

# No Small Potatoes: Agricultural Risk and Investment under Uncertainty\*

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## Abstract

A primary reason for poor agricultural yields in low-income countries is that farmers underinvest in their crops. Farmers face numerous sources of agricultural risk, and minimize their exposure by reducing their use of inputs, which also lowers their average productivity. I conduct a randomized control trial in Bangladesh to determine whether an alert system that enables farmers to take precautionary measures against crop disease would reduce risk and improve investment in inputs. The intervention reduces losses and increases investment, but only among farmers who can verify that they are receiving accurate alerts. These results demonstrate that interventions which allow people to learn about their efficacy are the ones most likely to be effective.

JEL: O13, C93, Q12, D83

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# 1 Introduction

Agrarian households in low-income countries produce significantly less with their land and labor than farmers in higher-income countries. This productivity gap has persisted over time. At the root of this gap lies agricultural risk: the chance that the rains necessary to sustain farmers' fields may come late, crop disease may strike, or infrastructural breakdowns may prevent bringing a harvest to market. In such an event a farmer loses not only their crop—already a significant loss—but also any additional investments. As a result, technologies and inputs that increase yields in expectation are not attractive if the farmer must also accept an enormous risk in purchasing them.

Farmers in high-income countries enjoy a wealth of credit and insurance products to compensate in the event of a loss; investment in productive technologies is high, so is productivity. Because the type of crop insurance sold to farmers in higher-income countries is unfeasible to implement for smallholder farmers living in remote areas, one solution has been index insurance. This insurance ties payouts to a remotely generated estimate of farmers' losses. For example, if a rainfall index falls below a threshold a farmer would receive compensation regardless if they realized losses. While experimental studies of index insurance have found it effective at increasing farmer investment (Karlan et al. 2014; Cole, Giné, and Vickery 2017), demand outside of experimental contexts for this type of insurance has been low (Mobarak and Rosenzweig 2012; Cole et al. 2013; Jensen, Barrett, and Mude 2016). Attempts to scale index insurance have painted a starker picture: farmers do not trust or want this type of insurance, even at subsidized prices (Ahmed, McIntosh, and Sarris 2020).

An important reason why farmers distrust index insurance is because of its basis risk: the likelihood that a farmer might pay for rainfall index insurance, suffer drought related losses, but not have those losses reflected in the index due to inaccuracies in

the remote sensing data (Mobarak and Rosenzweig 2013). In this sequence of events the farmer is strictly worse off than if they had not bought insurance at all. It is important to note that basis risk is not entirely a technical limitation of index insurance: demand is low because there is no easy way for farmers to learn about their specific basis risk. Insurance payouts to farmers occur at most once a season, and with fields geographically dispersed weather and losses can vary significantly across fields belonging to farmers within the same village. Farmers can learn from their neighbors' experience with index insurance, but this process is slow and does not produce a lasting increase in demand (Cole et al. 2013). By the time a farmer discovers that they are not covered by index insurance they will have already lost their crops and any additional investments. Essentially, to make use of index insurance farmers would have to incur significant risk in order to learn about their basis risk.

An ideal risk-reduction technology for smallholder farmers is one that can be deployed with low administrative costs like index insurance, but admits opportunities for farmers to learn about the level of risk reduction it offers. Instead of indemnifying a farmer after a loss, there is the possibility of offering farmers technology to minimize the likelihood of a loss occurring. There are many actions that farmers can take to minimize the likelihood of a significant loss occurring, such as spraying their crops to prevent disease and pests. What often constrains farmers is uncertainty of how to best allocate their highly constrained budget for combating these risks, and then how best to time their efforts.

In this paper I show how a crop disease alert system allows farmers to mitigate their own risk by optimizing when they spray fungicide. I conduct a randomized control trial in northwestern Bangladesh with potato farmers working to combat late fungal blight, a disease that poses a significant risk to their crops. I find that this system is effective in reducing losses, and leads to a “crowd-in” effect, where farmers spend

more on agricultural inputs. More importantly, I find that as farmers learn about the accuracy of the alerts, their behavior diverges sharply. Farmers with accurate alerts increase their investment in their crops, while farmers with inaccurate alerts reduce their investment. The risk reduction is only effective at increasing investment because farmers can verify during the course of the season whether it works.

## 2 Context

The district of Rangpur in northwestern Bangladesh is rural, agrarian, and poor. Small-holder farmers 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 *Phytophthora infestans*, known as late fungal blight. Blight is caused by a pathogen that first emerged in the 1840s, and attracted global infamy with the devastation of crops in Europe leading to the Irish potato famine. Blight is regarded as one of the most dangerous plant diseases, that continues to exact enormous losses on farmers worldwide and attracts an enormous amount of research into its lifecycle, mechanism of action, and methods of prevention (Haverkort et al. 2008; Vleeshouwers et al. 2011; Fry et al. 2015; Kamoun et al. 2015).

Blight is prevalent wherever potatoes are grown, appearing repeatedly during 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 blight is simple: an application of a prophylactic fungicide can

prevent infection for a period of three to five days if administered prior to blight emerging. If a farmer's application of fungicide correctly anticipates blight then their losses can go to zero. However, average losses of potatoes in Bangladesh are high, estimated at between 25 and 57% of the crop each year.<sup>1</sup> 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). Farmers in Bangladesh face a difficult decision in choosing how to contain blight. If farmers spray unnecessarily, when the risk of blight infection is low, they pay for the fungicide but receive no benefit. If farmers do not spray when the risk of infection is high, then an uncontrolled outbreak of blight can leave them ruined. Blight imposes both direct and indirect costs on farmers: first, in the immediate yield losses to the disease and the financial deprivation that ensues if farmers fail to spray fungicide when necessary. A ruined harvest is not merely lost income, but also lost investments in seed, fertilizer, and labor. The second cost is by limiting investment in their crops, as the possibility of losing a significant fraction of their harvest discourages investment in any additional inputs.

### 3 Intervention

The risk of potato blight disease can be predicted at a high temporal and spatial resolution, and a number of systems have been set up in the United States and Europe to provide alerts to farmers to spray their fields when the risk of blight in their area is estimated to be high.<sup>2</sup> GEOPOTATO is a similarly designed service that was created by Wageningen University & Research. GEOPOTATO integrates local weather station

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1. Rahman et al. 2008; Hossain et al. 2010.

2. See Akkerweb in the Netherlands, Blightwatch in the United Kingdom, and USA Blight in the United States.

data with satellite imagery and a crop growth model to forecast susceptibility to blight on an *upazila* and planting-cohort basis.

The GEOPOTATO system is calibrated using two parallel models: one tracking the growth of the potato crop and the other tracking the lifecycle of blight. The potato growth model is calibrated using data on local potato varieties and sowing dates, and is updated throughout the season using satellite data. The blight model takes local weather station data as an input to predict the likelihood of a blight outbreak. It is at the intersection of these models, a blight outbreak is predicted to be concurrent with a crop of potatoes that are at a susceptible point in their growth cycle, that GEOPOTATO triggers an alert.

When the GEOPOTATO system detects an elevated risk of blight, it sends an SMS and voice message in the local dialect to the farmer, 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. Previously, farmers have lacked information about when and when not to spray. Even experienced farmers who are familiar with the weather conditions conducive to blight cannot directly observe the presence of the fungal spores, or how small changes in weather patterns affect the risk their crops face based on their precise stage of growth. GEOPOTATO alerts remove the uncertainty and guesswork over the daily risk presented by blight. The risk of catastrophic crop loss effectively vanishes when the farmer acts upon the alert.

## 4 Agricultural Production and Risk

A risk averse potato farmer has CRRA preferences over the profits they generate from growing and selling their crops. An increasing amount of crops can be grown on the the land the farmer owns by investing more in inputs, primarily fertilizer. A farmer

can lose some of their production to blight disease. When blight pressure is high, the farmer loses more of their crops; when it is scarce, the farmer loses less. However, the farmer can use fungicide to combat blight to minimize their losses to the disease.

