Determinants of Anomalous Prevented Planting Claims: Theory and Evidence from Crop Insurance

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This study examines the factors that determine the likelihood of submitting a potentially fraudulent prevented planting claim. A theoretical model is developed and the theoretical predictions are empirically verified by utilizing a binary choice model and crop insurance data from the southern United States. The empirical results show that insured producers with higher prevented planting coverage, lower dollar value of expected yield, and a history of submitting prevented planting claims are more likely to submit an anomalous prevented planting claim. The empirical model also suggests revenue insurance plans may be more vulnerable to prevented planting fraud than the traditional yield-based insurance plan. Results of this study can be valuable to compliance offices in their efforts to find "indicators" of fraudulent behavior in crop insurance, especially with regard to prevented planting.

Key Words: crop insurance, falsification, fraud, moral hazard, prevented plantings

The prevented planting provision is a standard element of crop insurance contracts. This provision allows an insured producer to receive an indemnity payment if, due to a valid cause of loss, the producer fails to plant an insured crop before a designated planting date. The cause of loss must be "general" in the surrounding area and must have prevented similar producers in the area from planting their crops. However, there are cases where insured producers receive a prevented planting payment due to a cause of loss not common to other producers in the area [U.S. Department of Agriculture/Office of the Inspector General (USDA/OIG), 1999; U.S. General Accounting Office (U.S. GAO), 1999]. For example, a prevented planting claim with drought as a cause of loss may have been paid out to a single producer even if no other producer in that county received a prevented planting payment due to this cause of loss. These are anomalous cases which may be suggestive of fraud, waste, or abuse in the crop insurance program (USDA/OIG, 1999; U.S. GAO, 1999).

The Risk Management Agency's (RMA's) Compliance Office views prevented planting as a potential source of program vulnerability because producers can receive this payment without incurring the major costs of production associated with carrying the crop to harvest. Payment received due to prevented planting is a positive cash flow to the producer without expending the effort and financial resources to grow, tend, and harvest the crop. Hence, insured dishonest producers may have incentives to take advantage of this provision and submit a fraudulent prevented planting claim, instead of bringing their crop to harvest.

The objective of this analysis is to examine how producer choices of certain crop insurance contract elements may affect the likelihood of submitting potentially fraudulent prevented planting claims.

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A better understanding of this issue can provide information helpful to the RMA in formulating strategies for reducing the incentives for this kind of behavior. Crop insurance contract provisions can be revised or additional provisions can be incorporated to mitigate incentives for filing a fraudulent prevented planting claim, thereby reducing the number of excessive indemnity payments. Furthermore, if producers' choices of contract elements can provide an indication of whether or not a particular producer is likely to submit a fraudulent prevented planting claim, then the RMA Compliance Office can be proactive in investigating individuals making contract choices consistent with fraud behavior. Through these efforts, crop insurance program integrity may be improved.

Despite the strongly held belief of experts within the Risk Management Agency that about 5% of all claims are associated with fraud, waste, or abuse (U.S. GAO), studies assessing fraud behavior in crop insurance have been limited. Most studies of crop insurance have focused on moral hazard and adverse selection problems, rather than fraud, as sources of excessive losses in crop insurance (Knight and Coble, 1997).

Agricultural economists have examined various aspects of the moral hazard problem in crop insurance (Chambers, 1989; Horowitz and Lichtenberg, 1993; Quiggin, Karagiannis, and Stanton, 1993; Smith and Goodwin, 1996; Coble et al., 1997; Hyde and Vercammen, 1997), but no analyses have concentrated specifically on moral hazard related to prevented planting fraud behavior. A study focused explicitly on prevented planting claims may be of greater direct value to RMA compliance, in terms of attempting to identify insured producers prone to fraud, than more general studies of moral hazard. Therefore, this study contributes to the literature by providing further understanding about the factors affecting potential fraud behavior in the context of prevented planting in crop insurance.

The remainder of the article is organized as follows. A theoretical model elucidating the hypothesized effects of several insurance contract elements on the probability of filing a prevented planting claim is developed in the next section, followed by a discussion of the empirical methods and data. Results and conclusions are provided in the final two sections. An appendix is included to offer proof of the theoretical model's comparative statics.

The Theoretical Model

Consider a risk-averse producer with an Actual Production History (APH) crop insurance contract.[1] The APH contract is an individual yield insurance plan designed to protect producers against yield shortfalls if the actual yield falls below the guaranteed level.[2] APH insurance provides yield protection of up to 85% of the producer's average historical yield, with a premium based on a chosen yield coverage level. The APH contract pays an indemnity if the producer's actual yield (Y_a) falls below the guaranteed yield level (Y_g), but offers no price protection. The guaranteed yield is computed based on the following formula:

$$(1) \qquad Y_g = \theta_2 Y_e,$$

where θ_2 is the percentage of yield coverage chosen by the producer (θ_2 = 0.50, 0.55, 0.60, 0.65, 0.70, 0.75, 0.80, 0.85), and Y_e is the expected yield based on the average historical yield.[3]

If Y_a at harvest is greater than Y_g, then the insured producer does not receive an indemnity payment and the producer's payoff is $Y_aP_m ! C_p$, where P_m is the market price at harvest and C_p is the accumulated cost of production at harvest. If Y_a at harvest is less than Y_g, then the insured producer receives an indemnity payment with a payoff of $(\theta_2Y_e ! Y_a)P_g + Y_aP_m ! C_p$, where P_g is the guaranteed or elected price. The guaranteed price is a certain fixed proportion of the expected price, which is usually the USDA's projected farm-level price for the crop year. This chosen fixed proportion of the expected price ranges from 0.59 to 1.0. Assuming the insured producer has a von Neumann-Morgenstern utility function with UN > 0, UO < 0, the producer's expected utility can then be expressed as follows (assuming weather conditions would allow the producer to plant the crop):

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[1] Even if only APH crop insurance is modeled here, the authors believe the qualitative results will not be altered under revenue insurance. The empirical portion, however, will include an insurance type variable that may indicate whether alternative insurance plans have a significant effect on prevented planting fraud behavior.

[2] APH insurance includes catastrophic coverage (CAT) and optional buy-up levels of coverage above CAT. For a flat fee of $60 per crop per farm, CAT provides a 50% yield guarantee and pays an indemnity based on 55% of the projected price. In this analysis, we separate CAT and APH buy-up coverage and hereafter refer to APH buy-up as APH insurance.

[3] If the producer has no adequate yield history (i.e., a four-year yield history), assigned transitional yields (T-yields) are used in its place.

$$(2)\quad \int_0^{\theta_2 Y_e} U(W + \theta_2 D - Y_a P_g + Y_a P_m - C_p) f(Y_a)\, dY_a + \int_{\theta_2 Y_e}^{\infty} U(W + Y_a P_m - C_p) f(Y_a)\, dY_a,$$

where

$$\int_0^{\theta_2 Y_e} f(Y_a)\, dY_a$$

represents the probability of $Y_a < Y_g$, D is the dollar value of the expected yield ($D = Y_e P_g$), and W is the noncontingent wealth defined as the sum of initial wealth less the insurance premium ($W = W_0 - p(\theta_1, \theta_2)$). Note that the premium (p) is a function of the yield coverage level (θ_2) and the prevented planting guarantee reduction percentage (θ_1), as described in the following paragraph.

