Input Use Decisions with Greater Information on Crop Conditions: Implications for Insurance Moral Hazard and the Environment

Abstract

Emerging precision agriculture technologies allow farms to make input decisions with greater information on crop conditions. This greater information occurs by providing improved predictions of crop yields using remote sensing and crop simulation models and by allowing farms to apply inputs within the growing season when some crop conditions are already realized. We use a stylized model with uncertainty in yield and price to examine how greater information on crop conditions (i.e., a forecast) affects input use for insured and uninsured farms. We show that moral hazard decreases—farms apply more inputs—as the forecast accuracy improves when the forecast indicates good yields, and vice versa when the forecast indicates bad yields. In the long run, moral hazard decreases in response to an improvement in forecast accuracy. Even though moral hazard decreases in the long run, indemnity payments are likely to increase in the long run—driven by the increase in moral hazard when the forecast indicates bad crop conditions. We use the results of our model to discuss the potential impact of different technologies and types of inputs on the federal crop insurance program and the environment.

Key words: Crop Insurance, Moral Hazard, Forecast, Value of Information, Precision Agriculture

JEL classification: Q18, Q12

Subsidized crop insurance is widely considered the cornerstone of today's U.S. farm policy to support farm income. At the same time, new technologies are emerging that process massive amounts of data to provide farmers with improved information on crop conditions throughout the growing season. In this paper, we develop a model to understand how improved information on crop conditions affects input use decisions for insured and uninsured farms. We show that farmers with insurance respond differently to the improved information with important implications for moral hazard and the environment.

There is a large literature that studies moral hazard in crop insurance (e.g. Chambers 1989; Quiggin, Karagiannis, and Stanton 1993; Horowitz and Lichtenberg 1993; Ramaswami 1993; Babcock and Hennessy 1996; Smith and Goodwin 1996; Coble et al. 1997; Weber, Key, and O'Donoghue 2016; Mieno, Walters, and Fulginiti 2018). Yet nearly all of the previous literature focuses on inputs that are applied prior to planting when little is known about growing season conditions. Many of the previous studies implicitly assume that farmers have no information on whether yields in a particular year might be above or below average but farmers often have greater information about conditions when making decisions about inputs within the growing season. For example, pesticides are commonly applied during the season and it is also possible to apply fertilizer late in the growing season. The previous literature has paid little attention on the impacts of greater information during growing season on moral hazard in crop insurance programs.

New technologies have the potential to improve information on crop conditions. For example, Winfield United released the new R7® Field Forecasting Tool in 2018. Winfield United states, "the Field Forecasting Tool lets you run scenarios that tell you what you can expect if you implement various applications."[1] A farmer can simulate their final yield for different amounts of fertilizer applied, conditional on the crop conditions observed to the current point in the year. Farmers can use this type of tool to make input decisions based on crop conditions and prices, but clearly the likelihood of collecting an indemnity payment also affects decisions. Furthermore, these tools could make within-season application of fertilizer more profitable.

We model input decisions for a farm without any crop insurance and a farm with Revenue Protection. For the tractability of comparative statics, we consider a stylized model with four possible states: good weather and high price, bad weather and high price, good weather and low price, and bad weather and low price. The forecast changes the perceived probability of a bad yield. We use the model to understand how improvements in the forecast accuracy (i.e., improved information on crop conditions) affect input use and we also conduct numerical simulations to illustrate our results.

Our model shows that improved information on crop conditions increases moral hazard when the forecast predicts a bad yield and decreases moral hazard when the forecast predicts a good yield. Consider a motivating example of how moral hazard increases when indemnities are expected to trigger. Southwest Ohio experienced poor weather conditions in 2016. A farmer in the region stated "I bet there wasn't 20% of the normal fungicide sprayed on corn in our area, because for people who thought they might have a federal insurance claim, it was a non-recoverable cost" (Taylor 2016). A similar argument could be made for the major drought that struck the Corn Belt in 2012. By the middle of the growing season it was already evident to many farmers that they would receive crop insurance indemnities. There was little incentive to apply inputs in the middle of the season for farmers with crop insurance because yield gains would be offset by reduced indemnity payments. As new technologies improve crop yield predictions in the middle of the growing season, there will be greater opportunity to reduce input use in years when farmers collect indemnities. However, it is also important to consider the impact on input use of improved forecast accuracy when the forecast predicts indemnities will not be triggered.

We find that in the long run, moral hazard actually decreases due to improved information on crop conditions. That is, long-run average input use by farmers with insurance will be closer to input use without insurance as the accuracy of the forecast improves. Nevertheless, indemnities are likely to increase as the forecast accuracy improves. Intuitively, indemnities increase even though moral hazard decreases on average because the increase in moral hazard when the forecast predicts a bad yield has a larger impact on indemnities than the decrease in moral hazard when the forecast predicts a good yield. We also find it is ambiguous whether the incentive to adopt a technology that improves forecast accuracy is larger with insurance or without insurance.

Our paper contributes to the literature on moral hazard in crop insurance. Early empirical studies such as Chambers (1989), Quiggin, Karagiannis, and Stanton (1993), Horowitz and Lichtenberg (1993) and Smith and Goodwin (1996) estimate the effect of crop insurance on fertilizer or pesticide applications. Both positive and negative effects of crop insurance on input use have been documented. For example, Horowitz and Lichtenberg (1993) find increases in fertilizer applications and pesticide expenditures whereas Smith and Goodwin (1996) estimate a decrease in fertilizer expenditures. Quiggin, Karagiannis, and Stanton (1993) also find a decrease in chemical application. More recently, Weber, Key, and O'Donoghue (2016) find little impact of crop insurance adoption on fertilizer and chemical usage.

Relatively little attention has been given to how forecasts of crop conditions affect input demand for insured farms. Bontems and Thomas (2000) and Babcock (1990) study the role of forecasts in agricultural production and the value of information on uncertain environmental variables, but do not consider how the impact differs with insurance. One important exception is that Carriquiry and Osgood (2012) consider the impacts of forecasts due to El Niño events which may provide additional information prior to planting for index insurance. Another relevant study is Coble et al. (1997) who compare yields between insured and uninsured farms and find a significant difference in poor production years. Their result suggests moral hazard behavior and that farmers act strategically based on expected crop conditions.

We focus on how moral hazard incentives change for Revenue Protection participants as forecast accuracy improves. Revenue Protection is one of the most common products in the U.S. Federal Crop Insurance Program and indemnifies when the realized revenue is below the revenue guarantee (RMA 2016).[2] Few studies examine input use under revenue-based insurance (e.g., Mishra, Nimon, and El-Osta 2005; Babcock and Hennessy 1996). Babcock and Hennessy (1996) provide a general framework that describes the input demand of the farm with yield insurance and the farm with revenue insurance and show that whether yield or revenue insurance reduces the input demand or not depends on how the input affects the distributions of yields or revenues. The empirical analysis of Mishra, Nimon, and El-Osta (2005) finds that farms with revenue insurance apply less fertilizer than farms without insurance. We also contribute to this literature by investigating how moral hazard incentive of Revenue Protection participants differs from that of Yield Protection participants and how they respond differently to the improved forecast accuracy.

A Stylized Model: Four-state Framework

For simplicity, suppose that crop insurance choices and other planting decisions are treated as given. Our scope is to model the behavior of farms after the pre-planting production choices. For farm i with an acre of a single crop planted, the yield for farm i is described by:

$$y_i = f(x_i,\ \varepsilon)$$

where x_i is an input with price P_x and ε is a random shock that affects yield (e.g., a weather shock).

Our four-state framework assumes that the random crop yield shock, ε, takes only two values, w_g (good yield) and w_b (bad yield), and the harvest price, HP, takes only two values, P_h (high price) and P_l (low price). Thus, the four possible states are: 1) w_g and P_h, 2) w_g and P_l, 3) w_b and P_h and 4) w_b and P_l.

We denote the probability of experiencing the bad crop yield shock, $\varepsilon = w_b$, as τ_w. If the true state is $\varepsilon = w_g$, the conditional probability of having the low price is $\tau_{p|g}$. Similarly, if the true state is $\varepsilon = w_b$, the conditional probability of having the low price is $\tau_{p|b}$. We assume that $\tau_{p|g} \geq \tau_{p|b}$. That is, the probability of a low price is the same or larger when there is a good yield shock rather than a bad yield shock. In locations that have a large amount of global production (e.g., the Corn Belt), crop yield shocks are negatively correlated with prices. In other locations, crop yield shocks and prices may have no correlation. We have the following joint probability structure (see table 1): 1) w_g and P_h with $Prob = (1-\tau_w)(1-\tau_{p|g})$, 2) w_g and P_l with $Prob = (1-\tau_w)\tau_{p|g}$, 3) w_b and P_h with $Prob = \tau_w(1-\tau_{p|b})$ and 4) w_b and P_l with $Prob = \tau_w \tau_{p|b}$.