Let a farmer's yield be given by a Cobb-Douglas production function  $f(I, L)$ , which is determined by investment in inputs and land,  $I$  and  $L$ , respectively. Blight is realized on the interval  $\epsilon \in [0, 1]$ , where 0 indicates no blight, and 1 indicates constant pressure from blight disease. The farmer can purchase an equivalent measure of fungicide,  $\gamma \in [0, 1]$ . The farmer's losses to blight are defined by the metric  $d(\gamma, \epsilon) \rightarrow [0, 1]$  that maps the farmer's use of fungicide and the level of blight onto production. When the farmer uses sufficient fungicide,  $\gamma \geq \epsilon$  their losses go to zero, but when they use insufficient fungicide,  $\gamma < \epsilon$  their losses are increasing in the distance between the realization of blight and their use of fungicide.

$$d(\gamma, \epsilon) = \begin{cases} \gamma \geq \epsilon & 0 \\ \gamma < \epsilon & d(\gamma, \epsilon) \end{cases} \quad (1)$$

The farmer's production is then defined:

$$y = f(I, L) (1 - d(\gamma, \epsilon)) : f = I^\theta L^{1-\theta}; \theta \in (0, 1) \quad (2)$$

And profits are defined:

$$\pi = p_y y - p_I I - p_\gamma \gamma \quad (3)$$

Blight is realized each season as a continuous random variable. Without loss of generality, allow for blight to be distributed  $\text{Beta}(\alpha_0, \beta_0)$ , where a realization of zero indicates no risk of blight, and one indicates constant blight pressure. The farmer has prior beliefs over the distribution of blight,  $\hat{\epsilon} \sim (\alpha_i, \beta_i)$ . Allow for the farmer's

prior over blight to be located at the expected value of the true distribution, so that  $E[\hat{\epsilon}] = E[\epsilon]$ , so that the farmer’s expectation over the threat of blight is accurate, but their prior may be more or less diffuse. Allow for a farmer who elects to grow potatoes to choose a level of investment in fertilizer and expenditure on fungicide that maximizes their expected utility, given their prior over blight  $\hat{\epsilon}_i$ :

$$\max_{I^*, \gamma^*} u_i(\pi \mid \hat{\epsilon}) = p_y f(I^*, L) (1 - d(\gamma^*, \hat{\epsilon}_i)) - p_I I^* - p_\gamma \gamma^* \quad (4)$$

At the end of the season the farmer may have over-sprayed fungicide, where the realization of blight was less than they had understood, so that  $\epsilon < \gamma$  and the farmer would have enjoyed higher profits by purchasing less fungicide. The farmer may also have under-sprayed fungicide, where  $\epsilon > \gamma$ , so that had the farmer purchased and sprayed more fungicide, their profits—and utility—would have increased.

## 5 Farm & Farmer Characteristics and RCT Design

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 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. From this population I took a random sample of 410 villages, assigning villages to treatment, partial treatment (spillover), or control status, stratifying assignment at the *upazila* and union level. Table 1 shows the number of villages and farmers by treatment assignment. In treatment villages registered farmers received GEOPOTATO alerts, and in control villages registered farmers did not receive GEOPOTATO alerts. In spillover villages, approximately 50% of farmers who registered for GEOPOTATO were randomly selected to receive messages; the other



half did not receive GEOPOTATO alerts. Farmers are the relevant economic actors, sorted into one of three categories: those receiving alerts, those not receiving alerts but whose neighbors are, and those not receiving alerts in villages where no-one receives alerts. Data was gathered in two survey waves, an initial baseline after registration to collect participating farmer demographic characteristics, and an endline following harvest to record yields, losses, revenue, and expenses.

Table 1: Number of farmers by treatment assignment

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

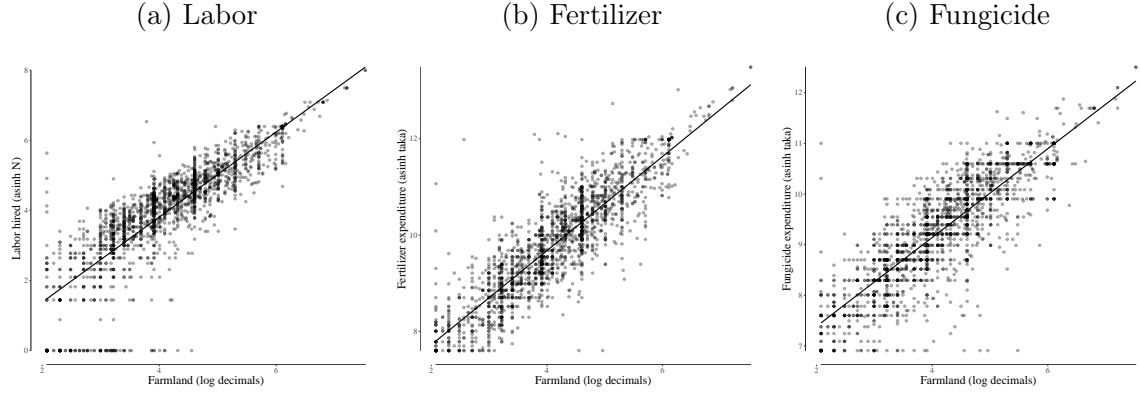
The majority of farmers registering for GEOPOTATO alerts are commercially oriented smallholders, devoting an average of approximately one acre (100 decimals) of land to growing potatoes between their rice harvests.<sup>3</sup> Potatoes are a simple if risky crop, requiring little more than labor, fertilizer, and fungicide to successfully cultivate. Almost all farmers use fertilizer, which they apply sequentially throughout the season. The vast majority of farmers hire labor, an average of 50 people during the season to help with land preparation, intraseasonal activities. Fungicide is also used extensively, with input amounts increasing linearly in farmland size. Farmers grow potatoes with the aim of selling them at the end of the season, but some consume their produce and others will keep their harvest in cold storage until later in the year in the hope of getting a higher price. To accommodate the small number of farmers reporting zero for the number of hired labor, and fertilizer and fungicide expenditure, the inverse hyperbolic sine transformation is used instead of a logarithmic transformation.

The average farmer in the sample is nearly forty, has at least attended primary school, and has grown potatoes for over a decade. Farmer demographics are presented

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3. Lowder, Skoet, and Raney (2016) use a cutoff of 2 hectares, or approximately 5 acres, for smallholder farms, which operate approximately 40% of the agricultural area in low-income countries.

Figure 1: Input Usage over Farmland



*Note:* 1 acre of land  $\approx$  100 decimals = 4.6 log decimals. 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 linearly in land size.

in table 2. There are no statistically significant differences in observable characteristics between farmers assigned to directly receive GEOPOTATO alerts, as given in the third column of the table.

## 5.1 Treatment

The GEOPOTATO system sends out text and voice alerts when it predicts a high risk of blight. The alerts advise farmers to spray spray fungicide within one to three days to prevent blight infection. Farmers in the treatment group were sent between one to ten alerts, each intended to correspond to a separate fungicide spray event, over the course of the season. Alerts were calibrated by farmer planting week (cohort) and *upazila*. Following the harvest, farmers assigned 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

Table 2: Treatment Arms Balance Table

Characteristic	Control	Spillover	Direct	p-value
Potato cropland (acres)	1.06 (1.61)	1.08 (1.34)	1.02 (1.12)	0.7
Age	39 (10)	39 (10)	38 (10)	0.5
Years farmed potatoes	12 (7)	12 (7)	12 (8)	0.4
Household members (N)	7.4 (3.7)	7.5 (3.7)	7.3 (3.7)	0.8
Female	0.6%	1.0%	0.8%	0.7
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%	
N	848	419	710	

<sup>1</sup> Sample averages, standard deviation in parentheses

<sup>2</sup> p-value calculated with one-way ANOVA.

the farmer.

Farmers who reported receipt were also asked if they had complied with the alerts, whether they had sprayed fungicide within the recommended three day window. A further 14% of farmers reported either not spraying after alerts, or spraying after the recommended timeframe. Non-compliance in a randomized control trial typically means that a participant does not take the induced action: they do not take out a micro-loan, or they do not use fertilizer or a high yield varietal seed. However, farmers reporting non-compliance with GEOPOTATO alerts use fungicide. If the benefit of the alerts is in allowing farmers to better time when they spray fungicide, then compliance is crucial. Or 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.

