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# Ex post Moral Hazard in Crop Insurance: Costly State Verification or Falsification?

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## Abstract

*This article examines the extent to which actual crop insurance indemnification behaviour conforms to the theoretical predictions of two ex post moral hazard models — costly state verification and costly state falsification — and then explores whether the closely conforming model can indeed help deter ex post moral hazard in the United States (US) crop insurance program. The results suggest that indemnification behaviour in crop insurance is more in line with the costly state verification model. Following the theoretical predictions of the costly state verification model, however, may not be the optimal policy to deter ex post moral hazard since it is possible for insured producers to deceive loss adjusters and for loss magnitudes to not be truthfully verified.*


## 1. Introduction

There is substantial agricultural economic literature about moral hazard in the US crop insurance program.[2] However, these studies mainly dealt with hidden action or ex ante moral hazard, where the insured takes less care to prevent a loss than they would if uninsured. In this case, the insured possess asymmetric information about their likelihood of suffering insurable losses and the incentive problem exists prior to the resolution of uncertainty. Another aspect of moral hazard that has not been fully explored in the crop insurance context is ex post moral hazard. Here the asymmetric information held by the insured involves the actual magnitude of the economic loss and the incentive problem exists following the resolution of uncertainty. Therefore, ex post moral hazard is normally taken as synonymous to insurance fraud because it occurs after the resolution of uncertainty.

Since the early 1990s, the need to reduce fraud in the US crop insurance program has been a recognized priority of the US Congress, the US Department of Agriculture (USDA), and the USDA's Risk Management Agency (RMA). Current estimates reveal that approximately 5 per cent of all crop insurance claims may be associated with fraud (US General Accounting Office, 1999). Therefore, in order to help government policy makers develop strategies that can mitigate fraud behaviour, it is important to understand the theoretical underpinnings of crop insurance indemnification behaviour aimed to deter fraud and to assess whether these theoretical predictions can mitigate fraud behaviour given the current crop insurance policy structure.

The theoretical literature on how to optimally deter ex post moral hazard may be divided into two distinct paradigms — costly state verification or costly state falsification. The costly state verification paradigm attributed to Townsend (1979) is where the insured knows the actual magnitude of the loss and the insurer can observe that loss only by incurring a fixed monitoring cost. Therefore, in this setting, the insurer can choose to eliminate the informational advantage of the insured, but in so doing must incur some cost. The relevant economic problem here is to find an optimal contract that utilizes the costly monitoring technology in an efficient fashion.

In the costly state falsification paradigm, attributed to Lacker and Weinberg (1989), it is assumed that there is no economically feasible monitoring technology that can be implemented by the insurer to alleviate the informational asymmetry. In this model the main assumption is that the insured's private information on the magnitude of the actual loss is immutable. Costly state falsification occurs because the insured is able to manufacture an observed claim that exceeds the loss actually suffered, by incurring a resource cost. The main economic problem in this case is to find an optimal contract that balances the need for insurance to smooth income with the incentives for claims falsification that insurance payments provide.

In the crop insurance area, Hyde and Vercammen (1997) is the only study that addressed the issue of optimal contract form in the presence of ex post moral hazard. However, their focus is mainly on the implications for optimal contract form under the condition of costly state verification — both with and without hidden action moral hazard. Although costly state falsification is somewhat addressed in the paper it was not the main focus of the modeling effort. Their purely theoretical findings suggest that the costly state verification model more accurately coincides with many important features of actual crop insurance contracts. Aside from Hyde and Vercammen (1997) there has been no published study in the crop insurance area that addressed the issue of both costly state verification and costly state falsification. Furthermore, no study has yet investigated whether the theoretical predictions from the costly state verification model or the costly state falsification model more closely reflect the actual indemnification behaviour in the crop insurance markets. Only Crocker and Tennyson (1999), who used actual claims data from bodily injury liability insurance, have empirically examined these predictions.

This article examines the extent to which actual crop insurance indemnification behaviour conforms to the theoretical predictions of the two ex post moral hazard models. This allows us to identify which of the two models can potentially explain actual crop insurance indemnification behaviour and discuss whether the model used can indeed optimally deter ex post moral in the US crop insurance program. The paper proceeds as follows. First, we review the economically optimal contract design and the corresponding theoretical predictions to deter ex post moral hazard, for the case of costly state verification and falsification, respectively. Then we use actual crop insurance data to empirically determine which ex post moral hazard model more closely coincides with actual behaviour. Then we discuss the appropriateness of using this theoretical paradigm to deter ex post moral hazard in practice, given the current structure of the US crop insurance program.