Prevented planting provisions are included in standard APH crop insurance contracts. As mentioned above, the prevented planting provision in the U.S. crop insurance program allows for insured producers to receive an indemnity payment if a producer fails to plant an insured crop before a designated planting date for that crop and county, due to a valid cause of loss. The cause of loss must be general in the surrounding area, and must have prevented similar producers in the area from planting their crops. Prevented planting payments are based on a guaranteed prevented planting yield computed as follows:

$$(3)\qquad Y_{gp} = \theta_1 \theta_2 Y_e = \theta_1 Y_g,$$

where θ_1 is the prevented planting guarantee reduction percentage chosen by the producer (θ_1 = 0.60, 0.65, 0.70).[4] Prevented planting guarantee reduction levels at 0.65 and 0.70 are additional buy-up coverage. If an insured producer is prevented from planting and receives a prevented planting payment, the producer's utility can be expressed as $U(W + \theta_1 \theta_2 D - C_{pp})$, where C_{pp} is the production cost incurred by the producer at the point that planting was prevented (i.e., fertilizer, herbicide, land rental, tillage cost, and other pre-planting costs). This definition of C_{pp} implies that C_p is an increasing function of C_{pp} [$C_p = f(C_{pp})$], where $f'(C_{pp}) > 0$.

An honest producer who is truly prevented from planting receives $U(W + \theta_1 \theta_2 D - C_{pp})$ even if this utility value is lower than the expected utility in (2). In contrast, a dishonest producer has the opportunity either to submit a fraudulent prevented planting claim or to carry the crop to harvest. Assume the decision to submit a fraudulent prevented planting claim is made after signing up for crop insurance coverage. This assumption implies producers could recognize an opportunity to take advantage of the system after signing up, and they have the option to pursue it or not. In the language of the insurance fraud literature, the producer can undertake "opportunistic" prevented planting fraud after signing up for crop insurance. In this case, a dishonest producer will submit a fraudulent prevented planting claim if and only if:

$$(4)\quad gU(W + \theta_1 \theta_2 D - C_{pp} - C_f) + (1 - g)U(W - F - C_{pp} - C_f) \geq \int_0^{\theta_2 Y_e} U(W + \theta_2 D - Y_a P_g + Y_a P_m - C_p) f(Y_a)\, dY_a + \int_{\theta_2 Y_e}^{\infty} U(W + Y_a P_m - C_p) f(Y_a)\, dY_a,$$

where g is the probability of successful fraud (fraud is not detected), C_f is the cost of generating a fraudulent prevented planting claim, and F is the monetary value of the penalty or punishment for submitting a fraudulent prevented planting claim. The cost (C_f) may include transactions costs for colluding with adjusters and agents to falsify the claim. Note that there will be no prevented planting payment if the dishonest producer gets caught submitting a fraudulent claim. Hence, the insured dishonest producer will submit a fraudulent prevented planting claim when the expected utility of the fraud gamble is greater than the expected utility of not taking the fraud gamble (for further information on fraud gambles, see Cummins and Tennyson, 1994).

An important behavioral assumption in (4) is that fraud is not found with a probability of one, in contrast to what is suggested in standard contracts (Townsend, 1979; Picard, 1996). The probability ($1 - g$) is lower than one for at least two reasons: either (*a*) the insurer does not audit the policy (absence of full commitment or random auditing), or (*b*) the insurer audits, but does not find any evidence of fraud even when fraud exists. Current RMA compliance practice is to randomly audit selected claims every year and to audit claims called in through fraud "hotlines." Collusion among producers, adjusters, and agents makes it possible for fraudulent prevented planting claims not to be detected by RMA compliance audits.

[4] The prevented planting guarantee reductions presented here apply to most crops (i.e., corn, wheat, grain sorghum, soybeans), but some crops have different selection guarantee reduction choices. For example, rice has prevented planting guarantee reductions of 0.45, 0.50, and 0.55, while cotton has prevented planting guarantee reductions of 0.50, 0.55, and 0.60.

Assume there exists a success probability of fraud ($\tilde{g}$) that makes a dishonest producer indifferent between submitting a fraudulent prevented planting claim and choosing to grow the crop to harvest:

$$(5)\quad \tilde{g}U(W+\theta_1\theta_2 D - C_{pp} - C_f) + (1-\tilde{g})U(W - F - C_{pp} - C_f) = \int_0^{\theta_2 Y_e} U(W + \theta_2 D - Y_a P_g + Y_a P_m - C_p) f(Y_a)\, dY_a + \int_{\theta_2 Y_e}^{\infty} U(W + Y_a P_m - C_p) f(Y_a)\, dY_a.$$

Equation (5) implies:

$$(6)\quad \tilde{g} = \frac{\int_0^{\theta_2 Y_e} U(W + \theta_2 D - Y_a P_g + Y_a P_m - C_p) f(Y_a)\, dY_a + \int_{\theta_2 Y_e}^{\infty} U(W + Y_a P_m - C_p) f(Y_a)\, dY_a - U(W - F - C_{pp} - C_f)}{U(W+\theta_1\theta_2 D - C_{pp} - C_f) - U(W - F - C_{pp} - C_f)}.$$

From (6), it can be shown that the choice of prevented planting guarantee reduction (θ_1) has a negative relationship with $\tilde{g}$ (i.e., $\partial\tilde{g}/\partial\theta_1 < 0$). But other insurance contract choice elements, such as θ_2, Y_e, and P_g, have an ambiguous relationship with $\tilde{g}$. Consequently, the dollar value of the expected yield (D) also has an ambiguous relationship with $\tilde{g}$.

Under certain reasonable conditions, however, it can be shown that $\partial\tilde{g}/\partial D > 0$ [see equation (A14) in the appendix]. Several non-contract choice elements can also be shown to have an unambiguous relationship with $\tilde{g}$: $\partial\tilde{g}/\partial P_m > 0$, $\partial\tilde{g}/\partial C_p < 0$, $\partial\tilde{g}/\partial F > 0$, and $\partial\tilde{g}/\partial C_f > 0$. Proof of these derivations can be seen in the appendix. Finally, the non-contract choice element C_{pp} has an ambiguous relationship with $\tilde{g}$ (i.e., $\partial\tilde{g}/\partial C_{pp}$ < or > 0) because C_p is a function of C_{pp} [see appendix equation (A13)].

Let α be a binary choice variable where α = 1 if the producer chooses to submit a fraudulent prevented planting claim, and α = 0 otherwise. The dishonest producer's problem is to choose α to maximize expected utility:

$$(7)\quad V = \alpha\big[gU(W+\theta_1\theta_2 D - C_{pp} - C_f) + (1-g) \times U(W - F - C_{pp} - C_f)\big] + (1-\alpha) \times \Big[\int_0^{\theta_2 Y_a} U(W + \theta_2 D - Y_a P_g + Y_a P_m - C_p) f(Y_a)\, dY_a + \int_{\theta_2 Y_e}^{\infty} U(W + Y_a P_m - C_p) f(Y_a)\, dY_a\Big].$$

This maximization implies:

$$(8)\quad \alpha = 1 \quad \text{if } g > \tilde{g},$$

$$(9)\quad \alpha = 0 \quad \text{otherwise [i.e., } g \le \tilde{g}].$$

Note, α = 0 even if $g = \tilde{g}$, because it will not be worth the effort to defraud considering the non-economic cost of being dishonest. From (8) and (9) and the first derivatives of (6) with respect to θ_1, it is clear that α is an increasing function of g, and consequently of θ_1. This theoretical result can be written as a proposition:

- PROPOSITION 1: *Producers who choose higher prevented planting guarantee reductions* (θ_1) *are more likely to submit a fraudulent prevented planting claim.*

This proposition is intuitive because higher insurance protection for prevented planting means the potential prevented planting payments will be more comparable to the payoffs at harvest, since the producer does not face the disutility caused by the risk, uncertainty, and costs associated with bringing the crop to harvest (i.e., weather, volatile production costs, uncertain prices, etc.). The fraud gamble becomes more attractive if the prevented planting guarantee reduction is higher. Proposition 1 is one hypothesis empirically tested in the next section.