With the joint probability structure in table 1, farm i solves the following expected utility maximization problem:

$$(1) \quad \begin{aligned} Max_x\ EU = & (1-\tau_w)(1-\tau_{p|g})u(\pi_{i1}(x)) + (1-\tau_w)\tau_{p|g}u(\pi_{i2}(x)) + \\ & \tau_w(1-\tau_{p|b})u(\pi_{i3}(x)) + \tau_w\tau_{p|b}u(\pi_{i4}(x)) \end{aligned}$$

where $u(\cdot)$ is a von Neumann-Morgenstern utility function and for the risk-neutral farms $u(\pi)$ is equal to π. Without any information on crop conditions, we assume that farms use the long-run expected probability of the bad yield shock, $\hat{\tau_w}$, as their perceived probability of experiencing the bad yield shock, τ_w.

We consider two types of farms: a non-insured farm ($i = n$) and a farm insured by revenue protection ($i = rp$). For the non-insured farm n, the profit function is represented as:

$$(2) \quad \pi_n = \begin{cases} \pi_{n1} = P_h f(x_n,\ w_g) - P_x x_n & with\ Prob(\pi_{n1}|x_n) = (1-\tau_w)(1-\tau_{p|g}) \\ \pi_{n2} = P_l f(x_n,\ w_g) - P_x x_n & with\ Prob(\pi_{n2}|x_n) = (1-\tau_w)\tau_{p|g} \\ \pi_{n3} = P_h f(x_n,\ w_b) - P_x x_n & with\ Prob(\pi_{n3}|x_n) = \tau_w(1-\tau_{p|b}) \\ \pi_{n4} = P_l f(x_n,\ w_b) - P_x x_n & with\ Prob(\pi_{n4}|x_n) = \tau_w\tau_{p|b} \end{cases}.$$

Now consider farm rp which is insured by Revenue Protection with the harvest price option. The harvest price option means that the revenue guarantee is calculated using the larger of the projected price (P_p) or the price at harvest (HP) times the guaranteed yield level ($\bar{y}$) for the respective coverage, i.e $max\{HP\bar{y},\ P_p\bar{y}\}$. For the insured farm rp, the profit function is:

$$(3)\qquad \pi_{rp} = \begin{cases} \pi_{rp1} = P_h f(x_{rp},\ w_g) - P_x x_{rp} & with\ P(\pi_{rp1}|x_{rp}) = (1-\tau_w)(1-\tau_{p|g}) \\ \pi_{rp2} = P_p\bar{y} - P_x x_{rp} & with\ P(\pi_{rp2}|x_{rp}) = (1-\tau_w)\tau_{p|g} \\ \pi_{rp3} = P_h\bar{y} - P_x x_{rp} & with\ P(\pi_{rp3}|x_{rp}) = \tau_w(1-\tau_{p|b}) \\ \pi_{rp4} = P_p\bar{y} - P_x x_{rp} & with\ P(\pi_{rp4}|x_{rp}) = \tau_w\tau_{p|b} \end{cases}.$$

Additionally, our stylized model has several assumptions in order to have tractable discussions while preserving core features of the problem.

Assumption 1. *(Production Function) The yield function satisfies* $f' = \frac{\partial f}{\partial x_n} > 0$, *and* $f'' = \frac{\partial^2 f}{\partial x_n^2} < 0$ *and the marginal product of the input* x_i *does not depend on the random shock, i.e.* $f(x,\ \varepsilon) = f(x) + \varepsilon$.

Our production function specification assumes that the input, x_i, does not affect the variance of yield so the input is risk-decreasing only to the extent that it increases the mean yield. Assumption 1 that, x_i, has no impact on the variance of yield allows us to more clearly isolate the impact of information about crop conditions on input use with insurance and to have tractable results. If the input decreases the variance of yield, then insurance creates an additional incentive to decrease input use, and vice versa.[3]

The second assumption compares expected utility with good and bad yield shocks.

Assumption 2. *(Yield Shocks) Yield shocks satisfy the following condition: for any given x, both types of farms,* $(i = n, rp)$ *are always better off in the "good yield" state compared to the "bad yield" state, i.e.* $(1-\tau_{p|g})u(\pi_{i1}(x)) + \tau_{p|g}u(\pi_{i2}(x)) > (1-\tau_{p|b})u(\pi_{i3}(x)) + \tau_{p|b}u(\pi_{i4}(x))$ *regardless of risk preferences.*

The inequality in assumption 2 simply states that the expected utility with the good yield shocks (states 1 and 2) is greater than the expected utility with the bad yield shocks (states 3 and 4). This assumption excludes the possibility that a bad yield shock could increase prices so much that farms are better off with the bad yield shock. In other words, assumption 2 implicitly places a bound on the degree of negative correlation between the yield shock and price.

The third assumption compares expected marginal utility with high and low harvest prices.

Assumption 3. *(Harvest Prices and Input Price) The price variables and the conditional probabilities satisfy the following condition: at optimum, any risk-averse and non-insured farm would always prefer additional profits in "low harvest price" states compared to additional profits in the "high harvest price" states, i.e.* $(1-\tau_w)\tau_{p|g}u'(\pi_{n2})+\tau_w\tau_{p|b}u'(\pi_{n4}) > (1-\tau_w)(1-\tau_{p|g})u'(\pi_{n1})+\tau_w(1-\tau_{p|b})u'(\pi_{n3})$.

The inequality in assumption 3 states that the expected marginal utility in the low price states (states 2 and 4) is greater than the expected marginal utility in the high price states (states 1 and 3). Intuitively, this assumption is satisfied by diminishing marginal utility, if expected utility is larger in the high price states.

Finally, we need an assumption to ensure that indemnities are triggered in states with either bad yield or low price (states 2, 3, and 4).

Assumption 4. *(Insurance Parameters) We assume that the parameters satisfy the following conditions for all* $x_{u,rp} > x_{rp} > x_{l,rp}$ *where* $x_{u,rp}$*, and* $x_{l,rp}$ *are the upper and the lower bounds of optimal* x^*_{rp}*:*

(i) $P_l f(x_{rp},\, w_g) < P_p\bar{y}$*,*

(ii) $f(x_{rp},\, w_b) < \bar{y} < f(x_{rp},\, w_g)$*,*

(iii) for any risk-averse farm, the difference between the utility in state 3 with indemnity triggered and that without indemnity triggered, i.e. $u(P_h\bar{y}-P_x x_{rp}) - u(P_h f(x_{rp},\, w_b)-P_x x_{rp})$*, is a decreasing and convex function of* x_{rp}*.*

Part (i) of assumption 4 states that price is sufficiently low in the low price state that the revenue guarantee is greater than revenue with low price and good weather. Part (ii) states that the yield guarantee is greater than the yield with the bad yield shock and less than the yield with the good yield shock. This implies indemnities are triggered in either of the states with the bad yield shock, but not with the good yield shock and high price. An important point in assumption 4 is that we assume it is never optimal to apply a large enough amount of inputs to avoid triggering indemnities in states 2, 3, or 4. Particularly, part (iii) relates to the state with high price and bad yield shock and implies that the additional benefits from increased crop revenue by applying greater inputs in this state are diminishing. Note that part (iii) is satisfied for a risk-neutral farm by the assumption that $f'' < 0$.

Now, suppose a farmer obtains information on crop conditions. This information may come through remote sensing, agronomic models that process high-resolution weather and soils data, or growing-season weather forecasts. The information can be used to make decisions about the use of inputs applied during the growing season such as pesticides and irrigation. Fertilizer is also increasingly recommended for application during the growing season to improve the timing of application. For succinctness, we refer to the information on crop conditions as a "forecast," but the source of this information is not necessarily a weather forecast. For example, algorithms could create a forecast of crop yield based solely on information up to the current point in the growing season.

