the farmer is unable to update because they are unable to learn about their own input quality from crop performance, due to highly noisy cultivation signals: there is simply too much noise to be able to pick up a reliable signal about the underlying attribute level x_{it}. If instead learning in that first step is possible but $\sigma^2_\mu \to \infty$, the farmer is unable to update because the information learned from their own crop is an unreliable indicator about average variety quality in the market, due to large imperfections in variety integrity.

2.3 Farmer choices

Finally, the following outlines how beliefs and learning affect input purchase decisions. Continuing from the above setup where priors are updated at the end of t_1, consider the beginning of t_2 where the farmer, who has already updated their beliefs, is now choosing which variety to purchase for cultivation in the new season. Here, I consider two possibilities for how farmers decide whether to repurchase or switch varieties: profit maximization or a heuristic rule (or a combination of the two).

If farmers repurchase the same variety as that cultivated in the previous period t_1, they will expect that, on average, the attribute level will equal the new updated belief x^*_{i1}. If they switch and therefore select from the wider variety pool, the attribute level will on average equal some overall market mean $\overline{x}$. Profit maximization therefore implies farmers will repurchase the variety when they expect $\pi(x^*_{i1}) > \pi(\overline{x})$, and switch otherwise. I assume the relative prices of varieties are fixed for the two periods, so that this simplifies to $x^*_{i1} > \overline{x}$.[6] Alternatively, farmers may simply pursue a heuristic rule in which the same variety is repurchased when its attribute level exceeded prior expectations, $x^*_{i1} > x^*_{i0}$, and switch when it disappointed. This may be driven by the information problem reducing confidence in evaluations of overall market averages, which may not be known with any precision particularly in the presence of a large number of different varieties.[7] Finally, farmers may take both considerations into account, comparing their updated belief both with the market mean and with prior beliefs.

[6] More specifically, I assume market surplus each period, with more inputs available for sale than being purchased. Though general excess supply is a stringent assumption, it can be applied to the Pakistani cotton market where x is Bt level, as farmers in the survey suggest there is easy access to seeds and that variety prices are not at all prohibitive. Excess supply also suggests that demand shifts in the second period can be met without a large relative change in prices, so that performance-improving varieties do not become too expensive and hence less desirable. Even if the relative price of in-demand varieties increases, as long as the relative x differential is still higher, the qualitative conclusions of the model hold but the extent of switching and of the benefits from learning (discussed in **Appendix B**) decrease. To simplify, I assume that the relative prices of different varieties are fixed between the two periods.

[7] In the PCS, for example, farmers purchased from 50 different varieties in 2013, so that it is highly unlikely a farmer will have had experience with all varieties.

Let S be the probability of switching varieties and a continuous function. Then:

$$S_{i2} = f\Big((1-h)(x^*_{i1} - \overline{x}) + h(x^*_{i1} - x^*_{i0})\Big) \qquad f' < 0 \tag{2.13}$$

where f is bound between 0 and 1 and $h \in [0,1]$ captures the extent to which farmers act on the heuristic rule. Equation (2.13) shows that farmers are less likely to switch when their updated belief is higher than the market mean, the prior belief, or a combination of the two.

Equation (2.13) forms the essence of the empirical strategy in Section 5, which uses information on switching decisions and on the underlying attribute level to test for learning. To see why, substitute Equations (2.1), (2.8), and (2.10) into Equation (2.13):

$$\begin{aligned}
S_{i2} &= f\Big((1-h)(x^*_{i1} - \overline{x}) + h(x^*_{i1} - x^*_{i0})\Big) \\
&= f\Big(x^*_{i1} - hx^*_{i0} - (1-h)\overline{x}\Big) \\
&= f\left(\frac{\tilde{x}_{i1}\nu^2_{i0} + x^*_{i0}(\sigma^2_e + \sigma^2_\mu)}{\nu^2_{i0} + \sigma^2_e + \sigma^2_\mu} - hx^*_{i0} - (1-h)\overline{x}\right) \\
&= f\left(\frac{(x_{i1} + e_{i1})\nu^2_{i0}}{\nu^2_{i0} + \sigma^2_e + \sigma^2_\mu} + \frac{x^*_{i0}(\sigma^2_e + \sigma^2_\mu - h(\nu^2_{i0} + \sigma^2_e + \sigma^2_\mu))}{\nu^2_{i0} + \sigma^2_e + \sigma^2_\mu} - (1-h)\overline{x}\right)
\end{aligned} \tag{2.14}$$

The partial derivative of the switching decision with respect to the underlying attribute is:

$$\frac{\partial S_{i2}}{\partial x_{i1}} = f' * \frac{\nu^2_{i0}}{\nu^2_{i0} + \sigma^2_e + \sigma^2_\mu} \quad \leq \quad 0 \tag{2.15}$$

Equation (2.15) shows that learning maps onto variety choices, so that we may be able to infer the former from the latter. Holding all else fixed and given $f' < 0$, if we observe farmers with higher underlying attribute levels switching less often ($\partial S_{i2}/\partial x_{i1} < 0$) then both noise from the cultivation signals (σ_e) and from imperfect variety integrity in the market (σ_μ) must be low enough to permit learning by doing. By contrast, if we do not observe this switching relationship ($\partial S_{i2}/\partial x_{i1} = 0$) and given $f' < 0$ and finite uncertainty by farmers in their own priors, then either σ^2_e and/or σ^2_μ are high enough to impede learning and to drive the above partial derivative to zero. The behavioral rule above only depends on the updated means, but if it also depends on the updated variances, the nature of the results does not change.[8]

The model also shows that the derivative of the probability of switching with respect to the *prior* is more ambiguous, depending on how farmers make input choices. If farmers act purely heuristically, the derivative will be equal in absolute magnitude to Equation (2.15) but with the opposite sign.[9] Therefore if farmers act heuristically, we would expect learning to map onto a positive coefficient for the prior, in that for the same attribute level farmers with a higher prior are more disappointed and will switch more often, while lack of learning maps onto a null coefficient. At the other extreme, if $h = 0$, then learning by doing would make the derivative approach zero while the absence of learning would make it approach $f' < 0$.[10] Farmers who can learn would rely very little on their prior to switch as it is mostly the signal which informs the posterior (and they compare this with market mean), whereas farmers who are unable to learn have their priors inform their posteriors more strongly, so that those with higher priors, and subsequently higher posteriors, switch less often. Given this ambiguity in the derivative with respect to the prior, I focus on the derivative in Equation (2.15) as a test for learning. Nonetheless, once it is established whether learning is present or not via Equation (2.15), one may be able to make a statement (following the above discussion) about whether the coefficient on the prior likely reflects heuristic or profit maximizing input choice.

Although the paper is primarily concerned with generating testable predictions about the presence or absence of learning by doing, in **Appendix B** I extend the model to explore the market-level consequences of such a learning process or lack thereof. I consider the presence of a range of varieties and model the consequences of learning and switching on the average change in the level of attribute purchased and consumed between t_1 and t_2. Let σ_η^2 be the variance of average quality *between* varieties, and A be a variable which captures

[8]Suppose farmers are more likely to respond to updated means when the variance falls more significantly, since the updating is more precise. This can be represented by $S_2 = g\left[\left((1-h)(x_1^* - \overline{x}) + h(x_1^* - x_0^*)\right)(\nu_2^2 - \nu_1^2)\right]$. Since the variance difference is negative, $g' > 0$. It can be shown that the results hold with this behavioral rule as well, but with uncertainty from σ_e and σ_μ exerting an even larger effect on switching decisions.

[9]This can be seen by substituting $h = 1$ in the expression multiplying x_{i0}^* in Equation (2.14), yielding the derivative $\frac{\partial S_{i2}}{\partial x_{i0}^*} = f' * \frac{-\nu_0^2}{\nu_0^2 + \sigma_e^2 + \sigma_\mu^2} \geq 0$.

[10]This can be seen by letting $h = 0$ and taking the limit of the coefficient on the prior as $\sigma_e^2 + \sigma_\mu^2$ approach zero or infinity, respectively.

the correlation between a farmer's prior about average variety quality and actual average variety quality (in relation to the market mean). Therefore $A > 0$ reflects more accurate farmer priors and $A < 0$ inaccurate priors. I show that, with a linear switching function and assuming excess supply, the average change in x between t_1 and t_2 is:

$$E(\Delta x) = \left(-\frac{\partial S_{i2}}{\partial x_{i1}} \sigma_\eta^2 \right) + \left(-\frac{\partial S_{i2}}{\partial x_{i0}^*} A \right) \tag{2.16}$$

The intuition for this result is as follows. First, note since $\frac{\partial S_{i2}}{\partial x_{i1}} \leq 0$, the first expression will always be nonnegative. If farmer priors are uncorrelated or only weakly correlated with actual variety quality (this appears to be the case in the PCS sample, for example; see **Appendix B**), one can focus on this first expression. Gains will be higher with greater learning and with higher variation in quality between varieties; the former allows for improving input choices while the latter expands the scope of possible benefits from this. Meanwhile, if farmer priors *are* correlated with variety quality, the second expression might be large in magnitude and its sign will depend on the farmer's input switching rules and the accuracy of their priors, and so these together will either reinforce or detract from learning gains.

Using Equation (2.16), regression coefficients can be used along with calibrated values for the other parameters to approximate short-run improvements that learning by doing generates, in terms of a change in the average x purchased between the two periods. This can then be translated into revenue changes. I illustrate this with an example in the Appendix.

3 Cotton production in Pakistan

Pakistan is the fourth largest producer of cotton in the world and also its fourth largest exporter after China, the US, and India. In 2019, it was estimated that over 1.6 million farmers cultivate cotton in Pakistan, with cotton cultivation accounting for 15% of all arable land during the Kharif (April-July) season and 26% of all farms in the country.[11] The

[11]For context on farmer activities, cotton farmers in Pakistan purchase seeds and sow them typically by June. The cotton is then cultivated and the harvest complete by the end of the year and subsequently sold. The vast majority of farmers are small, employing family labor. Farmers irrigate the crop through ground or canal irrigation, use Nitrogen fertilizer, and can apply chemical pesticides in multiple sprays to reduce pest

downstream textile industry is also integral to the country's economy, employing about 10 million people and generating 50% of all foreign exchange (USDA, 2019).

Pakistan's cotton farmers, based almost entirely in the Punjab (75%) and Sindh (24%) provinces, have increasingly adopted the genetically modified bollworm-resistant *Bacillus thuringiensis* (Bt) cotton over the past fifteen years. Evidence suggests that Bt use has reduced crop damage and improved yield (Ali and Abdulai, 2010; Kouser and Qaim, 2014). However, the way in which Bt has been adopted has been haphazard and largely unregulated. Bt cotton can rely on different *cry* proteins to generate toxins that confer the bollworm-resistance criterion, but the majority of Bt cotton varieties in Pakistan "rely on the *cry1Ac* gene from the MON-531 event developed by Monsanto [in 1996]." (Spielman et al, 2017; p.2) In the mid-2000s, lacking a formal system for proper Bt-variety acquisition because Monsanto was not willing to sell the technology in Pakistan,[12] Pakistani farmers began introgressing this specific gene into local germplasm to create locally specific hybrid Bt varieties. Farmers were therefore able to use trial and error and mixing with local germplasm to "effectively" introduce Bt to their cotton crop, despite intellectual property barriers.

Since adoption, the release and marketing of Bt cotton has been largely unregulated in Pakistan. Varieties sold in the market are often missing labels or contain incomplete or unregulated labelling. There is a lack of "regulatory systems.. [to properly] enforce rules requiring seed sellers to provide technical information on quality alongside their product.. [and] the judicial system does not provide sufficient recourse for farmers defrauded by seed sellers" (Spielman et al, 2015; p.1). Due to the inherent information problem in seed markets (a farmer cannot look at a seed and infer its quality), farmers are subject to an information problem when purchasing seeds in the absence of proper regulatory mechanisms.

Local mixing, which can result in poor breeding methods or improper genetic checks, and

damage. The Bt trait is another damage abating input as its expression produces a type of crystallized protein that is toxic to pests when ingested; the expression of the Bt trait depends on genetic background and possibly agroclimatic conditions. (Spielman et al, 2017)

[12]This is because Monsanto could not ensure royalties in the country. According to Monsanto, it was hardly offered any intellectual property (IP) protection, and attempts to obtain compensation or subsidies from the government of Pakistan in exchange for sale of the technology fell through (Rana, 2010). However, there is also evidence that the royalties demanded by Monsanto were excessive compared to its costs of development of these products and to Pakistan's budget allocation for agriculture (ibid).

poor regulatory capacities have resulted in the introduction of low-quality seed-embodied technologies in Pakistan's cotton seed market. In a survey of 20 districts in 2008-2009 with farmers who thought they were planting Bt cotton, Ali et al (2010) found that 10% of the samples from Punjab did not test positive for the *cry1Ac* gene and of those that tested positive, only 36% contained concentrations sufficiently lethal to kill bollworms; the numbers were 19% and 41% for samples from Sindh. In a later study on the 2011 season, Ali et al (2012) used different technology on another sample and found that 30% of all varieties tested were not positive for any *cry* gene.[13]

The PCS survey team sheds more light on this issue through two main papers. In Spielman et al (2017), the authors compare what the farmers are really planting to what they think they are planting. They find that a large portion of farmers believe they are planting Bt cotton when their variety does not actually express the Bt trait, but with more educated farmer slightly less likely to hold erroneous beliefs. However, they do not test for learning by linking Bt content with possible behavioral outcomes in the next season that could signal learning, as this paper does. In Ma et al (2017) the authors explore the cotton yield of the sampled farmers and find that, in a nonlinear damage abatement model,[14] effective expression of the Bt trait as measured by the PCS has a significant positive effect on farmer yield.