As mentioned above, the dollar value of expected yield (D) does not have a definitive general relationship with $\tilde{g}$, and consequently with α. Therefore, the relationship of this variable to the probability of submitting a fraudulent prevented planting claim is an empirical question. Nevertheless, we could theoretically show that the following relationship can hold under certain reasonable conditions: $\partial\tilde{g}/\partial D > 0$ [see appendix equation (A14)]. If this derivative holds, then α is a decreasing function of D, and the following proposition can be argued:

- PROPOSITION 2: *Producers who have higher dollar values of expected yield* (D) *are less likely to submit a fraudulent prevented planting claim.*

Proposition 2 is intuitive because higher expected yield dollar values suggest the producer has good insurance protection in the event of a low yield at harvest (i.e., a higher expected yield value will trigger indemnity payments more often). In other words, it is more attractive to bring the crop to harvest than to submit a fraudulent prevented planting claim, because the producer has good coverage at the end of harvest even if there is a probability of low yields. The expected utility of bringing the crop to harvest is likely greater than the expected utility of the fraud gamble. Proposition 2 is also empirically tested in the next section.

Although there are several non-contract choice variables with an unambiguous effect on $\tilde{g}$, and consequently on α, empirical data on these variables are not readily available. Hence, the relationship between the non-contract choice variables (P_m, F, C_p, C_f) and α is not empirically tested here. From the first derivatives of (6) with respect to the non-contract elements, we could show that α is a decreasing function of P_m, F, and C_f; and α is an increasing function of C_p (see appendix). If P_m is anticipated to be high and C_p is low, then it is more attractive for the producer to bring the crop to harvest. The payoffs at harvest time would potentially be greater if these conditions hold. On the other hand, higher F and C_f values indicate it is potentially more costly to submit a fraudulent prevented planting claim. The fraud gamble is less attractive in this case. These intuitive theoretical results are presented here for completeness, although they are not empirically tested in the next section.

Empirical Methods and Data

A binary choice model is used to empirically test the theoretical predictions noted above. An insured dishonest producer must make a single choice between submitting or not submitting a fraudulent prevented planting claim. From the theory, an insured dishonest producer will submit a fraudulent prevented planting claim if the expected utility of this fraud gamble is greater than the expected utility of bringing the crop to harvest. Since the expected utility of the fraud gamble is unobservable, we model the difference between the expected utility of the fraud gamble and bringing the crop to harvest as:

$$y_i^* = \boldsymbol{\beta}'\mathbf{x}_i + \varepsilon, \tag{10}$$

where y_i^* is the unobservable difference in expected utilities. The $\mathbf{x}_i$ vector represents the variables which affect fraud incentives, and $\boldsymbol{\beta}'$ is a vector representing the corresponding parameters. We assume ε has a normal (probit model) distribution with mean 0 and variance 1.

While expected utility is not observed, we do observe whether an anomalous prevented planting claim suggestive of fraud has been submitted or not. Thus, a binary variable can be defined as:

$$y = 1 \quad \text{if } y_i^* > 0, \tag{11}$$

$$y = 0 \quad \text{otherwise.} \tag{12}$$

In this case, $y = 1$ if an anomalous prevented planting claim suggestive of fraud has been submitted, and $y = 0$ otherwise. It follows that:

$$\begin{aligned} \text{Prob}(y = 1) &= \text{Prob}(\varepsilon > -\boldsymbol{\beta}'\mathbf{x}_i) \\ &= F(\boldsymbol{\beta}'\mathbf{x}_i), \end{aligned} \tag{13}$$

where F is the cumulative distribution function of ε (Greene, 2000). The probit form of the model is estimated here because a normal distribution is assumed for ε. The probit distribution is given by:

$$\text{Prob}(y = 1) = \int_{-\infty}^{\boldsymbol{\beta}'\mathbf{x}_i} \phi(t)\,dt = \Phi(\boldsymbol{\beta}'\mathbf{x}_i), \tag{14}$$

where ϕ represents the standard normal distribution. The maximum-likelihood procedure is used to estimate the parameters of the binary choice probit model above. Because the estimated coefficients arising from these regressions are not marginal effects, additional calculations are necessary. Following Greene (2000), the marginal effects for the probit model are given by:

$$\frac{\partial E[y|\mathbf{x}_i]}{\partial \mathbf{x}_i} = \phi(\boldsymbol{\beta}'\mathbf{x}_i)\boldsymbol{\beta}. \tag{15}$$

Note that the marginal effects in this study are computed at the means of $\mathbf{x}_i$.

For this analysis, only RMA data of insured producers for reinsurance year (RY) 2001 are considered, and catastrophic (CAT) insurance policies are excluded from the analysis. Only crop insurance data under the RMA's Southern Regional Compliance Office for corn, cotton, oats, onions, peanuts, rice, soybeans, and wheat are considered. Producers who bought a valid insurance policy are included in the data, regardless of whether they submitted a prevented planting claim or not. The data are aggregated at the crop policy level for a particular crop, crop type, and practice. Further, the data were grouped according to the yield coverage level because the majority of the observations are at the 65% level. To account for this fact, the probit regression equations are estimated for three different coverage levels (60%, 65%, and 70%) and the estimated parameters for each coverage level are compared.[5]

As mentioned above, the dependent variable in this study, anomalous prevented planting (*APP*), is a binary variable, where *APP* = 1 if the prevented planting claim is deemed anomalous and *APP* = 0 otherwise. Note, data do not exist to show whether a prevented planting claim is classified as definitively fraudulent or not. However, given that a prevented planting payment should be made only if the cause of loss is "general" in the surrounding area, claims not following this guideline can be identified. Therefore, an "anomalous" prevented planting claim in this case is one where the reported cause of loss that prevented a producer from planting is not "general" within the county; the primary cause of loss did not prevent other producers of the same crop, using the same practices, from planting. Hence, these are anomalous prevented planting claims suggestive of fraud. However, this does not necessarily mean the claim is truly fraudulent.

To make the identification of anomalous prevented planting claims more tractable, all the insurable causes of loss recognized by RMA are first grouped into five distinct cause-of-loss categories: (*a*) "too wet," (*b*) "too hot and dry," (*c*) "too cold," (*d*) "hail," and (*e*) "other." The following causes of loss are included in the "too wet" category: excess moisture or precipitation or rain, flood, cyclone, and hurricane/tropical depression. Drought, heat, failure of irrigation supply, excess sun, force fire, fire, and volcanic eruption are the insurable causes of loss grouped under the "too hot and dry" category. The "too cold" category includes the following causes of loss: frost, freeze, cold winter, and cold wet weather. "Hail" is grouped into one category by itself, while the "other" category includes all other causes of loss not mentioned above (e.g., plant disease, hot wind, insects, and other).

An example of how to identify anomalous prevented planting claims is as follows. First, assume that in a particular county there is one producer of nonirrigated corn for grain who was prevented from planting due to a cause of loss in the "too hot and dry" category (say, drought). But there are 19 other nonirrigated grain corn producers with insurance policies in the same county who did not claim a prevented planting claim for a cause of loss in the "too hot and dry" category. The one prevented planting claim with a cause of loss under the "too hot and dry" category is considered anomalous because only one out of 20 producers of nonirrigated grain corn in the area submitted a prevented planting claim for that cause-of-loss category. Nineteen other producers of the same crop could have potentially submitted a prevented planting claim due to causes under the "too hot and dry" category, but did not. Thus, the cause of loss claimed by the anomalous nonirrigated corn grain producer is not "general" in the area. In this case, 5% (1/20) of the total producers of a particular crop type and practice (nonirrigated grain corn) submitted a prevented planting claim due to a cause of loss under the "too hot and dry" category.