The "forecast," W, can take two values: 1) bad yield shock ($W = 0$) and 2) good yield shock ($W = 1$). We define the forecast accuracy, θ, as an incremental improvement from the long-run expected probability. We assume this improvement to be proportionally symmetric across the two states. After the forecast becomes available, the probability of experiencing the bad yield shock, τ_w, is now the probability of experiencing the bad yield shock conditional on the forecast, W:

(4) $$\tau_w(W, \theta) = \hat{\tau}_w - (W\hat{\tau}_w - (1 - W)(1 - \hat{\tau}_w))\,\theta$$

and the forecast quality, θ, ranges from zero to unity. The forecast quality, θ, represents a weight given to the forecast rather than the long-run probability of a bad yield shock. Note that if $\theta = 0$ then the forecast is perfectly uninformative and if $\theta = 1$ then farms receive a perfect forecast.[4] In other words, as the forecast becomes more accurate (i.e. the forecast quality, θ, increases) the correlation between the forecast and the realized shock becomes stronger.[5]

Figure 1 illustrates the timeline of the problem. We model the decision of how much inputs to apply (denoted as bold in figure 1) based on the information farms obtain on the likelihood of a bad yield shock and taking the insurance decision as given. We investigate the incentives to change the level of the input as forecasts become more accurate for two representative farms: a) a farm without any crop insurance, i.e. $i = n$, and b) a farm with revenue protection, i.e. $i = rp$. We analyze the optimization problems of the two farms under risk neutrality and risk aversion.[6]

Moral Hazard Incentives

In our stylized model, farms n and rp solve the optimization problem (1). Under risk neutrality, i.e. $u(\pi) = \pi$, the expected marginal profit of input x_n for farm n is:

$$(5) \quad E\pi_n' = \left((1-\tau_w)(1-\tau_{p|g}) + \tau_w(1-\tau_{p|b})\right) P_h f' + \left((1-\tau_w)\tau_{p|g} + \tau_w \tau_{p|b}\right) P_l f' - P_x.$$

and the optimal x_n^* is x_n that makes the expected marginal profit, (5), equal to zero. Similarly, under risk neutrality, the expected marginal profit of input x_{rp} for farm rp is:

$$(6) \quad E\pi_{rp}' = (1-\tau_w)(1-\tau_{p|g}) P_h f' - P_x$$

and the optimal x_{rp}^* is x_{rp} that makes the expected marginal profit, (6), equal to zero.

By comparing the two expected marginal profits, (5), and (6), we define the *moral hazard incentive* for risk-neutral and insured farms as follows.

Definition 1. *For risk-neutral and insured farms, we define the moral hazard incentive as the change in the marginal profit of input x_{rp} due to indemnity payments. Thus, the moral* *hazard incentive of Revenue Protection on the input application of risk-neutral and insured farms is*

$$\bar{MH}_{rp} = E\pi'_{rp} - E\pi'_n = -\tau_w(1-\tau_{p|b})P_h f' - \left((1-\tau_w)\tau_{p|g} + \tau_w\tau_{p|b}\right)P_l f'. \tag{7}$$

The first term represents the decrease in the marginal profit due to the loss of indemnity payments when prices are high and there is a bad yield shock multiplied by the probability of this event. The second term represents the loss of indemnity payments when prices are low multiplied by the probability of either low prices and a good yield shock or low prices and a bad yield shock. Unambiguously, the *moral hazard incentive* is negative—insured farms have an incentive to use fewer inputs—since increases in the input use always reduce the expected indemnity.

Under risk aversion, the expected marginal utility of farm n is:

$$\begin{aligned} EU'_n = (1-\tau_w)(1-\tau_{p|g})u'(\pi_{n1})(P_h f' - P_x) + (1-\tau_w)\tau_{p|g}u'(\pi_{n2})(P_l f' - P_x) + \\ \tau_w(1-\tau_{p|b})u'(\pi_{n3})(P_h f' - P_x) + \tau_w\tau_{p|b}u'(\pi_{n4})(P_l f' - P_x). \end{aligned} \tag{8}$$

And the optimal input, x_n^*, is x_n that makes the expected marginal utility, (8), equal to zero. Similarly, the expected marginal utility of farm rp is:

$$\begin{aligned} EU'_{rp} = (1-\tau_w)(1-\tau_{p|g})u'(\pi_{rp1})(P_h f' - P_x) - \\ \left((1-\tau_w)\tau_{p|g}u'(\pi_{rp2}) + \tau_w(1-\tau_{p|b})u'(\pi_{rp3}) + \tau_w\tau_{p|b}u'(\pi_{rp4}))\right)P_x. \end{aligned} \tag{9}$$

and again, the optimal x_{rp}^* is x_{rp} that makes the expected marginal utility, (9), equal to zero.

Similar to the discussion under the risk neutrality, we have the following definition of the *moral hazard incentive* for risk-averse and insured farms:

Definition 2. *For risk-averse and insured farms, we define the moral hazard incentive as the change in the marginal utility of input x_{rp} due to indemnity payments (Ramaswami 1993). Thus, the moral hazard incentive of Revenue Protection on the input application of risk-averse and insured farms is*

$$\tilde{MH}_{rp} = -\left(\tau_w(1-\tau_{p|b})u'(\pi_{rp3})P_h + \left((1-\tau_w)\tau_{p|g} + \tau_w\tau_{p|b}\right)u'(\pi_{rp2})P_l\right)f'. \tag{10}$$

The *moral hazard incentive* is derived by rewriting equation (9) as:

$$
\begin{aligned}
EU'_{rp} = {} & (1-\tau_w)(1-\tau_{p|g})u'(\pi_{rp1})(P_h f' - P_x) + (1-\tau_w)\tau_{p|g}u'(\pi_{rp2})(P_l f' - P_x) + \\
& \tau_w(1-\tau_{p|b})u'(\pi_{rp3})(P_h f' - P_x) + \tau_w\tau_{p|b}u'(\pi_{rp4})(P_l f' - P_x) - \\
& \left((1-\tau_w)\tau_{p|g}u'(\pi_{rp2})P_l f' + \left(\tau_w(1-\tau_{p|b})u'(\pi_{rp3})P_h + \tau_w\tau_{p|b}u'(\pi_{rp4})P_l\right) f'\right).
\end{aligned}
\tag{11}
$$

The definition of the *moral hazard incentive* for risk-averse and insured farms is similar to that of Ramaswami (1993). For risk-averse farms with Revenue Protection, the *moral hazard incentive* is defined as the last term in equation (11).[7] Note that the first four terms of equation (11) are analogous to that of equation (8), which is the expected marginal utility of a non-insured farm, but the values for a given x are different due to the different payouts between non-insured farm and insured farm.[8]

The moral hazard incentive under risk aversion is the same as that in the risk neutral case, (7), except that the high price is weighted by the marginal utility of state 3 and the low price is weighted by the marginal utility of state 2. Note that the marginal utility of state 2 is equal to the marginal utility in state 4. The moral hazard incentive becomes more negative as the marginal utility of events that trigger indemnities are larger. In other words, the moral hazard incentive would be more negative if the low price or bad yield shock cause larger losses in profits.

Conditional Responses to Forecast Accuracy

Now, we examine how the improvement in the forecast accuracy affects the optimal input use and the incentives for moral hazard conditional on each forecast announcement. For non-insured farms, we have the following proposition:

Proposition 1. *Conditional on the bad (good) yield forecast, the optimal input of uninsured and risk-neutral farms is increasing (decreasing) as the forecast accuracy becomes more accurate if* $\tau_{p|g} > \tau_{p|b}$. *If farms are risk-averse the analogous condition is* $\tau_{p|g} > \tau_{p|b}u'(\pi_{n4})/u'(\pi_{n2})$.

Proof Using the implicit function theorem, we know that the signs of $\frac{\partial x_n^*}{\partial \theta}$ conditional on the bad yield forecast ($W = 0$) or the good yield forecast ($W = 1$) are equal to those of $\frac{\partial E\pi_n'}{\partial \theta}|_{W=0}$ and $\frac{\partial E\pi_n'}{\partial \theta}|_{W=1}$ for risk-neutral farms. Thus, the proof is straightforward from differentiating equation (5) conditional on each yield forecast. Due to the concavity of f, the optimal input use increases as the expected price of the output increases and $\tau_{p|g} > \tau_{p|b}$ is the sufficient condition for the improvement of forecast accuracy to increase the expected price when the forecast is for a bad yield shock. Similarly, the signs of $\frac{\partial EU_n'}{\partial \theta}$ conditional on the bad yield forecast ($W = 0$) or the good yield forecast ($W = 1$) determine the direction of responses in the optimal input use for the risk-averse farms. With an additional assumption of $\tau_{p|g} > \tau_{p|b}\frac{u'(\pi_{n4})}{u'(\pi_{n2})}$, $\frac{\partial EU_n'}{\partial \theta}|_{W=0}$ is positive and $\frac{\partial EU_n'}{\partial \theta}|_{W=1}$ is negative. We provide a detailed proof in the online appendix.

With the bad yield forecast, the expected harvest price increases as the forecast becomes more accurate if $\tau_{p|g} > \tau_{p|b}$. Risk-neutral farms, thus, respond by increasing production with the bad yield forecast. The forecast accuracy has no impact on input use when $\tau_{p|g} = \tau_{p|b}$ for risk neutral farms. However, for risk-averse farms, the increase in the expected harvest price has to be large enough to compensate for risk aversion. Thus, if the probability of the low harvest price conditional on the good yield shock is large enough to satisfy $\tau_{p|g} > \tau_{p|b}\frac{u'(\pi_{n4})}{u'(\pi_{n2})}$, the optimal input of farm n increases as the forecast accuracy increases when the forecast indicates a bad yield. Note that $\frac{u'(\pi_{n4})}{u'(\pi_{n2})} > 1$ because the profits in state 4 are smaller than the profits in state 2, so the assumption is stronger than $\tau_{p|g} > \tau_{p|b}$ to the extent that the marginal utilities of the two states differ. An improvement in the forecast accuracy has the opposite effect with a good yield forecast.