4 Data

4.1 Structure

The Pakistan Cotton Survey consists of four sequential in-person surveys and one biophysical sample survey.[15] The surveys were conducted by the International Food Policy Research Institute (IFPRI) along with local agricultural scientists between March 2013 and January

[13]These results echo earlier findings about China, the largest cotton producer in the world, with Pemsl et al (2005) highlighting the lack of regulation, ubiquity of information imperfections, and subpar expression of the Bt trait in China's Bt cotton seed market at the time.

[14]This is a model in which yield is affected by two types of inputs, incorporated differently into the production function: conventional inputs which directly increase yield, and damage abating inputs which reduce crop damage. Bt expression as well as pesticide use are considered damage abating inputs.

[15]The surveys are accessible publicly from the Harvard Dataverse website.

2015, on a random stratified sample of farmers in Punjab and Sindh. These provinces account for 99% of all cotton production in the country, and the sample is representative of cotton-producing households in Pakistan.[16]

The first survey, Round 1.1, collected preliminary background data on the 727 cotton farmers through face to face interviews in March 2013, prior to the beginning of cultivation for the year. The farmers were asked about their personal and farming background and history and various plot characteristics. The second survey, Round 1.2, followed up with the farmers in October 2013 after seeds were sown, and only 601 of the farmers had sown cotton for the season. Farmers were asked about the variety purchased, whether they believed it was a Bt variety, cotton cultivation by plot, input use, and access to social networks and to credit, among other things.[17] The third survey, Round 1.3, followed up in February 2014 and at this time the last picking for the season (harvest) was complete. The farmers were asked about input use, quantities harvested and sold, revenue, and perceptions about crop performance. The fourth survey, Round 2.1, returned to these farmers in January 2015 and asked farmers the same questions as in Rounds 1.1-1.3, but this time for the 2014 harvest. The number of participants narrows further, as only 501 of those who cultivated cotton in 2013 also did so in 2014.

The Biophysical Sample Survey took place in July and August of 2013, between Round 1.1 and Round 1.2. For those who sowed cotton in 2013, the team obtained farmers' consent to randomly select a few cotton leaves and bolls at 70 and 120 days after sowing. The samples were taken to national laboratories and tested for the presence of specific genes and toxins that contribute to Bt expression; the methodology is detailed in Spielman et al (2017). Crucially to this study, the farmers were not made aware of the biophysical results for the 2013 crop until early 2015, at which point the 2014 growing season was also finished.

Although 501 farmers cultivated cotton in both seasons, some did not have samples taken

[16] Across 28 districts in Punjab and Sindh, 52 villages (smaller unit than a district) were randomly selected based on probabilities proportional to population size. 40 villages were in Punjab and 12 in Sindh, mirroring the distribution of cotton production in the country. From each village, 14 households were selected randomly with equal probabilities, resulting in a stratified sample of 728 farmers, although one farmer dropped out of the first survey.

[17] Farmer answers show that farmer cooperatives are nearly nonexistent and use of cash credit is negligible.

from their plots, or did not farm on the main plot on which sufficient information is available, or did not answer basic questions including on farming experience. This narrows those who cultivated cotton both seasons, and on whom sufficient information is available, slightly, to 469 farmers. To my knowledge, the PCS dataset has not been used beyond the studies by the survey teams in Spielman et al (2017), Ma et al (2017), and Kouser et al (2019).

4.2 Sampled farmers

The biophysical survey shows that the sampled farmers are not cultivating seeds with high effective expression of the Bt trait.[18] Meanwhile, the farmers rely on largely unverifiable information, at purchase point, about whether their variety expresses the Bt trait and to what extent.[19] Farmers who believed their variety was Bt were asked about the main source of information for this. **Figure 1** shows that for most farmers it was simply that the input seller told them this is a Bt variety, followed by being told as much by a progressive farmer, a landlord, or a friend/relative/neighbor; none indicated that they could rely on labelling or packaging to make the assessment that the variety is Bt. Farmers who believed they purchased a Bt variety were asked to further quantify this prior by indicating whether they believed the variety's "quality in controlling bollworms" was *Very bad, Bad, Average, Above average,* or *Very good.*[20] **Figure 2** shows no correlation between actual Bt levels and these prior beliefs.

[Figure 1 here]

[Figure 2 here]

The data structure informs how I employ the sample in the empirical application. I focus on a majority subset of the farmers (331) while confirming that the results hold when

[18] Across the dozens of varieties they purchase from in 2013, the average level of Bt expression is 0.877 micrograms of *cry* protein per gram of plant tissue. This is only moderately high: a measurement of 0.598 means the plant has 50% chance of killing bollworms at specific conditions while a level of 1.59 offers a 95% chance of doing so. (Ma et al, 2017)

[19] It should be noted that the farmers indicate they do not store cotton seed for use in the next cultivation period. Those who report cultivating the same variety in 2014 bought that variety again in 2014.

[20] Although it is unclear why a farmer would purchase a Bt variety they believe is very bad, only 2% of farmers answered *Very bad.* 41% of farmers answered *Average* and 45% answered *Above average.*

all 469 farmers who cultivated cotton both seasons and on whom information is available are included. The 331 farmers selected are those who (i) believed at the outset they were purchasing a Bt variety in 2013, answering *Yes* to this question, and (ii) cultivated only one variety on the main plot. Focusing on the *Yes* group allows me to further control for the extent to which they believed their variety expresses Bt, described above, which improves the precision of the proxy for the prior.[21] Focusing on farmers who cultivated only one variety allows for exact matching between the results from the biophysical test and the variety purchased; for farmers who cultivated more than one cotton variety on the plot from which the biophysical sample was taken it is impossible to tell which variety the lab tests correspond to. However, to check that the results are not driven by sample selection, I include a column in the empirical section with these farmers added back in.[22]

4.3 Measurement and selection

Two further aspects of the PCS inform the use of the data and interpretation of results. First, since the survey team aimed to collect both biophysical and household data, the cotton samples were not farmed and assessed under experimentally controlled greenhouse conditions, as is standard for studies with only a biophyiscal data focus. This generates some complexity in the measurement of effectiveness of Bt expression. Second, since the data is observational, the distribution of seeds to households is not experimentally randomized. This generates limitations on how results from regressions involving this variable can be interpreted.

On measurement, assessing seed quality in laboratories can be vexing in general (Beegle, 2021) but additional challenges are involved with assessing varieties grown in non-

[21]It also excludes having to deal with the second largest group which answered *I don't know*, and which it is not clear can be considered to have a common prior.

[22]To the 331 observations (one per farmer), I add 115 observations (still one per farmer) for the 43 *No* and 72 *I don't know* farmers who farmed only one variety. I then add the observations (more than one per farmer) for the 23 farmers who, across belief categories, cultivated more than one variety (for a total of 53 varieties among them). The result is 469 farmers across 499 observations. For this overall set of farmers, I use broad-belief (Yes, No, IDK) dummies and construct a 'pseudo' Bt variable for farmers who cultivated more than one variety, based on the average Bt for that variety found for the other (one-variety per plot) farmers in the sample. For example, suppose farmer i cultivated two varieties, k and j, which had underlying respective Bt levels x_{ik} and x_{ij}. These cannot be deduced from the biophysical sample results. Pseudo-Bt for variety k is calculated as $\hat{x}_{ik} = \frac{\sum x_K}{N_K}$ where K is the set of farmers who cultivated only variety k in their plots.

experimentally controlled conditions. The samples collected by the PCS were sent to different laboratories in Punjab versus Sindh, and the results of the tests can be sensitive to the laboratory environment. Furthermore, once Bt expression is measured, a challenge is that "a positive indicator of Bt gene expression [...] does not necessarily guarantee that the Bt cotton plant will effectively control the targeted pest" as the latter depends on factors including genetic background and agroclimatic conditions (ibid, p.10). Finally, it is particularly challenging to make deductions about effectiveness when different parts of the sampled plant exhibit different levels of Bt gene expression (ibid, p.11). The empirical exercises in this paper are informed in part by the above discussion: I control for province, regional differences and climatic conditions to the extent possible in the specifications, and I also check how results change when only observations where the measured expression is very similar across samples from the same plant are included. Although this does not eliminate the problem of measuring seed quality in varieties that are not grown in controlled conditions, it demonstrates that a cautious approach to the biophysical data is possible.[23]

In addition to issues of measurement of the primary variable of interest, the *distribution* of this variable across farmers was not a randomized experiment, with farmers themselves having selected and purchased the seeds for the 2013 season. Here, it is worth noting that the information problem studied by the paper renders the selection bias potentially less severe than in observational data where there is perfect information about the treatment variable. This is because farmers being unable to verify the Bt level of the seed they are purchasing likely introduces a component of randomness to this variable, which is supported by the absence of a correlation between farmer *characteristics* and the effective expression of the Bt trait in their seeds, as **Table 1** demonstrates.

[Table 1 here]

The absence of observable heterogeneity in key farmer characteristics as relates to the Bt

[23]Reassurance about the biophysical samples not being far off mark also come from Ma et al (2017), who estimate that Bt content as measured by the PCS predicts significant reduction in crop damage in the sample. The authors also discuss experiments at one of the two PCS labs which show a significant positive effect of Bt level scores measured with the same protocol as the PCS on the mortality of insects that ingest these leaves.

variable is reassuring as it suggests that *unobservable* farmer heterogeneity is unlikely to be driving results via selection bias. Despite the absence of correlations, in all specifications I still include a number of controls, all occurring in 2013 or earlier, in case they are correlated with Bt levels if the latter are not entirely random (Section 5.2). I also conduct a range of robustness tests to ensure the results are not driven by specification bias (Section 7).

5 Econometric methodology

5.1 Specifications

The main specification to test for learning is a linear approximation of Equation (2.13):

$$S_{i2} = \alpha_0 + \alpha_1(x^*_{i1} - hx^*_{i0} - (1-h)\overline{x}) \tag{5.1}$$

where the right hand side is bound between 0 and 1, and $\alpha_1 \equiv f' < 0$. Using Equation (2.14) to substitute for the expression in the parenthesis, we obtain:[24]

$$\begin{aligned} S_{i2} &= \alpha_0 + \frac{\alpha_1\nu_0^2}{\nu_0^2+\sigma_e^2+\sigma_\mu^2}(x_{i1}+e_{i1}) + \frac{\alpha_1(\sigma_e^2+\sigma_\mu^2 - h(\nu_0^2+\sigma_e^2+\sigma_\mu^2))}{\nu_0^2+\sigma_e^2+\sigma_\mu^2}x^*_{i0} - \alpha_1(1-h)\overline{x} \\ &= \beta_0 + \beta_1 x_{i1} + \beta_2 x^*_{i0} + \epsilon_i \end{aligned} \tag{5.2}$$

In the above, β_0 is a collection of constants,[25] ϵ_i is an unobserved stochastic term,[26] and the key parameter of interest is $\beta_1 \equiv \frac{\partial S_{i2}}{\partial x_{i1}} = \frac{\alpha_1\nu_0^2}{\nu_0^2+\sigma_e^2+\sigma_\mu^2} \leq 0$. The regression to estimate β_1 is:

$$Change_i = \beta_0 + \beta_1 BtLevel_i + \sum \beta_j Controls_{ji} + \epsilon_i \tag{5.3}$$

[24] Here, I assume a common imprecision of the prior ν_0, to enable estimation of an average slope-coefficient model.

[25] Specifically, $\beta_0 = \alpha_0 - \alpha_1(1-h)\overline{x}$ and $\epsilon_i = \frac{\alpha_1\nu_0^2}{\nu_0^2+\sigma_e^2+\sigma_\mu^2}e_{i1}$.

[26] In a regression with controls, this error term would include e_{i1} as well as any other variables which affect switching but are not controlled for. Note that the inclusion of e_{i1} in the stochastic term shows transparently that, for identification, it is necessary that x_{it} is distributed independently not just of unobservable farmer heterogeneity but also of unobservable noise heterogeneity, i.e. of factors which drive signal noise and remain in the error term in the regression. If this independence assumption is violated, the extent of learning on the field would need to be elicited directly, for example by randomizing distribution of x_{i1} to farmers and then asking them about the signal they receive $\tilde{x}_{i1}$, and not indirectly from farmer behavior.

Change takes a value of 1 if farmer i switched varieties in 2014 and 0 otherwise. *Bt level* is the effective expression of the Bt trait for the farmer's 2013 variety as measured by the Biophysical Sample Survey, in micrograms of the relevant protein per gram of leaf tissue.[27] If the effective expression of the Bt trait in the seed purchased in t_1 is random, due for example to the pervasiveness of the information problem, then using only information on switching and Bt (and controlling for seed price) will generate an unbiased estimator of β_1. If Bt level is not fully random, however, and also to increase precision, controls are necessary. I include factors, occurring in 2013 or beforehand, that can affect variety change and may be correlated with Bt level, if the latter is not entirely random, including farmer priors but also characteristics and experience; see Section 5.2 for a full discussion.

To the extent that the results of a regression following Equation (5.3) are identified, then with no learning by doing ($\beta_1 = 0$) a better understanding of what is impeding farmer learning would be valuable for gauging the nature of the information problem and for evaluating potential remedies. The following outlines specifications which are not structurally derived but which can help shed light on the main findings, particularly if a null result is obtained.