Anomalous prevented planting claims are flagged if the number of prevented planting claims for a particular crop, crop type, practice, and cause of loss combination divided by the total number of policies for the same crop, crop type, and practice in the county is less than or equal to 5%. As in the example above, this procedure identifies the prevented planting claims characterized as anomalous because they are not general in the area (i.e., only 5% or less of the total policies in the county claimed prevented planting for this cause of loss).

If a prevented planting claim is flagged as anomalous, then the dependent variable is assigned a value of one (*APP* = 1); otherwise *APP* = 0. For purposes of comparison and to explore the robustness of results, the empirical model is also implemented using 7.5% and 10% as thresholds to determine the number of anomalous prevented planting claims—i.e., *APP*75 = 1 if a prevented planting claim is flagged at the 7.5% threshold, otherwise *APP*75 = 0; *APP*10 = 1 if a prevented planting claim is flagged at the 10% threshold, otherwise *APP*10 = 0. There are three probit models (denoted models 1, 2, and 3) corresponding to the three alternative dependent variables. Therefore, a total of nine probit regression equations are estimated (three dependent variables for each of the three coverage levels).

The elements of vector $\mathbf{x}_i$ representing the independent variables of the model are listed in table 1. The variables *FIVE* and *TEN* are dummy variables indicating whether the producer bought additional 5% and 10% prevented planting coverage, respectively.[6] The excluded category is the "no buy-up"

[5] The probit regression models were also estimated at the 55% and 75% coverage levels, but are not presented here in the interest of space (results are available from the authors upon request).

[6] Dummy variables for the 5% and 10% additional prevented planting coverage were used here instead of dummies for the actual percentage coverage because some crops have different base prevented planting

Table 1. Definitions of Independent Variables Used in the Empirical Model

Variable Name	Definition
FIVE	Dummy variable representing additional 5% prevented planting coverage buy-up. *FIVE* = 1 if farmer bought an additional 5% prevented planting coverage; *FIVE* = 0 otherwise.
TEN	Dummy variable representing additional 10% prevented planting coverage buy-up. *TEN* = 1 if farmer bought an additional 10% prevented planting coverage; *TEN* = 0 otherwise.
D	Dollar value of expected yield.
*YR*1	Prevented planting history dummy variable. *YR*1 = 1 if farmer submitted a prevented planting claim last year (RY 2000); *YR*1 = 0 otherwise.
*YR*2	Prevented planting history dummy variable. *YR*2 = 1 if farmer submitted a prevented planting claim the last two years (RY 1999 and RY 2000); *YR*2 = 0 otherwise.
*CRP*1 – *CRP*8	Dummy variable representing the crop planted. The crops are: (1) cotton, (2) oats, (3) onions, (4) peanuts, (5) rice, (6) soybeans, (7) wheat, and (8) corn. Corn is the excluded category. *CRP*(*i*) = 1 if crop (*i*); *CRP*(*i*) = 0 otherwise (where *i* = crops 1 to 8 above).
APH	Dummy variable representing the standard APH (or MPCI) yield insurance plan. *APH* = 1 if insurance plan is APH; *APH* = 0 otherwise.
OTHER	Dummy variable representing other insurance plans aside from APH or CRC. *OTHER* = 1 if insurance plan is not APH or CRC; *OTHER* = 0 otherwise. CRC insurance plan is the excluded category.
IR	Irrigated dummy variable. *IR* = 1 if irrigated; *IR* = 0 otherwise.
*ST*1 – *ST*8	Geographical state dummy variable. The states in the RMA's Southern Regional Compliance Office are (1) Kentucky, (2) Louisiana, (3) Mississippi, (4) New Mexico, (5) Oklahoma, (6) Tennessee, (7) Texas, and (8) Arkansas. Arkansas is the excluded category. *ST*(*j*) = 1 if state is *j*; *ST*(*j*) = 0 otherwise (where *j* = states 1 to 8 above).

category, or the standard prevented planting coverage for crop insurance contracts. From proposition 1, these variables are expected to have a significant positive sign.

On the other hand, the dollar value of the expected yield (*D*) is expected to have a significant negative sign based on proposition 2. The variables *YR*1 and *YR*2 are dummy variables representing whether a producer submitted a prevented planting claim in the past year (*YR*1) or two years in a row (*YR*2). These variables are expected to have a significant positive sign because they proxy for the propensity of an individual producer to submit a prevented planting claim. It is reasonable to hypothesize that producers who have a propensity for submitting prevented planting claims are more likely to submit a fraudulent prevented planting claim. The remaining variables in the empirical model represent crop, practice, insurance plan, and state dummy variables, and there is no a priori expectation on the signs of these variables. Frequencies of the dummy variables are reported in table 2 for yield coverage levels of 60%, 65%, and 70%.

Results and Discussion

Estimation results of the probit models at three coverage levels (60%, 65%, and 70%) for the three dependent variables (*APP*, *APP*75, and *APP*10) are presented in tables 3, 4, and 5, respectively. Note that the variable *FIVE* was dropped in all the equations because there were not enough observations with *FIVE* = 1 (5% prevented planting buy-up) and also having an anomalous prevented planting claim. Thus, it does not help us in determining the probability of *APP* = 1 (completely determines failure). Several different variables in the estimated equations were similarly dropped in certain cases for the same reason.

The signs and significance of variables are relatively stable across the three thresholds used to determine the dependent variable. In general, as an increase occurs in the threshold used to determine the dependent variable, the magnitude of the estimated coefficients likewise increases. However, the signs and significant variables are observed to vary somewhat across the three coverage levels,

coverage levels (see footnote 4). However, all crops have either a 5% or 10% prevented planting buy-up option. For example, 60% is the base prevented planting coverage for corn, while 50% is the base coverage for cotton. But for both crops, a producer can buy an additional 5% or 10% prevented planting coverage (65% and 70% for corn, 55% and 60% for cotton).

Table 2. Frequency of the Dummy Variables Under Yield Coverage Levels of 60%, 65%, and 70%

A. 60% Yield Coverage Level (*n* = 8,582)

Variable	Frequency	Percent	Variable	Frequency	Percent
APP	28	0.33	*CRP*7	1,770	20.62
*APP*75	43	0.50	*CRP*8	2,103	24.50
*APP*10	66	0.77	*OTHER*	138	1.61
FIVE	0	0.00	*APH*	4,083	47.58
TEN	298	3.47	*IR*	2,141	24.95
*YR*1	154	1.79	*ST*1	90	1.05
*YR*2	35	0.41	*ST*2	497	5.79
*CRP*1	3,699	43.10	*ST*3	132	1.54
*CRP*2	10	0.12	*ST*4	261	3.04
*CRP*3	5	0.06	*ST*5	763	8.89
*CRP*4	137	1.60	*ST*6	214	2.49
*CRP*5	101	1.18	*ST*7	6,070	70.73
*CRP*6	757	8.82	*ST*8	555	6.47

B. 65% Yield Coverage Level (*n* = 82,807)

Variable	Frequency	Percent	Variable	Frequency	Percent
APP	348	0.42	*CRP*7	22,160	26.76
*APP*75	573	0.69	*CRP*8	26,851	32.43
*APP*10	746	0.90	*OTHER*	2,378	2.87
FIVE	13	0.02	*APH*	54,862	66.25
TEN	3,806	4.60	*IR*	18,767	22.66
*YR*1	1,044	1.26	*ST*1	2,375	2.87
*YR*2	291	0.35	*ST*2	2,354	2.84
*CRP*1	24,655	29.77	*ST*3	1,606	1.94
*CRP*2	418	0.50	*ST*4	561	0.68
*CRP*3	116	0.14	*ST*5	12,782	15.44
*CRP*4	1,403	1.69	*ST*6	1,306	1.58
*CRP*5	1,105	1.33	*ST*7	58,966	71.21
*CRP*6	6,099	7.37	*ST*8	2,857	3.45

