No Small Potatoes: Agricultural Risk and Investment under Uncertainty*

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Abstract

This paper investigates the role of learning in the use of agricultural technologies by smallholder farmers in low-income countries. I conduct a randomized experiment in Bangladesh to show that a risk-reducing technology can lead farmers to invest more in inputs such as fertilizer. Specifically, I use an alert system to enable farmers to take precautionary measures against crop disease. The intervention leads to higher yields as a result of increased investment. This outcome is driven by farmers who learn over the course of the season that they are receiving accurate alerts. This paper demonstrates how the effectiveness of an intervention is determined by how rapidly people can learn about its efficacy.

JEL: O13, C93, Q12, D83

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1 Introduction

Farmers in low-income countries produce significantly less with their land and labor than farmers in high-income countries. This productivity gap has persisted over time (Gollin, Lagakos, and Waugh 2014a, 2014b). One important contributor to this gap is vulnerability to agricultural risk: the chance that the rains necessary to sustain farmers' fields might come late, crop disease might strike, or infrastructural breakdowns might prevent bringing a harvest to market. If these risks materialize, farmers not only lose their crop, but also capital spent on complementary inputs, such as fertilizer and labor. This is a reason why farmers are often reluctant to take up new technologies or invest in complementary inputs (Jack 2013; Karlan et al. 2014; Donovan 2020).

An intervention that reduces agricultural risk can also increase the likelihood of farmers investing more in technologies and complementary inputs. A well-studied example of a risk-reducing intervention is index insurance. Index insurance offers farmers a contract that pays out when remote sensing data indicates crop losses, such as when a rainfall index indicates drought within a region. Despite its theoretical tractability, demand for this insurance has been limited (Mobarak and Rosenzweig 2012; Cole et al. 2013; Jensen, Barrett, and Mude 2016). Farmers are concerned about basis risk: if they suffer a loss that is not reflected by the index, they do not receive a payout. Attempts to scale index insurance have painted a stark picture: because farmers have difficulty learning about their individual basis risk, they do not trust or want index insurance, even at subsidized prices (Ahmed, McIntosh, and Sarris 2020).

This paper provides evidence on how a particular feature of a technology—whether farmers can learn about its efficacy through use—affects use and investment. An ideal risk-reduction technology for smallholder farmers is one that, like index insurance, can be deployed with low administrative costs, but additionally admits opportunities for farmers to learn about the level of risk reduction the technology offers. Instead of indemnifying a farmer after a loss, such a technology could minimize the likelihood of a loss occurring.

I explore whether providing farmers with advanced warning about the risks they face allows them to both mitigate their losses and increase their agricultural investments. While weather risk is unavoidable, farmers can take action to mitigate other risks, such as crop disease and pests, if given sufficient warning. Further, if farmers know the risks they face, they can calibrate their investments appropriately, increasing their investment in periods of low risk.

Specifically, I study how farmers cope with a virulent plant disease known as late fungal blight. In Bangladesh, where my study takes place, blight poses a significant risk to every potato farmer. In this region, losses to blight are high, ranging from 25-75% a year, leading to social upheaval, farmer suicide, and starvation (Fry 2016; Dey et al. 2018). Farmers combat blight with fungicide, which is most effective when applied before the onset of the disease. However, farmers cannot precisely anticipate when blight will arrive, and so *ex ante* investments in labor and fertilizer are rendered worthless if blight strikes.

Over the 2019-2020 growing season, I conducted a randomized control trial in northwestern Bangladesh with potato farmers in 410 villages. I used an alert system that combines satellite and weather data to predict blight risk at a high geographic and temporal resolution. The system sends messages to farmers' cell-phones notifying them when to spray their crops against blight. The alert system is designed to optimize when farmers spray fungicide, informing them exactly when their crops are most vulnerable.

My study has two main findings. First, the alert system created a "crowd-in" effect, where farmers who were sent alerts invested approximately 8% more in fertilizer, a yield-increasing input, than those in the control group. As a result, yields increased by approximately 7%. Second, I find that the efficacy of the intervention is determined by the ability of farmers to verify its accuracy. Before the start of the season, farmers provided an expected sowing date which was used to calibrate the blight alert system. However, many farmers planted two to three weeks later. The closer a farmer planted to their registered date, the more accurate a signal they received. Farmers who noted that the alerts accurately reflected the condition of their crops were the ones to invest more; those noticing a mismatch invested less.

Many RCTs use information and communication technologies (ICT) to send alerts and messages to induce farmers to adopt new technologies and invest more in their crops (Aker 2011; Fafchamps and Minten 2012; Nakasone, Torero, and Minten 2014; Aker, Ghosh, and Burrell 2016; Casaburi et al. 2019). This paper shows that harnessing that same technology can motivate economically significant investment in response to risk-reduction, which historically has been difficult due to issues of basis risk. While the alert system shares the same technical basis risk as index insurance, it provides multiple opportunities over the season for farmers to learn about their own specific basis risk.

Further, where ICT interventions have been successful, it can be be difficult to determine why—whether the information was salient or whether the alerts provided a behavioral nudge irrespective of accuracy. In my paper, I not only show that the alert system I used was effective at encouraging investment and increasing yields, but also demonstrate the mechanism behind this. The alert system used in this RCT differs from an insurance product because it tells farmers their risk *before* blight occurs, allowing them to condition their investments in complementary inputs accordingly.

The rest of this paper is organized as follows. Section 2 describes the context of the study and the disease. Section 3 describes the design of the RCT and provides summary statistics on farms and farmers. Section 4 presents results, and 5 presents the mechanisms driving these results. Section 6 concludes.

2 Context

The district of Rangpur in northwestern Bangladesh is rural, agrarian, and poor. Smallholder farmers in the district primarily grow rice, but some elect to cultivate potatoes in the winter months separating rice seasons as a way of more intensively making use of their land. Potatoes are a fast growing staple, valuable as a cash crop and as a source of vitamins and calories. Potatoes are also susceptible to the plant pathogen *Phytophtera infestans*, which causes late fungal blight. The pathogen first emerged in the 1840s and became infamous for the devastation of crops in Europe leading to the Irish potato famine.[1] Even today, blight is regarded as one of the most dangerous plant diseases, and continues to exact enormous losses on farmers worldwide (Haverkort et al. 2008; Vleeshouwers et al. 2011; Fry et al. 2015; Kamoun et al. 2015). Average losses of potatoes in Bangladesh are estimated to be high, between 25 and 57% of the crop each year (Rahman et al. 2008; Hossain et al. 2010). In extreme cases, such as the 2006-2007 season, 50 to 80% of all potato crops in Bangladesh were infected with blight, resulting in severe yield losses across the country (Dey et al., 2010).

Blight is prevalent wherever potatoes are grown, appearing repeatedly over the course of the growing season under cool, wet conditions. The spores of the disease spread quickly through wind and water. Blight first infects the leaves of the potato plant, moving down into the tuber, which will rot and deteriorate in the field. Left untreated, blight can destroy an entire crop within a week of infection. The remedy for

1. The emergence of potato blight in the 1840s commanded an enormous amount of attention from government bodies and the press. The progression of the disease throughout North America and Europe was followed on the front page of newspapers as government commissions attempted to convene committees to handle the outbreak (Berkeley 1846; Bourke 1964). Charles Darwin spent over forty years studying the disease (Ristaino and Pfister 2016).

blight is simple: an application of a prophylactic fungicide can prevent infection for a period of three to five days. If a farmer's application of fungicide correctly anticipates blight, their losses can go to zero (Kamoun et al. 2015; Fry et al. 2015).

Farmers are aware of the risk blight poses to their crops, and regularly use fungicide, but lack precise information over when to best apply it. If farmers spray when the risk of blight infection is low, they pay for the fungicide but receive no benefit. If farmers delay spraying when the risk of infection is high, then an uncontrolled outbreak of blight can ruin their harvest. Farmers rely on their own experience, intuition, and report seeking the advice of others to decide when to spray their crops. Crops planted at the same time in the same location will be similarly vulnerable, so farmers can learn from each other's decisions.

Predicting periods of high blight risk is difficult. A common heuristic for high risk is multi-day periods where temperatures lie between 50-60F and relative humidity exceeds 90%. However, this rule is only approximate, and small fluctuations in temperature or humidity can significantly inhibit or accelerate the development of blight. A number of systems have been developed in the United States, Europe, and elsewhere to forecast blight at a high temporal and spatial resolution. These systems utilize a combination of localized weather data, satellite imagery, and crop growth models to predict when blight risk is high during a season, and send alerts to farmers telling them to spray fungicide appropriately.[2]

For this RCT I use a blight forecast and alert service called GEOPOTATO that was created by Wageningen University & Research, Netherlands. GEOPOTATO integrates local weather station data with satellite imagery and a crop growth model to forecast short-term blight risk on a week-to-week basis for each sub-district in Rangpur. The

2. Examples of modern blight forecast and alert systems include Akkerweb in the Netherlands, Blightwatch in the United Kingdom, and USA Blight in the United States. Early efforts at blight prediction and alert system start with Blitecast in the 1970s and continue into the present (Krause, Massie, Hyre, et al. 1975; Fry 2016).