Isolating the relevant channels behind the outcome in Equation (5.3) would ideally involve the following additional information. First, if information was available on the signal, $\tilde{x}$, then examining the relationship between the signal and the underlying attribute level x would be directly informative about cultivation noise, regardless of any variety integrity issues. Second, if information was available on post-cultivation perceptions about the biophysical resistance of the seed, then regardless of how these perceptions are linked to cultivation experience, farmers would use them to inform variety choices next season *unless* uncertainty about variety integrity is high, in which case own seed resistance says little about variety resistance. This would then be informative about perceived variety integrity issues in the market.

Although explicit information about the signal $\tilde{x}$ is not available in the PCS, a useful

[27]For each farmer/variety, the survey team randomly collected 2 leaf and 2 boll tissues from the main plot, at both 70 days after sowing and 120 days after sowing, and measured the toxin expression for each of these in-lab using the ELISA sandwich test. My variable is an average of the measurements 70 days after sowing for each variety. The data for 120 days after sowing is less complete and has more variation per observation, but the results do not change even when I include it in the analysis.

variable on post-cultivation perceptions is. After the 2013 harvest was complete, farmers were asked to evaluate the bollworm resistance of their crop as poor, moderate, or very good. It is not clear from the phrasing of the question the extent to which farmer responses reflect an evaluation of the quality of the seed used versus externally favorable conditions, i.e. whether a farmer who answered 'very good' believes this is due to high inherent pest resistance of their seed or to low bollworm pressure or to a combination of the two. Nonetheless, to the extent that farmer responses reflect at least *partly* an evaluation of the underlying quality of the seed, we would expect farmers to take these perceptions into account when choosing varieties in the next season, *unless* farmers believe within-variety integrity is too low, in which case (perceived) own seed quality says little about variety quality. Therefore, I use the following regression as a litmus test for whether uncertainty about variety integrity is low or high:

$$Change_i = \tau_0 + \tau_1 ResistancePerception_i + \sum \tau_j Controls_{ji} + \epsilon_i \tag{5.4}$$

The variable *Resistance Perception* is higher when farmers evaluate their crop's bollworm resistance ex-post as better. If $\tau_1 < 0$, this suggests that farmers are in part evaluating the biophysical resistance of the input itself *and* that they believe variety imperfections are limited enough to make subsequent switching decisions an effective outlet for improving quality. By contrast, very high uncertainty about variety integrity (or evaluations reflecting solely external conditions) would drive $\tau_1 \to 0$.

To the extent that these post-cultivation bollworm resistance perceptions reflect an evaluation of seed quality (a $\tau_1 < 0$ is sufficient to show this), they can also be linked "backward" to Bt content to sharpen insight about sources of farmer uncertainty. If cultivation signals are not too noisy, seeds with greater effective expression of Bt would easily map onto improved farmer perceptions about the bollworm resistance of their seed, regardless of any concerns about broader market variety integrity. Therefore, I use the following regression as a litmus test for whether uncertainty about what is observed from cultivation is low or high:

$$ResistancePerception_i = \theta_0 + \theta_1 BtLevel_i + \sum \theta_j Controls_{ji} + \epsilon_i \tag{5.5}$$

If cultivation signals are not too noisy, we would expect $\theta_1 > 0$, in that farmers with higher Bt content seeds develop improved perceptions of the bollworm resistance of their crop; otherwise, we expect $\theta_1 = 0$.

Finally, it is possible to test whether farmers learn about Bt content but respond by changing pesticide use during cultivation instead of variety next season. The specification is:

$$Pesticide_i = \phi_0 + \phi_1 BtLevel_i + \sum \phi_j Controls_{ji} + \epsilon_j \tag{5.6}$$

Pesticide measures pesticide use per acre in 2013, constructed by adding the quantities of various pesticides and dividing by acres of cotton cultivated. Learning would imply $\phi_1 < 0$, since farmers realize that the plant itself is emitting toxins lethal to pests so that they can use less pesticide. With no learning, ϕ_1 is close to zero and insignificant.[28]

5.2 Controls

The following details controls used for the main regression, Equation (5.3), but most controls are also used in the other regressions (see below). First, by the theoretical model, farmer priors can affect switching decisions. Although farmer priors do not appear correlated to Bt levels in the sample (**Figure 2**) I include them in Equation (5.3), to improve precision and also to try to gauge the extent to which farmers act heuristically or as profit maximizers. Unsurprisingly, the PCS does not ask farmers to express their priors in micrograms of protein in the leaf tissue, so there is no indicator for x^*_{i0} measured in the same way as x_{i1}. However, as mentioned earlier, the PCS does inquire if farmers initially believed the variety they were planting expresses Bt and, for those who answered *Yes*, their corresponding belief in its quality in controlling bollworms. I focus on the *Yes* group and use their answers about bollworm control quality as a proxy for their prior x^*_{i0}, calling this the "effectiveness prior" in the result tables. I standardize this variable in the regressions by treating the 1-5 scale answer as a continuous variable and then subtracting the mean and dividing by the standard deviation

[28] However, this specification can only test for learning if farmers can learn about Bt content *before* cultivation is over, so that there is room for adjusting pesticide decisions in the same season. It is not clear if this is the case or not, so this specification is not the focus of the discussion but used as a supplemental result.

for each observation.[29] Standardizing also enables a comparison of the coefficient on the prior x_{i0}^* with the coefficient on the attribute level x_{i1} despite the differing measurement units.

Also in line with the theoretical model, I control for the price of the purchased cotton seeds, since this impacts profitability from input use and therefore any switching decisions and may also be correlated with seed quality.[30] I also control for geographical district, with each of the 28 districts belonging to particular province (Punjab or Sindh), and for time of sowing, adding these controls separably. District controls not only generate comparability of laboratory environment as mentioned Section 4, but they also help account for ecological and cultural properties that likely affect cultivation attitudes. Time-of-sowing in the PCS is divided into 10-day intervals and, in combination with geographic district, can help compare farmers who face similar agroclimatic conditions through the duration of the cultivation cycle.

Although it does not appear that farmer characteristics and experience are correlated with Bt levels (**Table 1**), there is some evidence about the importance of farmer education to the erroneousness of prior held beliefs about Bt content (Ma et al, 2017). In the regression, I control for farmer education. I also control for land owned as a proxy for wealth, years of general farming experience, years of experience cultivating what the farmer thinks is Bt cotton, and planting history for the specific 2013 variety. Even though these do not appear to be correlated with Bt levels or with accuracy of prior belief about it, they may be correlated with whether the farmer's prior was that the variety is better or worse than market average. Other controls include cotton output selling price, which may be correlated to Bt levels if bollworms cause damage not only to the quantity but also the quality of the lint, captured

[29] A common view is that treating ordinal variables as continuous can be justified unless the variable involves too few categories or has a skewed distribution (Rhemtulla et al, 2012), neither of which is the case for this variable in the data. More recent research suggests that treating ordinal variables as continuous in analysis can almost always be justified regardless of the number of categories or distribution (Robitzsch, 2020).

[30] In the data the correlation between Bt level and seed price is actually weak and nonsignificant, suggesting that the omission of this variable would not bias results. Meanwhile, in the surveys the farmers indicate that seed price is not a binding constraint in their purchase decisions, meaning that prices are relatively *low* regardless of underlying of Bt content. This suggests that the information problem exists on both sides of the market: sellers do not have a clear idea of the Bt content of the seeds they sell either, since otherwise they would charge higher prices for higher quality seeds. That prices appear similarly low regardless of Bt content also reinforces that if farmers *were* able to learn, they would behave as the model predicts, since at least in the short term higher Bt seeds would not be more expensive to purchase.

in the selling price variable,[31] as well as inputs including fertilizer, pesticide, and labor.

For Equations (5.4) and (5.5), I also control for seed purchase prices, district and sowing time controls, and farmer priors, characteristics, and experiences. For both specifications, exogenous pest intensity likely affects farmer perceptions (which is an independent variable in one specification and the dependent variable in another), so it should be controlled for. There is no reliable information in the PCS on exogenous pest intensity but the incidence and development of bollworms in Pakistan's cotton growing regions is correlated with temperature, humidity, and rainfall conditions (Ghaffar, 2002). Since pest intensity appears to be time- and space-dependent, the combination of geographical district and time-of-sowing dummies helps to compare farmers who face similar pest intensity conditions through the cultivation cycle. For Equation (5.6), I also control for soil type, as it impacts pesticide absorption.

The control variables are all measured in 2013 or beforehand, and are therefore predetermined relative to the main dependent variable *Change*. **Appendix C** details how the controls are constructed and illustrates their distribution in the data.

6 Results

6.1 Presentation

Table 2 shows the results from five versions of Equation (5.3). To facilitate interpretation, all are linear probability models, and the Bt variable is standardized. All regressions are run with robust standard errors (adjusted for heteroskedasticity), and the 95% confidence interval constructed from the robust standard errors is noted below each coefficient.

[Table 2 here]

The consistent result is that the effective expression of Bt as measured in-lab does not predict the proclivity to keep or change the variety in the next year. Point estimates are very small and close to zero. They indicate that a one standard deviation increase in Bt level is associated with a change in the probability of variety change of 1.2% to 2.6%, depending on

[31] Cotton selling price is exogenous to each farmer's production since the farmers are small and price takers.

the specification, with no significance. A 95% confidence interval can rule out negative effects larger than 5% in absolute value across all specifications. The coefficient on the standardized prior is also null, with very similar magnitudes and confidence intervals to the Bt coefficient.

Table 3 shows that the results change significantly when the extent of variety change is regressed on farmer perceptions of bollworm resistance, following Equation (5.4).

[Table 3 here]

The result across specifications is that more positive farmer perception of bollworm resistance for the 2013 season are associated with less frequent variety switching in 2014. Depending on the specification, farmers who viewed resistance as moderate are 14.4 to 16.0% less likely to change variety in the next year than those who viewed it as poor, and this is significant at the 10% or 5% level in all but one specification. Farmers who viewed resistance performance as very good are 18.5 to 20.5% less likely to change variety next year than those who viewed it as poor, and this is significant at the 5% level in all specifications.

To the extent that the null result in **Table 2** along with the significant result in **Table 3** identify effects, they would suggest that learning by doing is impeded and not because of concerns about variety integrity, but because of a high degree of noise in cultivation signals. To further explore this issue, **Table 4** reports the results of regressing farmers' post-cultivation perceptions on their seeds' underlying Bt content, as per Equation (5.5). The dependent variable is the perception of the farmer about bollworm resistance in 2013, lumped into Poor/Moderate or Very Good, and taking a binary value of 0 and 1 respectively, and the key independent variable is standardized Bt content.

[Table 4 here]

In all specifications Bt content does not predict perception formation. The coefficients on standardized Bt content are small and insignificant, and positive effects greater than 2.4% can be ruled out in all specifications at the 95% level.[32]

[32] I also include a column estimating the relationship between yield and perceptions. Yield cannot be included in the main regressions because it would be a main intermediate channel affected by Bt content (and

Finally, **Table 5** explores the possibility that Bt content can be uncovered and impact not variety choice next season but pesticide use in the same season, as per Equation (5.6). Across specifications, Bt content does not predict pesticide use.

[Table 5 here]

6.2 Discussion

The results are consistent with an interpretation that farmers are unable to learn about an important attribute of their seeds through cultivation experience, at least after one round of harvest, and that, as per the theoretical model in Section 2, this is because a high degree of noise in cultivation signals makes it difficult to make inferences about seed quality from cultivation. Underlying effectiveness of Bt expression is not associated with subsequent farmer perceptions about the bollworm resistance of their crop (**Table 4**) and therefore nor with their proclivity to keep or switch varieties the following year (**Table 2**). This is the case even as farmers do seem prepared to use perceptions formed during cultivation to make decisions about variety choice in the market, despite market imperfections (**Table 3**). Inability to gauge underlying expression of the Bt trait from cultivation alone may also be evident in the absence of an association between Bt levels and pesticide use, as these should be substitute inputs (**Table 5**). From the structurally derived specification (**Table 2**), the coefficient on the standardized prior also suggests that farmers make input choices heuristically.

Given the findings, it is worth highlighting that the failure to reject the null of no learning by doing is also accompanied by confidence intervals which rule out potentially meaningful magnitudes as relates to learning by doing. In **Table 2**, and across all specifications, the 95% confidence interval rules out that a one standard deviation increase of Bt content is associated with more than a 5% reduction in the probability of switching varieties next season. This is

other inputs) and in turn affecting perceptions and switching decisions if learning is possible; its coefficient would absorb much of the expected effects of Bt. Therefore, I include a regression of perceptions only on log of yield per acre and on sowing time and district controls. The association is positive and significant: a 1% increase in yield per acre is associated with 14% greater likelihood of viewing resistance as very good instead of poor/moderate. It is unclear whether yield informs perceptions or perception drives behavior which affects yield, since both variables were elicited during the same survey round, but the correlation is robust.

in contrast with the large magnitudes picked up by the regression of variety change on farmer perceptions (**Table 3**), where the results are not only statistically significant but also at the 95% level it is possible that very good farmer perceptions, compared to poor perceptions, are associated with a reduction of variety switching next season by up to 36%. Similarly, at the 95% level in **Table 4** we can rule out that a one standard deviation increase in Bt content is associated with more than a 2% increase in the likelihood that farmers perceive bollworm resistance as very good instead of moderate or poor.

The absence of learning by doing which the results lend support to would not be a trivial finding economically. It would imply that market outcomes are stagnant in a developing country where one-fourth of all farmers are cotton producers and where cotton is a major generator of downstream revenue and foreign exchange. Based on the expression for the average change in Bt level between periods, it is clear that with no learning by doing ($\beta_1 = 0$ and $\beta_2 = 0$) the average Bt content consumed does not change in the two periods. As I show in **Appendix B**, the gains that *would* materialize would be increasing in the extent of learning by doing. For more rough back-of-envelope projections of long-run losses from lack of learning, I use informed estimates on the effect of Bt on crop damage to estimate that if farmers are able to improve input choice such that mean Bt level of seeds consumed rises from the in-sample level of 0.88 $\frac{\mu g}{g}$ to the maximum-effectiveness level of 1.59 $\frac{\mu g}{g}$, industry revenue could improve by up to $170 million, or 12.5% of the 2014 revenue.