C. 70% Yield Coverage Level (*n* = 20,461)

Variable	Frequency	Percent	Variable	Frequency	Percent
APP	117	0.57	*CRP*7	8,092	39.55
*APP*75	247	1.21	*CRP*8	4,825	23.58
*APP*10	327	1.60	*OTHER*	2,239	10.94
FIVE	7	0.03	*APH*	8,153	39.85
TEN	1,939	9.48	*IR*	3,870	18.91
*YR*1	383	1.87	*ST*1	1,839	8.99
*YR*2	93	0.45	*ST*2	759	3.71
*CRP*1	4,155	20.31	*ST*3	532	2.60
*CRP*2	51	0.25	*ST*4	100	0.49
*CRP*3	15	0.07	*ST*5	6,762	33.05
*CRP*4	604	2.95	*ST*6	900	4.40
*CRP*5	321	1.57	*ST*7	8,474	41.42
*CRP*6	2,398	11.72	*ST*8	1,095	5.35

suggesting that prevented planting behavior may differ depending on the yield coverage level of the insured producer. Overall, the statistical significance of the variables at the 65% coverage level is relatively weaker compared to the higher coverage levels. Likelihood-ratio tests in all cases rejected the hypothesis that all coefficients are jointly zero.

Main Variables of Interest

In all of the estimated models, the signs of the coefficients for the variables *TEN*, *YR*1, and *YR*2 are consistent with our a priori expectations. First, the positive sign and the statistical significance of the coefficient for the variable *TEN* support our first proposition. Producers who choose to buy an additional 10% prevented planting coverage are more likely to submit an anomalous or potentially fraudulent prevented planting claim. In other words, a producer with a higher prevented planting guarantee percentage is more likely to submit an anomalous prevented planting claim. The estimated marginal effects indicate that for producers who buy an additional 10% prevented planting coverage, the probability of submitting a prevented planting claim is increased by 0.003 to 0.02, depending on the coverage level and dependent variable threshold.

The sign and significance of the 10% prevented planting buy-up coverage is robust across coverage levels, especially at the 65% and 70% coverage levels. Note, however, the effect of an additional 10% prevented planting coverage noticeably increases as the overall yield coverage level increases. This result is intuitive because as the yield coverage level increases, the absolute magnitude of a potential prevented planting pay-out (if claimed) would also increase.

Second, the positive signs for the coefficients of variables *YR*1 and *YR*2 at the 65% and 70% yield coverage levels also support our a priori expectations, although only the coefficient for *YR*1 is statistically significant in most cases. At the 60% coverage level, *YR*1 was statistically significant only for the case of the *APP*10 dependent variable. The significant positive signs in most of the estimated equations indicate that producers who have submitted a prevented planting claim in the past are more likely to submit a fraudulent prevented planting claim.

Another coefficient of interest in this study is associated with the variable denoting dollar value of expected yield (*D*). In all cases, the coefficient for *D* had a negative sign, but was only consistently significant at the 65% coverage level. Also, the magnitude of the coefficient is small relative to the other variables. Nevertheless, this empirical result provides some evidence that a producer with a higher expected yield value (based on the price elected) is less likely to submit an anomalous prevented planting claim (proposition 2).

The statistically significant marginal effects of *TEN*, *YR*1, and *D* suggest these variables may be important determinants of the likelihood of submitting potentially fraudulent prevented planting claims. Furthermore, we also observe an increase in the magnitude of the coefficients for *TEN* and *YR*1 as overall yield coverage increases—a finding which may provide useful insight for RMA compliance. These results can be used by RMA compliance offices to audit potentially fraudulent prevented planting claims after the season.

For example, anomalous prevented planting claims can first be identified based on the algorithm suggested in the empirical section of this study (i.e., finding individuals where the cause of loss claimed is not general in the area). Then this list of producers can be further reduced to focus more on producers having higher prevented planting coverage, low value of expected yields, and a past history of submitting claims. Including the above findings in a criterion for identifying producers worthy of further audit may improve the compliance offices' efficiency in allocating their investigative resources.

Other Variables

The coefficients related to insurance plans, irrigation, states, and crops also merit some discussion here. The coefficient of the *APH* insurance plan dummy variable reveals that producers who purchased APH contracts are less likely to submit an anomalous prevented planting claim relative to producers who bought a CRC insurance plan. In most of the estimated equations, the coefficient related to the *OTHER* dummy variable was positive and significant, suggesting producers who purchased other insurance plans, which are mostly other revenue-based plans like Revenue Assurance (RA) and Income Protection (IP), are more likely to submit an anomalous prevented planting claim. Based on these results, CRC and other revenue insurance plans may be more vulnerable to producers who want to submit a potentially fraudulent prevented planting claim. In addition, the coefficient

Table 3. Estimation Results of Probit Model 1 (dependent variable = *APP*)

	60% Yield Coverage		65% Yield Coverage		70% Yield Coverage	
Variable	Coefficient	Marginal Effect	Coefficient	Marginal Effect	Coefficient	Marginal Effect
Intercept	!2.4204***	—	!2.5430***	—	!2.7020***	—
	(0.3532)		(0.1215)		(0.2208)	
TEN	0.2924	0.0030	0.4192***	0.0065***	0.4680***	0.0083***
	(0.2801)	(0.0040)	(0.0664)	(0.0016)	(0.0968)	(0.0026)
D	!0.0007	!0.000005	!0.0006*	!0.000005*	!0.0005	!0.000006
	(0.0011)	(0.000008)	(0.0003)	(0.000003)	(0.0006)	(0.000006)
*YR*1	0.1673	0.0014	0.4922***	0.0087***	0.9153***	0.0324***
	(0.3974)	(0.0043)	(0.1109)	(0.0033)	(0.1492)	(0.0114)
*YR*2	0.4460	0.0059	0.1679	0.0019	0.3365	0.0056
	(0.5913)	(0.0130)	(0.1834)	(0.0026)	(0.1492)	(0.0055)
*CRP*1	0.9176	0.0006	0.1193*	0.0011*	0.3712**	0.0053**
	(0.2533)	(0.0018)	(0.0697)	(0.0007)	(0.1516)	(0.0030)
*CRP*2	—	—	!0.0340	!0.0003	—	—
			(0.3243)	(0.0026)		
*CRP*3	—	—	—	—	2.7573**	0.5184**
					(1.2135)	(0.4805)
*CRP*4	—	—	!0.5021	!0.0024	—	—
			(0.3299)	(0.0007)		
*CRP*5	—	—	0.5032***	0.0090***	0.8648***	0.0288***
			(0.1755)	(0.0053)	(0.3070)	(0.0211)
*CRP*6	0.0249	0.0002	0.2337***	0.0028***	0.1236	0.0015
	(0.2854)	(0.0021)	(0.0843)	(0.0013)	(0.1628)	(0.0021)
*CRP*7	0.2508	0.0021	0.1139**	0.0011**	0.1306	0.0014
	(0.2012)	(0.0021)	(0.0523)	(0.0005)	(0.1227)	(0.0014)
OTHER	—	—	0.1944*	0.0022*	0.3136***	0.0047***
			(0.1052)	(0.0015)	(0.1085)	(0.0023)
APH	0.1551	0.0011	!0.2111***	!0.0021***	!0.8954	!0.0009
	(0.1616)	(0.0011)	(0.0423)	(0.0005)	(0.0888)	(0.0009)
IR	!0.3577	!0.0200	!0.2770***	!0.0020***	!0.4565***	!0.0034***
	(0.2624)	(0.0011)	(0.0744)	(0.0004)	(0.1764)	(0.0009)
*ST*1	—	—	!0.5421***	!0.0025***	!0.4292*	!0.0029*
			(0.2073)	(0.0004)	(0.2307)	(0.0010)
*ST*2	!0.0749	!0.0005	0.1979	0.0023	!0.2675	!0.0020
	(0.3075)	(0.0175)	(0.1298)	(0.0019)	(0.3057)	(0.0016)
*ST*3	—	—	!0.6948**	!0.0027**	!0.3200	!0.0023
			(0.3049)	(0.0004)	(0.3540)	(0.0016)
*ST*4	0.2404	0.0023	0.3585*	0.0053*	0.6797*	0.0180*
	(0.3252)	(0.0042)	(0.1974)	(0.0044)	(0.3529)	(0.0180)
*ST*5	!0.2375	!0.0013	0.2243**	0.0025**	0.1661	0.0019
	(0.2896)	(0.0012)	(0.1100)	(0.0015)	(0.1855)	(0.0023)
*ST*6	—	—	!0.5743*	!0.0025*	—	—
			(0.3094)	(0.0005)		
*ST*7	!0.5158	!0.0054	!0.0438	!0.0004	!0.0825	!0.0008
	(0.2799)	(0.0043)	(0.1081)	(0.0010)	(0.1814)	(0.0018)
No. of Observations	7,893 [a]		82,678 [a]		18,899 [a]	
Log Likelihood	!170.83		!2,114.11		!627.70	
Likelihood Ratio χ^2 [df]	30.157*** [13]		273.80*** [20]		167.69*** [18]	
Pseudo R^2	0.0811		0.0608		0.1178	
Akaike's Info. Criterion	0.047		0.052		0.068	

