# *YIELD COVERAGE LEVELS AS DEDUCTIBLES IN CROP INSURANCE CONTRACTS: IS THE EFFECT ON FALSIFICATION BEHAVIOR SIGNIFICANT?*[i]

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**ABSTRACT**

Yield coverage levels serve as deductibles in crop insurance contracts. This paper examines the effect of yield coverage choice on falsification behavior and determines if this effect is significant in crop insurance. We theoretically show that lower yield coverage choice may increase the incentives for falsification behavior. A loss equation that corrects for sample selection bias was estimated using maximum likelihood to verify this proposition. Our empirical results indicate that the falsification effect of alternative yield coverage levels may not be significant in crop insurance and government resources may be well-spent on addressing fraud-related problems due to other crop insurance contract elements.

*Keywords:* Crop Insurance; Falsification; Fraud; Yield Coverage

**INTRODUCTION**

Yield coverage levels serve as deductibles in crop insurance contracts. The choice of yield coverage level determines the magnitude of insurable yield losses. Since the maximum allowable yield coverage level in crop insurance contracts is 85%, losses in crop insurance are not fully insurable and, thus, yield coverage levels are analogous to standard deductibles because they preclude full insurance of losses, as in other lines of insurance.

From the economic literature on insurance, the presence of deductibles in insurance contracts can be explained by the following problems of asymmetric information: adverse selection [16, 15], *ex ante* moral hazard [9, 17, 23], and *ex post* moral hazard under costly state verification [19, 5, 11, 1]. Hyde and Vercammen [10] further showed that optimal crop insurance contract form in the presence of *ex ante* and *ex post* moral hazard involves deductibles in the form of yield coverage levels or yield guarantees.

In theory, asymmetric information problems in crop insurance contracts should be minimized by the presence of alternative yield coverage levels, but these problems still seem to be prevalent in crop insurance [12, 3, 13].[1] In particular, *ex post* moral hazard or falsification behavior may be a problem even with the presence of deductibles if the insurance environment is not consistent with costly state verification. Furthermore, if there is no full commitment to auditing every claim then the fraud mitigating effect of deductibles in insurance contracts will not apply [14].

Therefore, if the market for crop insurance more likely follows the conditions of the costly state falsification model and full commitment is absent, then deductible contracts are not optimal to deter *ex post* moral hazard or fraud behavior. Yield coverage levels acting as deductibles in crop insurance contracts may then provide incentives for falsification behavior, much like what is observed in automobile insurance [4].

The objective of this study is to determine how yield coverage choice may affect falsification behavior and whether there is evidence that this effect on falsification behavior is significant in crop insurance. The extent of falsification behavior in crop insurance has not been fully investigated. Although the extent of falsification behavior has not been precisely estimated, the Risk Management Agency (RMA) believes that about 5% of all claims are associated with fraud, waste, or abuse [22]. And even though there are no exact estimates of the total dollar cost of fraud, waste, and abuse in crop insurance, RMA has documented numerous cases that ranges from minimal claims padding (in the hundreds of dollars) to coordinated fraud schemes among several parties (in the millions of dollars) [21]. Knowledge about the presence or absence of falsification effects due to yield coverage levels may show whether this incentive problem needs to be addressed. This study can show if yield coverage levels in crop insurance contracts contribute to the fraud behavior observed in crop insurance. If there is evidence of this falsification effect in crop insurance, then the industry may want to devote resources on this issue to determine actions to reduce the fraud incentives from alternative yield coverage choice. If there is no evidence of this falsification effect, then resources may be better allocated to examining other insurance contract elements that contribute to fraud, waste, and abuse in the crop insurance program.

The paper is organized as follows. In the next section, a theoretical model is developed to show how yield coverage levels acts as deductibles in crop insurance contracts and how it may affect falsification behavior. The empirical model, data, and results are then discussed in the next three sections, respectively. Concluding comments are presented in the last section.

## THEORETICAL MODEL

Consider a risk-averse farmer with an Actual Production History (APH) crop insurance contract. The APH contract is an individual yield insurance plan that protects farmers against yield shortfalls if the actual yield falls below the guaranteed level. 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 percent yield guarantee and pays an indemnity based on 55 percent of the projected price. In this paper, we separate CAT and APH buy-up coverage and hereafter refer to APH buy-up as APH insurance.

A deductible in APH insurance contracts is implicit in the choice of yield coverage levels that determines a farmer's yield guarantee. APH insurance provides yield protection of up to 85 percent of the farmer's average historical yield; with a premium based on a chosen yield coverage level. The APH contract pays an indemnity if the farmer'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:

$$Y^g = \theta Y^e, \tag{1}$$

where $\theta$ is the percent yield coverage chosen by the farmer ($\theta$ = 0.55, 0.6, 0.65, 0.7, 0.75, 0.8, 0.85) and $Y^e$ is the average historical yield based on the yield record submitted by the producer. Given $\theta$, the deductible for the APH contract can be defined as:

$$D(\theta) = (1-\theta)Y^e P^g \tag{2}$$

where $P^g$ is the guaranteed or elected price. Note that $D'(\theta) < 0$ and $D''(\theta) = 0$.