## 5.2 Spillovers

Farmers in spillover villages who were not targeted to directly receive alerts may still have benefited from the alerts. Farmers may have alerted others when they received a GEOPOTATO SMS. Farmers may have otherwise copied the spraying patterns of their neighbors. However, given that the alerts were calibrated to each farmers' sowing date, these alerts would not necessarily be relevant to a neighbor who had planted their crops at a different time. Finally, blight is a communicable disease, so that a subset of better protected fields could reduce the overall spread of blight within a village.

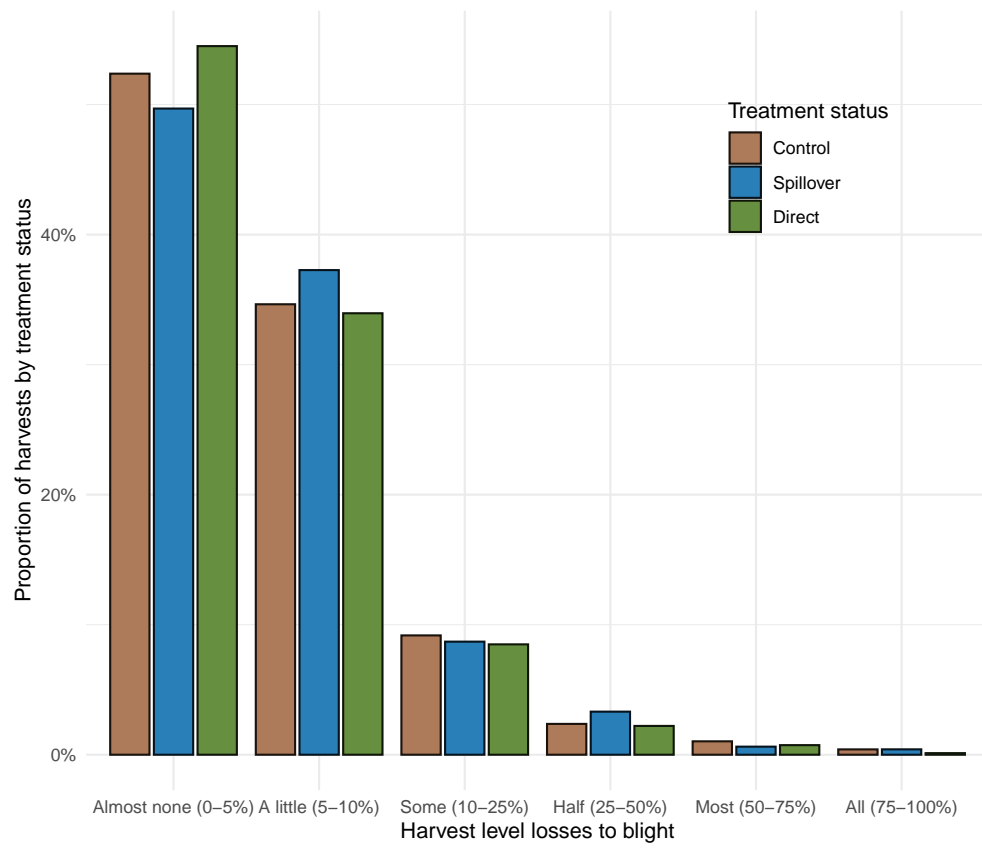
## 5.3 Losses to blight

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%. I show the comparison in realized losses by treatment status in figure 2. Farmers assigned to receive GEOPOTATO alerts are more likely to report almost no losses, and less likely to report higher losses.

## 6 Outcomes

Outcomes of interest for farmer  $i$  in village  $j$  located within *upazila*  $\nu$  include the amount spent on inputs; the percent of their harvest lost to blight; the amount of potatoes harvested; and the resulting revenue and profit. In the empirical regression specification, equation 5, the effect of GEOPOTATO alerts is given by  $\tau$ , and a set of farmer-level controls can be included in  $\mathbf{x}$ . I include a seasonal trend  $\psi$  to account for the change in growing conditions over time, and *upazila* fixed effects,  $\theta$  to control for unobserved variation at the sub-district level.

Figure 2: Distribution of Reported Harvest Losses to Blight



$$y_{ij\nu} = \alpha_0 + \tau (\text{treatment}_i) + \beta \mathbf{x}_{ij} + \theta_\nu + \psi_t + \varepsilon_{ij\nu} \quad (5)$$

## 6.1 Inputs and Investment

Potatoes farmers optimize across a small set of inputs, including the number of people they hire to work on the farm, and the total expenditures on fertilizer and fungicide. The intent-to-treat effect of assignment to treatment, spillover, and control groups on input use is estimated with a linear model in table 3. Labor use is unaffected, while fertilizer expenditures increase by approximately 8% for farmers assigned to directly receive GEOPOTATO alerts. The mechanism of action is that a reduction in risk increases the expected return to investment in fertilizer, a yield-increasing technology. Farmers, now more confident that they will not lose their crop to disease, invest more.

The effect of the GEOPOTATO alerts on fungicide usage is theoretically ambiguous. The alerts could reduce expenditures for farmers who faced less-than-expected blight risk; they could increase expenditures for farmers facing higher-than-expected blight pressure; and they might have no effect on expenditure, simply help farmers spray at more appropriate times. The GEOPOTATO estimates of the blight risk faced by farmers during the 2019-2020 season are displayed in figure 3, which shows the number of alerts generated for farmers, regardless of their assignment to treatment. Zero to one alerts suggests minimal risk from blight over that crop cycle, where twelve alerts is the maximum the system could send out, indicating a high risk of infection throughout the crop cycle. Most farmers planted their crops over a three week period 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.

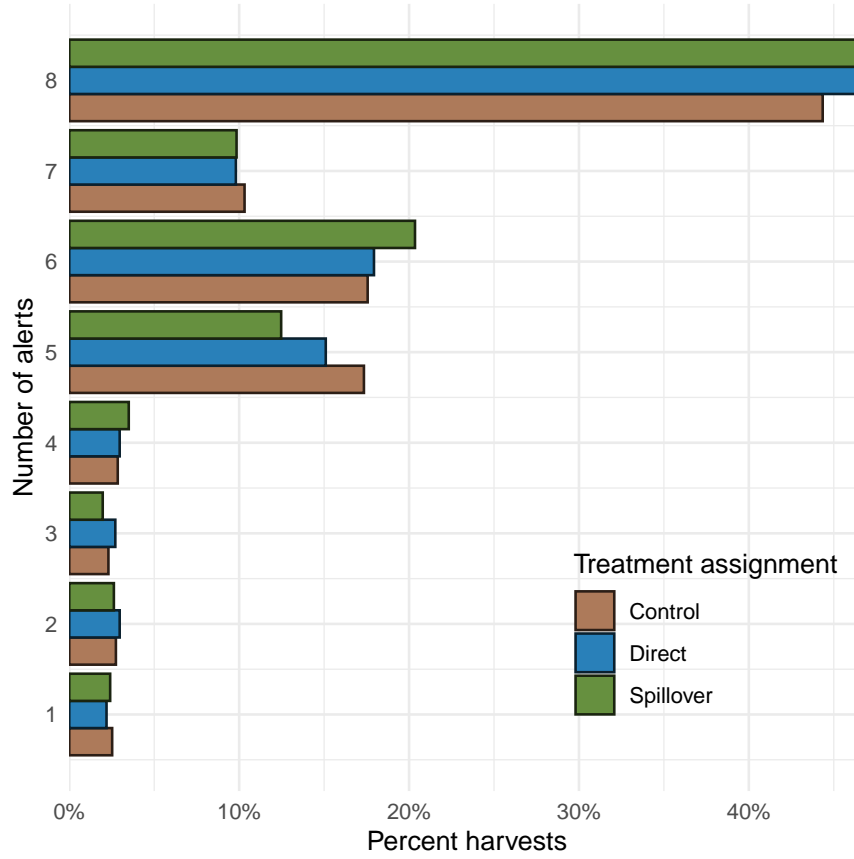
The results in table 3 show that both expenditures and the number of fungicide