GEOPOTATO system is built on two parallel models: one tracking the growth of the potato crop and the other tracking conditions conducive to blight. The potato growth model is initially calibrated using data on which local varietals farmers plant and their sowing dates. The model is continuously updated throughout the season using satellite data to estimate the susceptibility of the crops to blight. The blight model takes in local weather station data to estimate the likelihood of a blight outbreak.

When GEOPOTATO estimates that local crops are susceptible and that blight risk is high, it triggers an alert. The alert sends both an SMS and a voice message in the local dialect to the relevant farmers, telling them that they should spray a prophylactic fungicide within the next three days. Farmers can go to their village dealer to purchase fungicide and apply it to their fields.

3 RCT Design and Farm and Farmer Characteristics

The district of Rangpur is divided into eight sub-districts (*upazila*), further divided into seventy-six sub-sub-districts (unions), within which are individual villages. Approximately 41,000 potato farmers across Rangpur registered to receive GEOPOTATO alerts for the 2019-2020 season, providing their location and expected sowing date prior to the start of the season, which are used to calibrate the alerts.

The RCT is designed to test whether farmers who received alerts have better outcomes—defined in terms of losses to blight, investment in fertilizer, and crop yields—than farmers who did not receive alerts. A second question is whether there are spillover effects between farmers within a village. Because the information in the alerts is clearly non-rival, and farmers report basing their decision over when to spray their fields on the actions of their neighbors, I can test whether a farmer who does not directly receive alerts, but is in the same village as those receiving alerts, realizes fewer losses and increases their investment in fertilizer.

From the population of the 41,000 farmers who wanted access to GEOPOTATO alerts, I took a random sample of 410 villages, assigning villages to the control group, where no-one would receive alerts, the treatment group, where all surveyed farmers would receive alerts, and a spillover group, where approximately 50% of the surveyed farmers would receive alerts. Treatment assignment is stratified at the sub-district (*upazila*) and sub-sub-district (union) level, and table 1 shows the number of villages and farmers by assignment. Data was gathered in two survey waves, an initial baseline at the start of the season to collect farmer demographic characteristics, and an endline following harvest to record data on farmer outcomes.

Table 1: Number of villages and farmers by treatment assignment

	Direct Alerts	Spillover	Control
Villages	217	131	178
Farmers	710	429	848

The majority of farmers registering for GEOPOTATO alerts are commercially oriented smallholders. The average farmer in the sample is male, nearly forty, has at least attended primary school, and has grown potatoes for over a decade. Farmer demographics are presented in table 2. Farmers observed cool, rainy weather throughout the season, with an average of 25 days of weather conducive to the spread of blight—with temperatures between 12 and 25C and humidity over 85%. There are no statistically significant differences in observable characteristics between farmers in the treatment, spillover, and control groups, as shown in the forth column of table 2 with adjusted false discovery rate q-values.

Farmers devoted an average of approximately one acre of land to growing potatoes between their rice harvests.[3] Farmers planted in late fall and early winter of 2019, and

3. Smallholder farmers are generally defined as owning five or fewer acres of land. Smallholder

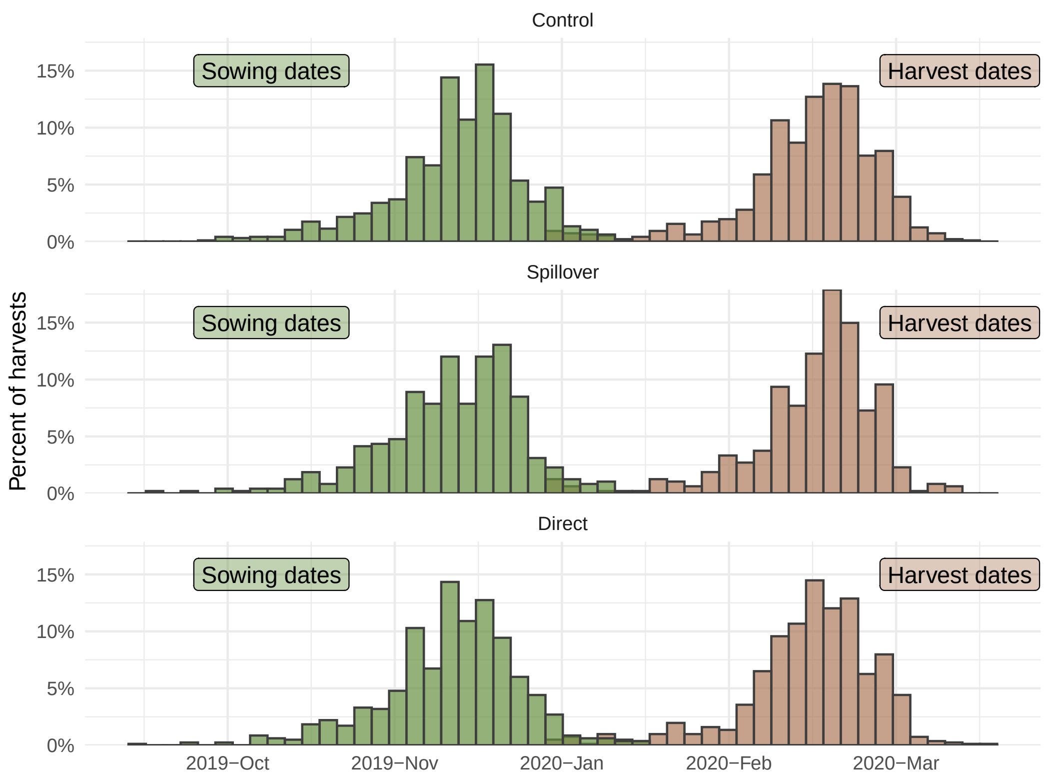

Figure 1: Distribution of Sowing and Harvest Dates by Treatment Assignment

Notes: Farmers reported harvest dates at the endline survey and the number of growing days for their crop. The average farmer sowed their crop in mid December 2019 and harvested in early March 2020.

harvested into early April of 2020. The distribution of sowing and harvest dates is shown in figure 1. Successfully cultivating potatoes requires inputs of labor, fertilizer, and fungicide. Almost all farmers use fertilizer, spending an average of approximately \$200 USD (17,000 taka) an acre, which they apply in a sequence of four applications that stretch throughout the growing season. Fertilizer increases a farmer's yield so long as they do not lose their crops to blight or other shocks. As shown in figure 2d, almost all farmers invest in fertilizer to prepare their land prior to the start of the season. Investment decreases significantly as the season progresses, with an increasing number of farmers choosing to invest nothing in fertilizer in subsequent rounds. The vast majority of farmers hire labor, an average of 50 people during the season to help with land preparation, intraseasonal cropping activities, and the harvest. Fungicide is also used extensively, an average of \$115 USD (9,700 taka) an acre. Farmers spray fungicide an average of 8-9 times over the course of the season. Input usage increases linearly in farmland size, shown in figure 2.

Farmers grow potatoes with the aim of selling them at the end of the season, where the average farmer who reported a sale realized estimated profits of \$780 USD (66,000 taka). Nearly 20% of farmers did not report selling their crop, either deciding to consume their harvest or to keep it in cold storage until later in the year in the hope of getting a higher price. To accommodate the farmers reporting zero hired labor, fertilizer, or fungicide expenditure, the inverse hyperbolic sine transformation is used instead of a logarithmic transformation, but which can be interpreted equivalently (Bellemare and Wichman 2020).

Farmers reported the fraction of each harvest lost to blight on an ordinal scale as "almost no loss," comprising 0-5% of their crop, "a little" (5-10%), "some" (10-25%), "half" (25-50%), "most" 50-75%, and catastrophically "all" 75-100%. Reported losses

farmers operate an estimated 40% of the agricultural area in low-income countries (Lowder, Skoet, and Raney 2016).