## 2. THEORY

*I Costly state verification*

The costly state verification paradigm is attributed to the work of Townsend (1979) and has been examined in an insurance context by Dionne and Viala (1992), Kaplow (1994), and Bond and Crocker (1997). The theoretical predictions elucidated here are based on the work of Bond and Crocker (1997) and are discussed in the context of multiple peril crop insurance (MPCI). In this model there exists a continuum of risk averse farmers, each of which possess a von Neumann Morgenstern utility function $U(W_i)$, where $W_i$ is the wealth of a farmer in state $i$. This wealth is a function of profits derived from his farming operation and his assets. Assume that each farmer has the same initial wealth $W$, but may suffer some financial loss due to adverse yields with probability $\pi$. Further assume that when a farmer suffers a loss it is publicly observable, but the magnitude of that loss is private information to the farmer suffering the loss. The actual loss can be verified, however, if the insurer bears the fixed monitoring cost $\gamma$. Moreover, it is assumed that the farmer cannot take actions that have the effect of manipulating the monitoring cost $\gamma$. Conditional on the farmer suffering a loss due to low yields, the actual magnitude of that loss is denoted as $x$ and is distributed on $[\underline{x},\bar{x}]$ according to the probability density function $g$.

In this situation, an insurance allocation $A \equiv \{p, r(x)\}$ consists of an insurance premium $p$, which is paid by the farmer prior to experiencing any loss, and a state-contingent indemnity payment, $r(x)$. The farmer's expected utility can then be expressed as:

$$V(A) \equiv \pi \int_{\underline{x}}^{\bar{x}} U(W - p - x + r(x))g(x)dx + (1-\pi)U(W-p) \quad (1)$$

The profit of the insurer can also be written as:

$$\Pi(A, M) \equiv p - \pi \int_{\underline{x}}^{\bar{x}} r(x)g(x)dx - \gamma\pi \int_{M} g(x)dx \quad (2)$$

where $M \subset [\underline{x},\bar{x}]$ denotes the range of losses where the insurer monitors (the monitoring region). An insurance contract $C \equiv \{A,M\}$ is a specification of both an allocation $A$, and a monitoring region, $M$.

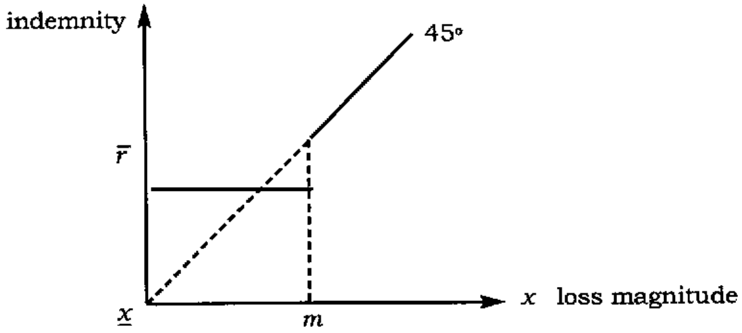
The magnitude of the actual loss is private information to the farmer, which places constraints on the structure of an implementable insurance contract. For example, to obtain truthful revelation of the actual loss due to adverse yields by the farmer in the no-monitoring region $M^c$, the optimal contract must specify a constant payment $\bar{r}$ for such losses. If not, the insured farmer would always elect to report the magnitude of loss associated with the highest indemnity in $M^c$. In addition, were the payment in $M^c$ to exceed that associated with a portion of the monitoring region $M$, then the insured farmer would elect to misrepresent any losses in this region of $M$. Formally, the incentive constraints created by the informational asymmetries of this model require that an optimal contract satisfies:

$$r(x) = \begin{cases} = \bar{r} & for \quad x \in M^c \\ \geq \bar{r} & for \quad x \in M \end{cases} \tag{3}$$

where $\bar{r}$ is a constant and $M^c$ is the complement of $M$.

Therefore, an optimal crop insurance contract with costly state verification is a solution to the problem that maximizes farmer's expected utility in (1) subject to the incentive constraints in (3) and the zero profit constraint for the insurers $\Pi(A, M) \geq 0$. Following this maximization, the optimal crop insurance contract with costly state verification entails a fixed payment $\bar{r}$ and no monitoring for losses less than a critical value $m(> \bar{r})$. Furthermore, the insured farmer is monitored and receives full indemnity ($r(x)=x$) for losses exceeding $m$. In other words, an optimal contract entails no monitoring and a fixed indemnity payment for small losses, and monitoring with full loss indemnification for more adverse outcomes (Figure 1). Formal proof of this general result can be seen in Bond and Crocker (1997) and a proof is also expressed within a crop insurance context in Hyde and Vercammen (1997). Note also that as the cost of monitoring $\gamma$ declines, both $m$ and $\bar{r}$ decline as well, resulting in an expansion of the monitoring region $M \equiv (m, \bar{x})$. In the extreme case of costless monitoring ($\gamma = 0$), insurers verify all claims ($M \equiv [\underline{x}, \bar{x}]$ and the insured farmers receive full indemnity for their losses ($r(x)=x$ for every $x$).