Further research can shed light on the extent to which, amid imperfect information, learning by doing materializes from cultivating crops with potentially noisy cultivation signals and/or variety integrity problems. For example, randomizing the distribution of inputs to farmers and collecting data, post-cultivation, on farmer perceptions around input quality can provide a direct test for the noisiness of cultivation signals.[33] In addition, obtaining these inputs from known market varieties and recording subsequent farmer purchase decisions can shed light on farmer perceptions about imperfections in the market. As another lens, research may collect observational data from a cohort of farmers over multiple seasons and

[33] For ethical reasons, this random assignment may cap the floor (lowest quality distributed) to be at the prevailing market average, while also potentially subsidizing input prices or compensating farmers ex-post.

records biophysical data, perceptions, and input choices each season, with the panel structure ameliorating the effect of potential unobserved heterogeneity on results. This would be useful for exploring the extent to which the consistency of farmer experiences with specific varieties informs their perceptions and choices. Measurement issues would remain a challenge in any study of inputs cultivated by farmers instead of grown in controlled greenhouses, but an upfront understanding of the relevant challenges can help researchers design careful approaches to the collection and analysis of the biophysical data.

7 Robustness checks

The following robustness checks are all presented in **Appendix D**. To check further for sample selection bias, **Table D1** shows that the results from the main regression in **Table 2** do not change when the pseudo-Bt measure is used for all farmers, including those who farmed one variety, for comparability. More broadly, **Table D2** shows that the farmers in the main analysis (331) and outside it (396), out of the total 727 farmers surveyed in Round 1.1 (but of whom only 501 finished all rounds), are similar in average age, years of farming experience, the area of the main plot they operate on, and the total area of land they own.[34] Hence, the results are arguably representative of farmers in the survey (who are in turn representative of cotton-producing households in Pakistan) and not driven by sample selection.

As discussed in Section 4.3, it is also possible that the sampling methods are sound but that measurement error obfuscates the results. Although sowing time and district fixed effects are used in all specifications to roughly account for laboratory and agroclimatic conditions, it is still possible that the null results are driven by attenuation bias due to measurement error in this variable. The Bt variable is based on a sample of two random plants from each farmer's plot, taking a leaf and a boll from each plant; whereas leaf values seem to be significantly correlated between the two plants for each farmer, the boll values seem to be much less

[34]The exception is education, with in-sample farmers having 0.6 years more of education on average. Since more educated farmers may be more likely to learn from cultivation experience if learning is possible, this would push results in the sample to show higher-than-average learning, but the results still support lack of learning by doing. The other difference is that in-sample group is more heavily skewed toward Punjab.

correlated. In **Table D3** I redefine Bt content variable to reduce possible measurement error and rerun the regression in Column 3 in **Table 2**. In Column 1, I use an average of the leaf values only instead of leaf and boll. In Column 2, I still use the leaf values but with one value as an instrument for the other.[35] In Column 3, I use a subsample where the leaf values per farmer are nearly identical. As shown, even measured more restrictively, Bt content does not predict variety choice as would be expected if learning is present.

In addition to sampling and measurement issues, I further check the robustness of the results in the main specification (**Table 2**) by focusing on Column 3 and introducing in **Table D4**: (i) a squared term for Bt level to allow for nonlinear effects, (ii) an interaction variable of Bt level with education to allow for differential effects by education level, and (iii) a variation where the variable "years that variety is grown" is a sequence of dummy variables, to allow for a nonlinear impact of cultivation years on variety choices. I also (iv) re-estimate the model with a logistic regression, using Firth's bias-reduced version of the logit which penalizes small sample size to prevent overfitting and small-sample bias.[36] To check the effects of clustering the dependent variable in **Table 4**, I estimate Column 3 as an ordered logit (**Table D5**). To test robustness much more widely, I use specification curve analysis, where all the plausible controls are combined and/or omitted in thousands of different ways, and the coefficient of interest estimated and plotted across all specifications (Simohnson et al, 2015; Rohrer, 2018; Orben et al, 2019). The results are shown for Equations (5.3)-(5.6), in **Figures (D1)-(D4)**, respectively. In all checks, the main findings remain robust.

Finally, the following considers additional potential issues but for which the data is not as well-suited for empirical testing. First, the exercises assume any learning comes from own experience. As a very rough attempt to check from learning from neighbors I identify the other farmers in the same village as potential peers and check that when such a peer variable is included in the main specification, the results remain largely the same (**Table D6**).[37]

[35]The idea is that this will eliminate correlated noise or measurement error; a similar approach is used in Ashenfelter and Krueger (1994).

[36]The desirable properties of Maximum Likelihood (ML) logit estimator assume large sample size, so bias is a concern with small samples. Firth regression reduces this possible bias (Fijorik and Sokolowski, 2012).

[37]I construct a variable which is the (average) Bt level for these "peers" who purchased a different variety. If there is social learning, we expect the coefficient on this to be positive, in addition to expecting the own-Bt

Second, the paper assumes farmers do not respond to discovered (low) Bt content in ways besides variety switching, such as changing suppliers or exiting cotton production. I check that there are no correlations between Bt levels and a rough proxy for supplier switching (omitted).[38] On exit, farmers who exited production in 2014 cited unrelated reasons in the surveys, largely to do with floods and similar natural disasters, and I find no difference in average Bt expression between the group that exited and that which did not (omitted).

8 Conclusion

In developing countries, information challenges are ubiquitous and pronounced. Agricultural producers in particular face rife information problems, including when they use input technologies for which local government certification and standardization are weak or nonexistent. In the absence of externally verifiable information and if heterogeneity of growing conditions mutes learning from peers, a process of learning from own experience will be valuable if it can allow farmers to make improved choices over time. At the same time, such a process will be constrained if it is difficult to interpret what is driving observed crop performance and/or if market imperfections diminish the usefulness of these signals for making inferences and decisions about input quality on the market.

Drawing on this context, I model a process whereby farmers facing an adverse information context can use Bayesian updating to learn from cultivation signals about input variety quality and to make improved purchase decisions in the next season. I then use this model to derive an econometric specification to test for learning, since whether agents can learn and redress information problems is ultimately an empirical question. I apply the empirical exercise to cotton cultivation in Pakistan, where there is imperfect information about an imported and locally adapted pest-resistance technology (the Bt gene).

coefficient to be negative. I was not able to construct a variable for the Bt level of "peers" who purchased the same variety, on which we would expect a negative coefficient, because for most farmers there are almost no other villagers farming the same variety.

[38] There is no data identifying suppliers but I assume the supplier changed if the farmer lists a different type of supplier institution in 2014 or if the farmer lists the same type of institution but the commuting time changed significantly. Based on this, I estimate that two-thirds of the farmers did not change their supplier, and find no correlation between this estimated switching variable and Bt levels.

I find that cultivation experience alone is unlikely to redress the information gap. Underlying effective expression of the Bt trait as measured in-lab is not associated with subsequent farmer perceptions about the bollworm resistance of their crop and, therefore, nor with their variety purchase decisions next period. This is the case even as farmers seem prepared to use what they observe during cultivation to make subsequent input choices, despite imperfections in variety integrity on the market. In line with the theoretical model, this can occur when cultivation signals are too noisy to allow farmers to make useful inferences about seed quality, and it can result in substantial losses to farmers owing to the persistence of subpar input quality on the market. The key Bt variable appears to have an element of randomness which mitigates concerns about selection bias driving the findings, and results are robust across different specifications which also take into account potential Bt measurement issues.

The paper points to the complexity and potential limitations of learning by doing in a rural context where input technologies have hidden characteristics and where regulatory capacities are weak. It provides results which suggest learning by doing difficulties in one such sector, the cotton cultivation sector that is prominent in Pakistan's economy, and where such challenges can complicate local efforts to use foreign technology for improving productivity. Further research can confirm the extent to which these challenges are market and input specific and how they impact agricultural sectors that are key to growth in developing countries.

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FIGURES

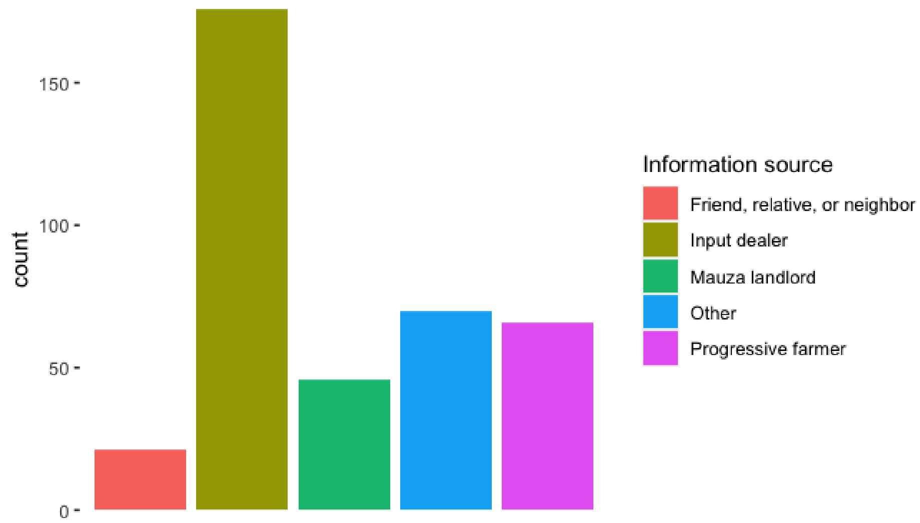

Figure 1: Sources informing prior belief on Bt presence

Figure 1 plots farmer answers about the main source informing their prior belief, before cultivation, that the variety they purchased in 2013 contains the Bt protein.

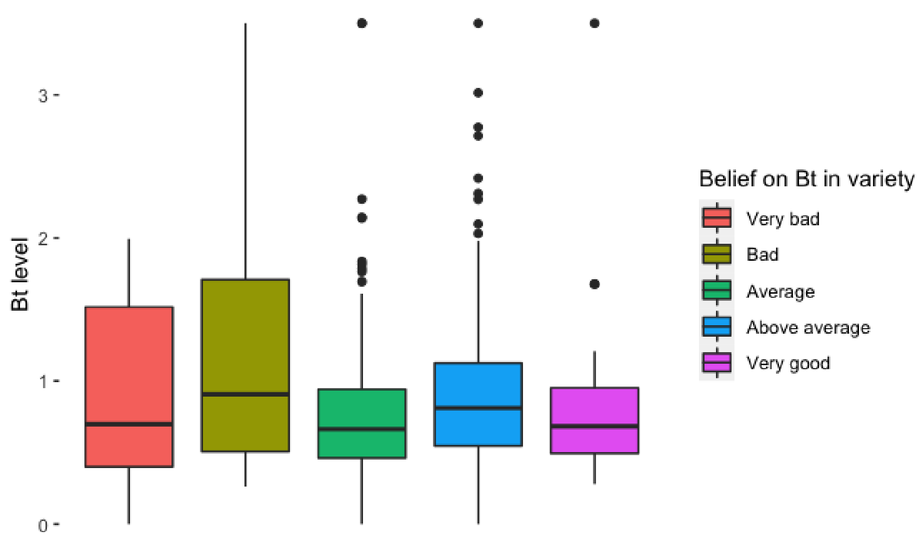

Figure 2: Correlation between prior belief on Bt effectiveness and actual Bt levels

Figure 2 plots the Bt levels as measured in-lab on the y-axis, against farmer's prior beliefs on how effectively their 2013 variety expresses Bt (elicited under 5 categories).

TABLES

Table 1: Correlation between Bt level and farmer characteristics

Parameter	Bt level	Education	Land owned	Farming exp.	Bt exp.
Bt level	1.00	**−0.004**	**−0.01**	**−0.09**	**−0.03**
Education	−0.004	1.00	0.31***	−0.12	0.19***
Land owned	−0.01	0.31***	1.00	0.05	0.14*
Farming exp.	−0.09	−0.12	0.05	1.00	0.19***
Bt exp.	−0.03	0.19***	0.14*	0.19***	1.000

Note: *p<0.1; **p<0.05; ***p<0.01

Table 1 demonstrates the coefficient of correlation between Bt level in the seed purchased by the farmer in 2013 and the following farmer characteristics: years of education, amount of land owned in acres, years of general farming experience, and years of experience with Bt cotton. Whereas some farmer characteristics are predictably significantly correlated with each other, such as more educated farmers also owning more land, there is no significant correlation between any of these characteristics and Bt level of the seed purchased in 2013.