If $Y^a < Y^g$, then an indemnity payment is triggered as follows:

$$I^T = \theta Y^e P^g - Y^a P^g. \tag{3}$$

Equation (3) can then be re-written as

$$I^T = \gamma_L^T - D(\theta) \tag{4}$$

where $\gamma_L^T = (Y^e P^g - Y^a P^g)$. Note that $\gamma_L^T$ represents the true total dollar value of the loss incurred by the farmer. Indemnity is paid based on the true total dollar value of the yield loss less the deductible.

Assuming that a farmer can falsify the total dollar value of the yield loss by misreporting his actual yields, then the total dollar value of the loss can be misrepresented as follows:

$$\gamma_L^F = (Y^e P^g - (Y^a - \lambda)P^g) \tag{5}$$

where $\lambda$ is the amount of reduction in the falsely reported yield.[2] Actual yield loss can be falsified, for example, if the producer colludes with the loss adjuster to misreport the actual yield. This type of fraud is called opportunistic fraud – there is an actual loss already and the insured has the "opportunity" to falsify the loss to his advantage. Equation (5) can then be re-written as follows:

$$\gamma_L^F = \gamma_L^T + L \tag{6}$$

where $L = \lambda P^g$. Therefore, the falsified total dollar value of the yield loss ( $\gamma_L^F$ ) is the sum of the true total dollar value of the yield loss plus an additional falsified amount (*L*). The indemnity payment in this case is $I^F = \gamma_L^T + L - D(\theta)$.

Consider a risk-averse farmer who is making the marginal decision to falsify the true dollar value of his yield loss ( $\gamma_L^T$ ), equivalent to the amount *L*. Assume that the insured producer have already signed an APH contract and chosen his yield coverage levels (or his deductibles). *Ex post*, his decision is to choose the level of falsification (*L*) to maximize his expected utility defined as:

$$pU(W + L - D(\theta) - c^p - c(L)) + (1-p)U(W - \gamma_L^T - c^p - c(L)) \tag{7}$$

where *U*(·) is a standard von Neumann Morgenstern utility function with *U'*(·) > 0, *U''*(·) < 0; *p* is the probability of successful fraud (falsification is not detected); $c^p$ is the cost of producing the crop; *c*(*L*) is the total cost of falsification as a function of the amount of falsified yield loss with *c'*(*L*) > 0 and *c''*(*L*) = 0; *W* is the level of wealth not contingent (i.e. *W* is the difference between initial wealth and the premium paid: ( $W = W_0 - P$ ); and, all the remaining variables are as defined before.

If the farmer truthfully reveals his loss then his wealth is defined as follows:

$$W - D(\theta) - c^p = W - \gamma_L^T + \gamma_L^T - D(\theta) - c^p. \tag{8}$$

This expression implicitly assumes that $\gamma_L^T > D(\theta)$ for the insured farmer to have a positive level of insurance coverage. If the farmer falsifies his loss and does not get caught then his wealth is defined as:

\

$$W + L - D(\theta) - c^p - c(L) = W - \gamma_L^T + \gamma_L^T + L - D(\theta) - c^p - c(L). \tag{9}$$

If the producer gets caught falsifying his actual yield loss, then he forfeits his insurance coverage and his wealth is defined as $W - \gamma_L^T - c^p - c(L)$. Therefore, falsification is costly if he is caught because of the insurance coverage forfeited equivalent to $\gamma_L^T - D(\theta)$.

An important behavioral assumption in (7) is that fraud is not found with probability one, in contrast to what is suggested in standard contracts with deductibles [18]. The probability *p* is lower than one for at least two reasons, either (i) the insurer does not audit the policy (absence of full commitment or random auditing) or (ii) it audits, but does not find any evidence of fraud even when there is fraud. This is consistent with the market for crop insurance. Current RMA compliance practice is to randomly audit selected claims every year or audit claims called in through the fraud “hotlines”. Collusion among producers, adjusters, and agents also makes it possible for fraudulent claims to not be detected by RMA compliance audits, which is consistent with (ii) above.

An insured farmer will falsify his actual yield if and only if:

$$pU(W+L-D(\theta)-c^p-c(L))+(1-p)U(W-\gamma_L^T-c^p-c(L))\geq U(W-D(\theta)-c^p). \quad (10)$$

That is, the insured producer will only falsify yields only if the expected utility of the fraud gamble is greater than the expected utility of not taking the fraud gamble. Assuming (10) holds, let us now consider the optimal level of falsification ($L^*$). Maximizing (7) with respect to $L$ results to

$$pU'(W+L-D(\theta)-c^p-c(L))(1-c'(L))+(1-p)U'(W-\gamma_L^T-c^p-c(L))(-c'(L))=0. \quad (11)$$