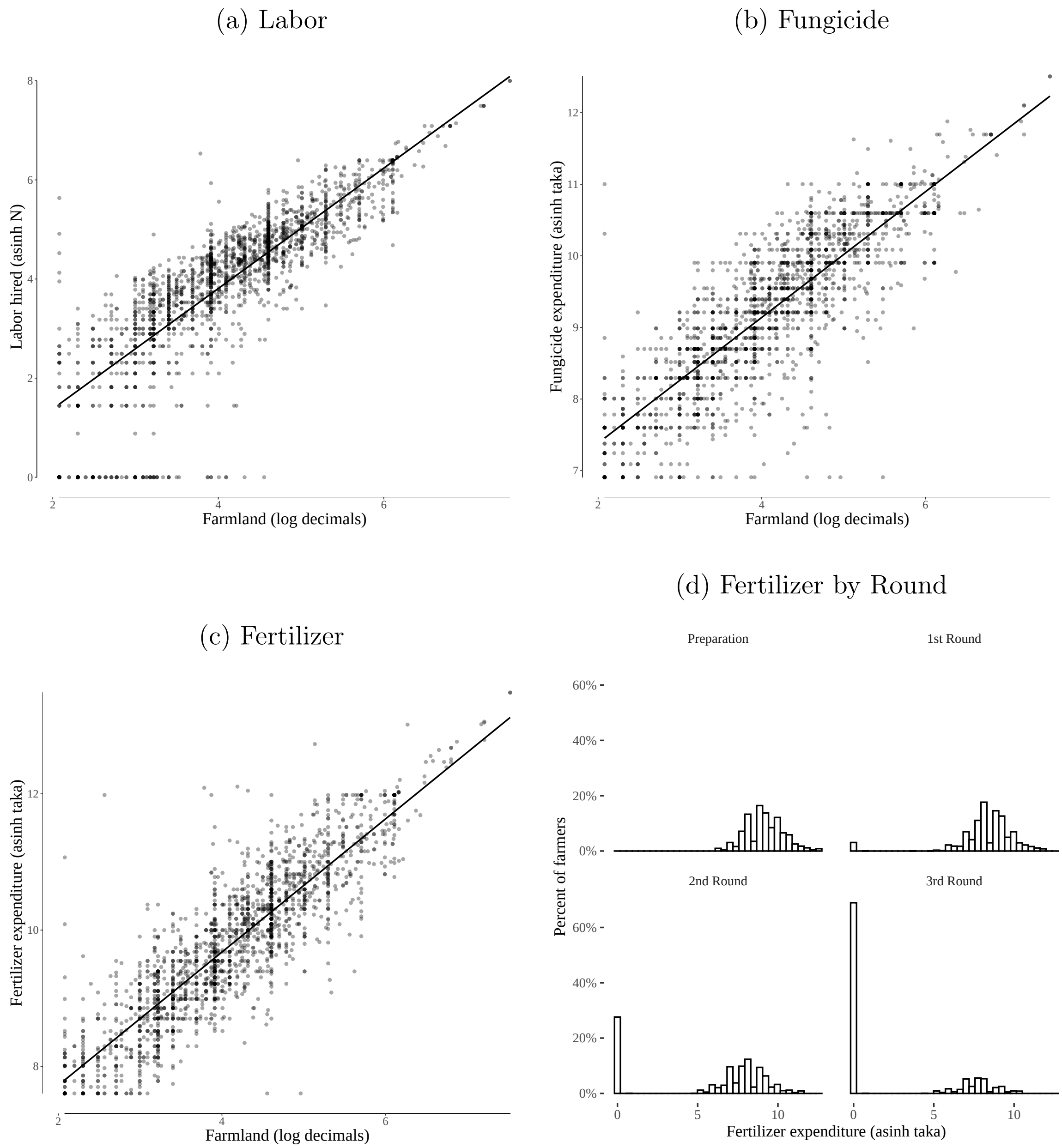

Figure 2: Farm Input Usage

Notes: Points represent individual farmers, and the line is a linear best fit of input expenditure over land. Farmers measure their land in decimals, where 100 decimals ≈ 1 acre. Labor is measured as the total number of people hired throughout the season, and fertilizer and fungicide are measured by expenditures in taka. Input use increases linearally with farmland.

Table 2: Farmer Demographics

Variable	Treatment Status: Control	Spillover	Direct	p-value	q-value
Age	39 (10)	39 (10)	38 (10)	0.5	0.9
Years farmed potatoes	12 (7)	12 (7)	12 (8)	0.4	0.9
Household members (N)	7.4 (3.7)	7.5 (3.7)	7.3 (3.7)	0.8	0.9
Female	0.6%	1.0%	0.8%	0.7	0.9
Education					
No formal education	9.4%	9.6%	11%		
Primary school	23%	27%	22%		
Secondary school	48%	45%	45%		
Above secondary school	20%	19%	22%		
Potato cropland (acres)	1.06 (1.61)	1.08 (1.34)	1.02 (1.12)	0.7	0.9
Hot weather days (> 30C)	1.79 (3.22)	1.76 (3.40)	1.74 (3.43)	>0.9	>0.9
Total rainfall (mm)	409 (130)	414 (139)	408 (150)	0.8	0.9
Blight risk days	25.1 (6.0)	26.1 (6.1)	25.3 (6.7)	0.025	0.2
N	848	419	710		

[1] Sample averages, standard deviation in parentheses.
[2] p-value calculated with one-way ANOVA.
[3] q-values with false discovery rate correction for multiple testing.

by treatment status are shown in figure 3.

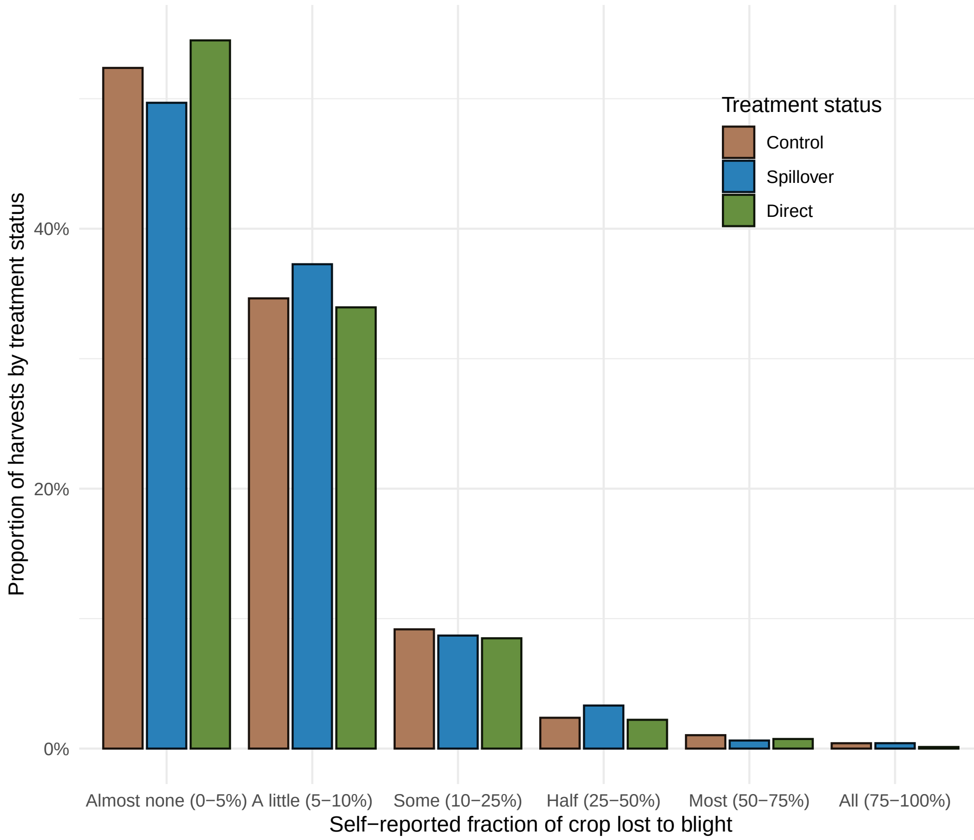

Figure 3: Distribution of Reported Losses to Blight

Notes: Farmers reported losses to blight on an ordinal scale from "almost none (0-5%)" to effectively "All (75-100%)." The height of each bar represents the proportion of farmers in the control, spillover, and treatment group reporting that level of loss.

3.1 Defining Treatment

The GEOPOTATO system sent out text and voice alerts when it predicted a high risk of blight. The alerts advise farmers to spray fungicide within the next three days to prevent blight infection. Farmers in the treatment group were sent between one to ten alerts over the course of the season. Alerts were calibrated by the farmer's planting week (cohort) and their sub-district (*upazila*). Following the harvest, farmers assigned

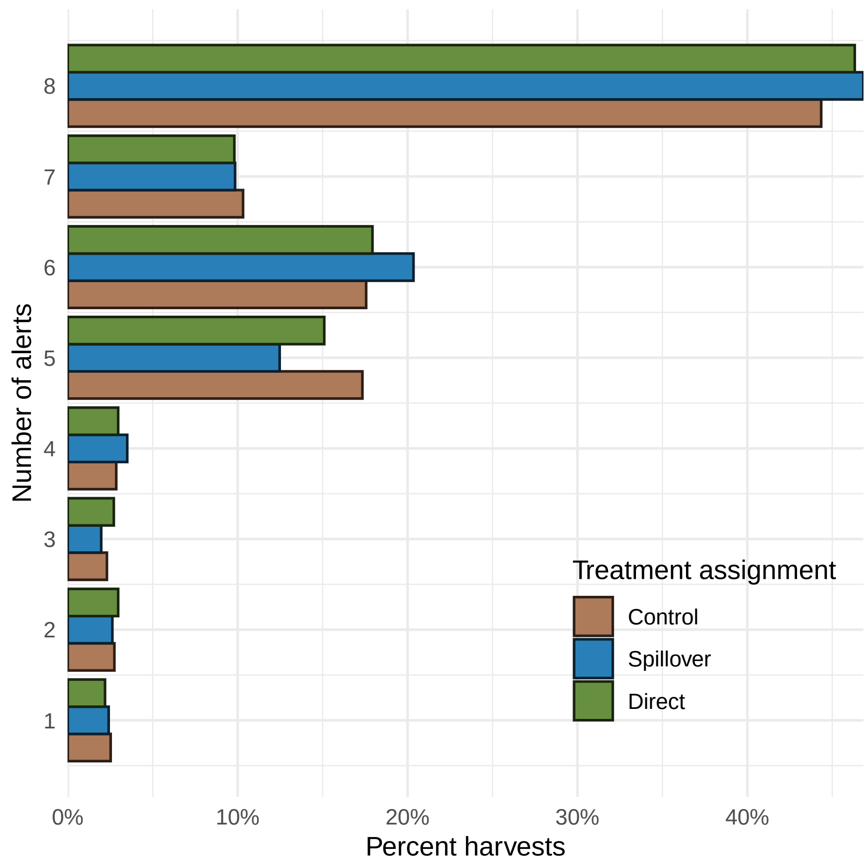

Figure 4: Number of alerts by treatment assignment

Notes: Alerts defined at the harvest level for farmers assigned to the treatment and control groups. Alerts were only sent out to those farmers assigned to directly receive alerts.

to directly receive alerts were asked whether they had actually received alerts, and if so, whether they had complied with them. Not everyone in the treatment group reported receipt; 14% of the farmers reported not receiving any alerts. Reasons for non-receipt may include the farmer's phone being off when the alerts were sent, out of a cellphone service area, other technical issues with the phone, or another family member using the phone and not reporting the alert to the farmer. A further 14% of farmers who reported receiving the alerts also reported that they had not complied with them, that they did not spray fungicide within the recommended three-day window.