Proposition 2. *Conditional on the bad (good) yield forecast, the moral hazard incentive of insured and risk-neutral farms increases (decreases) as the forecast accuracy increases. The same is true for risk-averse farms.*

Proof Again, for risk-neutral farms, the proof is straightforward from differentiating equation (7) with respect to θ conditional on W. Since $P_h > P_l$, $\frac{\partial \bar{MH}_{rp}}{\partial \theta}|_{W=0} < 0$ ($\frac{\partial \bar{MH}_{rp}}{\partial \theta}|_{W=1} > 0$) so the *moral hazard incentive* becomes more (less) negative as the forecast becomes more accurate. For risk-averse farms, we differentiate equation (10) with respect to θ and find that $\frac{\partial \tilde{MH}_{rp}}{\partial \theta}|_{W=0} < 0$ and $\frac{\partial \tilde{MH}_{rp}}{\partial \theta}|_{W=1} > 0$. The detailed proof is in the online appendix.

If the forecast indicates a bad yield shock and the forecast becomes more accurate, the moral hazard incentive increases, i.e. the terms, $\bar{MH}_{rp}$ and $\tilde{MH}_{rp}$, become more negative for risk-neutral farms. As the forecast of the bad yield shock becomes more informative, the expected loss in indemnity gets larger due to additional input use. Note that when the forecast indicates bad yield, the improved forecast accuracy also decreases the probability of state 2 – the state with the good yield and the low harvest price. Since $P_h > P_l$, the decrease in the expected indemnity payment from the decreased probability of state 2 is always smaller than the increase in the expected indemnity payment from the increased probabilities of states 3 and 4.

Similarly, for the risk-averse farms, the loss in the expected utility from the reduced indemnity gets larger as the forecast of the bad yield shock becomes more informative. Unlike risk-neutral farms, risk-averse farms value the loss in the indemnity of state 2 more than that of state 3 since $\pi_{rp3} > \pi_{rp2}$, and thus $u'(\pi_{rp3}) < u'(\pi_{rp2})$ for given x_{rp}. Thus, for insured and risk-averse farms, the sufficient condition to have greater moral hazard incentives as the bad yield forecast becomes more accurate is $(1-\tau_{p|b})u'(\pi_{rp3})P_h + \tau_{p|b}u'(\pi_{rp4})P_l > \tau_{p|g}u'(\pi_{rp2})P_l$. Assumption 2 and $u''(\cdot) < 0$ guarantee such condition.

To show our propositions graphically, we provide numerical illustrations of our stylized conceptual model. Details on the assumed functional forms and parameter values in the illustrations are provided in the online appendix B. All of our illustrations assume a risk averse farm. Parameterizing the model to a real-world input for a particular crop is not likely reasonable because the stylized model assumes only four states of nature. Therefore, our purpose for the numerical illustrations is to provide a visualization of the propositions rather than to predict the actual magnitude of the effects we describe in this paper.

Figure 2 illustrates the optimal input schedules of non-insured farms and Revenue Protection participants as responses to the changes in the forecast accuracy.[9] The optimal input schedules are represented as percentages of the optimal input of non-insured farms when the forecast is perfectly uninformative ($\theta = 0$). The upper (lower) panel shows the optimal input schedules when the forecast indicates a bad (good) yield shock.

Figure 2 shows that the optimal input schedules of non-insured farms and Revenue Protection participants diverge as the forecast becomes more accurate when the forecast indicates a bad yield shock. As we described with proposition 2, this is due to the increased moral hazard incentives. That is, when the forecast more accurately predicts a bad yield shock, then farms with Revenue Protection have a larger incentive to reduce input use. The opposite is observed when the forecast indicates the good yield. When the forecast more accurately predicts a good yield shock, then farms have less incentive to reduce input use.

Effects of Forecast Accuracy on Long-run Expected Input Use, Expected Indemnity Payments, and the Value of Forecast Accuracy

In the previous section, we discussed the impact of the forecast accuracy on input use conditional on a particular forecast. Next, we evaluate the impact on long-run input use given that the forecast will sometimes indicate the good yield shock and other times the bad yield shock. Then we evaluate the impact of improved forecast accuracy on long-run expected indemnity payments. Finally, we discuss how the value of improved forecast accuracy differs with insurance versus no insurance to understand if insurance increases or decreases the incentive to adopt technologies that improve the forecast accuracy.

We first present a relationship between the long-run expected probability of the bad yield shock, $\hat{\tau}_w$, and the long-run expected probability of the event that the forecast indicates bad yield, $Prob(W=0)$. Using Bayes' theorem and the definition of equation (4), we know that

$$\begin{aligned}\hat{\tau_w} &= Prob(\varepsilon = w_b|W=0) * Prob(W=0) + Prob(\varepsilon = w_b|W=1) Prob(W=1)\\ &= \tau_w(\theta,\ W=0) Prob(W=0) + \tau_w(\theta,\ W=1)(1 - Prob(W=0))\\ &= (\hat{\tau_w} + (1-\hat{\tau_w})\theta) Prob(W=0) + (\hat{\tau_w} - \hat{\tau_w}\theta)(1 - Prob(W=0))\\ &= \hat{\tau_w} - \hat{\tau_w}\theta + \theta Prob(W=0).\end{aligned} \tag{12}$$

For the forecast accuracy that is greater than zero, equation (12) is equivalent to

$$Prob(W=0) = \hat{\tau_w}, \tag{13}$$

which indicates that the long-run expected probability of the bad yield forecast, $Prob(W=0)$, is equal to $\hat{\tau_w}$ and does not change as the forecast accuracy changes.

Using equation (13), we can define the long-run expected optimal input for farm i, Ex_i^*, as

$$Ex_i^* = \hat{\tau_w} x_i^*|_{W=0} + (1-\hat{\tau_w}) x_i^*|_{W=1} \tag{14}$$

where $x_i^*|_{W=0}$ ($x_i^*|_{W=1}$) is the optimal input for farm i with the bad (good) yield forecast.

By the implicit function theorem, we obtain

$$\frac{\partial Ex_i^*}{\partial \theta} = -\hat{\tau_w} \frac{\partial EU'/\partial \theta|_{W=0}}{\partial EU'/\partial x_i|_{W=0}} - (1-\hat{\tau_w}) \frac{\partial EU'/\partial \theta|_{W=1}}{\partial EU'/\partial x_i|_{W=1}}. \tag{15}$$

Proposition 3. *The long-run expected optimal input of uninsured and risk-averse farms is non-increasing as the forecast accuracy increases if $\tau_{p|g}$ is substantially large, i.e. $\tau_{p|g} > \tau_{p|b} \frac{u'(\pi_{n4})}{u'(\pi_{n2})}$, and if farms have Constant Absolute Risk Aversion (CARA) or Decreasing Absolute Risk Aversion (DARA) preferences.*

Proof From the proof of proposition 1, we can rewrite expression 15 as

$$\frac{\partial Ex_n^*}{\partial \theta} = \hat{\tau_w}(1-\hat{\tau_w}) \left(\frac{\partial x_n^*}{\partial \tau_w}|_{W=0} - \frac{\partial x_n^*}{\partial \tau_w}|_{W=1} \right).$$

Thus, expression 15 is non-positive if $\frac{\partial x_n^*}{\partial \tau_w}|_{W=0} \leq \frac{\partial x_n^*}{\partial \tau_w}|_{W=1}$. With Assumptions 2 and 3, CARA or DARA preferences are sufficient conditions for $\frac{\partial x_n^*}{\partial \tau_w}|_{W=0} \leq \frac{\partial x_n^*}{\partial \tau_w}|_{W=1}$. See the detailed proof in the online appendix.

The change in the long-run expected optimal input use is a linear combination of the changes in the marginal expected utilities with respect to the improvement of forecast accuracy in each state of the forecast. The changes in the marginal expected utilities are weighted by the long-run probabilities of the forecast of bad or good yield shocks and the inverse of the second derivatives of the expected utilities in each state of the forecast.

The second derivatives of the expected utilities are related to the degrees of risk aversion and determine whether x_n^* is a concave function with respect to the perceived probability of the bad yield, τ_w. For CARA and DARA agents, with Assumptions 2 and 3, the absolute value of the second derivative of the expect utility is larger for a good yield forecast ($W=1$) than that of the bad yield forecast ($W=0$). In other words, the marginal expected utility in the state of the good yield forecast is valued more because CARA or DARA agents become less risk-averse with a good yield. Thus, the magnitude of the marginal decrease with the good yield forecast is larger than the magnitude of the marginal increase with the bad yield forecast.