Table 2: Regression of variety change on effective expression of the Bt trait

	Dependent variable:				
	CHANGED				
	(1)	(2)	(3)	(4)	(5)
Bt (standardized)	0.013	0.012	0.015	0.017	0.026
	(−0.052, 0.078)	(−0.053, 0.077)	(−0.049, 0.080)	(−0.048, 0.082)	(−0.034, 0.087)
Effectiveness prior (st.)	0.010	0.010	0.006	0.006	
	(−0.044, 0.065)	(−0.047, 0.066)	(−0.050, 0.062)	(−0.050, 0.062)	
Education		0.007	0.015**	0.014**	0.014***
		(−0.005, 0.018)	(0.003, 0.026)	(0.002, 0.026)	(0.004, 0.024)
Farming Experience			0.006**	0.005*	0.005**
			(0.001, 0.012)	(−0.0002, 0.011)	(0.001, 0.010)
Yrs grown variety			−0.091***	−0.092***	−0.069***
			(−0.142, −0.040)	(−0.144, −0.040)	(−0.111, −0.028)
Yrs grown Bt			−0.040**	−0.037**	−0.014
			(−0.073, −0.007)	(−0.070, −0.005)	(−0.043, 0.014)
Land owned			−0.008**	−0.009***	−0.007**
			(−0.014, −0.002)	(−0.015, −0.002)	(−0.013, −0.001)
Seed price		−0.0005*	−0.001**	−0.001**	−0.0004**
		(−0.001, 0.0001)	(−0.001, −0.0001)	(−0.001, −0.00001)	(−0.001, −0.00002)
Cotton selling price		−0.018	−0.020	−0.022	−0.010
		(−0.046, 0.010)	(−0.048, 0.008)	(−0.050, 0.006)	(−0.033, 0.014)
Irrigation				−0.0001	
				(−0.0002, 0.00001)	
Fertilizer				−0.0005	
				(−0.002, 0.001)	
Seed amount				0.025**	
				(0.0004, 0.050)	
Labor				0.0002	
				(−0.001, 0.001)	
Pesticide				−0.009	
				(−0.048, 0.030)	
Belief: No					0.117
					(−0.061, 0.295)
Belief: Don't know					0.046
					(−0.094, 0.186)
Bt*Belief: No					−0.041
					(−0.224, 0.141)
Bt*Belief:Don't know					0.026
					(−0.089, 0.141)
District and sowing time FE	Yes	Yes	Yes	Yes	Yes
Observations	331	331	331	331	499
R^2	0.231	0.245	0.311	0.328	0.235
Adjusted R^2	0.137	0.144	0.207	0.213	0.152
Residual Std. Error	0.464 (df = 294)	0.462 (df = 291)	0.445 (df = 287)	0.443 (df = 282)	0.459 (df = 449)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 2 demonstrates the results of OLS regressions of variety change in 2014 on effective expression of the Bt trait in their seeds as measured in-lab in 2013. Across specifications, expression of the Bt trait does not predict variety change next year.

Table 3: Regression of variety change on farmer perceptions

	Dependent variable:			
	CHANGED			
	(1)	(2)	(3)	(4)
Moderate	−0.144*	−0.160**	−0.145*	−0.117
	(−0.297, 0.009)	(−0.308, −0.012)	(−0.297, 0.007)	(−0.264, 0.030)
VeryGood	−0.199**	−0.205**	−0.185**	−0.190**
	(−0.365, −0.034)	(−0.363, −0.047)	(−0.346, −0.024)	(−0.344, −0.036)
Effectiveness prior (st.)	0.013	0.008	0.011	
	(−0.040, 0.066)	(−0.045, 0.061)	(−0.043, 0.064)	
Education		0.016***	0.016***	0.015***
		(0.004, 0.028)	(0.004, 0.028)	(0.005, 0.025)
Farming Experience		0.006**	0.007**	0.005**
		(0.001, 0.012)	(0.001, 0.012)	(0.001, 0.010)
Yrs grown variety		−0.086***	−0.088***	−0.067***
		(−0.137, −0.036)	(−0.138, −0.037)	(−0.109, −0.026)
Yrs grown Bt		−0.042**	−0.042**	−0.013
		(−0.074, −0.009)	(−0.075, −0.010)	(−0.041, 0.016)
Land owned		−0.008***	−0.008***	−0.007**
		(−0.014, −0.002)	(−0.014, −0.002)	(−0.013, −0.001)
Seed price		−0.001**	−0.001**	−0.0003*
		(−0.001, −0.0001)	(−0.001, −0.0001)	(−0.001, 0.00003)
Cotton selling price		−0.018	−0.017	−0.009
		(−0.046, 0.011)	(−0.046, 0.012)	(−0.033, 0.015)
Pesticide			−0.006	−0.002
			(−0.040, 0.027)	(−0.012, 0.009)
Log yield			−0.051	−0.011
			(−0.147, 0.044)	(−0.094, 0.073)
Belief: No				0.043
				(−0.358, 0.445)
Belief: Don't know				−0.063
				(−0.344, 0.219)
Moderate*Belief:No				0.054
				(−0.356, 0.463)
Moderate*Belief:Don't know				0.150
				(−0.168, 0.468)
VeryGood*Belief:No				0.161
				(−0.319, 0.640)
VeryGood*Belief:Don't know				0.066
				(−0.281, 0.412)
District and sowing time FE	Yes	Yes	Yes	Yes
Observations	331	331	331	499
R^2	0.246	0.326	0.329	0.245
Adjusted R^2	0.151	0.223	0.220	0.153
Residual Std. Error	0.460 (df = 293)	0.440 (df = 286)	0.441 (df = 284)	0.459 (df = 444)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 3 demonstrates the results from OLS regressions of variety change in 2014 on farmer perceptions about bollworm resistance formed at the end of the 2013 season. Across specifications, improved farmer perceptions are associated with a lower likelihood of variety switching.

Table 4: Regression of farmer perceptions on effective expression of the Bt trait

	Dependent variable:					
	VeryGood					
	(1)	(2)	(3)	(4)	(5)	(6)
Bt (standardized)	−0.029	−0.029	−0.030	−0.030	−0.035	
	(−0.082, 0.024)	(−0.082, 0.024)	(−0.083, 0.023)	(−0.084, 0.023)	(−0.081, 0.012)	
Effectiveness prior (st.)	0.023	0.021	0.023	0.022		
	(−0.032, 0.078)	(−0.036, 0.078)	(−0.035, 0.080)	(−0.036, 0.080)		
Education		0.002	0.002	0.002	−0.002	
		(−0.010, 0.014)	(−0.011, 0.014)	(−0.011, 0.014)	(−0.011, 0.007)	
Farming Experience			0.001	0.001	0.003	
			(−0.004, 0.007)	(−0.004, 0.007)	(−0.001, 0.008)	
Yrs grown variety			0.015	0.014	−0.009	
			(−0.039, 0.068)	(−0.040, 0.068)	(−0.051, 0.034)	
Yrs grown Bt			0.010	0.010	−0.006	
			(−0.025, 0.045)	(−0.025, 0.045)	(−0.032, 0.021)	
Seed price		0.00004	0.0001	0.00005	0.0002	
		(−0.0004, 0.0005)	(−0.0004, 0.001)	(−0.0004, 0.001)	(−0.0001, 0.001)	
Fertilizer			−0.0001	−0.0001	0.00003	
			(−0.002, 0.001)	(−0.002, 0.002)	(−0.0001, 0.0002)	
Pesticide				−0.004	0.007*	
				(−0.048, 0.040)	(−0.001, 0.016)	
Log yield						0.140***
						(0.051, 0.229)
Belief: No					−0.067	
					(−0.246, 0.111)	
Belief: Don't know					−0.107	
					(−0.236, 0.022)	
Bt*Belief:No					−0.005	
					(−0.148, 0.138)	
Bt*Belief: Don't know					0.011	
					(−0.065, 0.087)	
District and sowing time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	331	331	331	331	499	331
R^2	0.277	0.278	0.280	0.280	0.301	0.293
Adjusted R^2	0.189	0.184	0.175	0.173	0.224	0.209
Residual Std. Error	0.447 (df = 294)	0.449 (df = 292)	0.451 (df = 288)	0.452 (df = 287)	0.437 (df = 449)	0.441 (df = 295)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 4 demonstrates the results of OLS regressions of farmer's post-cultivation perceptions of bollworm resistance performance on expression of the Bt trait in their 2013 seeds. In Columns 1-5, expression of the Bt trait does not predict farmer perceptions. Column 6 shows that yield is positively correlated with farmer perceptions.

Table 5: Regression of pesticide use on effective expression of the Bt trait

	Dependent variable:				
	Pesticide use				
	(1)	(2)	(3)	(4)	(5)
Bt (standardized)	−0.038	−0.041	−0.022	−0.010	−0.040
	(−0.271, 0.196)	(−0.274, 0.192)	(−0.257, 0.212)	(−0.216, 0.197)	(−0.372, 0.292)
Effectiveness prior (st.)	−0.010	−0.042	−0.034	−0.044	
	(−0.159, 0.139)	(−0.190, 0.105)	(−0.178, 0.110)	(−0.187, 0.098)	
Education		0.034	0.038*	0.030	0.075
		(−0.008, 0.076)	(−0.006, 0.082)	(−0.014, 0.074)	(−0.027, 0.178)
Farming Experience			0.008	0.009	0.0003
			(−0.010, 0.026)	(−0.008, 0.026)	(−0.038, 0.039)
Yrs grown variety			−0.076	−0.092	−0.251
			(−0.218, 0.066)	(−0.228, 0.044)	(−0.596, 0.093)
Yrs grown Bt			−0.094	−0.085	0.415**
			(−0.209, 0.021)	(−0.192, 0.022)	(0.069, 0.761)
Land owned			−0.00001	0.007	0.004
			(−0.017, 0.017)	(−0.010, 0.023)	(−0.045, 0.053)
Area cultivated			0.003	0.001	−0.015
			(−0.016, 0.023)	(−0.018, 0.021)	(−0.041, 0.010)
Irrigation				0.0001	
				(−0.0002, 0.0004)	
Fertilizer				0.013***	
				(0.007, 0.019)	
Seed amount			0.100**	0.100***	−0.018
			(0.022, 0.179)	(0.031, 0.169)	(−0.167, 0.130)
Belief: No					−1.343**
					(−2.425, −0.261)
Belief: Don't know					−1.234***
					(−2.006, −0.463)
Bt*Belief: No					0.299
					(−0.269, 0.866)
Bt*Belief: Don't know					0.361
					(−0.117, 0.839)
District, sowing time, and soil FE	Yes	Yes	Yes	Yes	Yes
Observations	331	331	331	331	499
R^2	0.343	0.350	0.375	0.438	0.236
Adjusted R^2	0.259	0.266	0.279	0.347	0.151
Residual Std. Error	1.394 (df = 293)	1.388 (df = 292)	1.376 (df = 286)	1.309 (df = 284)	4.202 (df = 448)
Note:					*p<0.1; **p<0.05; ***p<0.01

Table 5 demonstrates the results of OLS regressions of farmers' pesticide use in 2013 on effective expression of the Bt trait in their 2013 seeds. Across specifications, expression of the Bt trait does not predict pesticide use in the same season.

APPENDIX

A Bayesian updating

Suppose a signal is observed $\tilde{x} \sim N(x, \sigma^2)$ where the prior is that x is distributed according to $x \sim N(m, v^2)$. The probability density function (pdf) of a continuous variable x with mean m and variance v^2 is:

$$f(x) = \frac{1}{\sqrt{2\pi v^2}} e^{-\frac{1}{2v^2}(x-m)^2}$$

The pdf of the signal follows the same form, adjusted for mean and variance. We are interested in calculating the posterior belief on x given that the signal $\tilde{x}$ was observed. By Bayes' rule, the posterior is proportional to the likelihood times the prior:

$$f(x|\tilde{x}) \propto f(\tilde{x}|x) f(x)$$

First, calculating the likelihood times the prior:

$$\begin{aligned}
f(\tilde{x}|x) f(x) &= \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{1}{2\sigma^2}(\tilde{x}-x)^2} * \frac{1}{\sqrt{2\pi v^2}} e^{-\frac{1}{2v^2}(x-m)^2} \\
&= \frac{1}{2\pi\sigma v} e^{\left[-\frac{1}{2\sigma^2}(\tilde{x}-x)^2 \, e^{-\frac{1}{2v^2}(x-m)^2}\right]} \\
&= \frac{1}{2\pi\sigma v} e^{\left[-\frac{1}{2\sigma^2}(\tilde{x}-x)^2 - \frac{1}{2v^2}(x-m)^2\right]} \\
&= \frac{1}{2\pi\sigma v} e^{\left[-\frac{1}{2}\left(\frac{\tilde{x}^2 - 2\tilde{x}x + x^2}{\sigma^2} + \frac{x^2 - 2xm + m^2}{v^2}\right)\right]} \\
&= \frac{1}{2\pi\sigma v} e^{-\frac{1}{2}\left(\frac{\tilde{x}^2 v^2 - 2\tilde{x}xv^2 + x^2v^2 + x^2\sigma^2 - 2xm\sigma^2 + m^2\sigma^2}{\sigma^2 v^2}\right)} \\
&= \frac{1}{2\pi\sigma v} e^{-\frac{1}{2}\left(\frac{\tilde{x}^2 v^2 + m^2\sigma^2}{\sigma^2 v^2} + \frac{(\sigma^2+v^2)x^2 - 2x(\tilde{x}v^2 + m\sigma^2)}{\sigma^2 v^2}\right)}
\end{aligned} \tag{A.1}$$

Dropping the multiplicative constant and also the first expression in the parenthesis because it is a collection of constants that do not affect the results, the posterior is therefore:

$$f(x|\tilde{x}) \propto e^{-\frac{1}{2}\left(\frac{(\sigma^2+v^2)x^2-2x(\tilde{x}v^2+m\sigma^2)}{\sigma^2 v^2}\right)} \tag{A.2}$$

Dividing both the numerator and denominator in the parenthesis expression by $\sigma^2 + v^2$ we obtain:

$$f(x|\tilde{x}) \propto e^{-\frac{1}{2}\left(\frac{x^2-2x\frac{(\tilde{x}v^2+m\sigma^2)}{\sigma^2+v^2}}{\frac{\sigma^2 v^2}{\sigma^2+v^2}}\right)} \tag{A.3}$$