**Figure 1. Optimal indemnification profile with costly state verification**



*II Costly state falsification*

The costly state falsification paradigm was first attributed to Lacker and Weinberg (1989) and subsequently extended by Crocker and Morgan (1998). We follow the format of Crocker and Morgan (1998) in the discussion here. Again we consider a setting in which farmers possess a von Neumann Morgenstern utility function $U(W_i)$, where $W_i$ is the wealth of a farmer in state $i$. As before, all farmers have the same utility function $U$ and initial wealth $W$, and may suffer a financial loss due to adverse yields $x = \in [\underline{x}, \overline{x}]$, the magnitude of which is assumed to be private information to the farmer suffering the loss. Under this paradigm, the farmer can generate an observed claim $y$ that differs from the actual loss $x$ suffered due to adverse yields.[3] The difference between the farmer's actual loss and the loss observed by the insurer, $|x - y|$, is defined here as claims falsification. In order to falsify a claim, the insured farmer incurs a falsification cost $s(x - y)$, which is assumed to be an increasing function of the amount of falsification.

Assuming that the actual loss is $x$, the farmer's final wealth can be expressed as:

$$W - x + r - s(x - y) \tag{4}$$

where $r$ is the indemnity payment. Letting $\pi$ be the probability of a loss occurring due to adverse yields, $f$ be the distribution of the loss magnitudes given that some loss has occurred, and $p$ be the premium paid by the farmer prior to the loss occurring, the farmer's expected utility can be written as:

$$V(C) \equiv \pi \int_{\underline{x}}^{\overline{x}} U(W + r - p - x - s(x - y)) f(x) dx + (1 - \pi) U(W - p) \tag{5}$$

In this case the insurance contract $C \equiv (r, y, p)$ is a specification of a constant premium $p$, and an indemnity payment $r$ associated with each observed claim $y$. The profit of the insurer can be written as:

$$\Pi(C) \equiv p - \pi \int_{\underline{x}}^{\overline{x}} r(x) f(x) dx \tag{6}$$

The revelation principle is used here to characterize a solution because the magnitude of actual loss is private information (Myerson, 1979). Letting $C \equiv \{r(\hat{x}), y(\hat{x})\}$ denote the contractual allocation assigned to an insured who announces his type to be $\hat{x}$, incentive compatibility requires that a contract must satisfy the following constraint:

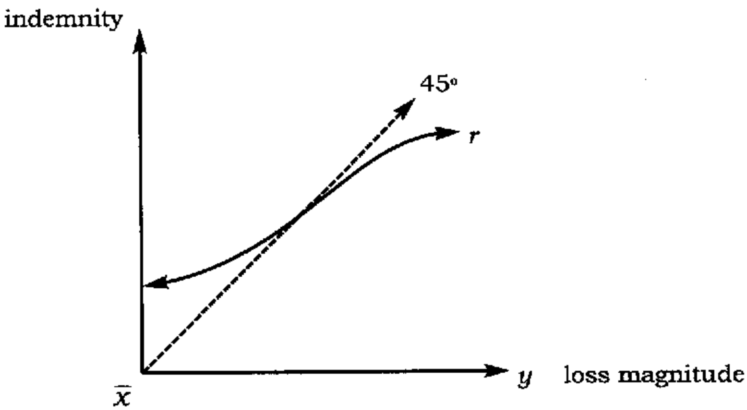
$$U(W + r(x) - p - x - s(x - y(x))) \geq U(W + r(x') - p - x - g(x - y(x'))), \tag{7}$$

for every $x, x' \in [\underline{x}, \overline{x}]$

An optimal insurance contract for the costly state falsification case is a solution to the problem that maximizes farmer's utility in (5) subject to the incentive compatibility constraint in (7) and the zero profit constraint for the insurers $\Pi(A, M) \geq 0$. This maximization results in an optimal insurance contract for costly state falsification where there is overpayment of small claims ($r > y$) and underpayment of large claims ($r < y$). In addition, all insured farmers except those with the smallest ($\underline{x}$) or largest ($\overline{x}$) possible losses engage in some claims falsification. Formal proof of this theoretical prediction is seen in Crocker and Morgan (1998).