The receipt of alerts is clearly an important condition for their efficacy. However, receipt may be endogenous to farmer concerns over blight and their effort to safeguard their crop. Where non-compliance in a RCT typically means that the participant does not take up the proposed technology, farmers self-reporting non-compliance with the alerts did use fungicide, just not at the advised times. If the benefit of the alerts is in allowing farmers to optimize when they spray fungicide, then compliance is crucial. However, if many farmers used the alert system as a backstop against catastrophic loss, then adherence to the alerts may not matter for farmers facing either low or as-expected blight risk.

Farmers directly receiving alerts may notify others in their village to spray fungicide. Even if they keep the alerts private, other farmers can still observe them spraying their fields. Because blight is a communicable disease, even a subset of better protected fields could reduce the overall spread of blight within a village. This may lead to farmers who are not direct recipients of the alerts to benefit, subsequently reducing their losses and increasing their investment in fertilizer and yields. However, because the alerts are calibrated to each farmers' sowing date, they would not necessarily be relevant to a neighbor who had planted their crops at a different time.

4 Outcomes

Outcomes of interest for farmer i in village j located within sub-district (*upazila*) ν who sowed their crops on date t include their losses to blight; the amount spent on inputs: fertilizer, fungicide, and labor; and the amount of potatoes harvested. In the empirical regression specification, equation 1, the effect of assigning a farmer to receive GEOPOTATO alerts is given by τ, and a set of farmer-level demographic control variables are included in $\mathbf{x}$. I include a time trend ψ to account for the change in growing conditions over the season, and sub-district level fixed effects, θ to control for unobserved variation at that level. Standard errors are clustered at the village level.

$$y_{itj\nu} = \tau\,(\text{treatment}_i) + \beta\mathbf{x}_{ij} + \theta_\nu + \psi_t + \varepsilon_{ij\nu} \tag{1}$$

Beyond assignment to treatment, the additional effect of receipt and compliance with GEOPOTATO alerts is also of interest. However, because both receipt and compliance may be endogenous to farmer concern over blight and their skill at farming. I can instrument for these outcomes using the initial assignment to treatment, shown in equation 2.

$$\begin{aligned} \text{receipt}_{ijt\nu} &= \kappa_1\,(\text{treatment}_i) + \beta\mathbf{x}_{ij} + \theta_\nu + \psi_t + \epsilon_i \\ \text{compliance}_{ijt\nu} &= \kappa_2\,(\text{treatment}_i) + \beta\mathbf{x}_{ij} + \theta_\nu + \psi_t + \epsilon_i \end{aligned} \tag{2}$$

4.1 Reduced Losses to Blight

Farmers assigned to receive alerts reported fewer losses than those in the spillover or control groups, but this effect is imprecise, and the difference was not statistically significant. Conditioning on self-reported receipt and compliance increases the magnitude of the point estimate. Farmers reporting compliance with the alerts, spraying when advised to do so, did experience significantly lower losses. The reason why the treatment effect on losses is imprecise is explored further in section 5, which examines the accuracy of the alerts. Interestingly, the farmers who reported receipt but not compliance showed higher losses. There do not appear to be any significant spillover effects for farmers not directly assigned alerts, but living in villages where others were assigned to receive them. Losses are positively correlated with the number of times a farmer sprays, which is endogenous to periods of high blight risk. More experienced farmers realized fewer losses, while the farmer's gender and education did not significantly correlate with losses.

Figure 5 shows the estimated marginal treatment effect of GEOPOTATO from the second column of table 3 at the sample means, with the predicted probability of reporting harvest losses in each category for farmers in the treatment, spillover, and control groups. Assignment to receive alerts shifts probability mass from higher loss categories to "almost none."

4.2 Inputs and Investment

Farmers optimize across a small set of inputs: the number of people they hire to work on the farm and their total expenditures on fertilizer and fungicide. The intent-to-treat effect on input use is estimated with a linear model in table 4. While labor use is unaffected, expenditure on fertilizer increases by approximately 8% for farmers assigned to directly receive GEOPOTATO alerts. Farmers, facing less risk and uncertainty over their potential losses to blight, chose to invest more heavily in their production.

The effect of the GEOPOTATO alerts on fungicide usage is theoretically ambiguous. The alerts could reduce expenditures for farmers who faced less blight risk than they would have otherwise expected; they could increase expenditures for farmers facing higher-than-expected blight risk. The alerts could also have no effect on expenditure, where farmers would spend the same amount, but spray at times more closely preceding periods of high blight risk. GEOPOTATO estimates of blight risk, the closest to an objective measure of blight over the 2019-2020 season, are shown in figure 4. The figure shows the number of alerts generated for each farmer, regardless of their assignment to treatment. Zero to one alerts suggests minimal risk from blight over that farmer's crop cycle, where twelve alerts is the maximum the system could send out, indicating a high risk of infection. Most farmers planted their crops over a three week period

Table 3: Effect of GEOPOTATO on self-reported losses to blight

	Dep. Var = Losses to blight (ordinal scale)			
	ITT	ITT	Receipt	Compliance
GEOPOTATO				
Assigned	-0.14	-0.14		
	(0.10)	(0.10)		
Received			-0.17	
			(0.11)	
Complied				-0.25^{**}
				(0.11)
Didn't comply				0.38^{*}
				(0.21)
Spillover	0.09	0.07	0.06	0.06
	(0.12)	(0.12)	(0.11)	(0.11)
Fungicide (N sprays)	0.72^{***}	0.71^{***}	0.71^{***}	0.72^{***}
	(0.11)	(0.12)	(0.12)	(0.11)
Land (ln dec)	-0.15^{***}	-0.15^{***}	-0.15^{***}	-0.15^{***}
	(0.05)	(0.05)	(0.05)	(0.05)
Female		0.42	0.40	0.43
		(0.52)	(0.52)	(0.52)
Experience (ln years)		-0.18^{**}	-0.18^{**}	-0.17^{**}
		(0.07)	(0.07)	(0.08)
No schooling		0.21	0.20	0.20
		(0.15)	(0.15)	(0.15)
Upazila FE	Yes	Yes	Yes	Yes
Seasonal Trend	Yes	Yes	Yes	Yes
Observations	1972	1953	1953	1953

Cluster robust standard errors at the village level (G = 407).
$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