Let $W_F^N=W+L-D(\theta)-c^p-c(L)$ be the farmer's wealth when fraud is not detected and let $W_F^D=W-\gamma_L^T-c^p-c(L)$ be the farmer's wealth when fraud is detected. An interior solution to (11) implies that $(1-c'(L))>0$. The second-order condition is always verified under risk aversion and can be written as:

$$H\equiv pU''(W_F^N)(1-c'(L))^2+(1-p)U''(W_F^D)(-c'(L))^2<0. \quad (12)$$

Since we are interested in the fraud incentive effects of chosen deductibles or yield coverage levels in APH crop insurance, we want to examine the relationship between $L$ and $D(\theta)$. This relationship can be derived by taking the total differentiation of (11) with respect to $L$ and $D(\theta)$. Under risk aversion, this results to:

$$\frac{dL}{dD(\theta)}=\frac{pU''(W_F^N)(1-c'(L))}{H}>0. \quad (13)$$

Hence, higher deductibles or lower yield coverage levels increase the incentives for fraudulent behavior. If the producer has a lower yield coverage level, then we should observe higher yield loss magnitudes reported when falsification behavior is present. Lower yield coverage levels means that a higher yield loss magnitude is needed to trigger an indemnity. If the producer has an opportunity to falsify his loss, then the producer would want to falsely increase the magnitude of the loss to always trigger an indemnity payment. The magnitude of the falsified loss depends on the parameters on the right-hand side of equation (13). In general, however, we would expect that the magnitude of the falsified loss would be enough to trigger an indemnity payment and cover the premiums paid by the producer.

From (11), we can also show that

$$\frac{dL}{dp} = -\frac{U'(W_F^N)(1-c'(L)) - U'(W_F^D)(-c'(L))}{H} > 0 \,. \tag{14}$$

This means that incentives for fraudulent behavior increases as the probability of successful fraud increases. Another interesting relationship to examine is the effect of $p$ on $dL/dD(\theta)$. That is, the effect of the probability of successful fraud on the falsification incentives created by different deductibles (or yield coverage levels). From (13) we can show that

$$\frac{d^2 L}{dDdp} = 2\frac{d(dL/dD)}{dp} > 0 \tag{15}$$

if $\frac{c'(L)}{(1-c'(L)} \geq \frac{1-p}{p}$ and if the producer has constant absolute risk aversion (See Appendix for the proof). Consequently, $p$ must be sufficiently high in order to obtain the desired result. The expression in (15) means that fraud incentives created by deductibles increases as the success probability of fraud increases.

## EMPIRICAL MODEL AND DATA

The theory above suggests that higher deductibles or lower yield coverage levels increases incentives for falsification behavior. This means that observed loss magnitudes should be higher for farmers with lower yield coverage levels, if falsification behavior is present. This is especially true if the probability of detecting fraud is small. Thus, our empirical hypothesis is as follows: the magnitude of the observed dollar value of yield loss is higher when the yield coverage level of the crop insurance contract is lower.

Note that when there is full commitment by the insurers to audit each and every crop insurance policy, observed loss magnitudes should not be affected by fraud behavior and, consequently, by the level of the deductible or yield coverage. Moreover, under pure adverse selection and pure *ex ante* moral hazard, the loss should be lower when the yield coverage is lower, since good risks chose lower yield coverage (or higher deductible), and a lower yield coverage level (higher deductible) also introduces more *ex ante* incentives to reduce the likelihood of a loss. Our empirical hypothesis above will then hold true only if there is significant fraud behavior or falsification behavior present in crop insurance data. This is the only asymmetric information problem consistent with the empirical hypothesis. If the empirical hypothesis does not hold then the incentives for falsification behavior created by alternative yield coverage choice is not significant in crop insurance. Other asymmetric information problems such as *ex ante* moral hazard and adverse selection may then be more significant in crop insurance in this case.

A loss equation, with yield coverage level as one of the independent variables, needs to be estimated to verify the empirical hypothesis of the study. Consistent estimation of a loss equation using crop insurance claims data requires that losses be reported regardless of size. That is, the observed dollar value of the yield loss ( $Y^e P^g - Y^a P^g$ ) should be reported even if the actual yield value is not below the guaranteed yield level (i.e. $\theta Y^e P^g < Y^a P^g$ or $\theta Y^e P^g - Y^a P^g < 0$ ). But as we know, losses are reported and observed only if actual yield is below the guaranteed level ( $\theta Y^e P^g > Y^a P^g$ or $\theta Y^e P^g - Y^a P^g > 0$ ). In other words, yield loss is only reported if the total loss is greater than the deductible (i.e. $Y^e P^g - Y^a P^g > (1-\theta) Y^e P^g$ ). Thus, a lower yield coverage level or a higher deductible ( $D(\theta) = (1-\theta) Y^e P^g$ ) lowers the probability of reporting a yield loss.