Next, we evaluate the impact of the forecast accuracy on the long-run moral hazard incentive. Similar to the expression of the long-run expected optimal input, (15), we can write down the long-run expected value of the change in the optimal input that is attributed to the moral hazard incentive as

$$(16) \quad \frac{\partial E x_{rp}^*}{\partial \theta}|_{\tilde{MH}} = -\hat{\tau_w} \frac{\partial \tilde{MH}_{rp}/\partial \theta|_{W=0}}{\partial EU'_{rp}/\partial x_{rp}|_{W=0}} - (1-\hat{\tau_w}) \frac{\partial MH_{rp}/\partial \theta|_{W=1}}{\partial EU'_{rp}/\partial x_n|_{W=1}}.$$

Proposition 4. *The long-run expected value of the reduction in the optimal input x_{rp}^* that is attributed to the moral hazard incentive of insured and risk-averse farms decreases as the forecast accuracy increases (i.e., there is less reduction in input use) if $\tau_{p|g}$ is substantially large, i.e. $\tau_{p|g} > \tau_{p|b} \frac{u'(\pi_{n4})}{u'(\pi_{n2})}$, and if farms have Constant Absolute Risk Aversion (CARA) or Decreasing Absolute Risk Aversion (DARA) preferences.*

Proof From the proof of proposition 2, we can rewrite (16) as

$$\frac{\partial E x_{rp}^*}{\partial \theta}|_{\tilde{MH}} = \hat{\tau_w}(1-\hat{\tau_w}) \left(\frac{\partial x_{rp}^*}{\partial \tau_w}|_{W=0,\tilde{MH}} - \frac{\partial x_{rp}^*}{\partial \tau_w}|_{W=1,\tilde{MH}} \right),$$

where $\frac{\partial x^*_{rp}}{\partial \tau_w}|_{W,\tilde{MH}}$ indicates the input change attributed to the moral hazard incentive conditional on the forecast, W. The long-run expected reduction in the input due to the moral hazard incentive decreases as θ increases if $\frac{\partial x^*_{rp}}{\partial \tau_w}|_{W=0,\tilde{MH}} \leq \frac{\partial x^*_{rp}}{\partial \tau_w}|_{W=1,\tilde{MH}}$. With Assumptions 2 and 4, CARA and DARA preferences are the sufficient conditions for $\frac{\partial x^*_{rp}}{\partial \tau_w}|_{W=0,\tilde{MH}} \leq \frac{\partial x^*_{rp}}{\partial \tau_w}|_{W=1,\tilde{MH}}$. See the detailed proof in the online appendix.

Similar to proposition 3, the change in the moral hazard incentive in the state of the good yield forecast is valued more because CARA or DARA agents become less risk-averse with Assumptions 2 and 4. In other words, CARA or DARA agents value more the reduction in the moral hazard incentive with the good yield forecast compared to the increase in the moral hazard incentive with the bad yield forecast. Thus, the magnitude of the marginal decrease in the moral hazard incentive with the good yield forecast is larger than the magnitude of the marginal increase in the moral hazard incentive with the bad yield forecast.

Figure 3 illustrates propositions 3 and 4. The long-run expected optimal input use is represented as a percentage of the long-run expected optimal input of a non-insured farm when the forecast is perfectly uninformative ($\theta = 0$). In this illustration, the long-run expected input of uninsured farms changes by little due to improvements in the forecast whereas the long-run expected input of insured farms becomes closer to that of uninsured farms as the forecast becomes more accurate. In other words, there is less reduction in input use due to the moral hazard incentive as described by proposition 4, leading to an overall increase in input use under insurance as the forecast becomes more accurate.

The long-run expected indemnity is likely to increase as the forecast accuracy improves. Analytically, the sign of the change in the long-run expected indemnity is ambiguous, but numerical illustrations and intuition suggest that indemnities nearly always increase with forecast accuracy.[10] Figure 4 illustrates changes in the long-run expected indemnity for various $\hat{\tau}_w$. We observe that the increases in the long-run expected indemnity are larger when the long-run probability of the bad yield shock is small. Intuitively, indemnities increase as the forecast accuracy increases because the increase in moral hazard when the forecast indicates a bad yield shock leads to larger indemnities than the decrease in moral hazard when the forecast indicates the good yield. So even though long-run moral hazard is decreasing, long-run indemnities are increasing as the forecast accuracy improves.[11] The only time that indemnities decrease with improvements in the forecast accuracy in our numerical illustrations is when the probability of a bad yield shock is greater than 0.5 ($\hat{\tau}_w > 0.5$), which is unlikely to hold in reality.

Finally, we evaluate how the incentive to adopt technologies that improve forecast accuracy differ for insured and uninsured farms. Figure 5 illustrates "values of forecast accuracy" for various $\hat{\tau}_w$. The value of the forecast accuracy is defined as the difference between the long-run expected certainty equivalent of a given forecast accuracy compared to the situation of perfectly uninformative forecasts. The upper panel represents the value of an almost perfect forecast ($\theta = 0.99$) and the lower panel represents the values of an imperfect forecast ($\theta = 0.5$).[12] The value of adopting the forecast technology for the uninsured farm is highest when the long-run probability of the bad yield shock is about 50% (i.e., when the states are most uncertain).

Apart from moral hazard, we would expect uninsured farms to value the forecast technology more since the information can provide them with a risk management tool. However, insured farms are also able to benefit from moral hazard as the forecast accuracy improves so it is possible that the benefits from adopting the forecast technology are larger for insured farms. For example, the simulations in figure 5 show that the benefit from adopting the technology are larger for insured farms than uninsured when $\hat{\tau}_w$ is sufficiently small and when the forecast has 50% accuracy.[13] This occurs because the forecast accuracy improvement leads to larger increases in indemnities for lower values of $\hat{\tau}_w$ (figure 4). Overall, whether insurance encourages adoption of the forecast technology or not depends on the degree of risk aversion and the riskiness of the production environment.

Does Yield Protection Provide Different Incentives for Moral Hazard?

We showed that for revenue protection, an improvement in the forecast accuracy decreases the long-run moral hazard incentives. In this subsection, we investigate how the moral hazard incentive differs with yield protection.

The indemnity payments for Yield Protection is based on the projected price. For Revenue Protection, the projected price is used only when the harvest price is lower than the projected price. Thus, the projected price affects the moral hazard behavior differently for the farms with different types of insurance. In the context of the Supplemental Agricultural Disaster Assistance program, Smith and Watts (2010) provide a related discussion: they describe possible greater incentives for moral hazard behavior when the harvest price is lower than the projected price.[14] We provide more explicit discussion on how the projected price and the moral hazard behavior interact and how the impacts of forecast accuracy improvements depend on the projected price.

Consider farm yp which is insured by Yield Protection with yield guarantee $\bar{y}$ and projected price P_p. We assume that with $\varepsilon = w_b$, $y_{yp} < \bar{y}$ for any value of x_{yp}. In other words, we assume that indemnities are triggered in the event of a bad yield shock for any amount of input applied. We also assume that with $\varepsilon = w_g$, $y_{yp} > \bar{y}$ for any value of x_{yp} so that indemnities are not triggered in the event of a good yield shock. The high harvest price P_h is higher than the projected price, P_p, and the low harvest price P_l is lower than P_p. The profit function is:

$$\pi_{yp} = \begin{cases} \pi_{yp1} = P_h f(x_{yp},\ w_g) - P_x x_{yp} & with\ P(\pi_{yp1}|x_{yp}) = (1-\tau_w)(1-\tau_{p|g}) \\ \pi_{yp2} = P_l f(x_{yp},\ w_g) - P_x x_{yp} & with\ P(\pi_{yp2}|x_{yp}) = (1-\tau_w)\tau_{p|g} \\ \pi_{yp3} = P_h f(x_{yp},\ w_b) + P_p(\bar{y} - f(x_{yp},\ w_b)) - P_x x_{yp} & with\ P(\pi_{yp3}|x_{yp}) = \tau_w(1-\tau_{p|b}) \\ \pi_{yp4} = P_l f(x_{yp},\ w_b) + P_p(\bar{y} - f(x_{yp},\ w_b)) - P_x x_{yp} & with\ P(\pi_{yp4}|x_{yp}) = \tau_w \tau_{p|b} \end{cases}.$$

Following similar steps as those of revenue protection, we define the *moral hazard incentive* of Yield Protection for risk-neutral and risk-averse agents as:

$$
\begin{aligned}
(17)\quad \bar{MH}_{yp} &= E\pi'_{yp} - E\pi'_n \\
&= -\tau_w P_p f'
\end{aligned}
$$

and

$$
\begin{aligned}
(18)\quad \tilde{MH}_{yp} &= -\left(\tau_w(1-\tau_{p|b})u'(\pi_{yp3}) + \tau_w\tau_{p|b}u'(\pi_{yp4})\right)P_p f' \\
&= -\left(\tau_w u'(\pi_{yp3}) + \tau_w\tau_{p|b}(u'(\pi_{yp4}) - u'(\pi_{yp3}))\right)P_p f'.
\end{aligned}
$$