Table 3: Intent to treat effect of alerts on fungicide and fertilizer

	Fungicide (asinh taka)		Fertilizer (asinh taka)		Labor (asinh N)	
	(1)	(2)	(3)	(4)	(5)	(6)
GEOPOTATO						
Assigned	0.08*** (0.03)	0.08*** (0.03)	0.08*** (0.03)	0.08** (0.03)	-0.01 (0.04)	-0.00 (0.04)
Spillover	-0.00 (0.04)	0.01 (0.04)	0.01 (0.03)	0.00 (0.03)	0.04 (0.05)	0.06 (0.05)
Land (ln acres)	0.86*** (0.01)	0.86*** (0.01)	0.96*** (0.01)	0.96*** (0.01)	1.22*** (0.02)	1.21*** (0.02)
Female		-0.19 (0.15)		0.09 (0.16)		-0.44* (0.22)
Experience (ln years)		0.02 (0.02)		0.02 (0.02)		0.06** (0.03)
Education						
No formal education		-0.06 (0.05)		-0.03 (0.04)		-0.15* (0.09)
Primary school		-0.05 (0.04)		-0.05 (0.04)		-0.09 (0.06)
Secondary school		-0.03 (0.03)		-0.01 (0.03)		-0.01 (0.05)
Upazila FE	Yes	Yes	Yes	Yes	Yes	Yes
Seasonal trend	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1977	1958	1977	1958	1977	1958
Adj. R <sup>2</sup>	0.71	0.71	0.78	0.78	0.69	0.69
Adj. R <sup>2</sup> (proj)	0.69	0.69	0.76	0.76	0.68	0.68

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

Figure 3: Number of alerts by plot and treatment assignment



sprays increased by approximately 8% for farmers directly receiving alerts. The increase in both may represent a higher-than-expected risk of blight during the 2019-2020 season, a use of more expensive fungicides due to belief in their increased efficacy, or both.

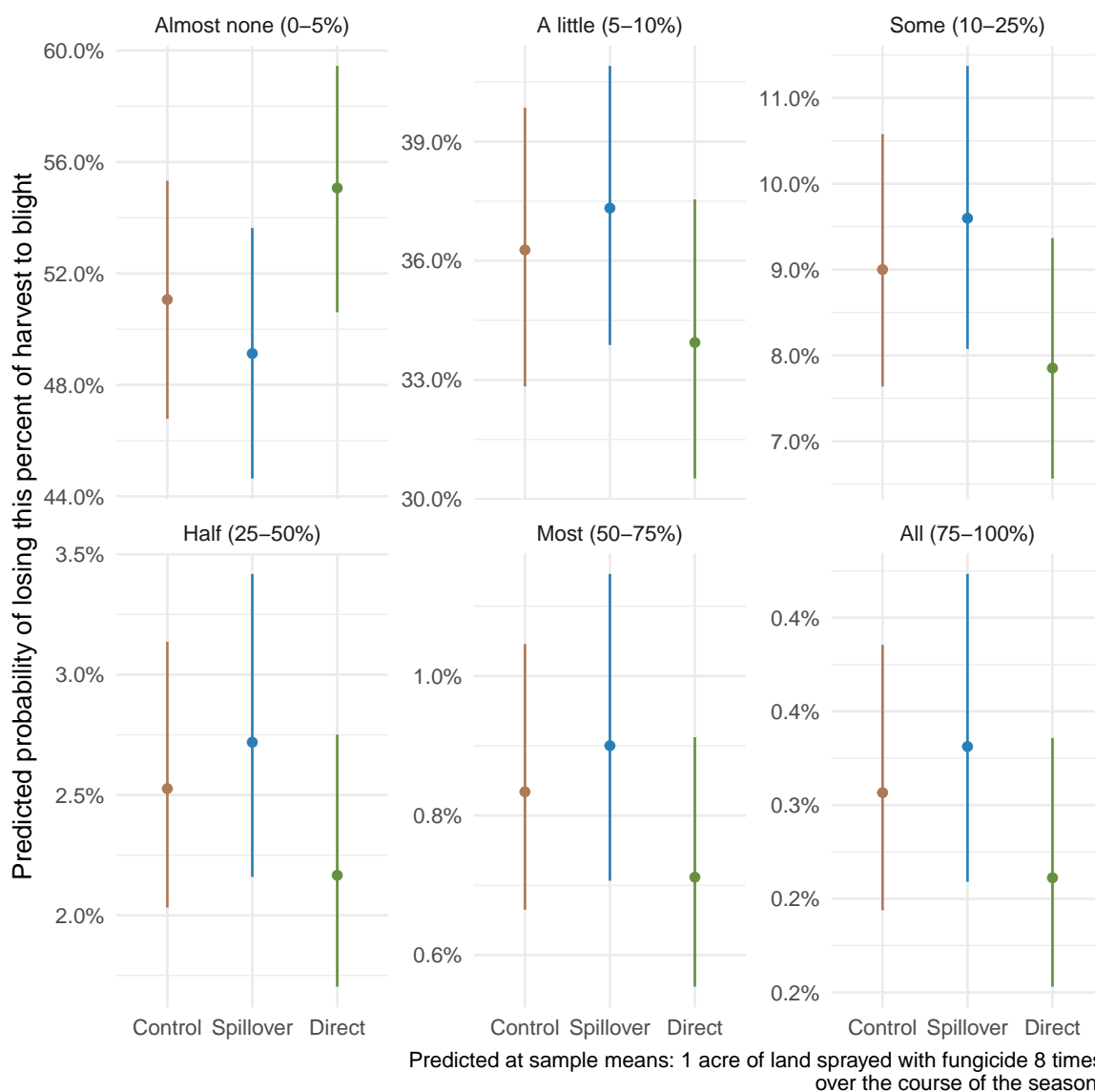
## 6.2 Reduced Losses to Blight

GEOPOTATO alerts may have allowed farmers to better time the application to precede periods of high blight risk. Because farmers report harvest-level losses to blight on an increasing scale, I estimate the intent to treat effect of GEOPOTATO alerts with an ordinal logit. The results in table 4 show that the likelihood of reporting higher levels



of crop loss to blight is significantly lower for farmers assigned alerts. Figure 4 shows the estimated marginal treatment effect of GEOPOTATO from model (2) in table 4 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 moves probability mass from higher loss categories to “almost none.”

Figure 4: Estimated probability of losses to blight by treatment status



Despite the potential for neighboring farmers to benefit from information spillovers,

Table 4: Intent to treat effect of GEOPOTATO on self-reported losses to blight

	Dep. Var = Losses to blight (ordinal scale)		
	(1)	(2)	(3)
GEOPOTATO			
Assigned	−0.16 (0.10)	−0.16** (0.06)	−0.17*** (0.07)
Spillover	0.07 (0.12)	0.08 (0.05)	0.05 (0.05)
Fungicide (arcsinh n sprays)	0.58*** (0.12)	0.65*** (0.13)	0.65*** (0.13)
Land (ln dec)	−0.09** (0.05)	−0.08 (0.06)	−0.08 (0.05)
Female			0.45*** (0.00)
Experience (ln years)			−0.16** (0.07)
Education			
No formal education			−0.04 (0.07)
Primary school			−0.23*** (0.09)
Secondary school			−0.25*** (0.08)
N hot days (max temp > 30C)		0.00 (0.00)	0.00 (0.00)
Total rainfall (mm)		−0.00 (0.00)	−0.00 (0.00)
Upazila FE	Yes	Yes	Yes
Observations	2266	2266	2245

Cluster robust standard errors at the village level ( $G = 407$ ).

\*\*\* $p < 0.01$ ; \*\* $p < 0.05$ ; \* $p < 0.1$ .

there do not appear to be any robust secondary 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.

### **6.3 Yields**

GEOPOTATO alerts increase investment in fertilizer and reduce losses; they are likely to increase yields. The treatment effect of GEOPOTATO can be parsed as the intent to treat, the assignment to receive direct alerts, or further conditioned on self-reported receipt, and then compliance. Because reported receipt and compliance may be endogenous to farmer characteristics, I instrument for this using the initial assignment to receive alerts. The 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, although not by a statistically significant degree. Instrumenting for compliance and receipt increase the standard errors, but is with the OLS estimate.