In addition, the decision by an insured to report a loss may also depend on unobserved individual factors. For example, there may be transactions cost to submitting a claim that, in the farmer's view, may not make it worth it to submit a claim (i.e. $\theta Y^e P^g < Y^a P^g + \psi$, where $\psi$ = transaction costs in this example). The farmer only reports a loss and submits a claim if $Y^e P^g - Y^a P^g > (1-\theta) Y^e P^g + \psi$. The threshold ( $(1-\theta) Y^e P^g + \psi$ ) is not observable and is individual specific.

Given the conditions above, the observed loss in crop insurance data has sample selection bias due to the incidental truncation of the loss variable [7, 8, and 6, p. 928-933]. The observed loss data in this case is nonrandomly selected. Without appropriate corrections, the magnitude of the parameter associated with the yield coverage level in the loss equation will be biased upward [6, p. 929 for a proof].

The objective is to estimate the parameters of the model:

$$y_i = \boldsymbol{\beta}' \boldsymbol{x_i} + \varepsilon_i , \tag{16}$$

when $y_i$ is observed only if:

$$z_i^* = \boldsymbol{\gamma}' \boldsymbol{w_i} + u_i > 0 . \tag{17}$$

The notations in (16) and (17) are as follows: $y_i$ is the observed dollar value of the yield loss (i.e. $Y^e P^g - Y^a P^g$ ), $z_i^*$ is the sample selection variable defined as the difference between the dollar value of the guaranteed yield and the actual yield plus other individual specific factors ( $\theta Y^e P^g - Y^a P^g - \psi$ ), $\boldsymbol{\beta}'$ and $\boldsymbol{\gamma}'$ are vectors of parameters, $\boldsymbol{x_i}$ and $\boldsymbol{w_i}$ are vectors of regressors, and, $\boldsymbol{\varepsilon_i}$ and $\boldsymbol{u_i}$ are disturbance terms. Further, assume that $\boldsymbol{\varepsilon_i}$ and $\boldsymbol{u_i}$ have bivariate normal distributions with zero means and correlation $\rho$. The model above implies that:

$$\begin{aligned} E[y_i \mid y_i \text{ is observed}] &= E[y_i \mid z_i^* > 0] \qquad (18) \\ &= E[y_i \mid u_i > -\boldsymbol{\gamma}' \boldsymbol{w_i}] \end{aligned}$$

$$= \boldsymbol{\beta' x_i} + E[\varepsilon_i \mid u_i > -\boldsymbol{\gamma_i w_i}]$$
$$= \boldsymbol{\beta' x_i} + \rho\sigma_\varepsilon \lambda_i(\alpha_u)$$

where $\alpha_u = -\boldsymbol{\gamma' w_i} / \sigma_u$ and $\lambda(\alpha_u) = \phi(\boldsymbol{\gamma_i w_i} / \sigma_u) / \Phi(\boldsymbol{\gamma_i w_i} / \sigma_u)$.[3] The expression in (18) indicates that least squares regression using only the observed data produces inconsistent estimates of $\boldsymbol{\beta}$, unless $\rho = 0$.

Since $z_i^*$ is unobserved, we can reformulate the model as follows:

[Selection equation]:

$z_i^* = \boldsymbol{\gamma' w_i} + u_i$, where $z_i$=1 if $z_i^*$>0 and $z_i$=1 otherwise; (19)

Prob( $z_i$ =1) = $\Phi(\boldsymbol{\gamma' w_i})$ and Prob( $z_i$ = 0) = 1- $\Phi(\boldsymbol{\gamma' w_i})$ .

[Regression model]:

$y_i = \boldsymbol{\beta' x_i} + \varepsilon_i$ observed only if $z_i$ (20)

$(\boldsymbol{u_i}, \boldsymbol{\varepsilon_i})$~ bivariate normal [0, 0, 1, $\sigma_\varepsilon$ , $\rho$].

This implies that $E[y_i \mid z_i = 1] = \boldsymbol{\beta' x_i} + \rho\sigma_\varepsilon \lambda(\boldsymbol{\gamma' w_i})$ .

The parameters of the model above are consistently estimated using the maximum likelihood (ML) procedure. A Wald test is also undertaken to test for the significance of all the coefficients in the model. Moreover, a likelihood ratio test is also undertaken to see if there is indeed selection bias in the data (i.e. test if $\rho = 0$).

In this study, only RMA data of insured producers for reinsurance year (RY) 2000 are considered. Catastrophic (CAT) insurance policies and non-APH policies are excluded from the analysis. Furthermore, only corn and soybeans produced in Illinois are included in the analysis. Note that average Illinois corn and soybean yields for 2000 were approximately 151 bushels/acre and 44 bushels/acre, respectively. Average corn and soybean prices for Illinois in 2000 were about \$1.91/bushel and \$4.85/bushel. The resulting data set includes 4,472 observations, where 46 observations have unobserved $y_i$ and 4,426 observations have observed $y_i$. Thus, the dependent variable has 46 censored observations and 4,426 uncensored observations.