Adding and subtracting $\left(\frac{\tilde{x}v^2+m\sigma^2}{\sigma^2+v^2}\right)^2$ from the numerator in the exponent, we obtain:

$$f(x|\tilde{x}) \propto e^{-\frac{1}{2}\frac{\left(x-\frac{\tilde{x}v^2+m\sigma^2}{\sigma^2+v^2}\right)^2-\left(\frac{\tilde{x}v^2+m\sigma^2}{\sigma^2+v^2}\right)^2}{\frac{\sigma^2 v^2}{\sigma^2+v^2}}} \tag{A.4}$$

Since the second term in the numerator of Equation (A.4) is a collection of constants it can be dropped, so that the posterior distribution is as follows:

$$f(x|\tilde{x}) \propto e^{-\frac{1}{2}\frac{\left(x-\frac{\tilde{x}v^2+m\sigma^2}{\sigma^2+v^2}\right)^2}{\frac{\sigma^2 v^2}{\sigma^2+v^2}}} \tag{A.5}$$

Comparing this to the probability density function of the normal distribution we see that the posterior mean is $\frac{\tilde{x}v^2+m\sigma^2}{\sigma^2+v^2}$ while the posterior variance is $\frac{\sigma^2 v^2}{\sigma^2+v^2}$. In the model in Section 2, $\tilde{x} = \tilde{x_{i1}}$, $\sigma^2 = \sigma_e^2 + \sigma_\mu^2$, $m = x_{i0}^*$, and $v^2 = v_{i0}^2$. Therefore, substituting these in, we obtain:

$$x_{i1}^* = \frac{\tilde{x}_{i1}v_{i0}^2 + x_{i0}^*(\sigma_e^2+\sigma_\mu^2)}{\sigma_e^2+\sigma_\mu^2+v_{i0}^2} \tag{A.6}$$

$$v_{i1}^2 = \frac{(\sigma_e^2+\sigma_\mu^2)v_{i0}^2}{\sigma_e^2+\sigma_\mu^2+v_{i0}^2} \tag{A.7}$$

B Market outcomes

B.1 Deriving the equation for average x change

Section 2 outlined the learning process for a single farmer, and to do so it was possible to consider only the variety the farmer planted and their beliefs about that variety. To model the market-level consequences of learning by doing or lack thereof, the broader range of variety qualities must be considered. Let there be a continuum of varieties $j \in (1, J)$. Each variety has a real mean x_j^* so that the unknown attribute level for farmer i who cultivates variety j in t_1 is as follows:[39]

$$x_{ij1} = x_j^* + \mu_{ij1} \tag{B.1}$$

Suppose all varieties have equal levels of integrity, so that $\mu_{ij1} \sim N(0, \sigma_\mu^2)$ for each variety j. Moreover, the mean *across* varieties is $\overline{x}$ so that $x_j^* = \overline{x} + \eta_j$, where $\eta_j \sim N(0, \sigma_\eta^2)$ reflects the spread of average quality between varieties. The (unobserved) attribute level for the farmer is therefore distributed as follows:

$$x_{ij1} = \overline{x} + \eta_j + \mu_{ij1} \tag{B.2}$$

For each farmer, the expected level of x in the purchased input next season is a function of their switching decision. A farmer who switches varieties and goes back to pick from the pool of varieties at random will receive on average $\overline{x}$,[40] while a farmer who repurchases the same variety will receive on average x_j^*. Letting $S \in [0, 1]$ be the probability of switching:

$$E(x_{i2}) = S\overline{x} + (1 - S)x_j^* \tag{B.3}$$

[39] This is the same as Equation (2.2) but now the variety j is explicit. Note that the subscript ij should be considered as a single unit: a farmer i will have purchased only variety j in t_1. In other words, ij does not indicate a panel structure where each farmer i possesses multiple j's.

[40] More precisely, the farmer will receive on average x_{-j}^*, but, in the presence of many varieties on the market, this can be approximated by the overall average.

The expected *change* in attribute level for farmer with x_{ij1} between t_1 and t_2 is therefore:

$$\begin{aligned} E(\Delta x_i) &= E(x_{i2}) - x_{ij1} \\ &= S\overline{x} + (1-S)x_j^* - x_{ij1} \end{aligned} \tag{B.4}$$

Assume there are many farmers, each of whom had received an independent random realization of x from the variety j's distribution in t_1, updated their beliefs, and made the switching decision in t_2 as described in Section 2, resulting in the expected change in x in Equation (B.4). To find the average change in x across all farmers, we weigh the expected change for each initial realization by its probability of occurrence in the first period and sum across. Let the probability density function of x_{ij1}, distributed as in Equation (B.2), be $g(x)$. Then expected change in the attribute level across the market is[41]

$$\begin{aligned} E(\Delta x) &= \int g(x)\Big[S\overline{x} + (1-S)x_j^* - x_{ij1}\Big]dx \\ &= \int g(x)\Big[S\overline{x} + (1-S)(\overline{x}+\eta_j) - x_{ij1}\Big]dx \\ &= \int g(x)\Big[\overline{x} + (1-S)(\eta_j) - x_{ij1}\Big]dx \\ &= \overline{x}\int g(x)dx + \int g(x)(1-S)\eta_j dx - \int g(x)x_{ij1}dx \\ &= \overline{x} + \int g(x)(1-S)\eta_j dx - E(x_{ij1}) \\ &= \overline{x} + \int g(x)(1-S)\eta_j dx - \overline{x} \\ &= \int g(x)\Big[(1-S)\eta_j\Big]dx \end{aligned}$$

Substituting the linear approximation for S in Equation (5.2) and letting $\psi_1 = \frac{v_0^2}{v_0^2+\sigma_e^2+\sigma_\mu^2}$ and $\psi_2 = \frac{\sigma_e^2+\sigma_\mu^2-h(v_0^2+\sigma_e^2+\sigma_\mu^2)}{v_0^2+\sigma_e^2+\sigma_\mu^2}$, we obtain:

[41] It can be shown that the same results are obtained by first integrating per variety and then integrating across varieties.

$$
\begin{aligned}
E(\Delta x) &= \int g(x)\left[\left(1-\left[\alpha_0+\alpha_1(x^*_{ij1}-hx^*_{ij0}-(1-h)\overline{x})\right]\right)\eta_j\right]dx \\
&= \int g(x)\left[\left(1-\left[\alpha_0+\alpha_1\{\psi_1(x_{ij1}+e_{ij1})+\psi_2 x^*_{ij0}-(1-h)\overline{x}\}\right]\right)\eta_j\right]dx \\
&= \int g(x)\left[\left(1-\left[\alpha_0+\alpha_1\psi_1(x_{ij1}+e_{ij1})+\alpha_1\psi_2 x^*_{ij0}-\alpha_1(1-h)\overline{x}\right]\right)\eta_j\right]dx \\
&= \int g(x)\eta_j dx - \int g(x)\big(\alpha_0+\alpha_1\psi_1(x_{ij1}+e_{ij1})+\alpha_1\psi_2 x^*_{ij0}-\alpha_1(1-h)\overline{x}\big)\eta_j dx \\
&= (1-\alpha_0+\alpha_1(1-h)\overline{x})\int g(x)\eta_j dx - \alpha_1\psi_1\int g(x)(x_{ij1}+e_{ij1})\eta_j dx - \alpha_1\psi_2\int g(x)x^*_{ij0}\eta_j dx \\
&= 0-\alpha_1\left[\psi_1\int g(x)(x_{ij1}+e_{ij1})\eta_j dx+\psi_2\int g(x)x^*_{ij0}\eta_j dx\right]
\end{aligned}
$$

Note that the above expression can be written in terms of the mean $\overline{x}$. First, $x_{ij1} = \overline{x} + \eta_j + \mu_{ij1}$, as defined in Equation (B.2). Second, the prior x^*_{ij0} can be expressed as an added "wedge" to the mean, so that $x^*_{ij0} = \overline{x} + \gamma_{ij1}$, where $\gamma_{ij1} > 0$ means the farmer's prior was that the variety is better than the market average and vice versa. Substituting these into the above, we obtain:

$$
E(\Delta x) = -\alpha_1\left[\psi_1\int g(x)(\overline{x}+\eta_j+\mu_{ij1}+e_{ij1})\eta_j dx+\psi_2\int g(x)(\overline{x}+\gamma_{ij0})\eta_j dx)\right]
$$

Considering that $\overline{x}$ is a constant and therefore not correlated with the error term η_j, and that imperfections in within-variety integrity (μ) and in signals from crop performance (e) are assumed uncorrelated with average variety quality, hence with η_j, the above reduces to:

$$
\begin{aligned}
E(\Delta x) &= -\alpha_1\psi_1 E(\eta_j^2) - \alpha_1\psi_2 Cov(\gamma_{ij0}\eta_j) \\
&= -\alpha_1\psi_1\sigma_\eta^2 - \alpha_1\psi_2 Cov(\gamma_{ij0}\eta_j)
\end{aligned} \tag{B.5}
$$

A comparison with Equation (5.2) shows that $\alpha_1\psi_1 = \beta_1$ and $\alpha_1\psi_2 = \beta_2$, where β_1 and β_2 are the regression coefficients of switching on the attribute level and the prior, respectively, shown in Equation (5.2). Therefore, Equation (B.5) can be rewritten as follows:

$$E(\Delta x) = \Big(- \beta_1 \sigma^2_\eta \Big) + \Big(- \beta_2 Cov(\gamma_{ij0}\eta_j) \Big) \tag{B.6}$$

B.2 Losses from lack of learning

The results from the empirical analysis suggest that there is little learning by doing, with $\beta_1 = 0$ and $\beta_2 = 0$. By Equation (B.6) this implies that average Bt content would be stagnant between any two periods. To understand better the opportunity cost of this to farmers, I approximate the gain for Pakistani farmers if learning by doing was easier.

I proceed as follows. First, it would be necessary to use the relevant parameters to simulate potential improvements in x from learning. In the PCS sample, $Cov(\gamma\eta)$ can be calculated to be -0.02.[42] Farmer priors are therefore not very accurate. Meanwhile, the variance among variety averages in the sample $\sigma^2_\eta = 0.37$. Given that it appears farmers make input choices heuristically (see Section 6), then with learning we would have $\beta_2 = -\beta_1$; this suggests the second expression in Equation (B.6) would be positive, reinforcing market gains from learning. Using simple calibration from the data, Equation (B.52) becomes:

$$\begin{aligned} E(\Delta x) &= \big(- \beta_1 * 0.37 \big) + \big(\beta_1 * -0.02 \big) \\ &= -\beta_1 (0.37 + 0.02) \\ &\approx -\beta_1 * 0.40 \end{aligned} \tag{B.7}$$

Suppose, for example, that we find that the coefficient of switching on (*non-standardized*) Bt levels in Equation (5.3) is $\beta_1 = -0.17$. Then $E(\Delta x) = 0.17 * 0.40 = 0.068$. Therefore, we would approximate that Bt shifts from the in-sample average of 0.88 to 0.95 $\frac{\mu g}{g}$.

Second, it is necessary to estimate how varying levels of Bt, a damage abatement technology, can translate to cotton yields and revenues. To approximate the effect of Bt improvement

[42] To generate γ, I re-center the effectiveness prior so that the farmer answer for *Very bad* is -2, *Below average* is -1, *Average* is 0, while *Above average* is 1, and *Very good* is 2. To generate η, I calculate the difference between average Bt content of the variety purchased by the farmer and overall Bt content in the sample. I then calculate the covariance between the two variables in the sample.

on yield and revenue, Ma et al (2017) suggest the following breakdown of lethality:

Table B1: Bt content and pest lethality

Bt content ($\mu g/g$)	Lethal level (% pests killed)
0.60	50
0.70	60
0.88	70
1.06	80
1.34	90
1.59	95

Table B1 can be used to extrapolate differences in lethality based on Bt content. For example, an improvement in mean Bt content from 0.88 $\frac{\mu g}{g}$ to 0.95 $\frac{\mu g}{g}$ would approximately raise killing effectiveness from 70% to about 74%. The question is how this corresponds to output gain. Research suggests that Bt can protect half of all yield from destruction; if a maximum lethal level of 100% effective expression of the Bt trait improves yield by 50%, then 4% increase in lethal levels may as a rough approximation improve yield by 2%.

Third, calculating the size of Pakistan's cotton cultivation industry is necessary for applying the estimated percentage revenue changes. In the 2014-2015 season, the year for which I test learning and heuristic response by farmers, cotton production in Pakistan in 2014-2015 totaled 13,960,000 bales, equivalent to about 2.37 billion kg. From my data, the average price, in Pakistani Rupees, that farmers received for their 2014 crop per 40 kg mound of cotton was about 2313 PR, or 23 USD. Since 2.37 billion kg is equivalent to 59.3 million (40 kg) mounds, multiplying that amount by the price received per mound totals 1.364 billion USD, or 0.5% of the country's GDP for that year. Therefore, an improvement in mean Bt content consumed from 0.88 to 0.946 which improves yields by 2% would result in gains of 27 million USD for the industry.

The two-period model can only approximate gains (losses) from learning by doing (lack thereof) in the short run. To provide very rough back-of-the-envelope estimates of long term implications of input quality improvement for Pakistani cotton farmers, I use **Table B1** to estimate the consequences of being able to eventually purchase, on average, maximum effectiveness seeds. If expression of the Bt trait improves in the long run from the in-sample mean level of 0.88 $\frac{\mu g}{g}$ to the maximum-effectiveness level of 1.59 $\frac{\mu g}{g}$, this 25% improvement in percent of lethal pests killed may protect up to 12.5% of yield and therefore generate gains of up to 170 million USD in 2014. Actual long term gains would of course depend on shifts in relative prices between less and more effective varieties.