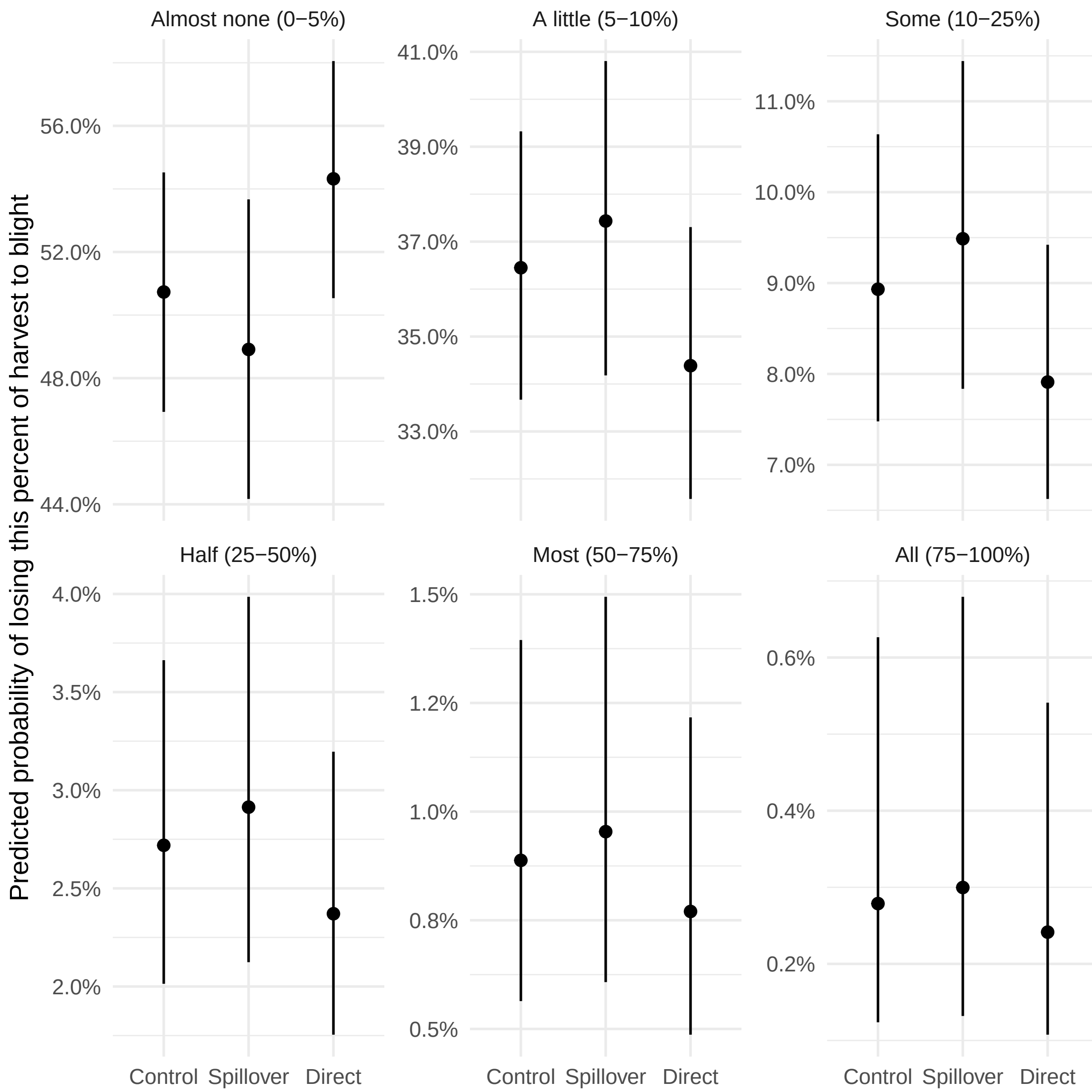

Figure 5: Estimated probability of losses to blight by treatment status

Notes: Predicted from the ordinal logit model in table 3 at the sample means of a farmer with 12 years of experience sowing 1 acre of land in mid-December, and spraying fungicide 8 times over the course of the season.

Table 4: Intent to treat effect of alerts on input usage

	Fungicide (asinh taka)		Fertilizer (asinh taka)		Labor (asinh N)	
	(1)	(2)	(3)	(4)	(5)	(6)
GEOPOTATO						
Assigned	0.08^{***}	0.08^{***}	0.08^{***}	0.08^{**}	-0.01	-0.00
	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)
Spillover	-0.00	0.01	0.01	0.00	0.04	0.05
	(0.04)	(0.04)	(0.03)	(0.03)	(0.05)	(0.05)
Land (ln acres)	0.86^{***}	0.86^{***}	0.96^{***}	0.96^{***}	1.22^{***}	1.21^{***}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
Female		-0.19		0.08		-0.45^{**}
		(0.15)		(0.16)		(0.23)
Experience (ln years)		0.02		0.01		0.05^{*}
		(0.02)		(0.02)		(0.03)
No schooling		-0.03		-0.01		-0.11
		(0.05)		(0.04)		(0.07)
Upazila FE	Yes	Yes	Yes	Yes	Yes	Yes
Seasonal trend	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.71	0.71	0.78	0.78	0.69	0.69
Observations	1977	1958	1977	1958	1977	1958

Cluster robust standard errors at the village level (G = 407).
$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

between late November and early December, which coincided with high levels of blight pressure. Consequently, there was relatively little variation in the amount of risk that farmers faced.

The results in table 4 show that both expenditures and the number of fungicide sprays increased by approximately 8% for farmers assigned to receive alerts. The increase may represent a riskier-than-expected season, a use of more expensive and higher quality fungicides if the farmer knew that the application was well-timed, an increase in the salience of spraying fungicide for the farmer, or a combination of all three. Despite the potential for information to flow between farmers within the same village, there do not appear to be any robust spillover effects. Farmers in villages where others are receiving alerts do not appear to modify their input usage or to report lower crop losses. Due to the lack of a first-stage effect, I combine the farmers in the spillover and control groups.

4.3 Yields

Yields were likely to increase for farmers assigned to receive GEOPOTATO alerts, as they invested more in fertilizer and realized marginally fewer losses. The treatment effect of GEOPOTATO can be parsed as an intent to treat (assignment), an average treatment effect (receipt), or treatment on the treated (compliance). Because reported compliance may be endogenous to farmer characteristics, I instrument for this using the initial assignment to receive alerts shown in equation 2. The treatment effect of GEOPOTATO on yields is reported in table 5, which leads to an estimated increase of yields of 5-9%. Conditioning on self-reported receipt and compliance increases the magnitude of the point estimate, the estimates are not significantly different from the intent to treat. Instrumenting for compliance and receipt increase the standard errors of the estimate, and is consistent with the OLS estimate.

Table 5: Effect of GEOPOTATO on Production (arcsinh kg potatoes)

	ITT	ATE	TOT		
	(1)	(2)	(3)	(4)	IV
GEOPOTATO					
Assigned	0.05^{*}				
	(0.03)				
Received		0.07^{**}			
		(0.03)			
Complied			0.09^{***}	0.08^{***}	0.07^{*}
			(0.03)	(0.03)	(0.04)
Land (ln acres)	1.10^{***}	1.10^{***}	1.10^{***}	1.10^{***}	1.10^{***}
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Female				0.13	
				(0.12)	
Experience (ln years)				0.04	
				(0.03)	
No schooling				−0.04	
				(0.05)	
Upazila FE	Yes	Yes	Yes	Yes	Yes
Seasonal trend	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.76	0.76	0.76	0.78	0.76
Observations	1977	1977	1977	1958	1977

Output measured in arcsinh kilograms.
Standard errors clustered at the village level (G = 407).
$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

5 Accuracy of Alerts and Rational Compliance

Non-compliance with interventions in RCTs poses more than just a problem in terms of the estimation of treatment effects—there may be participant-level heterogeneity that is crucial to determining compliance, and which can explain much about the intervention's real world efficacy (Barrett and Carter 2010; Athey and Imbens 2017). In many agricultural interventions we can observe non-compliance, for example where farmers either choose not to adopt or actively disadopt a new technology, but often we do not know why (Emerick et al. 2016; Maertens, Michelson, and Nourani 2020). Similarly, many interventions that employ information and communication technologies to send alerts and advice to farmers can recover an intent to treat effect, but cannot explain why these alerts are effective (Fabregas, Kremer, and Schilbach 2019).

This study provides an opportunity to understand the causal mechanism behind why farmers complied with the GEOPOTATO alerts, and how this produced an effect in terms of losses to blight and investment in fertilizer. GEOPOTATO was not designed to convince farmers to use fungicide to combat blight; they already were, and in significant quantities. The goal was to improve on farmers' baseline understanding of when to spray fungicide, which could reduce their risk and increase their investment.

However, the GEOPOTATO alert system suffers from the same inherent basis risk as index insurance: the remote data used in the system may fail to reflect conditions on each farmer's plot of land. GEOPOTATO alerts can fail in two separate ways: the system may alert the farmer to spray fungicide when the risk of blight is actually low, and the system may fail to alert the farmer to spray when the risk of blight is actually high, type I and II errors, respectively. While type I errors are not easily observed, farmers may notice type II errors in the form of blight in their fields with no corresponding alert.

By observing false negatives, disease but no alert, farmers can learn whether the alerts are accurate for them. I test this using variation in predicted sowing date (which defines alerts) and actual sowing date (which defines true blight risk). Before the start of the season farmers registered a sowing date with the GEOPOTATO system. Many farmers however, did not plant on the date they registered. Figure 6 shows the distribution of the deviation between registered and actual sowing dates for farmers assigned to directly receive alerts, spillover, or control groups. On average farmers planted 20 days later than they registered.[4] The alerts would be increasingly mistimed for farmers whose sowing dates differed significantly from the ones they registered. This deviation in registered versus actual sowing date provides an instrument for the underlying accuracy of the alert system.

After the harvest, farmers reported whether or not they had observed false negatives: whether they had found blight in their fields and not received an alert.[5] The likelihood of a farmer reporting a false negative increases with the absolute deviation from their registered sowing date. Figure 7 shows that the further the actual sowing date was from the one they had registered, the more likely farmers were to report false negatives. Sowing within twenty days of the registered date produces a false negative rate of approximately 25%, this increases to nearly 100% as farmers sow at dates further from their registered date and the alerts become correspondingly more irrelevant.

By interacting the assignment to receive alerts with the absolute number of days between their registered and actual sowing dates, I find that the alerts were effective in reducing losses—but only for farmers receiving accurate signals. Table 6 shows the effect of accurate signals on realized losses. Assignment to receive GEOPOTATO alerts becomes increasingly less effective at reducing losses the further the farmer sows from

4. Farmers were asked at the endline survey when they had harvested their crop and then how many days it had grown for, allowing the calculation of their actual planting date.

5. Specifically, farmers were asked: "This season did you find blight on your potatoes when you hadn't received a GEOPOTATO alert?"