As mentioned above, the dependent variable in the model is the observed loss per acre equivalent to ( $Y^e P^g - Y^a P^g$ ). The regressors $\boldsymbol{x_i}$ are the following: acreage (ACRE), insured share (SHR), yield coverage dummies (YC65-YC80), crop dummy (CORN), a non-irrigated practice dummy (NIR), and reinsurance organization dummies (See Table 1 for the description of the variables). The acreage variable is included to see the effects of farm acreage on loss magnitudes per acre. The insured share is a behavioral variable to determine if the effect of share amount on the loss. Crop and practice (non-irrigated vs. irrigated) dummies are included to see if there are crop-specific or practice specific effects. The reinsurance organization is also included in the model to capture if there are firm-specific effects. Lastly, the yield coverage dummies are the main variables of interest in this study and are included to verify our empirical hypothesis above. If the empirical hypothesis holds, then we would expect that the yield coverage dummies should have a positive sign and the magnitude of the effect should decrease as the yield coverage increases.

**Table 1**
**Description of variables used in the empirical analysis based on a RMA data set for corn and soybeans in Illinois (reinsurance year 2000).**

| Variable | Description |
|---|---|
| LOSS | Observed dollar value of the yield loss per acre; equivalent to $(Y^e P^g - Y^a P^g)$ |
| ACRE | Farm acreage |
| YE | Expected yields |
| PE | Price election |
| SHR | Insured's share |
| YAPM | Dollar value of actual yields |
| YC65-YC80 | Dummy variables representing the yield coverage level chosen (coverage levels (*j*) = 65%, 70%, 75%, 80%). The 85% coverage level is the excluded category. YC(*j*)=1 if chose yield coverage *j*; YC(*j*)=0 otherwise. |
| CORN | Dummy variable representing the crop. CORN=1 if corn crop, CORN=0 otherwise. |
| NIR | Dummy variable representing crop practice (irrigated vs. non-irrigated). NIR=1 if non-irrigated, NIR=0 otherwise. |
| RO1 – RO10 | Dummy variable representing the reinsurance organization of the insured. RO(*i*) =1 if reinsurance organization I; RO(*i*) = 0 otherwise. |

For the vector $w_i$, one model (ML1) uses expected yield (YE) as the only regressor in the selection equation and another model includes expected yield (YE), and price election (PE), insured share (SHR) and acreage (ACRE) as regressors in the selection model. The regressors in the selection equation were chosen because they are the variables that affect the likelihood of a loss to be observed. Two sets of regressors were run to see if there are large differences in the magnitudes and significance of the parameters. Summary statistics for the continuous variables and the frequencies for the dummy variables are seen in Tables 2 and 3, respectively.

**Table 2**
**Summary statistics for the continuous variables used in the empirical analysis based on a RMA data set for corn and soybeans in Illinois (reinsurance year 2000).**

| Variable | No. of Obs. | Mean | St. Dev. | Min. | Max. |
|---|---|---|---|---|---|
| LOSS | 4426 | 192.95 | 40.80 | 82.97 | 353.4 |
| ACRE | 4472 | 45.18 | 44.80 | 0.40 | 519.10 |
| YE | 4472 | 59.57 | 36.71 | 17.00 | 188.00 |
| PE | 4472 | 4.28 | 1.44 | 1.77 | 5.16 |
| SHR | 4472 | 0.68 | 0.28 | 0.04 | 1.00 |

**Table 3**
**Frequency of the dummy variables used in the empirical analysis based on a RMA data set for corn and soybeans in Illinois (reinsurance year 2000).**

| Variable | Frequency | Percent | Variable | Frequency | Percent |
|---|---|---|---|---|---|
| YC65 | 2252 | 50.36 | RO3 | 210 | 4.70 |
| YC70 | 731 | 16.35 | RO4 | 520 | 11.63 |
| YC75 | 1009 | 22.56 | RO5 | 121 | 2.71 |
| YC80 | 202 | 4.52 | RO6 | 533 | 11.92 |
| CORN | 1199 | 26.81 | RO7 | 66 | 1.48 |
| NIR | 4454 | 99.60 | RO8 | 1004 | 22.45 |
| RO1 | 100 | 2.24 | RO9 | 154 | 3.44 |
| RO2 | 820 | 18.34 | RO10 | 635 | 14.20 |

## RESULTS AND DISCUSSION

The results of the loss equation estimation are presented in Table 4. We first estimated the parameters using ordinary least squares (OLS). Then, the loss equation is estimated using maximum likelihood to correct for sample selection. As mentioned above, two versions of the model are estimated using maximum likelihood: (1) one where expected yield (YE) is the only regressor in the selection equation, and (2) one where expected yield (YE), and price election (PE), insured share (SHR) and acreage (ACRE) are regressors in the selection equation. The parameter estimates for the selection equation are in Table 5.

In terms of signs and statistical significance the results are quite robust across the different estimated models for the loss equations. However, the magnitudes of the parameters are mostly different between OLS and ML. The magnitudes of the parameter estimates for the OLS model are generally higher than the ML estimates. This is expected because OLS estimates do not correct for sample selection bias and are biased upwards.