Notes: Asterisks *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively; standard errors are in parentheses.

[a] Observations were dropped because some independent variables predict failure perfectly (i.e., there are no cases where the independent variable predicts *APP* = 1).

Table 4. Estimation Results of Probit Model 2 (dependent variable = *APP*75)

	60% Yield Coverage		65% Yield Coverage		70% Yield Coverage	
Variable	Coefficient	Marginal Effect	Coefficient	Marginal Effect	Coefficient	Marginal Effect
Intercept	!2.6181*** (0.3387)	—	!2.5063*** (0.1133)	—	!2.5529*** (0.2002)	—
TEN	0.4672** (0.2243)	0.0076** (0.0060)	0.3875*** (0.0605)	0.0080*** (0.0018)	0.6055*** (0.0787)	0.0193*** (0.0040)
D	!0.0009 (0.0011)	!0.000008 (0.00001)	!0.0012*** (0.0003)	!0.00001*** (0.000003)	!0.0005 (0.0005)	!0.000009 (0.000009)
*YR*1	0.0211 (0.3917)	0.0002 (0.0036)	0.4438*** (0.1019)	0.0102*** (0.0037)	0.7502*** (0.1392)	0.0315*** (0.0111)
*YR*2	0.3427 (0.5912)	0.0048 (0.0125)	0.1515 (0.1718)	0.0024 (0.0032)	0.3509 (0.2152)	0.0091 (0.0082)
*CRP*1	0.1046 (0.2387)	0.0009 (0.0021)	0.2885*** (0.0598)	0.0044*** (0.0011)	0.2659* (0.1429)	0.0054* (0.0035)
*CRP*2	—	—	!0.3159* (0.1912)	!0.0061* (0.0053)	—	—
*CRP*3	—	—	—	—	2.7760** (1.1624)	0.5944** (0.4461)
*CRP*4	—	—	!0.0959 (0.2247)	!0.0011 (0.0022)	—	—
*CRP*5	—	—	0.9491*** (0.1474)	0.0416*** (0.0136)	0.7616*** (0.2897)	0.0326*** (0.0231)
*CRP*6	0.3863 (0.2502)	0.0054 (0.0052)	0.2812*** (0.0752)	0.0050*** (0.0018)	0.0164 (0.1475)	0.0003 (0.0025)
*CRP*7	0.5634*** (0.1825)	0.0008*** (0.0040)	0.2821*** (0.0451)	0.0043** (0.0008)	0.4451*** (0.1060)	0.0084*** (0.0023)
OTHER	—	—	0.2425*** (0.0849)	0.0042*** (0.0019)	0.1588** (0.0782)	0.0031** (0.0018)
APH	0.0552 (0.1406)	0.0004 (0.0012)	!0.1835*** (0.0354)	!0.0026*** (0.0005)	!0.0819 (0.0067)	!0.00013 (0.0011)
IR	!0.4330* (0.2523)	!0.0029* (0.0013)	!0.3831*** (0.0710)	!0.0038*** (0.0005)	!0.4993*** (0.1588)	!0.0059*** (0.0012)
*ST*1	—	—	!0.4123** (0.1867)	!0.0033** (0.0008)	!0.4361** (0.2037)	!0.0048** (0.0014)
*ST*2	0.2496 (0.2741)	0.0029 (0.0043)	0.3521*** (0.1174)	0.0007*** (0.0034)	!0.0066 (0.2254)	!0.0001 (0.0037)
*ST*3	—	—	!0.2574 (0.1875)	!0.0024 (0.0012)	!0.4593 (0.3467)	!0.0046 (0.0018)
*ST*4	0.2147 (0.3128)	0.0024 (0.0047)	0.2685 (0.1935)	0.0049 (0.0048)	0.3256 (0.3493)	0.0082 (0.0125)
*ST*5	!0.0105 (0.2636)	!0.0001 (0.0022)	0.3399*** (0.1022)	0.0060*** (0.0024)	0.2443 (0.1855)	0.0045 (0.0034)
*ST*6	—	—	!0.5521* (0.3103)	!0.0037* (0.0009)	—	—
*ST*7	!0.1849 (0.2592)	!0.0018 (0.0292)	0.0622 (0.1009)	!0.0008 (0.0012)	!0.3034* (0.2002)	!0.0049* (0.0026)
No. of Observations	7,893 [a]		82,678 [a]		18,899 [a]	
Log Likelihood	!240.73		!3,165.16		!1,136.32	
Likelihood Ratio χ^2 [df]	52.57*** [13]		509.40*** [20]		360.83*** [18]	
Pseudo R^2	0.0984		0.0745		0.1370	
Akaike's Info. Criterion	0.065		0.077		0.122	

Notes: Asterisks *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively; standard errors are in parentheses.
[a] Observations were dropped because some independent variables predict failure perfectly (i.e., there are no cases where the independent variable predicts *APP*75 = 1).

Table 5. Estimation Results of Probit Model 3 (dependent variable = *APP*10)