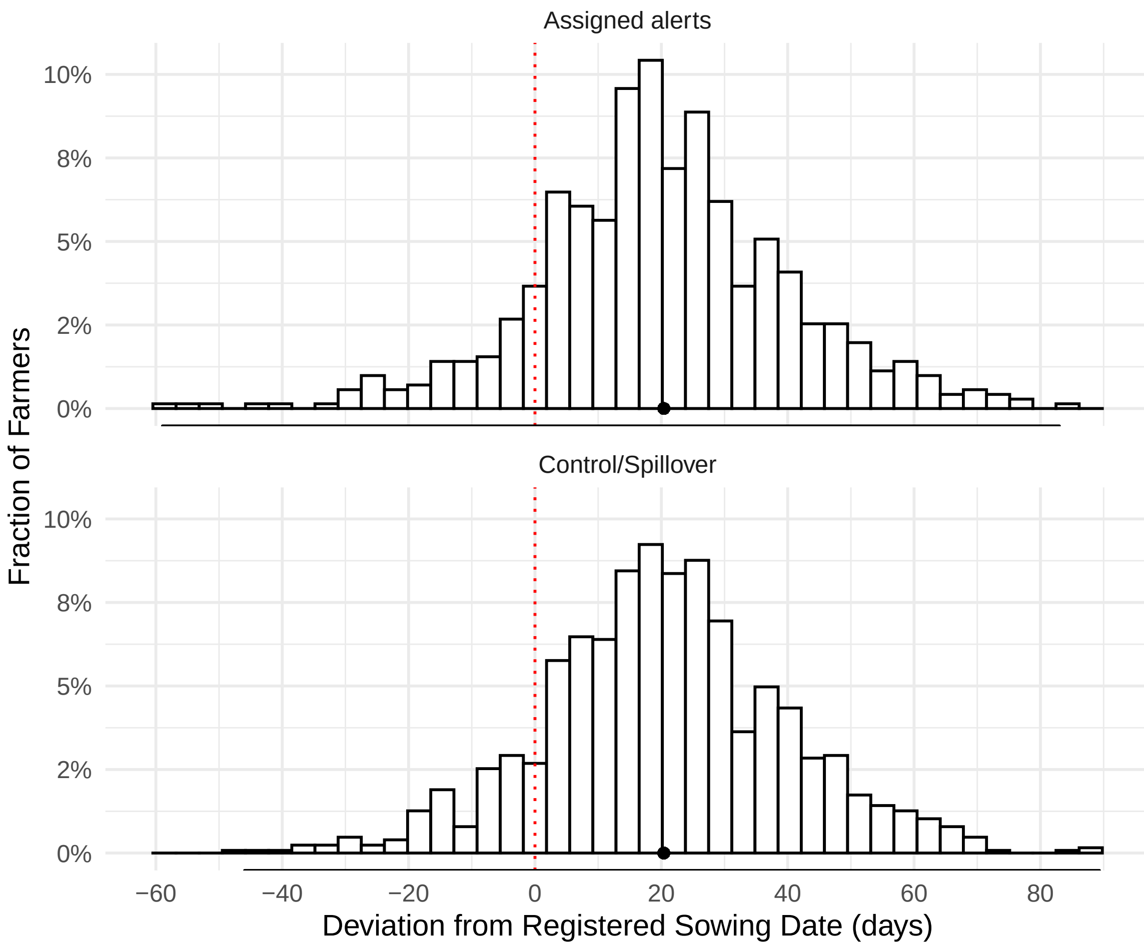

Figure 6: Deviation Between Actual vs. Registered Sowing Dates

Notes: Distribution of the deviation from registered sowing date and the sowing date calculated at the endline. Points represent the average deviation by assignment to treatment.

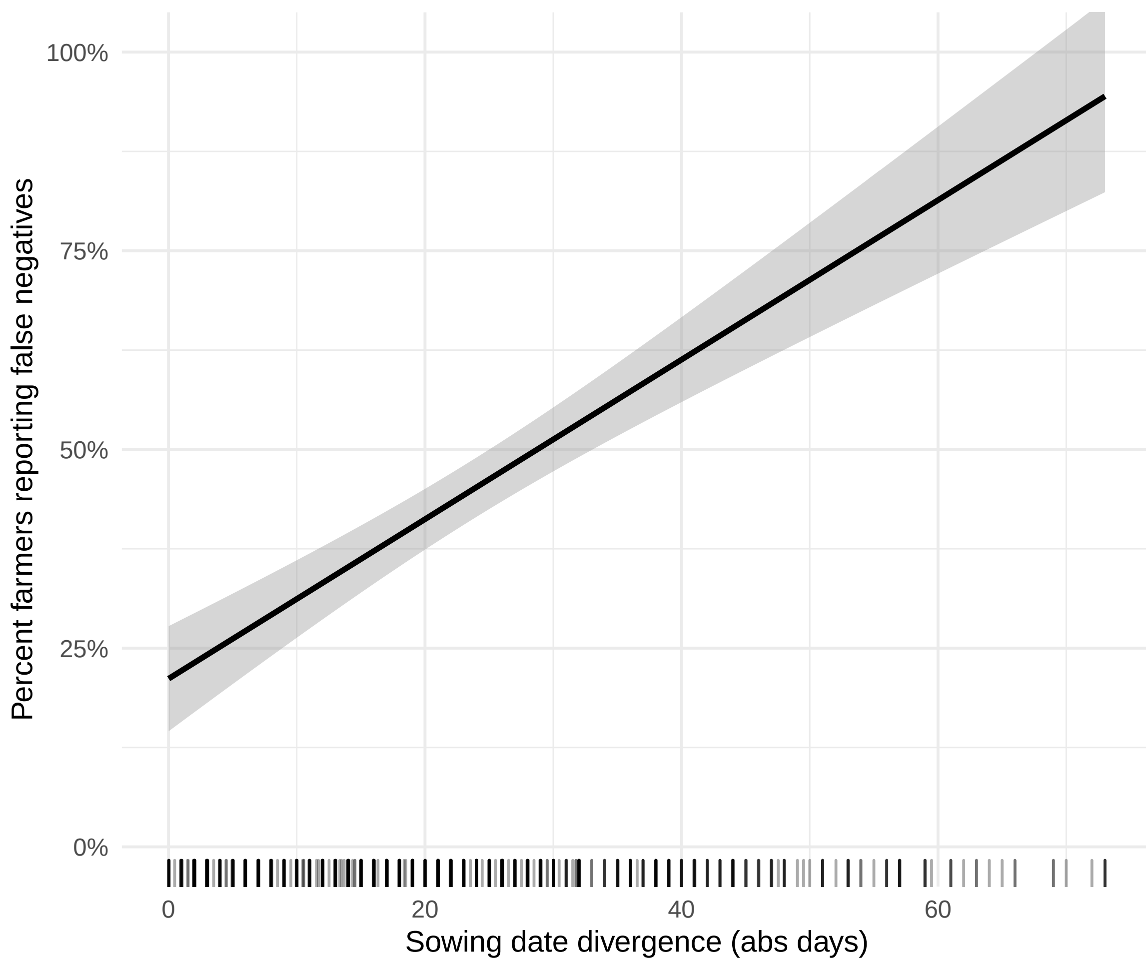

Figure 7: Percent of farmers reporting false negatives

Notes: Dashed lines show the empirical distribution of sowing date deviations. Reports of false negatives from farmers assigned to and reporting receipt of GEOPOTATO alerts. The line shows a linear best fit with a 95% confidence interval. The baseline incidence of false negatives is approximately 25%, which increases to 100% the further a farmer plants from their registered sowing date.

their registered date. The estimated effect of alerts on losses by the divergence between the farmers registered and actual sowing date is shown in figure 8. Accordingly, the second and third columns in table 6 show that losses are only lower for farmers that receive GEOPOTATO but do not report observing false negatives.

Table 6: Effect of GEOPOTATO Accuracy on Losses to Blight

	Dep. Var = Losses to blight (ordinal)		
	(1)	(2)	(3)
GEOPOTATO			
Assigned	-0.40^{**}		
	(0.16)		
GEOPOTATO × divergence	0.01^{**}		
	(0.00)		
Accurate signal		-0.46^{***}	-0.47^{***}
		(0.14)	(0.14)
Inaccurate signal		0.17	0.17
		(0.14)	(0.14)
Spillover alerts	0.09	0.09	0.09
	(0.12)	(0.11)	(0.12)
Fungicide (N sprays)	0.73^{***}	0.73^{***}	0.74^{***}
	(0.12)	(0.12)	(0.12)
Land (ln dec)	-0.15^{***}	-0.14^{***}	-0.14^{***}
	(0.05)	(0.05)	(0.05)
Accurate = Inaccurate Signal (p-value)		< 0.01	< 0.01
Upazila FE	Yes	Yes	Yes
Seasonal Trend	Yes	Yes	Yes
Observations	1972	1972	1970

Cluster robust standard errors at the village level (G = 407).
$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Farmers can adjust their investment in fertilizer for their crops during the growing season as they observe and evaluate the accuracy of the GEOPOTATO alerts. If the risk of blight limits investment, then only farmers who learn that they are receiving accurate alerts should invest more. Farmers apply fertilizer in four rounds: an initial preparation phase prior to planting, and then a second, third, and fourth application