In terms of farm characteristics, it seems that the two variables that statistically affects the magnitude of the loss consistently across models are farm size (ACRE) and the insured's share amount (SHR). However, the effect of the SHR variable is only significant at the 5% level. The signs of the variables suggest that farm size is positively related to the loss magnitude, while share amount is negatively related to the loss amount. The bigger volume of production in large acreage farms makes it logical to expect the positive effect of the ACRE variable on loss magnitudes. The effect of share amount might be negative because non-single ownership arrangements spread the risk across individuals. Since single ownership means that one individual bears all the risk, then this individual is more likely to reduce the probability of a loss.

Other farm characteristic variables such as the crop dummy variable (CORN) was significant at the 5% level in the OLS and ML2 models, while the crop practice variable (NIR) was not significant across models. The dummy variables representing the reinsurance organizations suggest that firm-specific effects may exist. Five out of ten reinsurance organization dummy variables are statistically significant across models and all five of this reinsurance organization dummies have negative signs. This means insured producers that are associated with these reinsurance organizations tend to have lower loss magnitudes.

**Table 4**
**Estimation results for the loss equation that is used to test the effect of coverage levels on falsification behavior, using data for corn and soybeans in Illinois (reinsurance year 2000).**

| Variables | Parameter estimates (standard errors in parentheses) | | | | | |
|---|---|---|---|---|---|---|
| | OLS | | ML1 | | ML2 | |
| Intercept | 204.31 | * | 205.64 | * | 204.29 | * |
| | (10.15) | | (9.88) | | (9.08) | |
| ACRE | 0.07 | * | 0.07 | * | 0.07 | * |
| | (0.01) | | (0.01) | | (0.01) | |
| SHR | -0.05 | ** | -0.05 | ** | -0.05 | ** |
| | (0.02) | | (0.02) | | (0.02) | |
| YC65 | -16.42 | * | -15.82 | * | -15.75 | * |
| | (2.60) | | (2.60) | | (2.63) | |
| YC70 | -9.77 | * | -9.21 | * | -9.10 | * |
| | (2.87) | | (2.87) | | (2.90) | |
| YC75 | -7.42 | * | -7.29 | * | -7.57 | * |
| | (2.76) | | (2.75) | | (2.78) | |
| YC80 | -6.65 | | -6.55 | | -6.96 | |
| | (3.72) | | (3.71) | | (3.75) | |
| CORN | 3.25 | ** | 2.12 | | 3.40 | ** |
| | (1.37) | | (1.40) | | (1.38) | |
| NIR | 7.41 | | 6.70 | | 6.87 | |
| | (9.45) | | (9.16) | | (8.27) | |
| RO1 | -28.41 | * | -29.11 | * | -23.68 | * |
| | (4.66) | | (4.65) | | (3.81) | |
| RO2 | -8.21 | * | -8.44 | * | -8.04 | * |
| | (2.69) | | (2.66) | | (2.69) | |
| RO3 | 3.02 | | 2.74 | | 3.00 | |
| | (3.61) | | (3.58) | | (3.65) | |
| RO4 | -14.01 | * | -14.10 | * | -11.54 | * |
| | (2.90) | | (2.86) | | (2.93) | |
| RO5 | -6.30 | | -6.80 | | -6.42 | |
| | (4.30) | | (4.28) | | (4.33) | |
| RO6 | -2.83 | | -2.62 | | -2.67 | |
| | (2.87) | | (2.83) | | (2.88) | |
| RO7 | 1.24 | | 1.12 | | 1.59 | |
| | (5.45) | | (5.42) | | (5.51) | |
| RO8 | -9.58 | * | -9.92 | * | -9.25 | * |
| | (2.63) | | (2.60) | | (2.63) | |
| RO9 | -5.88 | | -6.26 | | -5.85 | |
| | (3.97) | | (3.94) | | (3.92) | |
| RO10 | -7.75 | * | -7.83 | * | -7.16 | * |
| | (2.79) | | (2.77) | | (2.78) | |
| R-squared (OLS) | 0.0481 | | - | | - | |
| Wald test (Chi-sq.) | - | | 219.52* | | 197.98* | |
| LR test ($\rho = 0$) | - | | 32.43* | | 264.98* | |
| Log likelihood | - | | -22825.27 | | -22702.55 | |

*(**) – Denotes statistical significance at the 1% (5%) level.