## **7 Basis Risk of GEOPOTATO and Rational Compliance**

As in many interventions on agricultural risk, the goals of GEOPOTATO are two-fold: first, to reduce farmer losses, and second, to increase investment. Achieving these goals requires farmers to comply with the intervention. Compliance however, is poorly understood. In Emerick et al. (2016) farmers either adopt the new technology (drought resistant seeds) or they do not, but the study cannot tell us about what unobservable

Table 5: Effect of GEOPOTATO on Yields (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***	0.07***	
			(0.03)	(0.03)	
Complied (IV)					0.07*
					(0.04)
Land (ln dec)	1.10***	1.10***	1.10***	1.10***	1.10***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Female				0.12	
				(0.11)	
Age (ln years)				−0.16*	
				(0.08)	
Experience (ln years)				0.07**	
				(0.04)	
Education					
No formal education				−0.02	
				(0.05)	
Primary school				0.03	
				(0.04)	
Secondary school				−0.01	
				(0.04)	
Upazila FE	Yes	Yes	Yes	Yes	Yes
Seasonal trend	Yes	Yes	Yes	Yes	Yes
Observations	1977	1977	1977	1958	1977
Adj. R <sup>2</sup> (full)	0.76	0.76	0.76	0.78	0.76
Adj. R <sup>2</sup> (proj)	0.73	0.73	0.73	0.75	0.73

Output measured in arcsinh kilograms.

Standard errors clustered at the village level ( $G = 407$ ).\*\*\* $p < 0.01$ ; \*\* $p < 0.05$ ; \* $p < 0.1$ .

characteristics make some farmers were more willing to comply with the intervention. Similarly, many interventions leveraging remote alerts can show an intent to treat effect on losses and yields, but what constitutes compliance with those interventions is unclear (Fabregas, Kremer, and Schilbach 2019).

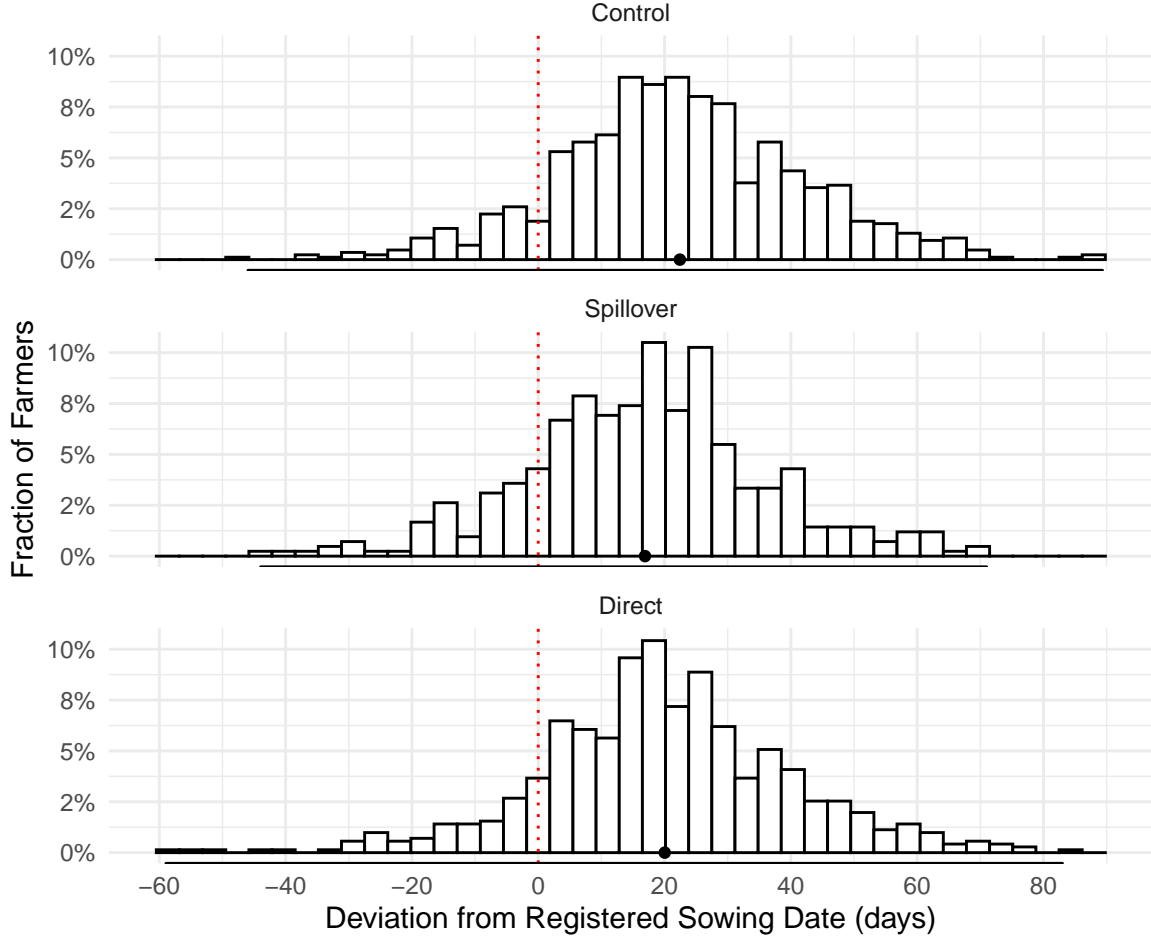
The response of farmers to GEOPOTATO alerts provides an opportunity to actually observe compliance and therefore the mechanism of action of the intervention—how the alerts led to increased investment. This allows me to answer questions such as whether the intervention might be effective in a different year, or a non-experimental context.

Before GEOPOTATO farmers were already using fungicide, and in significant quantities. GEOPOTATO alerts are designed to mitigate risk by improving on farmers’ baseline understanding of when to spray fungicide to combat blight. Yet the basis risk, the disparity between what the system predicts and what the farmer experiences, remains. If the alerts are accurate, they offer a way for farmers to reduce a major agricultural risk to zero. GEOPOTATO alerts however, may 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 blight in their fields and the lack of a corresponding alert. In this way farmers can resolve their basis risk with GEOPOTATO during a season, something impossible to do with index insurance.

Before the start of the season farmers registered a sowing date with the GEOPOTATO system. However, many farmers did not plant on the date they registered. Figure 5 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. Because GEOPOTATO alerts are

calibrated to the sowing week, small deviations are relatively unimportant. However, the alerts would be increasingly mistimed and only fractionally appropriate for farmers whose sowing date differed significantly from the one they registered.

Figure 5: Deviation in Actual vs. Registered Sowing Dates for Farmers Assigned to Receive GEOPOTATO alerts



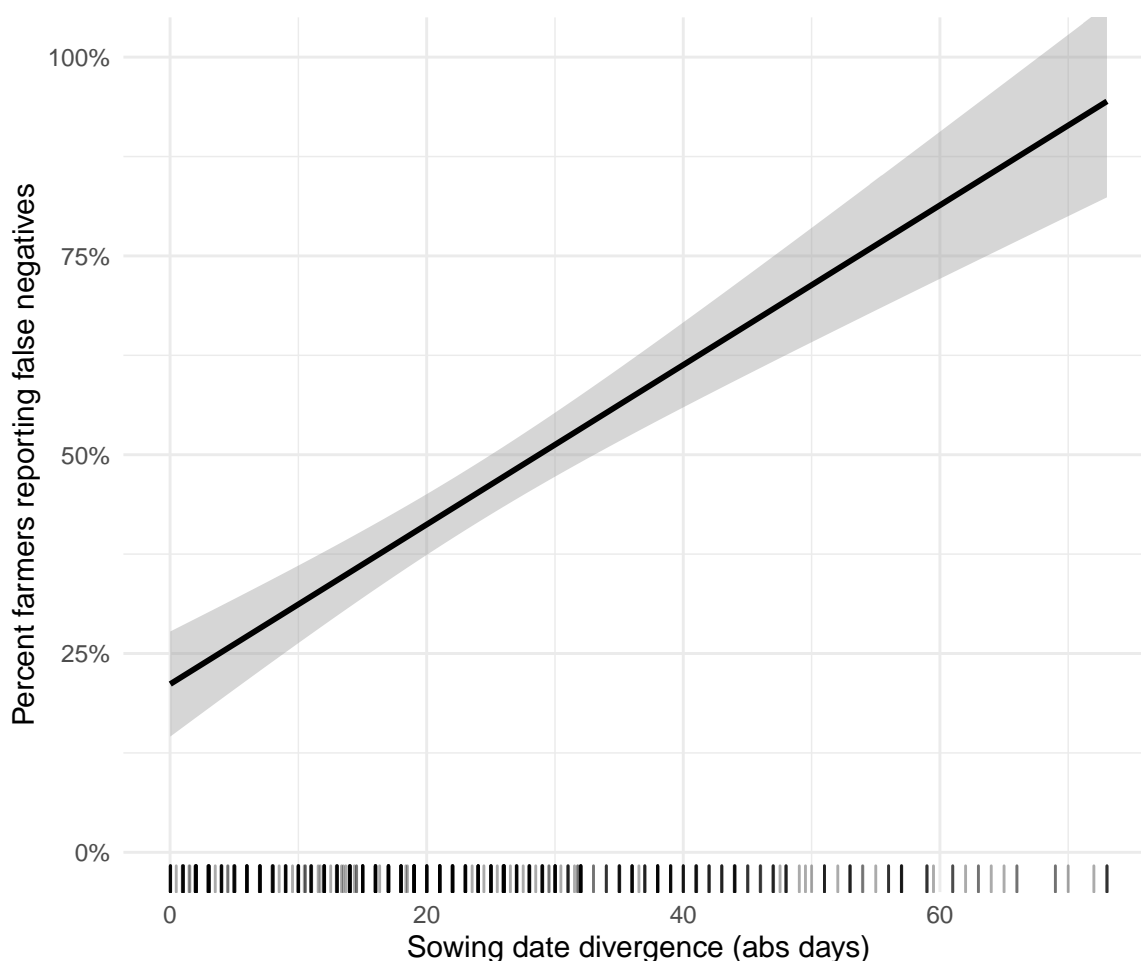
*Note:* Distribution of the deviation from registered sowing date and the sowing date calculated at the endline. Points represent the average deviation by treatment status.