Proposition 5. *If farms are risk-neutral, Revenue Protection leads to a greater negative moral hazard incentive on input use* ($|\bar{MH}_{rp}| > |\bar{MH}_{yp}|$) *when* $P_p < (1-\tau_{p|b})P_h + \left(\frac{1-\tau_w}{\tau_w}\tau_{p|g} + \tau_{p|b}\right)P_l$ *at a given x. If farms are risk-averse, the condition for Revenue Protection to give a greater negative moral hazard effect is* $P_p < \frac{\left(\tau_w(1-\tau_{p|b})u'(\pi_{rp3})P_h + \left((1-\tau_w)\tau_{p|g} + \tau_w\tau_{p|b}\right)u'(\pi_{rp2})P_l\right)}{\left(\tau_w u'(\pi_{yp3}) + \tau_w\tau_{p|b}(u'(\pi_{yp4}) - u'(\pi_{yp3}))\right)}$ *at a given x.*

The detailed proof is in the online appendix. Proposition 5 is derived by simply comparing equations (7) and (17) and comparing equations (10) and (18). Intuitively, Revenue Protection tends to have a greater moral hazard effect because it provides indemnities in three states rather than only the two states in the case of Yield Protection. However, Yield Protection can have a greater moral hazard effect when the projected price is large because greater production with Yield Protection reduces indemnities valued at the projected price whereas greater production with Revenue Protection decreases indemnities valued at the expected price. Yield Protection is also more likely to have a greater moral hazard effect when the probability of a bad yield shock is relatively large—the states when Yield Protection provides indemnities.

Figures 6 and 7 illustrate proposition 5. The figures illustrate the optimal input schedule represented as a share of the optimal inputs of the non-insured farm when the forecast is perfectly uninformative ($\theta = 0$). The upper panels of figures 6 and 7 represent the optimal input schedules when the forecast indicates a bad yield and the lower panels of the figures represent the optimal input schedules when the forecast indicates a good yield.

Figure 6 illustrates how the farms with Yield and Revenue Protections respond differently to the forecast accuracy improvements when the projected price is low. Consistent with proposition 5, when the projected price is low enough, the moral hazard incentive of the farms who are insured with Revenue Protection is always greater than that of the farms with Yield Protection. Figure 7 illustrates the opposite case when the projected price is sufficiently large.[15]

Implications of the Model for Precision Agriculture

Next, we discuss the implications of our conceptual model for precision agriculture. We focus our discussion on aspects of precision agriculture that improve information on crop conditions within the growing season.[16]

An important innovation in precision agriculture is to provide improved predictions of crop yields at a high resolution such that the forecast can be used for field-specific—or even within field—management decisions. Data from high-resolution remote sensing or drone imagery combined with advances in machine learning algorithms provide predictions within the growing season of final crop yields. Another advance is to compute agronomic simulation models for individual fields using high-resolution data on weather, soils, and farmer-specified parameters. The crop simulation models can be used to help the farmer understand the implications of alternative management decisions on final yields. These advances provide farmers greater information on crop yields when making input use decisions.

Improvements in crop yield predictions affect the use of inputs that are traditionally applied within the growing season such as fungicides, herbicides, insecticides, and irrigation water. However, another aspect of precision agriculture is to improve the timeliness of input applications so that more inputs are applied within the growing season instead of before the growing season. Fertilizer is a key input in crop production that has traditionally been applied prior to the growing season or early within the growing season. But there are options for applying fertilizer within the growing season through high-clearance equipment, fertigation through center pivot irrigation, or aerial application of granular fertilizer. Advantages of applying fertilizer within the growing season are that less fertilizer is lost from the field and the farmer can apply less fertilizer in years when the crop uses less.

In our stylized framework, an increase in the forecast accuracy, i.e. an increase in θ, is analogous to the adoption of the precision agriculture technologies that improve information on crop conditions, such as algorithms to predict final crop yields based on high resolution data. Treating the insurance decision and the technology adoption decision as given, we can draw some implications for the precision agriculture technologies and the moral hazard incentives from crop insurance by revisiting our propositions.

Conventional wisdom is that precision agriculture results in improved environmental outcomes (Bongiovanni and Lowenberg-Deboer 2004). The usual assumption is that farmers can apply fewer inputs in order to obtain the same yield, so input usage decreases. Economists recognize that there could be a rebound effect because the increase in efficiency provides an incentive to increase use of the input (Gillingham, Rapson, and Wagner 2016). But the impact on the environment may still be positive if more inputs (like nutrients) that are applied to the field are used by the crop rather than being lost due to runoff or leaching into surface and groundwater (e.g., Nangia et al. 2008).

An insight from our model is that precision agriculture also affects input use through the moral hazard incentive which can amplify or counteract the conventional positive environmental benefit of precision agriculture. In the case where the environmental damages are larger in the bad state, then the moral hazard incentive from precision agriculture could amplify the positive environmental benefits. This is simply because of that fact that the moral hazard incentive increases (decreases) with the bad yield (good yield) forecast as the forecast accuracy, θ, increases as stated in proposition 2.

However, when the damages are the same in the two states or larger in the good state, then moral hazard from precision agriculture counteracts the conventional positive environmental impacts. As stated in proposition 4, the long-run expected value of the reduction in the optimal input x_{rp}^* that is attributed to the moral hazard incentive decreases as the forecast accuracy increases. This indicates that the farms with crop insurance may apply more inputs in the long run when they adopt technologies with better forecast accuracy. An important example is water quality, where nutrient losses are larger in the good state when rainfall is more abundant (Cisneros et al. 2014). Therefore, we expect the moral hazard incentive to counteract the nutrient loss reductions from adopting precision agriculture.

Conventional wisdom also suggests that precision agriculture will reduce yield variability. Most of the literature focuses on the potential of site-specific management to reduce yield variability by applying inputs to locations in the field that need it most and thus avoiding yield losses (Lowenberg-DeBoer and Swinton 1997; Lowenberg-DeBoer 1999). The same principle applies that precision agriculture could reduce yield variability by providing farmers with information on nutrient deficiencies or pest infestations within the growing season and allow farmers to apply the necessary nutrients or pesticide to reduce or avoid crop yield losses. This reduction in yield variability could eventually be reflected in lower indemnities and eventually lower crop insurance premiums.

Our model illustrates that behavioral adjustments of insured farmers counteracts the conventional wisdom that precision agriculture reduces yield variability and indemnities. Our results indicate that for most plausible parameter values, indemnity payments increase as the forecast accuracy improves (figure 4). The increase in indemnity payments stems from the fact that moral hazard incentives are getting larger when the forecast predicts bad crop yields and the forecast becomes more accurate. The increase in indemnity payments should eventually get reflected in higher crop insurance premiums.

Another implication of our model is that it is not clear, *a priori*, whether the availability of insurance increases or decreases the incentive to adopt these type of precision agriculture technologies (figure 5). On one hand, improved predictions of final crop yields have greater value to farmers without insurance because the technology allows them to make more informed decisions to manage risk that is more highly valued without insurance. On the other hand, farmers with insurance can use the new technology to extract more benefits from the crop insurance program by increasing moral hazard in years with bad yields.

Conclusion

We develop a model of input decisions in the middle of the growing season with crop insurance. The model assumes that there are four states: 1) high price, good weather; 2) low price, good weather; 3) high price, bad weather; and 4) low price, bad weather. Although the four state framework is a simplification of reality, the framework provides new insights by allowing us to derive analytical results on the moral hazard incentives of crop insurance.

We show that the incentives for moral hazard decrease as the accuracy of the forecast improves when the forecast indicates good yields, and vice versa when the forecast indicates bad yields. In the long run, we find that moral hazard incentives decrease with an improvement of the forecast accuracy when the agents become less risk-averse with the good yield outcome. This is because they value more the reduction in the moral hazard incentive with the good yield forecast compared to the increase in the moral hazard incentive with the bad yield forecast.

In contrast to the conventional wisdom that precision agriculture leads to better environmental outcomes, our findings suggest that the improved forecast accuracy combined with crop insurance may worsen long-run environmental outcomes. This occurs when the marginal environmental damage in the good yield state is greater than or equal to that in the bad yield state. When assessing the environmental consequence of adopting new technologies, crop insurance and behavioral adjustment need to be carefully considered.

We also find that the long-run expected indemnity increases as the accuracy of the forecast improves. The increase in moral hazard with the bad yield forecast leads to larger indemnities than the decrease in moral hazard with the good yield forecast. Therefore, the improved forecast accuracy is likely to increase the cost of crop insurance programs.

Our model has several limitations. In order to obtain the tractability of our analytical discussion, we utilize a static model. Dynamic aspects of the input decision with crop insurance may affect the results. For example, poor yield performances impact the future actual production history (APH) which affects the yield guarantee and the premium and insured farms may consider the APH reduction when they make input decisions (Mieno, Walters, and Fulginiti 2018). We also assume that marginal product of the input is the same in the states with bad and good yield shocks which may not be true for some types of inputs. While much of our discussion remains valid even with relaxing this assumption, future research on the impact of improved forecast accuracy on various types of inputs would have important implications for policy.