**Table 5**
**Estimation results for the selection equation that controls for selection bias in the loss equation (based on data for corn and soybeans in Illinois, reinsurance year 2000).**

| | Parameter estimates (standard errors in parentheses) | | | | |
|---|---|---|---|---|---|
| **Variables** | **OLS** | **ML1** | | **ML2** | |
| Intercept | - | 1.52 | * | -10.86 | * |
| | | (0.13) | | (0.44) | |
| YE | - | 0.01 | * | 0.09 | * |
| | | (0.002) | | (0.01) | |
| PE | - | - | | 1.61 | * |
| | | - | | (0.04) | |
| ACRE | - | - | | -0.0005 | |
| | | - | | (0.001) | |
| SHR | - | - | | 0.001 | |
| | | | | (0.002) | |
| Rho ($\rho$) | - | -0.85 | | -0.99 | |
| | - | | | | |

*(**) – Denotes statistical significance at the 1% (5%) level

The variables of main interest in this study are the dummy variables for yield coverage choice. Across all estimation procedures undertaken, the dummy variables associated with yield coverage choice have negative signs and are significant, except for YC80 where it is not statistically significant. The negative signs means that losses are lower when the yield coverage level is lower than 85% (the excluded yield coverage dummy variable). Furthermore, the absolute value of the magnitudes of the dummy variables increases as the yield coverage level decreases. This means that the magnitude of the loss becomes lower as the yield coverage chosen is reduced. Note that this is not consistent with the empirical hypothesis that we put forward above. If falsification behavior is prevalent, we expected that lower yield coverage levels should have higher losses and as yield coverage level is reduced the magnitude of the loss should be greater. Given that our empirical results do not support this hypothesis, this means that other asymmetric information problems like *ex ante* moral hazard and adverse selection may be the more prevalent problem in crop insurance. The *ex ante* moral hazard and adverse selection effects that are embodied in the choice of yield coverage levels overwhelms the potential effect of the falsification behavior.

These results do not necessarily mean that falsification effects from the choice of alternative yield coverage levels are not present in crop insurance, the results just show that other asymmetric information problems may be more prevalent in this market. The falsification incentives from yield coverage levels acting as deductibles are still there but it is not significant in the market for crop insurance. Previous studies that investigated adverse selection and *ex ante* moral hazard in crop insurance have shown that these asymmetric information problems are indeed present in crop insurance, even though the magnitude of each problem is still not fully understood [12, 13]. Our results here suggest that in crop insurance, the asymmetric information problems related to adverse selection and *ex ante* moral hazard may be more significant in magnitude than falsification problems or opportunistic fraud. In contrast, studies using data from the automobile insurance markets have empirically shown that there is no strong evidence that adverse selection and *ex ante* moral hazard are significant problems in this market [2]. Consequently, Dionne and Gagné [4] have shown that deductible contracts in automobile insurance do significantly affect falsification behavior. They found that higher deductibles do increase the loss magnitudes and, therefore, this may be the more significant asymmetric information problem in automobile insurance.

## CONCLUDING COMMENTS

Falsification behavior that can be attributed to the fraud incentives created by yield coverage levels was not found to be significant in crop insurance. Hence, policy makers investigating contract elements that contribute to fraud behavior in crop insurance should probably focus more on other aspects of crop insurance contracts that are more vulnerable to fraud, waste, or abuse. For example, the optional unit provisions that make it possible to undertake yield-switching behavior. The presence of optional units provides producers the opportunity to manipulate their yield history (by yield-switching) and artificially increasing their yield guarantees. This in turn increases the likelihood of receiving a loss and a potential indemnity payment. The optional unit provision in crop insurance contracts may then provide more incentives to defraud than the choice of yield coverage levels and should be studied further. Even though falsification behavior due to alternative yield coverage levels do not seem to be prevalent in crop insurance based on our results, fraud behavior due to other crop insurance contract elements that give incentives to defraud may still be significant and these should be studied further if program integrity is to improve.

Note, however, that this study only focused on insured corn and soybean producers in Illinois. An extension of the study to include other states and other crops would be very useful. This type of extension can show if there are other crops and/or regions where falsification behavior due to yield coverage levels are indeed significant. Note that insured corn and soybean producers in Illinois have been historically known as “low” loss producers relative to producers of other crops in other states. Therefore, falsification behavior may generally be lower in this case for this crop-region combination. Cotton production in the Southern U.S., on the other hand, is generally known as a “higher” loss region where falsification behavior may be more prevalent [18]. Although our empirical results did not provide evidence of the falsification effects of yield coverage levels in Illinois corn and soybeans, this does not preclude the possible existence of this relationship in other regions. A more comprehensive study that utilizes the entire RMA data base (for the whole nation and for all crops) may provide further insights as to the extent of the fraud incentive effects of yield coverage levels.

Further studies should also be undertaken to more fully understand the magnitude and extent of asymmetric information problems in the U.S. crop insurance program. This will allow for better prioritization of resources to reduce excessive indemnity payments arising from these problems. Although this study reinforces the notion that adverse selection and *ex ante* moral hazard may be the more pressing issues in crop insurance, these two problems of asymmetric information are significant here relative only to the fraud behavior effects of alternative yield coverage levels acting as deductibles. Investigating the magnitude of fraud problems due to all the different elements of the crop insurance contract vulnerable to fraud, may suggest otherwise. One might find that fraud or *ex post* moral hazard may generate more excess losses than the other two problems of asymmetric information.