The optimal contract under costly state falsification is graphically depicted in Figure 2. If insurers are able to costlessly observe the actual loss, then the optimal contract coincides with the 45-degree line and entails full indemnification for any losses suffered. On the other hand, when the actual loss is private information to the farmer and the insurer can only observe a potentially falsified claim, the optimal contract exhibits a reduced sensitivity of the indemnity to the observed claim amount. This feature reduces the returns to claims falsification. At the extreme, a fixed indemnity payment $\bar{r}$ can eliminate the incentive to falsify completely, but this fixed payment does not smooth the wealth of the farmer over the various loss states. Therefore, the optimal contract for the case of costly state falsification exhibits a tradeoff between reducing incentives for claims falsification and income smoothing.

**Figure 2. Optimal indemnification profile with costly state falsification**




## 3. DATA AND EMPIRICAL METHODS

This study utilizes MPCI data from the Risk Management Agency (RMA) of the US Department of Agriculture (USDA) for reinsurance year (RY) 2000. In the spirit of homogeneity, only MPCI policies for non-irrigated cotton production are considered for analysis. To further assure a similar claiming environment, cotton farmers with 65 percent coverage levels, average production history (APH) of 545 lbs/acre, and price election of \$0.62/lb are the only ones considered in the analysis.[4] Limiting the observations allow us to estimate a profile with only one threshold level ($m$). The threshold level determines the deductible in crop insurance contracts. In a crop insurance context, the deductible ($/acre) is defined as:

$$\text{Deductible} = (1 - \text{Coverage level})*\text{APH}*\text{Price Election} \tag{8}$$

If we do not limit the observations of interest to have the same coverage level, APH, and price election, then deductibles for each observation may differ, and this is not consistent with the theoretical profiles in the preceding section. Given our choices of coverage level, APH, and price election, the deductible in the empirical analysis here is at $118.26/acre.

The RMA dataset contains information about the indemnity payments and the actual yield magnitudes of insured farmers at the crop unit level. Indemnities were extracted from RMA's data on each insured's claims record (Type 21 record) in 2000 and actual yield magnitudes were extracted from each insured's yield history record (Type 15 record) in 2001. The actual yield is reported by the insured farmer in the following year's yield history record (RY 2001 in our case) in order to compute the applicable APH for that year. Thus, we have yield data for insured producers regardless of whether or not they have submitted a claim and received an indemnity in RY 2000. The actual yield data, coverage level, APH, and price election allows us to compute for the loss magnitude ($/acre), defined as follows:

$$\text{Loss Magnitude} = \text{APH}*\text{Price Election} - \text{Actual Yield}*\text{Price Election} \tag{9}$$

Using the RMA data on loss magnitudes and indemnities paid makes it possible to estimate an indemnification profile.

The resulting dataset used in the analysis has 175 observations with a mean indemnity and mean loss magnitude of $138.89/acre and $239.00/acre, respectively. The standard deviations are $6.16/acre and $8.77/acre for the indemnity and loss magnitude, respectively. Indemnity values ranged from zero to $219.5/acre and loss values ranged from zero to $337.9/acre. The distribution of loss magnitudes and indemnities are reported in Table 1 (see appendix). Furthermore, the resulting dataset had observations from the following states: Alabama, Florida, Georgia, Missouri, North Carolina, South Carolina, and Texas.

The theoretical predictions in the previous section provide testable hypotheses about the indemnification behaviour associated with each *ex-post* moral hazard paradigm. The costly state verification framework predicts an indemnification profile where there is a minimum payment of $\bar{r}$ for any claim below some threshold $m$. In the case of crop insurance, $\bar{r} = 0$ and the threshold $m$ is determined by equation (8). All claims above the threshold level should be fully insured so that the indemnity paid should equal to the actual loss magnitude (less the deductible). In contrast, under the costly state falsification paradigm, the theoretical prediction is that small claims should be overpaid and large claims underpaid, so that the slope for indemnity payments as a function of the loss magnitude should be less than one. Therefore, these are the two hypotheses that we wish to empirically test using the crop insurance dataset.

Given these two hypotheses, we are interested in the empirical relationship between the indemnities paid and the actual loss magnitude. A nonparametric regression technique called locally weighted regression (LOESS), which is attributed to Cleveland (1979), is used here to estimate this relationship. We use a nonparametric approach because we do not want to arbitrarily impose a functional form on the relationship between indemnities and actual loss magnitudes. Furthermore, this nonparametric technique smoothes the data and is robust to potential outliers (Cleveland, 1979; Hardle, 1990). LOESS compromises between a global assumption of functional form and purely local averaging by using a weighted least squares algorithm. LOESS accommodates data of the form:

$$y_i = g(x_i) + \varepsilon_i \tag{10}$$

where $g$ is a smooth regression function and $\varepsilon_i$ is a random error with mean zero and a constant scale. In our case, the dependent variable $y$ represent the indemnity paid and the independent variable $x$ represents the loss magnitude.