Despite its limitations, our conceptual framework generates important discussion and serves as a basis for future research on how crop insurance, improved technologies, and production decisions interact. For example, our analysis on the value of improved information on crop conditions motivates future research on whether crop insurance encourages technology adoption or not. Also, this article motivates future research on production impacts of crop insurance and improved technologies. The long-run increase of input use due to an improved forecast accuracy indicates positive production impact of improved technologies and the long-run indemnity increase also may cause more crop acreage.[17] Future research investigating potential production impacts could be important to understand the economic consequences of improved technologies when farms are insured by crop insurance.

Notes

[1]Obtained from https://www.answertech.com/News/The-Future-of-In-Season-Management-/361.

[2]Revenue insurance products were first introduced in 1996 (Glauber 2013). The revenue guarantee is the maximum of the realized harvest price and the projected price—the projected price is estimated at the beginning of the growing season—times the yield guarantee.

[3]While the further research with different input - yield relationships would shed more lights on the topic, we limit our focus on the risk-neutral input case to have clearly isolated impacts of improved forecast.

[4]Unlike Babcock (1990), we assume that farms know the long-run expected probability of $\varepsilon = w_b$ and update the probability based on the forecast. The updated probability depends on the forecast accuracy, θ.

[5]Differentiating 4 with respect to W yields:

$$\frac{\partial \tau_w}{\partial W} = -\theta$$

which indicates that there is no correlation between τ_W and W when the forecast is perfectly uninformative ($\theta = 0$), and τ_W and W are perfectly and negatively correlated (i.e. $\frac{\partial \tau_w}{\partial W} = -1$, when the forecast is perfectly informative, $\theta = 1$).

[6]We consider risk neutrality because analytical results are often cleaner, but we also extend the results to risk averse farmers.

[7]The simplification results from the fact that $u'(\pi_{rp2}) = u'(\pi_{rp4})$ because the farmer receives revenue of $P_p\bar{y}$ in both states.

[8]This difference is also analogous to the *risk reduction effect* of Ramaswami (1993).

[9]The functional forms and the parameters are listed in the online appendix A.

[10]The online appendix provides the analytic expression of $\partial EI_{rp}/\partial\theta$.

[11]Our stylized model does not include the endogenous decision of whether to purchase insurance. Obviously, increasing indemnities due to greater moral hazard would also increase the premium rates that farms face and thus, deter insurance participation. One can also think of this problem in a dynamic optimization framework as in Mieno, Walters, and Fulginiti (2018) where the degree of moral hazard is smaller for forward looking farms than the case of myopic farms. Future research could examine the impact of improved forecast technologies on the cost of crop insurance programs.

[12]Note that there is no uncertainty with a perfect forecast ($\theta = 1$).

[13]Note that the difference depends on the degree of risk aversion.

[14]The Supplemental Agricultural Disaster Assistance program is a disaster payment program that guarantees a certain level of crop revenue when an area or a farm faces a catastrophic yield loss.

[15]Also, note that the direction of the long-run impacts of the improved forecast accuracy on moral hazard and indemnities is similar for Yield Protection.

[16]A large emphasis in precision agriculture is to provide site-specific management, but we do not consider these types of technologies because they do not improve information on the likelihood of a low yields that trigger indemnity payments in a given year, which is our definition of the forecast accuracy.

[17]For example, the positive effect of subsidized crop insurance on crop acreage is documented by several recent studies (e.g., Goodwin, Vandeveer, and Deal 2004; Yu, Smith, and Sumner 2017; Yu and Sumner 2018).

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Figures

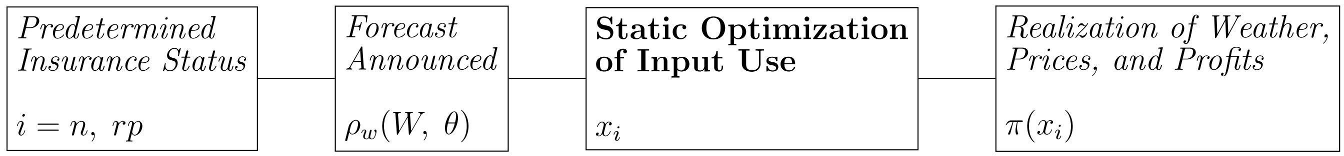

Figure 1. Timeline of the problem

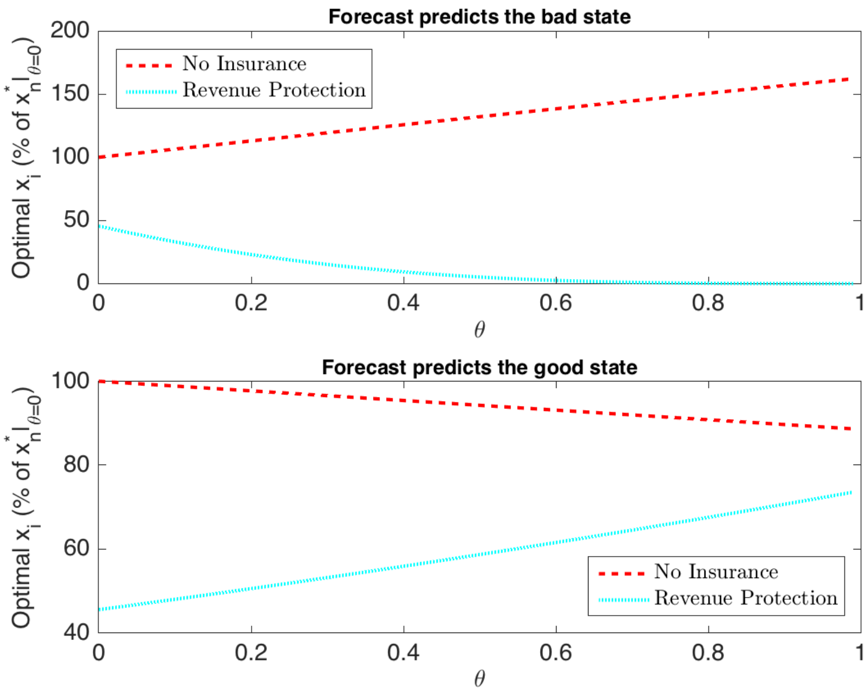

Figure 2. Numerical illustration of optimal input schedules, x_i^*, as responses to forecast accuracy

Note: The results in this figure represent numerical simulations of our stylized conceptual model for a hypothetical input. Functional forms and parameters used in the simulations are described in appendix A.

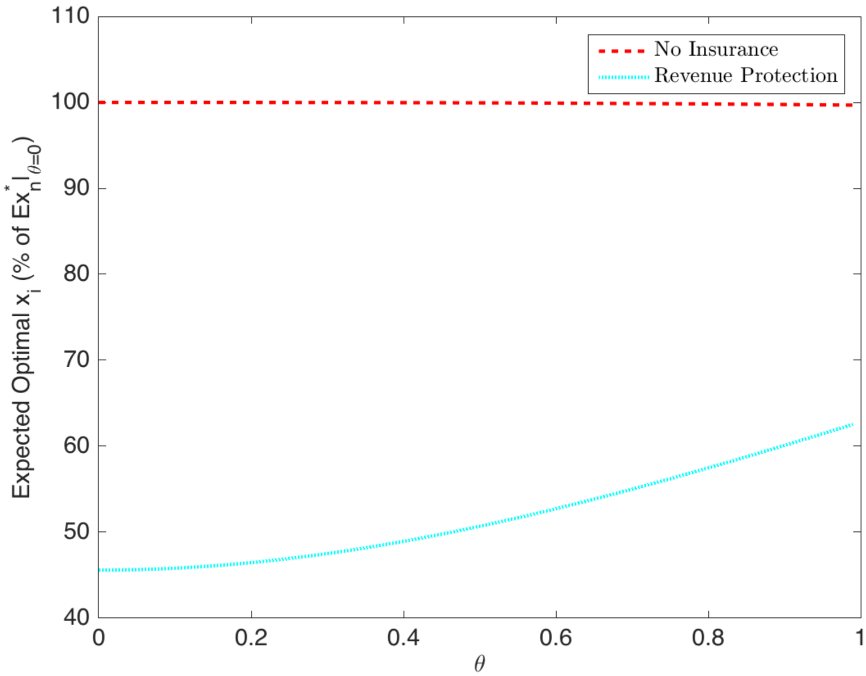

Figure 3. Numerical illustration of the impact of forecast accuracy on the long-run expected optimal input x_i

Note: The results in this figure represent numerical simulations of our stylized conceptual model for a hypothetical input. Functional forms and parameters used in the simulations are described in appendix A.