## ENDNOTES

[1] Alternative yield coverage levels minimize *ex ante* moral hazard, in theory, because less than full insurance coverage gives some incentive to reduce the probability of a loss. Problems of adverse selection is also theoretically minimized with alternative yield coverage levels because this serves as a "self-selection mechanism" that allows different risk types to choose different coverage levels. *Ex post* moral hazard is minimized with deductibles because incentives for falsification will be reduced at the lower loss states.

[2] The magnitude of the yield loss can also be falsified by manipulating the yield records that determine $Y^e$. This type of fraud is ignored to simplify the model. This simplification does not change the theoretical predictions of the model.

[3] The expressions $\phi(\cdot)$ and $\Phi(\cdot)$ represent the normal density and the standard cumulative normal, respectively.

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**Appendix**

In this appendix, we present the conditions that would show that $d^2L/dDdp > 0$. To do this, we totally differentiate twice the first-order condition in (11) with respect to *L*, *D*, and *p*. This results to

(A1) $$HdL + JdD + Kdp = 0,$$

where $J \equiv -pU''(W_F^N)(1-c'(L)) > 0$,
$K \equiv U'(W_F^N)(1-c'(L)) - U'(W_F^D)(-c'(L)) > 0$, and
*H* is as defined in the text. From (A1), (13) and (14), we can show that

(A2) $$dL = \frac{\partial L}{\partial D}dD + \frac{\partial L}{\partial p}dp.$$

Totally differentiating (A2), we have

(A3)

$$d^2L = \frac{\partial(\partial L/\partial D)}{\partial D}dD^2 + \frac{\partial(\partial L/\partial D)}{\partial p}dDdp + \frac{\partial(\partial L/\partial p)}{\partial D}dpdD + \frac{\partial(\partial L/\partial p)}{\partial p}dp^2$$

By symmetry

(A4) $$\frac{\partial(\partial L/\partial D)}{\partial p} \equiv \frac{\partial(\partial L/\partial p)}{\partial D},$$

and, therefore,

(A5) $$\frac{d^2L}{dDdp} = 2\frac{\partial(\partial L/\partial D)}{\partial p}.$$

At this point we need to examine the sign of $\frac{\partial(\partial L/\partial D)}{\partial p}$ to determine whether $d^2L/dDdp > 0$.

From (13), we can re-write $\frac{\partial(\partial L/\partial D)}{\partial p}$ as

(A6) $$\frac{\partial\left(\frac{pU''(W_F^N)(1-c'(L))}{H}\right)}{\partial p}.$$

By differentiating the expression in (A6) we obtain

(A7)
$$\frac{U''(W_F^N)(1-c'(L))}{H}-\frac{pU'(W_F^N)(1-c'(L))}{H^2}\left(U''(W_F^N)(1-c'(L))^2-U''(W_F^D)(-c'(L))\right).$$

The first term is strictly positive because H<0 and $U''(W_F^N)<0$ under risk aversion. To sign the second term, we need to re-write the second term of (A7) using the first-order condition in (11). This results to

(A8)
$$-\frac{pU''(W_F^N)(1-c'(L))}{H^2}\left[\frac{U''(W_F^N)(1-c'(L))}{pU'(W_F^N)}-\frac{U''(W_F^D)(c'(L))}{(1-p)U'(W_F^D)}\right].$$

Assuming constant absolute risk aversion, the expression in (A8) can be written as:

(A9)
$$-\frac{pU''(W_F^N)(1-c'(L))}{H^2}\left(-\frac{U''(W_F^N)}{U''(W_F^N)}\right)\left[\frac{(c'(L))}{(1-p)}-\frac{(1-c'(L))}{p}\right].$$

Multiplying (A9) by $(1-p)^2/p(1-c'(L))>0$, which does not change the signs of the expression, yields

(A10)
$$-\frac{pU''(W_F^N)(1-c'(L))}{H^2}\left(-\frac{U''(W_F^N)}{U''(W_F^N)}\right)\left[\frac{(1-p)(c'(L))}{p(1-c'(L))}-\frac{(1-p)^2}{p^2}\right].$$

The expression $\frac{(1-p)(c'(L))}{p(1-c'(L))}$ is strictly less than one because from the first-order condition in (11) the expected marginal benefit of fraud $p(1-c'(L))$ has to be greater than the expected marginal benefit of fraud $(1-p)(c'(L))$. Consequently, if the resulting sign of the expression in scarred brackets in (A10) is greater than zero, the whole expression (A10) would be positive. This is true when $\frac{c'(L)}{(1-c'(L)}\geq\frac{1-p}{p}$ , which is the case if the success probability of fraud is sufficiently high.

Therefore, assuming constant absolute risk aversion and $\frac{c'(L)}{(1-c'(L)}\geq\frac{1-p}{p}$ , the expressions (A10), (A7), (A6) and (A5) are positive. This means that constant absolute risk aversion and $\frac{c'(L)}{(1-c'(L)}\geq\frac{1-p}{p}$ are the conditions that makes $d^2L/dDdp>0$ .

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