After the harvest, farmers reported whether they had observed false negatives, where they had found blight on their fields and not received an alert.<sup>4</sup> Unsurprisingly,

4. Specifically, farmers were asked “This season did you find blight on your potatoes when you hadn’t received a GEOPOTATO alert?”

the likelihood of a farmer reporting a false negative increases with the absolute deviation from their registered sowing date. Figure 6 shows the increasingly likelihood of a farmer who reported receiving alerts also reporting a false negative. 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.

Figure 6: Fraction of farmers reporting false negatives



*Note:* Reports of false negatives from farmers receiving GEOPOTATO alerts. The line is a linear best fit with a 95% confidence interval.

GEOPOTATO alerts reduce losses to blight, but only for farmers receiving accurate alerts. Table 6 shows the effect of the accurate signals on realized harvest-level

losses. Assignment to receive GEOPOTATO alerts significantly reduces losses, but becomes increasingly less effective the further the farmer sows from their registered date. Accordingly, losses are only lower for farmers that receive GEOPOTATO but do not report observing false negatives. The estimated effect of alerts by the divergence between the farmers registered and actual sowing date are shown in figure 7.

Table 6: Effect of GEOPOTATO Accuracy on Losses to Blight

	Dep. Var = Losses to blight (ordinal)		
	(1)	(2)	(3)
GEOPOTATO			
Assigned	−0.50*** (0.00)		
Accurate signal		−0.49*** (0.00)	−0.50*** (0.00)
Inaccurate signal		0.16*** (0.00)	0.16*** (0.00)
GEOPOTATO × divergence	0.01*** (0.00)		
Fungicide (arcsinh n sprays)	0.68*** (0.01)	0.58*** (0.01)	0.66*** (0.01)
Land (ln dec)	−0.08*** (0.02)	−0.09*** (0.02)	−0.07*** (0.02)
N hot days (max temp > 30C)	0.00 (0.00)		0.00 (0.00)
Total rainfall (mm)	−0.00*** (0.00)		−0.00*** (0.00)
Upazila FE	Yes	Yes	Yes
Seasonal Trend	Yes	Yes	Yes
Observations	2266	2266	2266

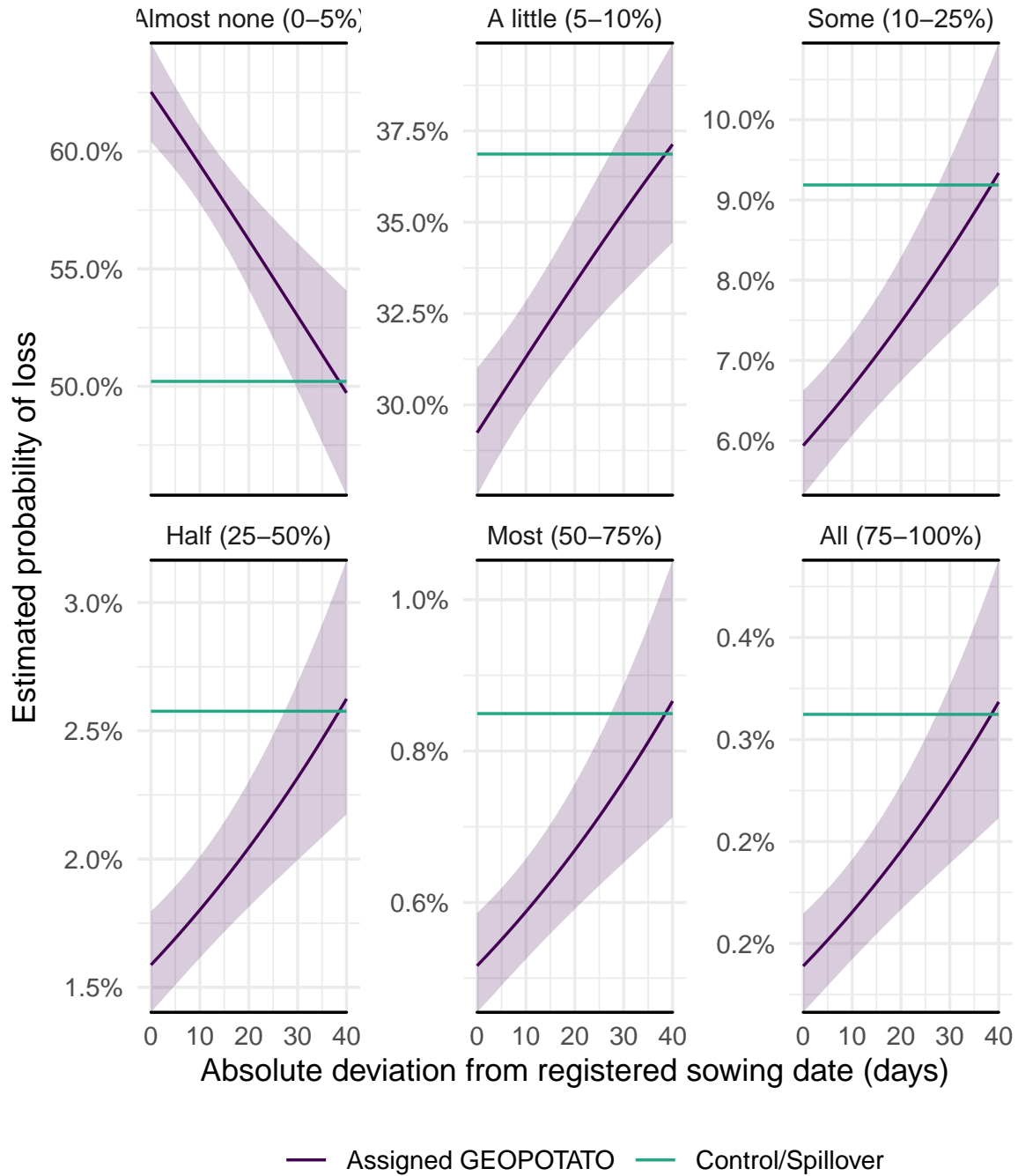
Cluster robust standard errors at the village level ( $G = 407$ ).

\*\*\* $p < 0.01$ ; \*\* $p < 0.05$ ; \* $p < 0.1$ .

A farmer observing significant basis risk would have no reason to increase their investment, as their risk from blight is unaffected. Conversely, a farmer observing accurate predictions could decide to invest more heavily in their crops if they believe



Figure 7: Effect of GEOPOTATO by deviation from reported sowing date



*Note:* 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.