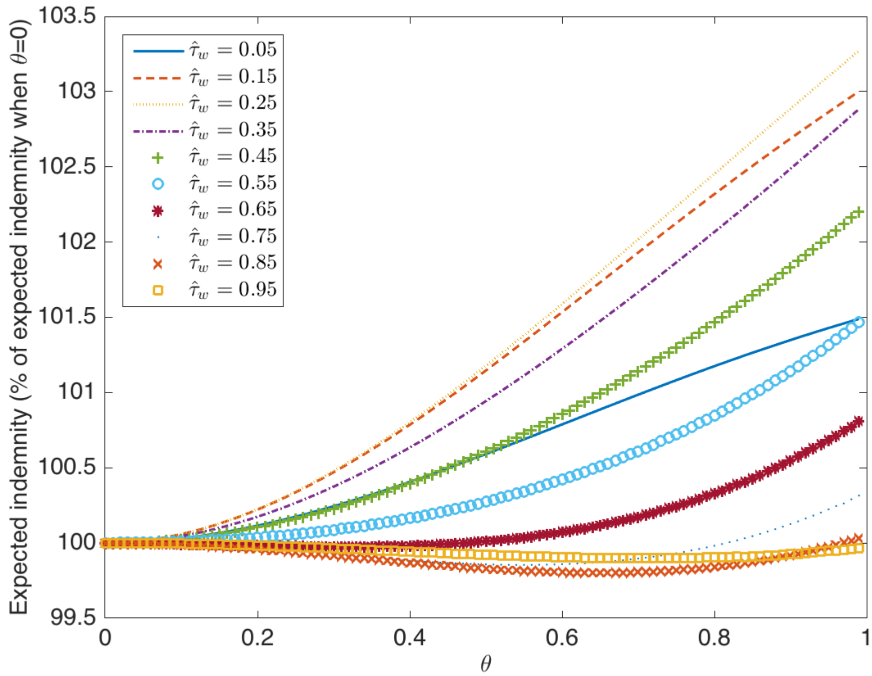

Figure 4. Numerical illustration of the impact of forecast accuracy on long-run expected indemnities for various $\hat{\tau}_w$

Note: The results in this figure represent numerical simulations of our stylized conceptual model for a hypothetical input. Functional forms and parameters used in the simulations are described in appendix A.

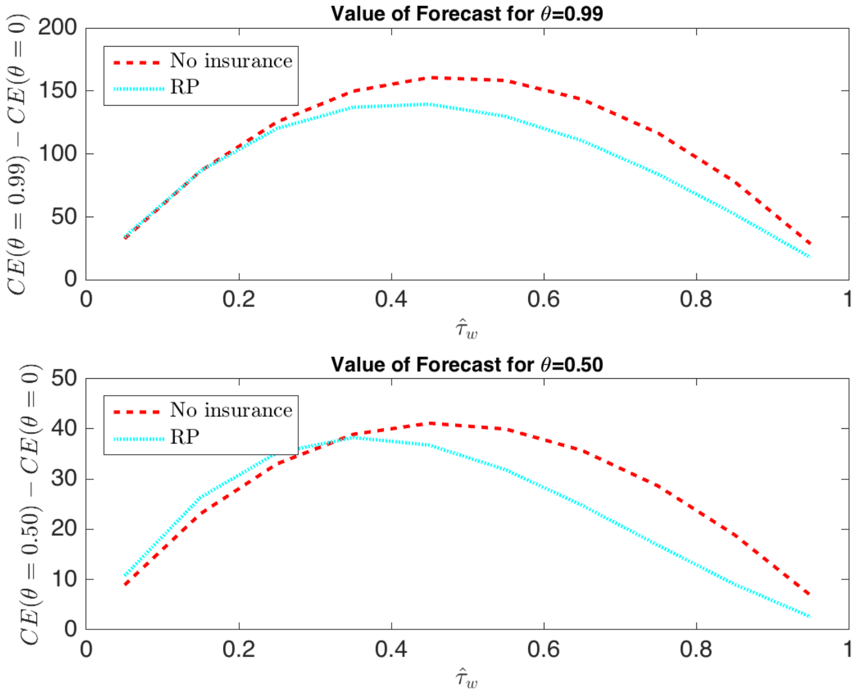

Figure 5. Values of forecast for various $\hat{\tau}_w$

Note: The results in this figure represent numerical simulations of our stylized conceptual model for a hypothetical input. Functional forms and parameters used in the simulations are described in appendix A.

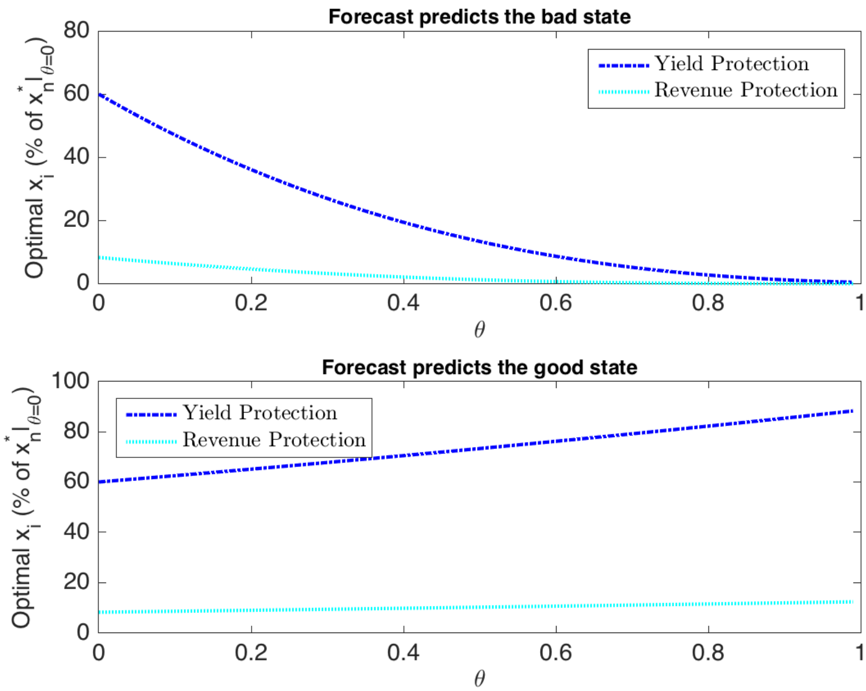

Figure 6. Optimal Inputs x_{yp} and x_{rp} when the Projected Price is Low

Note: The results in this figure represent numerical simulations of our stylized conceptual model for a hypothetical input. Functional forms and parameters used in the simulations are described in appendix A.

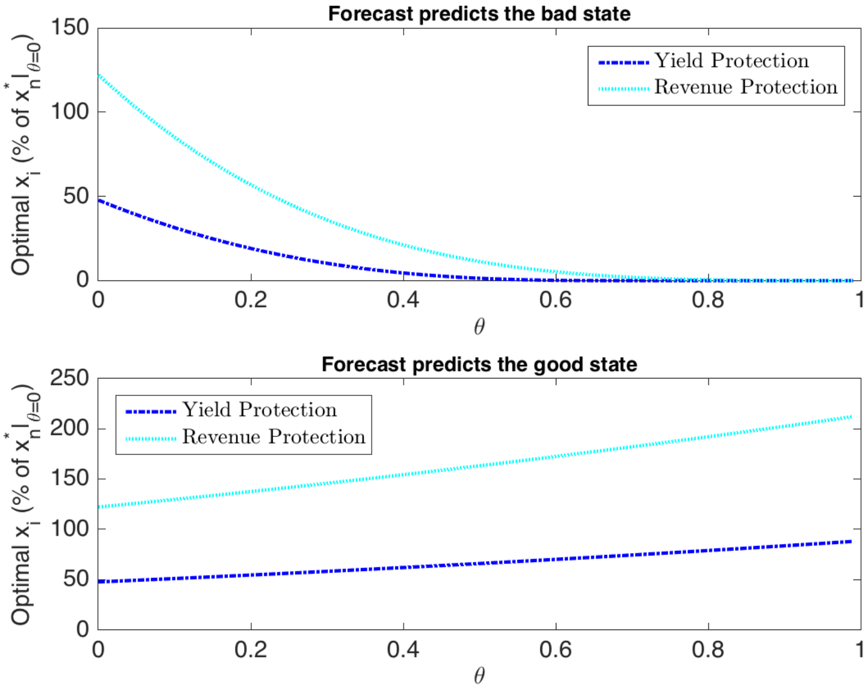

Figure 7. Optimal Inputs x_{yp} and x_{rp} when the Projected Price is High

Note: The results in this figure represent numerical simulations of our stylized conceptual model for a hypothetical input. Functional forms and parameters used in the simulations are described in appendix A.

Tables

Table 1. Probability Structure of Four-State Framework

	P_h	P_l
w_g	$(1-\tau_w)(1-\tau_{p\|g})$	$(1-\tau_w)\tau_{p\|g}$
w_b	$\tau_w(1-\tau_{p\|b})$	$\tau_w\tau_{p\|b}$