	60% Yield Coverage		65% Yield Coverage		70% Yield Coverage	
Variable	Coefficient	Marginal Effect	Coefficient	Marginal Effect	Coefficient	Marginal Effect
Intercept	!2.4929*** (0.3097)	—	!2.3981*** (0.1052)	—	!2.3594*** (0.1861)	—
TEN	0.4699** (0.2101)	0.0075** (0.0055)	0.4312*** (0.0539)	0.0112*** (0.0021)	0.5917*** (0.0738)	0.0206*** (0.0041)
D	!0.0007 (0.0011)	!0.000006 (0.000009)	!0.0012*** (0.0003)	!0.00002*** (0.000004)	!0.0007 (0.0005)	!0.00001 (0.00001)
*YR*1	0.5105** (0.2539)	0.0088** (0.0076)	0.5001*** (0.0904)	0.0147*** (0.0044)	0.6926*** (0.1345)	0.0299*** (0.0106)
*YR*2	!0.2291 (0.5186)	!0.0014 (0.0023)	0.1239 (0.1544)	0.0023 (0.0032)	0.3142 (0.2124)	0.0087 (0.0082)
*CRP*1	0.1091 (0.2358)	0.0009 (0.0021)	0.1446*** (0.0558)	0.0024*** (0.0010)	0.0680 (0.1305)	0.0013 (0.0027)
*CRP*2	—	—	!0.3357** (0.1645)	!0.0080** (0.0056)	—	—
*CRP*3	—	—	—	—	3.1090*** (1.1187)	0.7304*** (0.3622)
*CRP*4	—	—	!0.0714 (0.2049)	!0.0011 (0.0027)	—	—
*CRP*5	—	—	0.8518*** (0.1438)	0.0354*** (0.0121)	0.6890** (0.2806)	0.0298** (0.0215)
*CRP*6	0.2608 (0.2339)	0.0030 (0.0036)	0.2406*** (0.0666)	0.0049*** (0.0017)	!0.1344 (0.1332)	!0.0022 (0.0019)
*CRP*7	0.6627*** (0.1670)	0.0101*** (0.0043)	0.2395*** (0.0395)	0.0043*** (0.0008)	0.3437*** (0.0888)	0.0071*** (0.0021)
OTHER	—	—	0.1463* (0.0815)	0.0027* (0.0018)	0.2890*** (0.0696)	0.0074*** (0.0024)
APH	0.0669 (0.1331)	0.0006 (0.0011)	!0.1908*** (0.0319)	!0.0032*** (0.0006)	!0.0299 (0.0602)	!0.0006 (0.0011)
IR	!0.6584** (0.2625)	!0.0039** (0.0012)	!0.4374*** (0.0675)	!0.0052*** (0.0006)	!0.5581*** (0.1556)	!0.0071*** (0.0013)
*ST*1	—	—	!0.5093*** (0.1845)	!0.0045*** (0.0008)	!0.5365*** (0.2012)	!0.0062*** (0.0014)
*ST*2	0.1519 (0.2503)	0.0013 (0.0104)	0.4623*** (0.1073)	0.0127*** (0.0046)	!0.0955 (0.2055)	!0.0001 (0.0047)
*ST*3	—	—	!0.3362* (0.1855)	!0.0035* (0.0012)	!0.4632 (0.3404)	!0.0052 (0.0020)
*ST*4	0.6549*** (0.2551)	0.0134*** (0.0104)	0.4185** (0.1655)	0.0111** (0.0068)	0.5794** (0.2891)	0.0223** (0.0190)
*ST*5	!0.0728 (0.2340)	!0.0006 (0.0017)	0.4056*** (0.0953)	0.0092*** (0.0030)	0.2742* (0.1535)	0.0058* (0.0037)
*ST*6	—	—	!0.4003* (0.2346)	!0.0039* (0.0013)	!0.7457*** (0.3364)	!0.0660*** (0.0120)
*ST*7	!0.3890* (0.2330)	!0.0044* (0.0035)	0.0910 (0.0943)	0.0013 (0.0013)	!0.2872* (0.1552)	!0.0051* (0.0027)
No. of Observations	7,893[a]		82,678[a]		19,799[a]	
Log Likelihood	!309.20		!3,896.41		!1,415.20	
Likelihood Ratio χ^2 [df]	144.54*** [13]		716.73*** [20]		501.81*** [19]	
Pseudo R^2	0.1894		0.0842		0.1506	
Akaike's Info. Criterion	0.082		0.095		0.145	

Notes: Asterisks *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively; standard errors are in parentheses.

[a] Observations were dropped because some independent variables predict failure perfectly (i.e., there are no cases where the independent variable predicts *APP*10 = 1).

and marginal effect of the irrigated dummy variable (*IR*) indicates that producers with irrigation are less likely to submit an anomalous prevented planting claim relative to their counterparts who do not irrigate.

The coefficients and marginal effects of the crop dummy variables (*CRP*1–*CRP*7) confirm there are significant crop-specific effects. A Wald test also rejects the hypothesis that all of these crop dummy variables are jointly zero. The empirical results vary somewhat depending on the yield coverage levels. But at 65% coverage, results suggest producers of cotton, rice, soybeans, and wheat tend to have a higher probability of submitting an anomalous prevented planting claim relative to the excluded crop (corn). The coefficients and marginal effects of the state dummy variables (*ST*1–*ST*7) also show there are significant geographical effects.

Conclusions

This study has examined whether certain crop insurance elements are correlated with the probability of submitting a potentially fraudulent prevented planting claim. The empirical results provide evidence that producers with higher prevented planting guarantee, lower dollar value of expected yield, and past history of submitting prevented planting claims, are more likely to submit an anomalous prevented planting claim. Also, the empirical results show that CRC or other revenue-based insurance plans tend to be more vulnerable to potential prevented planting fraud relative to APH plans.

Results of this study can be valuable to RMA compliance offices in their efforts to find "indicators" of fraudulent behavior in crop insurance. Given that prevented planting is believed to be prone to fraud, knowledge of insurance contract elements which reveal information about the propensity of submitting fraudulent prevented planting claims can be used to identify and prioritize anomalous producers who may warrant further investigation or audit. Furthermore, using producer contract choices as determinants of anomalous behavior allows compliance agents to proactively investigate individuals immediately after signing up for insurance coverage. Thus, in addition to the auditing of suspicious prevented planting claims ex post (after submission of a claim), suspect individuals can be identified and investigated ex ante (right after sign-up).

Although this research advances our understanding of the factors that may affect the probability of submitting potentially fraudulent claims, further investigation is needed. A potential extension of this study is to empirically examine whether the non-contract variables in the theoretical model—such as cost of production, market prices, and fraud penalties—do indeed significantly affect the probability of submitting a fraudulent prevented planting claim.

Another avenue for further research is to identify other dependent variables depicting fraud behavior and determine whether the results found here still hold. Recall that we define an anomalous prevented planting claim as one where the cause of loss is not "general" in the immediate geographic area. For example, if detailed weather data are available for each farm, a dependent variable reflecting whether or not the cause of loss of the prevented planting claim is supported by the weather data can be used. A dependent variable would be equal to one if the weather data do not support the cause of loss (e.g., the stated cause of loss is drought when the rainfall data reveal the farm had adequate rainfall)—clearly, this is potentially fraudulent behavior. Of course, the best dependent variable for testing the above model would be data documenting whether a prevented planting claim is proven in court to be fraudulent or not. No such data are currently available.

A final avenue for suggested further research is to assess whether the results reported in this study are consistent with data applicable to other parts of the country, or for other crops. The focus of this analysis was on the southern region of the United States; an extension of this study to other U.S. regions and crops would be useful.

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Appendix: Proof of the Comparative Statics

In this appendix, we show that the following first derivatives associated with text equation (6) have definitive signs: $\partial\tilde{g}/\partial\theta_1 < 0$, $\partial\tilde{g}/\partial P_m > 0$, $\partial\tilde{g}/\partial C_p < 0$, $\partial\tilde{g}/\partial F > 0$, and $\partial\tilde{g}/\partial C_f > 0$. We also show that $\partial\tilde{g}/\partial C_{pp}$ and $\partial\tilde{g}/\partial D$ have theoretically ambiguous signs, but we identify the conditions for which $\partial\tilde{g}/\partial D > 0$.