GEOPOTATO offers them superior protection. Accurate alerts would therefore lead to more spending on fungicide and fertilizer. Specifically, farmers apply fertilizer in four rounds: an initial preparation phase prior to planting, and then a second, third, and fourth application as the potatoes grow. This means that farmers have the opportunity to modify their investment as they learn about the efficacy of GEOPOTATO signals.

Because the self-report of receiving alerts and false negatives may be endogenous to farmer characteristics or concern over blight, I instrument for the 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 6.

$$\left. \begin{array}{l} \text{false negative} \mid \text{GEOPOTATO received} \\ \text{!false negative} \mid \text{GEOPOTATO received} \end{array} \right\} = \beta_1 (\text{GEOPOTATO assigned}) + \beta_2 (\text{GEOPOTATO assigned} \times \text{abs(days diverged)}) \quad (6)$$

Table 7 shows the instrumented effect of receiving an accurate versus inaccurate alert. The entire increase in investment is through farmers receiving accurate alerts, who increase their expenditures on fungicide and fertilizer by approximately 23% and 14%, respectively. Receiving an inaccurate signal has no statistically significant affect on farmer fungicide and fertilizer usage. Farmers update and respond rationally to the quality of the signal that they receive. Farmers with inaccurate signals do not modify their expenditure or number of fungicide sprays.

Because farmers apply fertilizer in four distinct rounds, I can estimate the effect of an (instrumented) accurate signal on each round, shown in table 8. Farmers with

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*** (0.04)	0.23*** (0.08)	0.05 (0.03)	0.16** (0.07)	0.06 (0.04)	0.14* (0.08)
Inaccurate signal	0.07** (0.03)	-0.07 (0.09)	0.04 (0.03)	-0.04 (0.07)	0.10*** (0.04)	0.03 (0.08)
Land (ln acres)	0.86*** (0.01)	0.85*** (0.02)	0.18*** (0.01)	0.17*** (0.01)	0.96*** (0.01)	0.96*** (0.01)
Experience (ln years)	0.03 (0.02)	0.03 (0.02)	-0.00 (0.02)	-0.00 (0.02)	0.02 (0.02)	0.02 (0.02)
Education						
No formal education	-0.06 (0.05)	-0.06 (0.05)	0.02 (0.04)	0.02 (0.04)	-0.02 (0.05)	-0.02 (0.05)
Primary school	-0.05 (0.04)	-0.05 (0.04)	0.02 (0.03)	0.02 (0.03)	-0.04 (0.04)	-0.04 (0.04)
Secondary school	-0.03 (0.03)	-0.04 (0.04)	0.01 (0.03)	0.00 (0.03)	-0.00 (0.03)	-0.01 (0.03)
Upazila FE	Yes	Yes	Yes	Yes	Yes	Yes
Seasonal trend	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R <sup>2</sup>	0.71	0.71	0.14	0.13	0.78	0.78
Observations	1958	1958	1958	1958	1958	1958

Fertilizer and fungicide are transformed with the inverse hyperbolic sine.

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

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 sharply. Farmers receiving accurate alerts, as instrumented by assignment to receive alerts and the divergence between their registered and actual sowing date, invest more heavily in fertilizer, while those receiving inaccurate alerts reduce their investment.

The timing of the response suggests that farmers delay investing more into their crops until they can verify whether GEOPOTATO is reducing their risk. As farmers learn that they have lower risk because GEOPOTATO alerts are accurate, they invest more. Conversely, as farmers learn that they have no additional protection against blight, they invest less. The magnitude of the investment response is shown in figure 8, where accurate signals lead to a massive increase investment in the last round of fertilizer application.

## 8 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 unlocking productivity gains that can lead to the structural transformation of rural economies. Although index insurance is promising in theory, farmer disinterest severely limits its real-world applications. In my study of potato farmers in Bangladesh, I find a perfectly rational response to a simple, relatively cheap, and easily scalable technology: farmers invest more when it works, and less when it does not. Both GEOPOTATO alerts and index insurance contain significant basis risk for farmers, but where they differ is that farmers can learn about the accuracy

Table 8: Effect of GEOPOTATO Accuracy on Fertilizer Usage by Round

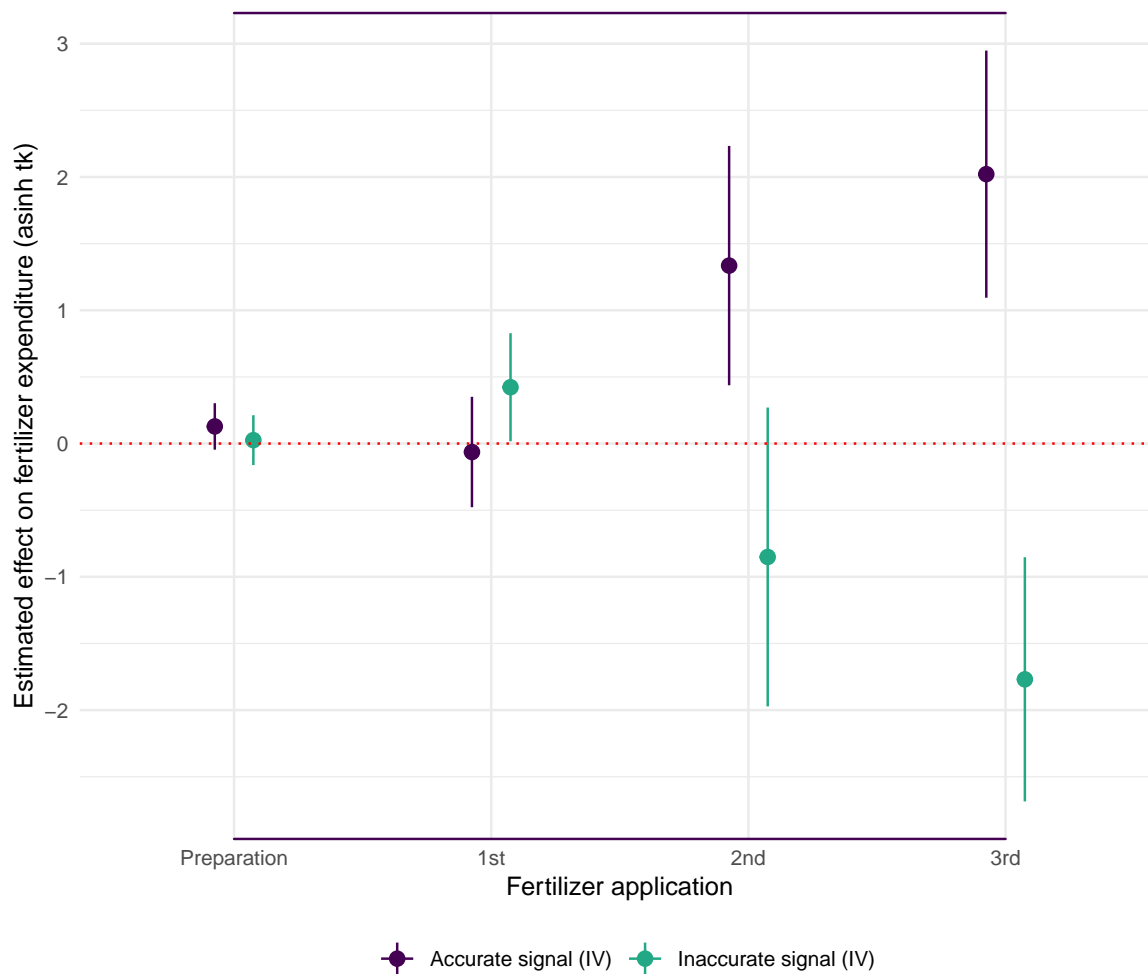
	Dep. Var = asinh(fertilizer taka)			
	Preparation	1st round	2nd round	3rd round
GEOPOTATO				
Accurate signal (IV)	0.13 (0.09)	−0.06 (0.21)	1.34*** (0.46)	2.02*** (0.47)
Inaccurate signal (IV)	0.03 (0.10)	0.42** (0.21)	−0.85 (0.57)	−1.77*** (0.47)
Spillover alerts	−0.01 (0.04)	0.09 (0.10)	0.31 (0.20)	−0.11 (0.20)
Land (ln dec)	0.97*** (0.02)	0.97*** (0.04)	1.55*** (0.07)	0.95*** (0.09)
Age (ln years)	−0.12* (0.07)	−0.50** (0.21)	−0.32 (0.39)	−0.55 (0.40)
Experience (ln years)	0.05* (0.03)	0.23*** (0.08)	−0.15 (0.15)	0.14 (0.16)
Education				
No formal education	−0.05 (0.06)	−0.15 (0.18)	0.47 (0.31)	0.07 (0.32)
Primary school	−0.05 (0.04)	0.01 (0.11)	0.10 (0.23)	−0.11 (0.25)
Secondary school	−0.00 (0.04)	−0.08 (0.10)	0.05 (0.20)	−0.33 (0.23)
Upazila FE	Yes	Yes	Yes	Yes
Time trend	Yes	Yes	Yes	Yes
Observations	1958	1958	1958	1958
Adj. R <sup>2</sup> (full)	0.72	0.28	0.20	0.09
Adj. R <sup>2</sup> (proj)	0.70	0.25	0.17	0.08

Fertilizer and fungicide are transformed with the inverse hyperbolic sine.