C Variable construction and distribution

The personal, price, and input controls are constructed as follows.

Education is the number of years of schooling of the household head by 2013. *Farming experience* is the years of general farming experience of the head by 2013. *Years Bt grown* is the total number of years that the household has grown (what they think are) Bt varieties, including and up to 2013. *Years variety grown* is the number of years in total that the farmer has grown the specific 2013 variety, including and up to 2013. *Land owned* is the amount of land, in acres, owned by the household in 2012.

Seed purchase price is the price, in 2013 Pakistani rupees, at which the farmer purchased one kilogram of seeds of the target variety in 2013. *Selling price* is the price, in 2013 hundreds of Pakistani rupees, at which the farmer sold one 40 kilogram mound of the variety cultivated and harvested in 2013; it is obtained from the farmers' answers in Round 1.3 about how much they sold their cotton crop for.

Irrigation is a measure of the total minutes of irrigation per acre of cotton cultivated in 2013. *Fertilizer* measures the extent of nitrogen-fertilizer used, as kilograms per acre of cotton cultivated in 2013. I calculate it by multiplying the nitrogen percent of each type of fertilizer with the amount (in kg) used. *Seed amount* is the amount of seeds sowed for that variety in kilograms per acre of cotton cultivated in 2013. *Labor* measures the total number of labor hours that were reported worked, per acre, during the 2013 season.

Table C1 provides a summary of the distribution of key variables in the data, including the dependent variables. It shows that the average farmer sampled has 5 years of education, 16 years of general farming experience, 4 years of experience cultivating Bt varieties, and has cultivated the 2013 variety for 2 years (including 2013); owns 6.5 acres of agricultural land; purchased seeds for about 280 Pakistani rupees ($1.80) per kilogram of seeds and sold the crop at 2,700 rupees ($17.30) per 40 kg mound of cotton; irrigated each acre cultivated for 23 hours total; applied 85 kilograms of fertilizer and 2.4 liters of pesticide per acre cultivated; sowed 7 kilograms of seeds per acre; and put in 163 hours of labor total per acre.

The histograms in **Figure C1** illustrate these distributions.

Table C1: Distribution of Variables

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Changed	331	0.538	0.499	0	0	1	1
Bt level ($\mu g/g$)	331	0.88	0.57	0.00	0.48	1.14	3.50
Effectiveness prior (scale)	331	3.45	0.79	1	3	4	5
Education	331	5.0	4.8	0	0	9	20
Farming experience	331	16.1	10.7	2	7	22	49
Years variety grown	331	2.1	1.1	1	1	3	7
Years Bt grown	331	4.2	1.6	1	3	5	11
Land owned (acres)	331	6.7	9.3	0.0	2.0	8.0	67.0
Seed price (PR)	331	289.4	126.8	100.0	200.0	350 .0	900.0
Selling price ('00 PR)	331	27.7	2.6	18.0	26.4	29.7	34.0
Irrigation (mts/acre)	331	1,388	776	120	810	1,835	4,620
Fertilizer (kg/acre)	331	85.62	36.77	0	59.80	103.00	236.00
Seed amount (kg/acre)	331	6.94	2.81	2.00	5.00	9.00	16.00
Pesticide (L/acre)	331	2.41	1.62	0.00	1.30	3.20	10.00
Labor (hours/acre)	331	163.4	93.7	36.0	103.6	204.6	500.0

Table C1 summarizes the distribution of the key variables used in the analysis.

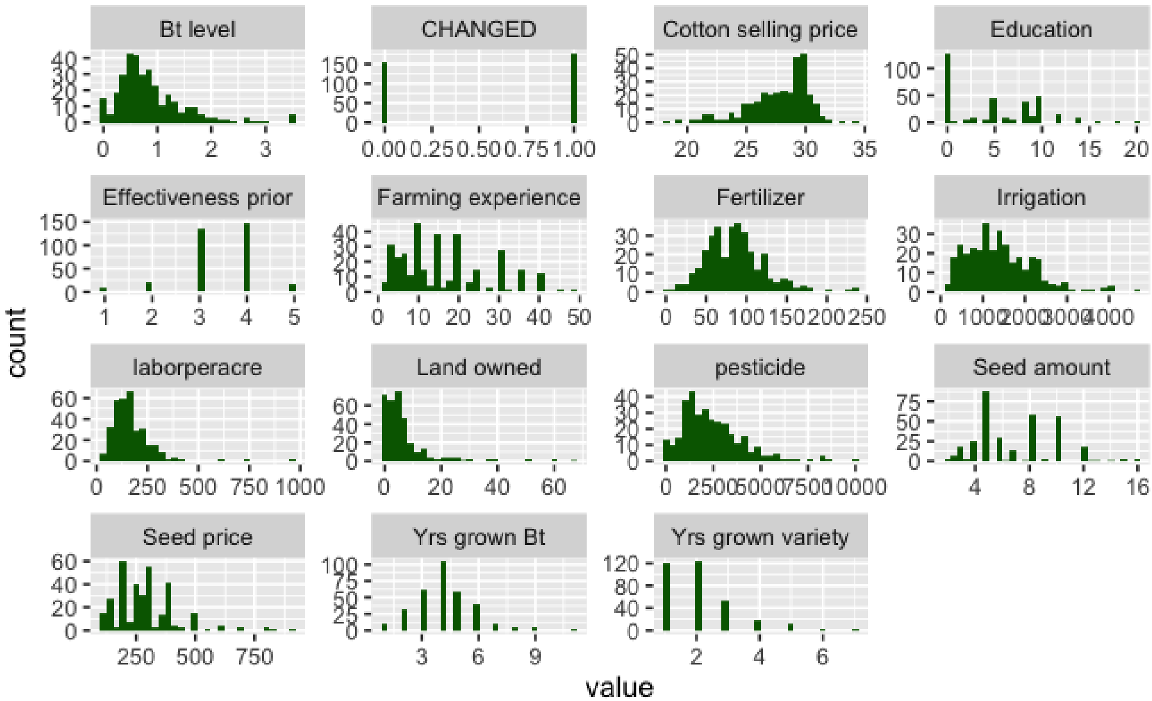

Figure C1: Distribution of Variables

Figure C1 illustrates the distribution of the key variables used in the empirical methodology, across the 331 farmers who are the focus of analysis. Values are on the x-axis while counts are on the y-axis. For example, the first plot shows that Bt content ranges between 0 and 3.5 micrograms of the Bt protein per gram, with the most common value (mode) for a farmer being about 0.5.

D Robustness checks

Table D1: Using pseudo-Bt measure for all farmers

	Dependent variable:			
	CHANGED			
	(1)	(2)	(3)	(4)
Pseudo Bt (standardized)	−0.020	−0.018	−0.017	−0.019
	(−0.079, 0.039)	(−0.077, 0.040)	(−0.075, 0.040)	(−0.081, 0.043)
Effectiveness prior (st)	0.003	−0.001	−0.002	−0.001
	(−0.048, 0.054)	(−0.053, 0.051)	(−0.054, 0.050)	(−0.052, 0.050)
Education		0.009^{*}	0.015^{***}	0.013^{**}
		(−0.001, 0.020)	(0.004, 0.026)	(0.002, 0.024)
Farming Experience			0.006^{**}	0.005^{*}
			(0.001, 0.011)	(−0.001, 0.010)
Yrs grown variety			-0.088^{***}	-0.088^{***}
			(−0.137, −0.040)	(−0.136, −0.040)
Yrs grown Bt			−0.018	−0.017
			(−0.049, 0.013)	(−0.048, 0.014)
Land owned			-0.009^{***}	-0.009^{***}
			(−0.015, −0.002)	(−0.015, −0.003)
Seed price		−0.0003	−0.0004	−0.0003
		(−0.001, 0.0002)	(−0.001, 0.0001)	(−0.001, 0.0002)
Cotton selling price		−0.012	−0.014	−0.018
		(−0.038, 0.014)	(−0.041, 0.012)	(−0.044, 0.009)
Irrigation				-0.0001^{**}
				(−0.0002, −0.00000)
Fertilizer				0.0002
				(−0.0001, 0.0004)
Seed amount				0.028^{**}
				(0.004, 0.053)
Labor				−0.0001
				(−0.0002, 0.0001)
Pesticide				−0.00001
				(−0.00002, 0.00001)
District and sowing time FE	Yes	Yes	Yes	Yes
Observations	379	379	379	379
R^2	0.205	0.216	0.271	0.294
Adjusted R^2	0.122	0.125	0.177	0.191
Residual Std. Error	0.466 (df = 342)	0.465 (df = 339)	0.451 (df = 335)	0.448 (df = 330)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table D1 combines single and multiple variety farmers who believed they were purchasing Bt. It runs OLS regressions of variety change on the constructed pseudo-Bt measure for all farmers, including for single-variety farmers. Pseudo-Bt is constructed as the average Bt expression for all other farmers with that variety. This facilitates comparison with the multiple-variety group.

Table D2: Farmer characteristics - In sample vs out of sample

Statistic	Out of sample, N=396	In sample, N=331	p. overall
Head Age	47.4 (12.1)	46.4 (11.3)	0.250
Head Education	4.37 (4.61)	5.02 (4.75)	0.067
Farming Experience	14.5 (13.1)	15.8 (11.1)	0.150
Main Plot Area	5.73 (6.75)	6.68 (11.0)	0.174
Land Owned	5.78 (10.4)	6.75 (9.27)	0.185
Province:			<0.001
PUNJAB	268 (67.7%)	291 (87.9%)	
SINDH	128 (32.3%)	40 (12.1%)	

Table D2 compares key characteristics of the farmers in the sample, $N = 331$, to all the other farmers that were not included in the sample but were part of the Pakistan Cotton Survey, $N = 396$ (total $N = 727$). For the non-region variables, means are provided with the standard deviation in brackets. The last column reports the p-value for the null hypothesis that the means are the same for both groups.

Table D3: Accounting for measurement error

	Dependent variable:		
	CHANGED		
	OLS	*IV*	*OLS*
	(1)	(2)	(3)
Bt - leaves	−0.007		
	(−0.070, 0.056)		
Bt - instrumented		−0.008	
		(−0.171, 0.154)	
Bt - correlated			−0.076
			(−0.266, 0.115)
Effectiveness prior (st)	0.007	−0.0004	−0.084
	(−0.050, 0.064)	(−0.065, 0.064)	(−0.209, 0.041)
Education	0.015**	0.015**	0.023
	(0.003, 0.027)	(0.003, 0.028)	(−0.006, 0.053)
Farming experience	0.006**	0.007**	0.012*
	(0.001, 0.012)	(0.001, 0.013)	(−0.002, 0.026)
Yrs grown variety	−0.091***	−0.096***	−0.142**
	(−0.142, −0.040)	(−0.152, −0.040)	(−0.261, −0.023)
Yrs grown Bt	−0.041**	−0.043**	−0.149***
	(−0.073, −0.008)	(−0.078, −0.008)	(−0.226, −0.072)
Land owned	−0.008**	−0.008**	−0.005
	(−0.015, −0.002)	(−0.014, −0.001)	(−0.017, 0.008)
Seed price	−0.001**	−0.001**	−0.001
	(−0.001, −0.0001)	(−0.001, −0.0001)	(−0.002, 0.001)
Cotton selling price	−0.020	−0.027*	−0.020
	(−0.048, 0.008)	(−0.055, 0.002)	(−0.087, 0.046)
District and sowing time FE	Yes	Yes	Yes
Observations	329	310	74
R^2	0.308	0.304	0.676
Adjusted R^2	0.204	0.191	0.343
Residual Std. Error	0.446 (df = 285)	0.448 (df = 266)	0.396 (df = 36)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table D3 demonstrates the results from reconstructing the Bt variable to reduce measurement error and re-estimating the regressions of variety change on Bt level. Column 1 reconstructs Bt content as an average, for each farmer, of the leaf values only because they are more strongly correlated with each other than boll values. Column 2 uses one leaf value as an instrument for the other to eliminate (the correlated) measurement error. Column 3 keeps Bt content as the average of the leaf and boll values but applies it only to a limited set of observations where the two leaf values are almost identical.

Table D4: Additional robustness checks

	Dependent variable:			
	CHANGED			
	(1: LPM)	(2: LPM)	(3: LPM)	(4: Logit)
Bt level (standardized)	0.008	0.004	0.017	0.061
	(−0.092, 0.108)	(−0.063, 0.070)	(−0.047, 0.081)	(−0.299, 0.424)
Bt level squared	0.004			
	(−0.033, 0.042)			
Effectiveness prior (st)	0.006	0.005	0.003	0.049
	(−0.051, 0.062)	(−0.051, 0.061)	(−0.056, 0.061)	(−0.248, 0.351)
Education	0.015**	0.014**	0.016**	0.077**
	(0.003, 0.027)	(0.002, 0.026)	(0.004, 0.028)	(0.015, 0.140)
Bt level*Education		0.004		
		(−0.007, 0.014)		
Farming experience	0.006**	0.006**	0.006**	0.033***
	(0.001, 0.012)	(0.001, 0.012)	(0.001, 0.012)	(0.006, 0.062)
Yrs grown variety	−0.091***	−0.091***		−0.461***
	(−0.142, −0.039)	(−0.142, −0.040)		(−0.725, −0.212)
Yrs grown Bt	−0.040**	−0.040**	−0.042**	−0.209**
	(−0.073, −0.008)	(−0.073, −0.008)	(−0.075, −0.009)	(−0.391, −0.035)
Land owned	−0.008**	−0.008**	−0.008***	−0.040***
	(−0.014, −0.002)	(−0.014, −0.002)	(−0.015, −0.002)	(−0.071, −0.011)
Seed price	−0.001**	−0.001**	−0.001**	−0.003***
	(−0.001, −0.0001)	(−0.001, −0.0001)	(−0.001, −0.0001)	(−0.006, −0.001)
Cotton selling price	−0.020	−0.019	−0.015	−0.110
	(−0.048, 0.008)	(−0.047, 0.009)	(−0.043, 0.014)	(−0.285, 0.040)
Variety grown dummies	No	No	Yes	No
District and sowing time FE	Yes	Yes	Yes	Yes
Observations	331	331	331	331
R^2	0.311	0.312	0.325	
Adjusted R^2	0.205	0.206	0.210	
Residual Std. Error	0.445 (df = 286)	0.445 (df = 286)	0.444 (df = 282)	
Note:			*p<0.1; **p<0.05; ***p<0.01	

Table D4 introduces different specifications to Column 3 in Table 2. Column 1 adds a Bt squared variable to allow for nonlinear effects, Column 2 adds an interaction term between Bt content and education to allow for different effects by education, Column 3 uses a sequence of dummy variables the planting history (omitted from table) to allow for nonlinear effects, and Column 4 uses a bias-reducing logit instead of a linear probability model.