To limit notational clutter, let:

(A1) $$\Phi_A = \theta_2 D - Y_a P_g + Y_a P_m - C_p,$$

(A2) $$\Phi_B = Y_a P_m - C_p,$$

(A3) $$\Phi_C = \theta_1\theta_2 D - C_{pp} - C_f,$$

and

(A4) $$\Phi_D = F + C_{pp} + C_f.$$

These simplifications then imply:

(A5) $$\tilde{g} = \frac{\int_0^{\theta_2 Y_e} U(W+\Phi_A)f(Y_a)\,dY_a + \int_{\theta_2 Y_e}^{\infty} U(W+\Phi_B)f(Y_a)\,dY_a - U(W-\Phi_D)}{U(W+\Phi_C) - U(W-\Phi_D)}.$$

Further, let Λ be the denominator, and let Ψ be the numerator of equation (A5) above:

(A6) $$\Lambda = U(W+\Phi_C) - U(W-\Phi_D),$$

(A7) $$\Psi = hU(W+\Phi_A) + (1-h)U(W+\Phi_B) - U(W-\Phi_D).$$

▪ PROOF OF $\partial\tilde{g}/\partial\theta_1 < 0$. Assuming the numerator and denominator are positive, then the first derivative of $\tilde{g}$ with respect to θ_1 is:

(A8) $$\frac{\partial\tilde{g}}{\partial\theta_1} = \frac{\begin{aligned}&\Big\{\Big[-\int_0^{\theta_2 Y_e} U'(W+\Phi_A)p'(\theta_1,\theta_2)f(Y_a)\,dY_a - \int_{\theta_2 Y_e}^{\infty} U'(W+\Phi_B)p'(\theta_1,\theta_2)f(Y_a)\,dY_a + U'(W-\Phi_D)p'(\theta_1,\theta_2)\Big]\big[\Lambda\big]\Big\}\\&- \Big\{\Big[U'(W+\Phi_C)(\theta_2 D - p'(\theta_1,\theta_2)) + U'(W-\Phi_D)p'(\theta_1,\theta_2)\Big]\big[\Psi\big]\Big\}\end{aligned}}{\Lambda^2} < 0.$$

The first expression of the numerator in braces, $\{\cdot\}$, is negative because

$$\Big[\int_0^{\theta_2 Y_e} U'(W+\Phi_A)f(Y_a)\,dY_a + \int_{\theta_2 Y_e}^{\infty} U'(W+\Phi_B)f(Y_a)\,dY_a\Big] > U'(W-\Phi_D).$$

The second expression of the numerator in braces is positive because $\theta_2 D > p'(\theta_1, \theta_2)$ and $U'(W + \Phi_C) > U'(W - \Phi_D)$. Given the signs of these expressions, the numerator of (A8) is negative. Since the denominator in (A8) is positive, the overall sign of (A8) is negative. Q.E.D.

▪ PROOF OF $\partial\tilde{g}/\partial P_m > 0$. The first derivative of $\tilde{g}$ with respect to P_m is as follows:

(A9) $$\frac{\partial\tilde{g}}{\partial P_m} = \frac{\Big[\int_0^{\theta_2 Y_e} U'(W+\Phi_A)Y_a f(Y_a)\,dY_a + \int_{\theta_2 Y_e}^{\infty} U'(W+\Phi_B)Y_a f(Y_a)\,dY_a\Big]\big[\Lambda\big]}{\Lambda^2} > 0.$$

The first term of the numerator in brackets is positive and the second term is positive, making the entire numerator in (A9) positive. Hence, (A9) is positive because the denominator is also positive. Q.E.D.

▪ PROOF OF $\partial\tilde{g}/\partial C_p < 0$. The first derivative of $\tilde{g}$ with respect to C_p is as follows:

(A10) $$\frac{\partial\tilde{g}}{\partial C_p} = \frac{\Big[-\int_0^{\theta_2 Y_e} U'(W+\Phi_A)f(Y_a)\,dY_a - \int_{\theta_2 Y_e}^{\infty} U'(W+\Phi_B)f(Y_a)\,dY_a\Big]\big[\Lambda\big]}{\Lambda^2} < 0.$$

The first term of the numerator in brackets is negative and the second term is positive, which makes the whole numerator in (A10) negative. Since the denominator in (A10) is positive, the overall sign of (A10) is negative. Q.E.D.

▪ PROOF OF $\partial \tilde{g}/\partial F > 0$. The first derivative of $\tilde{g}$ with respect to F is as follows:

$$\text{(A11)}\quad \frac{\partial \tilde{g}}{\partial F} = \frac{[U'(W-\Phi_D)\Lambda] - [U'(W-\Phi_D)\Psi]}{\Lambda^2} > 0.$$

The two terms of the numerator in brackets are both positive. Thus, the sign of (A11) depends on the magnitudes of Λ and Ψ. Since we know that $0 < \tilde{g} < 1$, then $\Lambda > \Psi$. This indicates the numerator of (A11) is positive and the overall sign of expression (A11) should be positive. Q.E.D.

▪ PROOF OF $\partial \tilde{g}/\partial C_f > 0$. The first derivative of $\tilde{g}$ with respect to C_f is as follows:

$$\text{(A12)}\quad \frac{\partial \tilde{g}}{\partial C_f} = \frac{\big[U'(W-\Phi_D)\Lambda\big] - \big[U'(W-\Phi_D) - U'(W+\Phi_C)\big]\big[\Psi\big]}{\Lambda^2} > 0.$$

The first bracketed term in the numerator is positive. Since $U'(W - \Phi_D) < U'(W + \Phi_C)$, then the outcome of the next two bracketed terms multiplied together is negative and the numerator of expression (A12) is positive. Since the denominator in (A12) is positive, the overall sign of (A12) is positive. Q.E.D.

▪ PROOF OF $\partial \tilde{g}/\partial C_{pp} \geq$ or ≤ 0 (theoretically ambiguous). The first derivative of $\tilde{g}$ with respect to C_{pp} is as follows:

$$\text{(A13)}\quad \frac{\partial \tilde{g}}{\partial C_{pp}} = \frac{\begin{array}{c}\Big\{\Big[-\int_0^{\theta_2 Y_e} U'(W+\Phi_A) f'(C_{pp}) f(Y_a)\, dY_a \\ - \int_{\theta_2 Y_e}^{\infty} U'(W+\Phi_B) f'(C_{pp}) f(Y_a)\, dY_a \\ + U'(W-\Phi_D)\Big]\big[\Lambda\big]\Big\} \\ + \Big\{\big[U'(W-\Phi_D) + U'(W+\Phi_C)\big]\big[\Psi\big]\Big\}\end{array}}{\Lambda^2}.$$

Assuming $f'(C_{pp}) > 0$, then the first term of the numerator in brackets is negative because

$$\Big[\int_0^{\theta_2 Y_e} U'(W+\Phi_A) f(Y_a)\, dY_a + \int_{\theta_2 Y_e}^{\infty} U'(W+\Phi_B) f(Y_a)\, dY_a\Big] > U'(W-\Phi_D),$$

and Λ is positive. On the other hand, the second term of the numerator in braces is positive. Thus, the sign of (A13) will depend on the relative magnitudes of both expressions in braces in the numerator. Q.E.D.

▪ PROOF OF $\partial \tilde{g}/\partial D > 0$ (under certain reasonable conditions). The first derivative of $\tilde{g}$ with respect to D is as follows:

$$\text{(A14)}\quad \frac{\partial \tilde{g}}{\partial D} = \frac{\begin{array}{c}\Big[\int_0^{\theta_2 Y_e} U'(W+\Phi_A)(\theta_2) f(Y_a)\, dY_a\Big]\big[\Lambda\big] \\ - \big[U'(W+\Phi_C)\theta_1\theta_2\big]\big[\Psi\big]\end{array}}{\Lambda^2}.$$

The sign of (A14) depends on the magnitudes of the two terms in the numerator. All bracketed terms on the numerator are positive. Since we know that $0 < \tilde{g} < 1$, then $\Lambda > \Psi$. Thus, the sign of (A14) will depend on whether:

(i) $\int_0^{\theta_2 Y_e} f(Y_a)\, dY_a \geq$ or $\leq \theta_1$,

and

(ii) $\Phi_A \geq$ or $\leq \Phi_C$.

Under the reasonable conditions

(i) $\int_0^{\theta_2 Y_e} f(Y_a)\, dY_a < \theta_1$

and

(ii) $\Phi_A > \Phi_C$,

the sign of expression (A14) would therefore be positive ($\partial \tilde{g}/\partial D > 0$). Q.E.D.