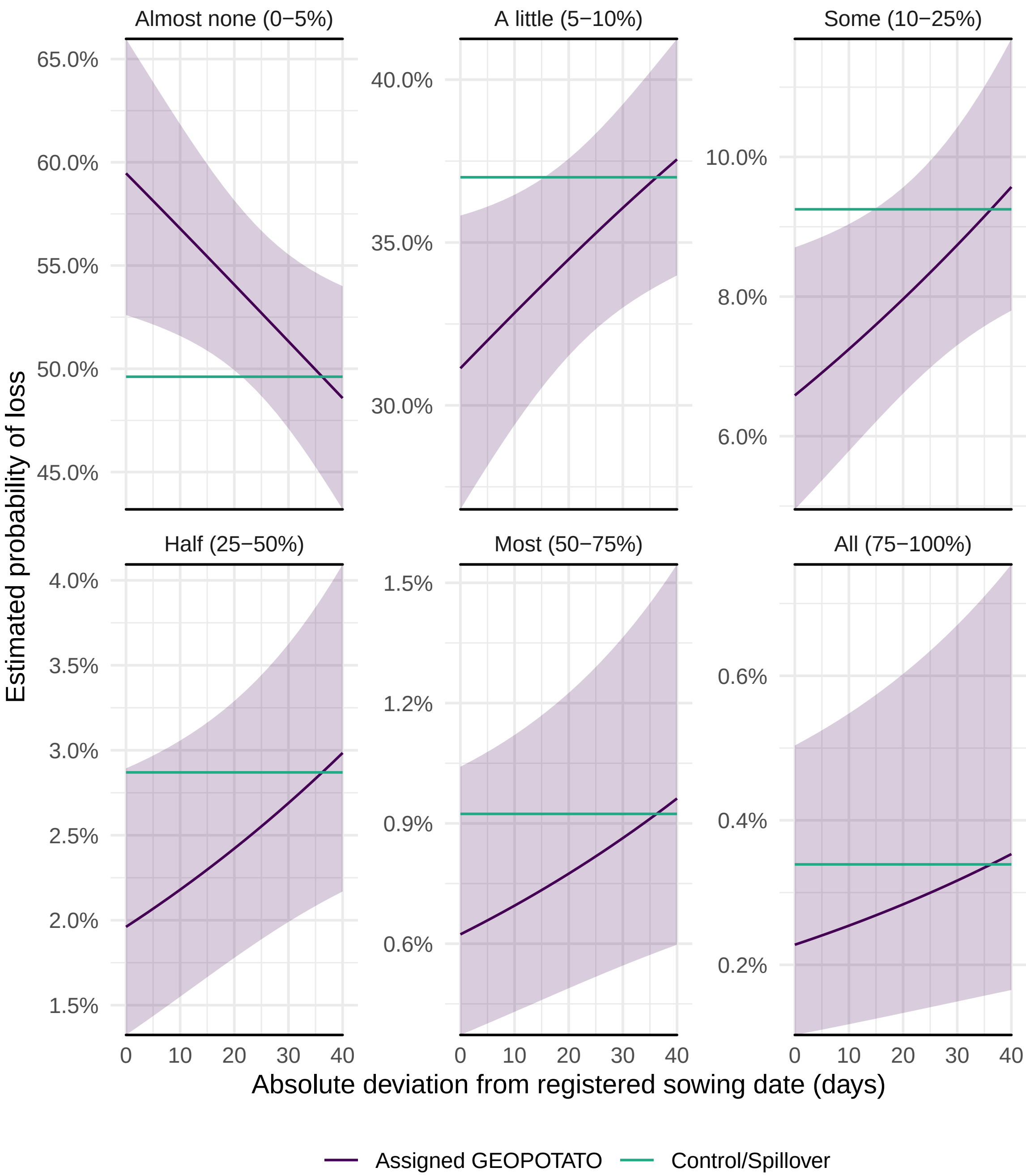

Figure 8: Effect of GEOPOTATO by deviation from reported sowing date

Notes: Estimated at the empirical means from model (1) in table 6. The average absolute deviation from the registered sowing among farmers assigned to receive GEOPOTATO was 23 days.

as the potatoes grow. Farmers may not significantly modify their investment in the initial rounds, but those who receive accurate alerts may increase their investment in the later rounds of fertilizer application.

Because the self-report of receiving alerts and observing false negatives may be endogenous to farmer skill and demographic characteristics, or their concern over blight, I instrument for a farmer receiving GEOPOTATO alerts and reporting a false negative by their assignment to receive alerts interacted with the divergence between their reported and registered sowing date in equation 3.

$$
\begin{aligned}
\text{false negative}_{ijt\nu} &= \eta_1 \left(\text{GEOPOTATO assigned}_i\right) + \eta_2 \left(\text{abs(days diverged)}_i\right) \\
&+ \eta_3 \left(\text{GEOPOTATO assigned}_i \times \text{abs(days diverged)}_i\right) \\
&+ \beta \mathbf{x}_i + \theta_\nu + \psi_t + \epsilon_i \\
\text{no false negative}_{ijt\nu} &= \eta_4 \left(\text{GEOPOTATO assigned}_i\right) + \eta_5 \left(\text{abs(days diverged)}_i\right) \\
&+ \eta_6 \left(\text{GEOPOTATO assigned} \times \text{abs(days diverged)}_i\right) \\
&+ \beta \mathbf{x}_i + \theta_\nu + \psi_t + \epsilon_i \\
y_{itj\nu} &= \widehat{\text{false negative}}_i + \widehat{\text{no false negative}}_i + \beta \mathbf{x}_i + \theta_\nu + \psi_t + \varepsilon_{ij\nu}
\end{aligned} \tag{3}
$$

Table 7 shows the effect of accurate versus inaccurate alerts on investment in fungicide and fertilizer. The naive OLS estimates and the instrumented parameters are presented together. In the naive specification, the effect of self-reported accurate and inaccurate signals—whether the farmer observed a false negative—are equivalent. Instrumenting for the accuracy of the signal produces a divergent estimate, where accurate signals induce greater investment, while inaccurate signals do not. The instrumented effect of receiving an accurate signal leads to an increase in expenditures on fungicide and fertilizer by approximately 22% and 18%, respectively, while the effect

Table 7: Effect of GEOPOTATO Accuracy on Input Usage

	Fungicide (tk)		Fungicide (N)		Fertilizer (tk)	
	OLS	IV	OLS	IV	OLS	IV
GEOPOTATO						
Accurate signal	0.11***	0.23***	0.05	0.16**	0.06*	0.14*
	(0.04)	(0.08)	(0.03)	(0.07)	(0.04)	(0.08)
Inaccurate signal	0.07**	−0.07	0.04	−0.04	0.10***	0.03
	(0.03)	(0.09)	(0.03)	(0.07)	(0.04)	(0.08)
Land (ln acres)	0.86***	0.85***	0.18***	0.17***	0.96***	0.96***
	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Female	−0.18	−0.15	0.09	0.12	0.08	0.10
	(0.15)	(0.15)	(0.12)	(0.12)	(0.16)	(0.16)
Experience (ln years)	0.02	0.02	−0.00	−0.00	0.01	0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
No schooling	−0.02	−0.02	0.01	0.01	−0.01	−0.01
	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)
Accurate=Inaccurate (p-val)	0.32	0.07	0.74	0.08	0.51	0.47
Upazila FE	Yes	Yes	Yes	Yes	Yes	Yes
Seasonal trend	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.71	0.71	0.14	0.13	0.78	0.78
Observations	1958	1958	1958	1958	1958	1958

Fertilizer and fungicide expenditures are transformed with the inverse hyperbolic sine.
Cluster robust standard errors at the village level (G = 407).
$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

of inaccurate signals is not statistically significant.

Because farmers apply fertilizer in a sequence of four distinct rounds, I can estimate the impact of an (instrumented) accurate signal on each round of investment. The results in table 8 show that farmers with accurate and inaccurate signals apply fertilizer in similar amounts as those in the spillover and control groups during the preparatory and initial rounds. As farmers learn about the accuracy of GEOPOTATO alerts over the course of the season, however, their behavior diverges. Farmers receiving accurate alerts invest significantly more in fertilizer, while those receiving inaccurate alerts reduce their investment.