Table D5: Ordered logit

	Dependent variable:
	Perception (Ordered)
	Logit
Bt level (standardized)	−0.023
	(−0.304, 0.259)
Effectiveness prior (st)	0.008
	(−0.247, 0.263)
Education	0.018
	(−0.036, 0.073)
Farming experience	0.008
	(−0.017, 0.033)
Years variety grown	0.081
	(−0.142, 0.304)
Years Bt grown	−0.030
	(−0.132, 0.192)
Seed price	−0.001
	(−0.002, 0.002)
District and sowing-time FE	Yes
Observations	331

*p<0.1; **p<0.05; ***p<0.01

Table D5 re-estimates the regression of farmer perceptions on Bt levels by including all three levels of farmer perceptions in the dependent variable, with an ordered logit. This serves as a check on the main results in Table 4, which uses a linear probability model by clustering perceptions into a binary ‘poor/moderate’ versus ‘very good’ variable.

Table D6: Learning from others

	Dependent variable:			
	CHANGED			
	(1)	(2)	(3)	(4)
Bt level	−0.025	−0.032	−0.034	−0.036
	(−0.118, 0.068)	(−0.125, 0.060)	(−0.127, 0.059)	(−0.128, 0.056)
Effectiveness prior	0.010	0.012	0.004	0.004
	(−0.060, 0.080)	(−0.061, 0.084)	(−0.069, 0.077)	(−0.067, 0.076)
Diff Bt Neighbor	0.132	0.142	0.122	0.227**
	(−0.104, 0.367)	(−0.100, 0.384)	(−0.102, 0.346)	(0.00003, 0.453)
Education		0.005	0.017**	0.017**
		(−0.008, 0.019)	(0.004, 0.031)	(0.003, 0.030)
Farming experience			0.007**	0.006*
			(0.001, 0.014)	(−0.001, 0.013)
Years variety grown			−0.105***	−0.109***
			(−0.170, −0.041)	(−0.172, −0.046)
Years Bt grown			−0.058***	−0.054***
			(−0.097, −0.018)	(−0.094, −0.015)
Land owned			−0.011***	−0.011***
			(−0.018, −0.004)	(−0.018, −0.005)
Purchase price (seed)		−0.0003	−0.0005*	−0.0003
		(−0.001, 0.0002)	(−0.001, 0.0001)	(−0.001, 0.0002)
Selling price (cotton)		−0.021	−0.021	−0.026
		(−0.053, 0.012)	(−0.053, 0.011)	(−0.058, 0.007)
Irrigation				−0.0001*
				(−0.0002, 0.00001)
Fertilizer				−0.001
				(−0.002, 0.001)
Seed amount				0.044***
				(0.017, 0.071)
Labor				0.0003
				(−0.0005, 0.001)
Pesticide				−0.00001
				(−0.0001, 0.00004)
Observations	260	260	260	260
R^2	0.144	0.155	0.255	0.294
Adjusted R^2	0.041	0.040	0.138	0.165
Residual Std. Error	0.484 (df = 231)	0.484 (df = 228)	0.459 (df = 224)	0.452 (df = 219)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table D6 includes a rough measure of peer effects in the regressions of variety change on Bt level. Specifically, the measure for peer effects is the average Bt level of farmers who may count as peers (same village) and who cultivated a different variety in 2013. With social learning, this coefficient would be positive while the coefficient on own-Bt would be negative.

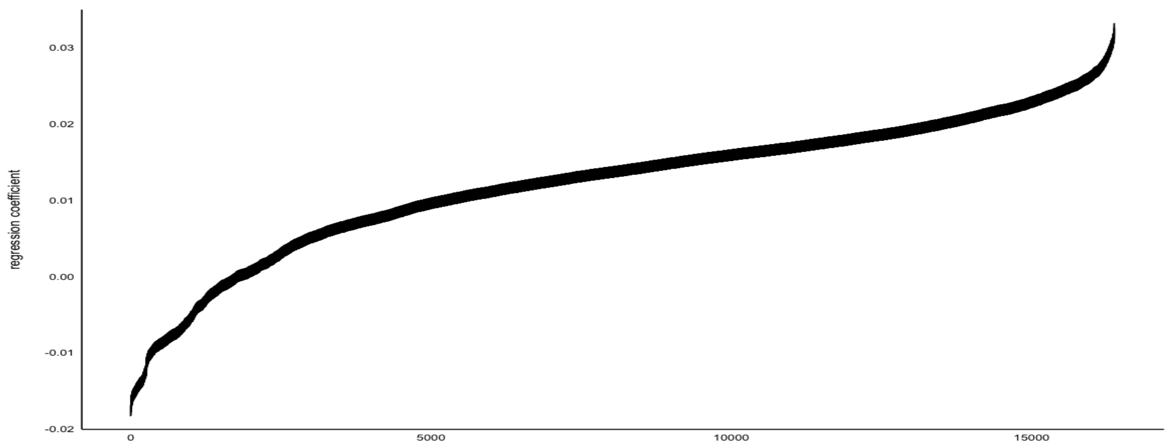

Figure D1: Estimated coefficient from regression of variety change on Bt level

The x-axis is the number of specifications, and the y-axis is the estimated coefficient from regressing variety change on Bt level, following Equation (5.3). *Black* denotes an insignificant coefficient while *light grey* denotes a significant coefficient, at the 10% significance level. The specifications combine all the controls in thousands of different ways. In all of these specifications the coefficient is close to zero and insignificant, indicating that a one standard deviation increase in Bt level does not predict variety change.

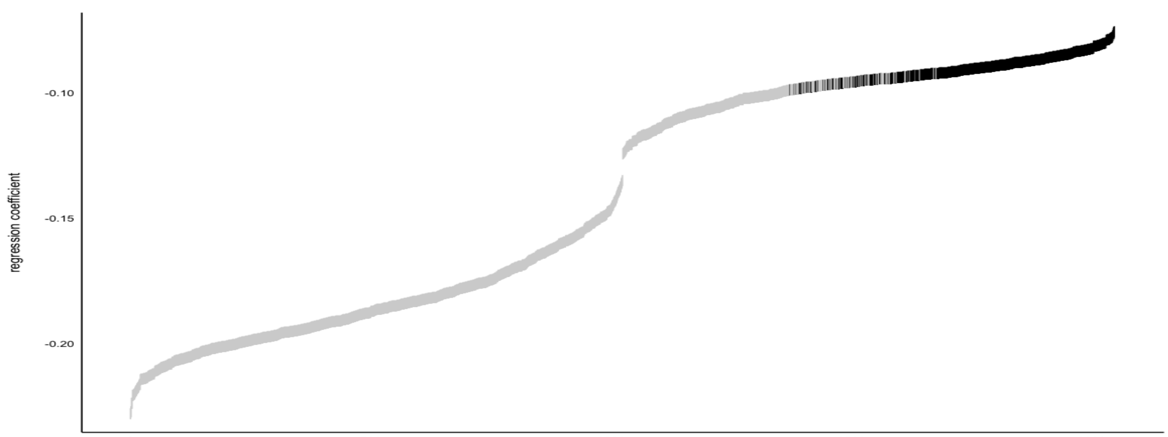

Figure D2: Estimated coefficient from regression of variety change on farmer perceptions

The x-axis is the number of specifications, and the y-axis is the estimated coefficient from regressing variety change on post-cultivation farmer perceptions, following Equation (5.4). *Black* denotes an insignificant coefficient while *light grey* denotes a significant coefficient, at the 10% significance level. The specifications combine the controls in thousands of different ways. In the majority, the coefficient is negative and significant, indicating that farmers who view bollworm resistance performance as better are less likely to switch varieties next year. The exceptions in the upper right corner are the specifications that omit district controls, which is not a valid omission since district-specific cultivation attitudes are likely correlated with both perceptions and seed switching behaviors, and district/province also affects Bt measurement.

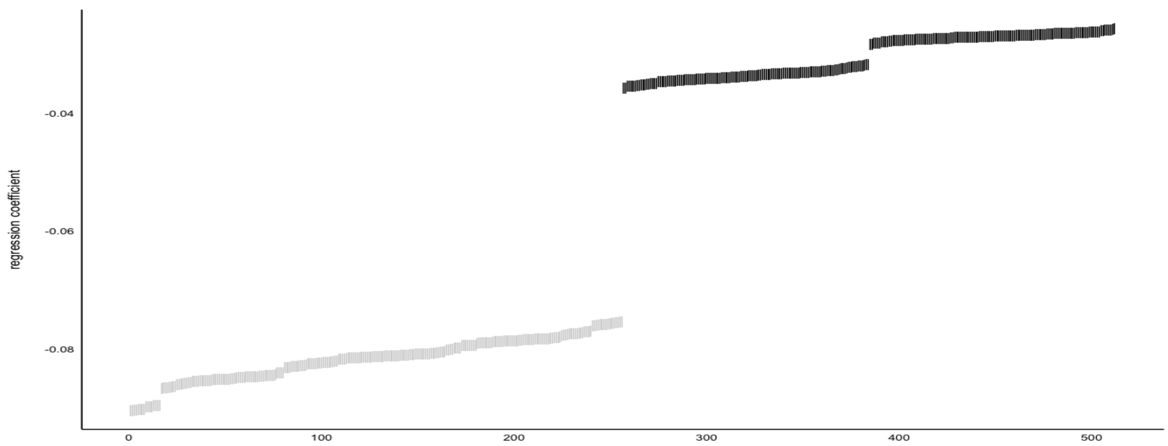

Figure D3: Estimated coefficient from regression of farmer perceptions on Bt level

The x-axis is the number of specifications, and the y-axis is the estimated coefficient from regressing farmer perceptions on Bt level, following Equation (5.5). *Black* denotes an insignificant coefficient while *light grey* denotes a significant coefficient, at the 10% significance level. The specifications combine the controls in hundreds of different ways. In the specifications which exclude district controls (the lower left corner), the estimated coefficient is negative and significant. However, in the more plausible specifications which include district controls (upper left), the estimated coefficients are closer to zero and insignificant, indicating that a one standard deviation in Bt level does not predict farmer perceptions post-cultivation.

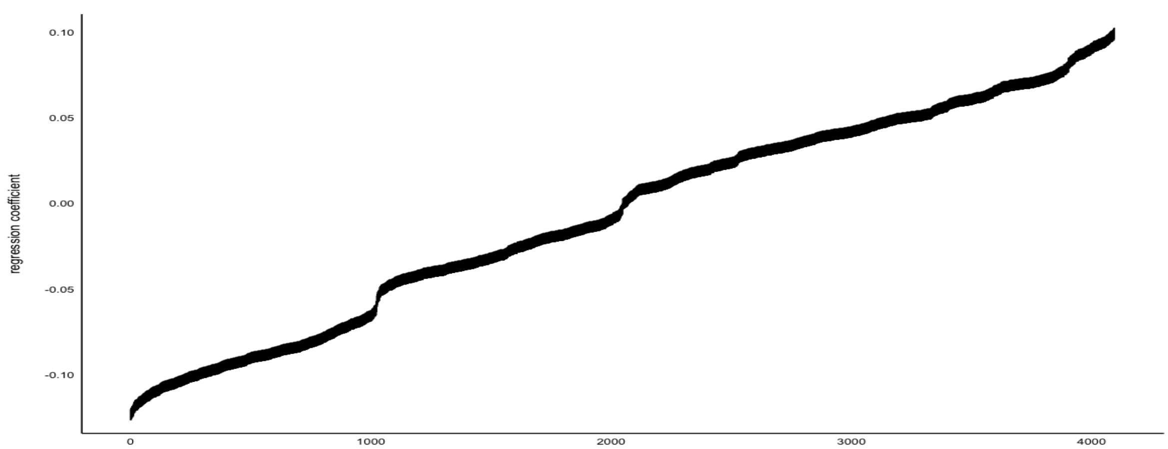

Figure D4: Estimated coefficient from regression of pesticide use on Bt level

The x-axis is the number of specifications, and the y-axis is estimated coefficient from regressing pesticide use on Bt level, following Equation (5.6). *Black* denotes an insignificant coefficient while *light grey* denotes a significant coefficient, at the 10% significance level. The specifications combine the controls in thousands of different ways. In all specifications the estimated coefficient is close to zero and insignificant, indicating that a one standard deviation in Bt level does not predict farmer use of pesticides during the season.