Cluster robust standard errors at the village level (G = 407).

\*\*\* $p < 0.01$ ; \*\* $p < 0.05$ ; \* $p < 0.1$ .

Figure 8: Effect of Signal Accuracy by Fertilizer Application by Round



*Note:* Effect of receiving and accurate or inaccurate signal on fertilizer investment. Estimated coefficients are instrumented with assignment to receive alerts and the deviation from the registered sowing date, from table 8, and shown with 95% confidence intervals.

of GEOPOTATO within the growing season. Blight risk is persistent throughout the growing season, so that farmers can update their beliefs about whether the alert system works through the observation of false negatives. Index insurance admits far fewer opportunities for farmers to discover their individual risk.

Importantly, the investment response produced by GEOPOTATO alerts does not require a complex theory of risk aversion, or assumptions over farmer education or abilities in order to parse. Farmers invest more when they can verify that they are protected. GEOPOTATO alerts do not solve the problem of basis risk in a technical sense, but through repeated observation farmers can learn whether the alerts are accurate for their specific crop.

The GEOPOTATO study highlights that the value of agricultural technology interventions are limited by whether 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 how it will benefit them.

## References

- Ahmed, Shukri, Craig McIntosh, and Alexandros Sarris. 2020. “The impact of commercial rainfall index insurance: Experimental evidence from ethiopia.” *American Journal of Agricultural Economics* 102 (4): 1154–1176.
- Cole, Shawn, Xavier Giné, Jeremy Tobacman, Petia Topalova, Robert Townsend, and James Vickery. 2013. “Barriers to household risk management: Evidence from India.” *American Economic Journal: Applied Economics* 5 (1): 104–35.
- Cole, Shawn, Xavier Giné, and James Vickery. 2017. “How does risk management influence production decisions? Evidence from a field experiment.” *The Review of Financial Studies* 30 (6): 1935–1970.
- Emerick, Kyle, Alain de Janvry, Elisabeth Sadoulet, and Manzoor H Dar. 2016. “Technological innovations, downside risk, and the modernization of agriculture.” *American Economic Review* 106 (6): 1537–61.
- Fabregas, Raissa, Michael Kremer, and Frank Schilbach. 2019. “Realizing the potential of digital development: The case of agricultural advice.” *Science* 366 (6471).
- Fry, WE, PRJ Birch, HS Judelson, NJ Grünwald, G Danies, KL Everts, AJ Gevens, BK Gugino, DA Johnson, SB Johnson, et al. 2015. “Five reasons to consider *Phytophthora infestans* a reemerging pathogen.” *Phytopathology* 105 (7): 966–981.
- Haverkort, AJ, PM Boonekamp, R Hutten, E Jacobsen, LAP Lotz, GJT Kessel, RGF Visser, and EAG Van der Vossen. 2008. “Societal costs of late blight in potato and prospects of durable resistance through cisgenic modification.” *Potato Research* 51 (1): 47–57.



- Hossain, MT, SMM Hossain, MK Bakr, AKM Matiar Rahman, and SN Uddin. 2010. "Survey on major diseases of vegetable and fruit crops in Chittagong region." *Bangladesh Journal of Agricultural Research* 35 (3): 423–429.
- Jensen, Nathaniel D, Christopher B Barrett, and Andrew G Mude. 2016. "Index insurance quality and basis risk: evidence from northern Kenya." *American Journal of Agricultural Economics* 98 (5): 1450–1469.
- Kamoun, Sophien, Oliver Furzer, Jonathan DG Jones, Howard S Judelson, Gul Shad Ali, Ronaldo JD Dalio, Sanjoy Guha Roy, Leonardo Schena, Antonios Zambounis, Franck Panabières, et al. 2015. "The Top 10 oomycete pathogens in molecular plant pathology." *Molecular plant pathology* 16 (4): 413–434.
- Karlan, Dean, Robert Osei, Isaac Osei-Akoto, and Christopher Udry. 2014. "Agricultural decisions after relaxing credit and risk constraints." *The Quarterly Journal of Economics* 129 (2): 597–652.
- Lowder, Sarah K, Jakob Skoet, and Terri Raney. 2016. "The number, size, and distribution of farms, smallholder farms, and family farms worldwide." *World Development* 87:16–29.
- Mobarak, Ahmed Mushfiq, and Mark R Rosenzweig. 2012. "Selling formal insurance to the informally insured."
- . 2013. "Informal risk sharing, index insurance, and risk taking in developing countries." *American Economic Review* 103 (3): 375–80.
- Rahman, MM, TK Dey, MA Ali, KM Khalequzzaman, MA Hussain, et al. 2008. "Control of late blight disease of potato by using new fungicides." *International Journal of Sustainable Crop Production* 3 (2): 10–15.

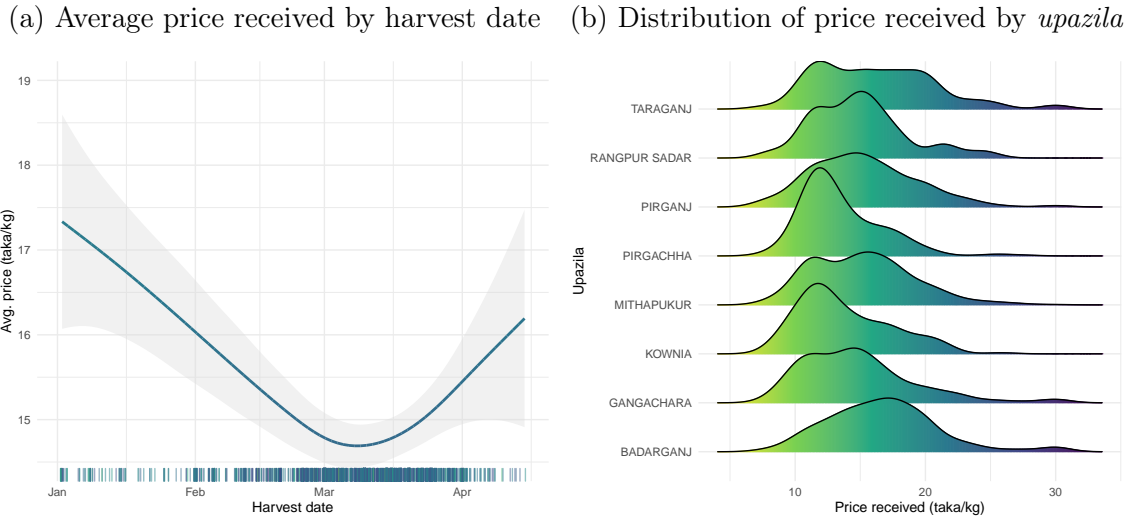
Vleeshouwers, Vivianne GAA, Sylvain Raffaele, Jack H Vossen, Nicolas Champouret, Ricardo Oliva, Maria E Segretin, Hendrik Rietman, Liliana M Cano, Anoma Lokossou, Geert Kessel, et al. 2011. “Understanding and exploiting late blight resistance in the age of effectors.” *Annual Review of Phytopathology* 49:507–531.

## 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 9a 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 9: Crop prices



*Note:* 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 10 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 10: Total Profits by Farm Size



**B   Deviation from Registered Date**

**C   Survey Attrition**