Table 8: IV Estimates of GEOPOTATO Accuracy on Fertilizer Usage by Round

	Dep. Var = asinh(fertilizer taka)			
	Preparation	1st round	2nd round	3rd round
GEOPOTATO				
Accurate signal	0.17^{*}	-0.10	1.51^{***}	2.77^{***}
	(0.09)	(0.20)	(0.46)	(0.47)
Inaccurate signal	-0.01	0.40^{*}	-1.31^{**}	-2.52^{***}
	(0.09)	(0.20)	(0.58)	(0.49)
Land (ln acres)	0.97^{***}	0.97^{***}	1.55^{***}	0.95^{***}
	(0.02)	(0.04)	(0.07)	(0.09)
Female	0.05	0.43^{*}	0.91	0.83
	(0.14)	(0.23)	(0.71)	(1.01)
Experience (ln years)	0.02	0.10	-0.21^{*}	0.01
	(0.02)	(0.06)	(0.12)	(0.13)
No schooling	-0.05	-0.19	0.36	0.19
	(0.05)	(0.15)	(0.27)	(0.28)
Upazila FE	Yes	Yes	Yes	Yes
Time trend	Yes	Yes	Yes	Yes
Observations	1958	1958	1958	1958
Adj. R^2 (full)	0.72	0.28	0.18	0.03
Adj. R^2 (proj)	0.70	0.25	0.15	0.02

Fertilizer expenditures are transformed with the inverse hyperbolic sine.
Cluster robust standard errors at the village level (G = 407).
$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

The timing of the effect of GEOPOTATO on investment between the first and second rounds of fertilizer application suggests two explanations. First, farmers are delaying their investment until they can verify that GEOPOTATO alerts are accurate. This is why farmers' investment in the first two rounds of application is not statistically different from those in the control and spillover groups. Only once farmers realize their alerts are accurate later in the growing season, and therefore their risk of loss to blight is lower, do farmers invest more. The change in investment can also be explained by differential losses. Figure 8 shows that farmers with accurate signals realize significantly fewer losses to blight. So farmers with accurate signals would have more of their crop in which to invest. Differential losses contribute to the divergence in investment patterns between farmers receiving accurate and inaccurate signals, shown in figure 9, but the magnitude of change in investment is too large to be purely a function of the shift in likelihood of losses from "little" to "almost none."

6 Discussion

The premise of agricultural interventions that reduce farmer risk is that they will induce farmers to invest more heavily in their land and their crops. Unlocking this investment is considered key to productivity gains that can lead to the structural transformation of agrarian economies. Many interventions that aim to reduce risk, like index insurance, fail to find widespread adoption because farmers cannot easily evaluate the chance that they will receive a payout in the event of a loss. In my study of potato farmers in Bangladesh, I find a rational response to a simple, relatively cheap, and easily scalable technology: farmers invest more when it works, and less when it does not. GEOPOTATO alerts provide multiple opportunities for farmers to learn whether they are accurate.

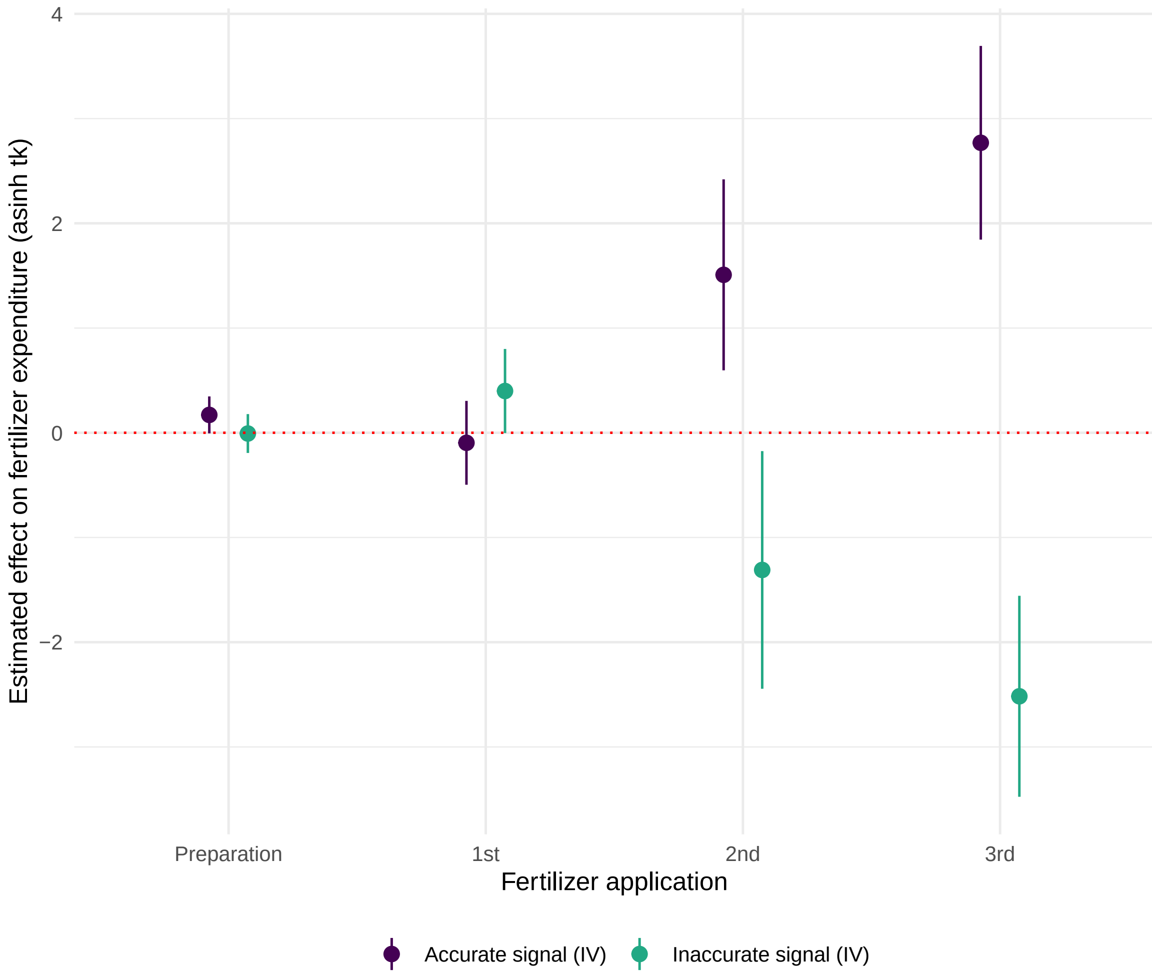

Figure 9: Effect of Signal Accuracy by Fertilizer Application by Round

Notes: Effect of receiving and accurate or inaccurate signal on fertilizer investment. Estimated coefficients are shown with 95% confidence intervals, taken from table 8, where receiving an accurate or inaccurate signal is instrumented with assignment to receive alerts and the farmer's deviation from the registered sowing date.

My study of the GEOPOTATO alert system highlights that the value of agricultural technology interventions are limited by whether or not farmers can learn about their properties. Even technologies that offer a significant benefit to the average farmer may go unused if a farmer cannot verify that it will help them.

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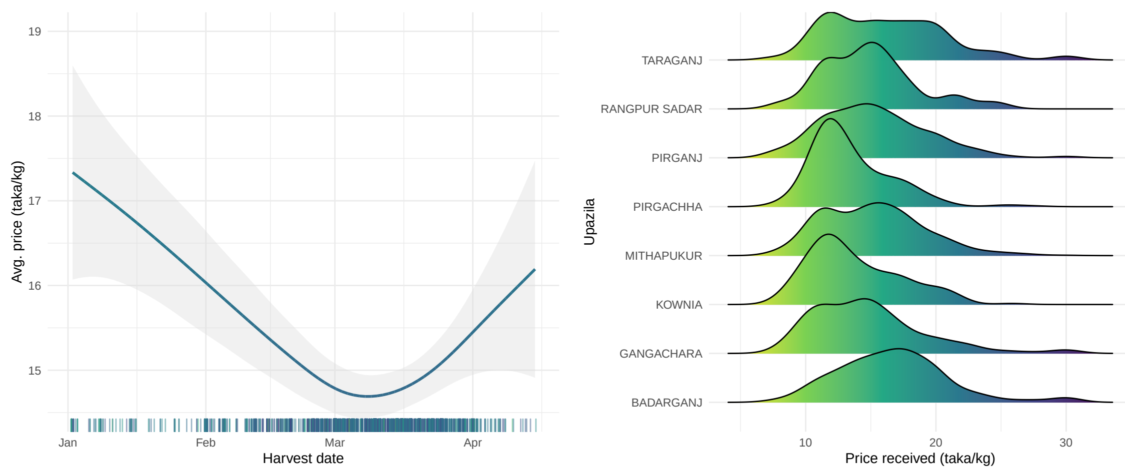
A Prices and Profits

A.1 Prices

Farmers received vastly different prices for their crop. Prices varied over the course of the season, falling by approximately 20% from their peak at the start of the year. Figure 10a shows the decline in price received during the season, as more farmers harvest their crop and supply increases. Even within each harvest week, prices are hugely dispersed. The primary reason for this volatility in prices is the lack of futures markets: farmers bring their potatoes to nearby towns where they receive spot prices from local middlemen. Farmers can only conduct limited negotiations in advance, and are often reluctant to store their crops.

Figure 10: Crop prices

(a) Average price received by harvest date (b) Distribution of price received by *upazila*



Notes: Average price received by harvest date is fit with a natural cubic spline and a 95% confidence interval. Prices are only recorded for farmers who reported selling their crop at the time of the survey. Some farmers chose to eat their crop, others to store to sell at a later date.

A.2 Profits

Profits are measured as the revenue the farmer received less the cost of fungicide, fertilizer, and labor. In the case where the farmer did not report a sale, the median price for their *upazila*-harvest week is used to compute the present economic value of their harvest. Larger farms had higher profits and losses. Figure 11 fits a cubic spline of the amount of land used and profits farmers who lost money and made money, respectively. The average profit was 63,000 taka, or $743 USD. However, splitting the sample between those who lost and made a profit, the average loss was 21,500 taka, or $255 USD, and the average gain was approximately 82,500 taka, or $975 USD.

Figure 11: Total Profits by Farm Size