The 'local' part of LOESS refers to a 'k-nearest neighbor (K-NN)' type neighborhood. The K-NN is specified as a proportion a of the n data points to be used at each point of estimation. There are a variety of methods to choose the proportion or 'bandwidth' ($\alpha$) in a LOESS procedure. Many of these methods choose a smoothing parameter which minimizes a criterion that incorporates both tightness of fit and model complexity of the form

$$\ln(\hat{\sigma}^2) + \psi(L) \tag{11}$$

where $\hat{\sigma}^2$is an average residual sum of squares and $\psi(.)$ is a penalty function designed to decrease with increasing smoothness of fit. Here $L$ is the smoothing matrix of the method. This matrix satisfies $\hat{y} = Ly$, where $y$ is the vector of observed values and $\hat{y}$ is the corresponding vector of the predicted values. Examples of specific criteria obtained with this methodology are generalized cross-validation (Craven and Wahba, 1979), the classical Akaike Information Criterion (AIC) (Akaike, 1973), and the bias corrected Akaike Information Criterion (Hurvich and Simonoff, 1998).

Here the bias corrected Akaike Information Criterion (BAIC) is used to choose the appropriate smoothing parameter. This criterion is given by:

$$BAIC = n\ln(\hat{\sigma}^2) + n\frac{\delta_1/\delta_2(n+\nu_1)}{\delta_1^2/\delta_2 - 2} \tag{12}$$

where $n$ is the number of observations, $\delta_1 \equiv Trace\,(I-L)^T(I-L)$, $\delta_2 \equiv Trace$ $[(I-L)^T(I-L)]^2$ and $\nu_1 = Trace($. This criterion was chosen because Hurvich and Simonoff (1998) has shown that the BAIC avoids the tendency to undersmooth that often occurs when using the classical AIC or generalized cross-validation.

In Figure 3, we see that the bandwidth with the lowest BAIC (BAIC = 1152.26) is at 0.46 and, thus, this is the bandwidth we use for the LOESS.

For each value of $x_i$, the $n$ points are ranked according to the absolute value of their distance from $x_i$, and the $k = \alpha n$ nearest points are identified. Let $d = |x_i - x_k|$ be the distance from $x_i$ to the $k$th nearest neighbour $x_k$. A weighted least squares linear regression is fitted to the $\alpha n$ points. The weights $w_m(x_i)$ decrease as the distance from $x_i$ increases:

$$w_m(x_i) = W(d^{-1}(x_m - x_i)) \tag{13}$$

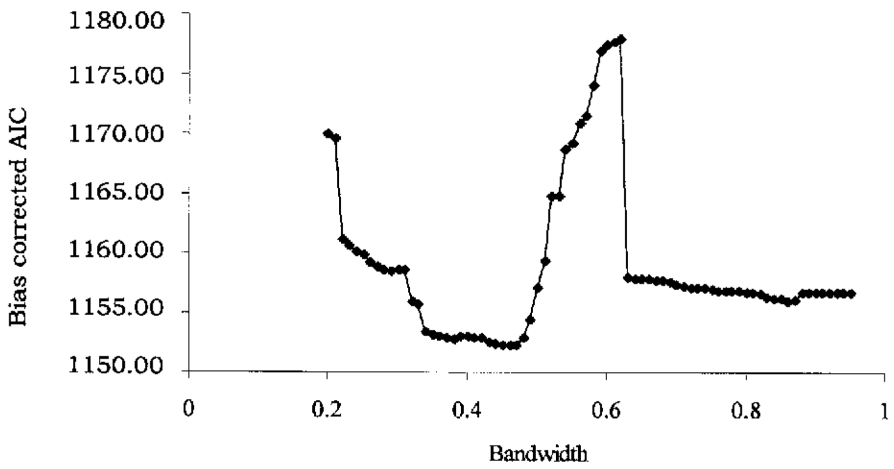
where $d^{-1}$is the inverse of $d$, $(x_m - x_i)$ is the distance of the $m$th observation ($m$ = 1,...,$k$) from $x_i$, and $W$ is the tricube weight function $W(u) = (1 - u^3)^3$ . Thus, points close to (far from) $x_i$ play a large (small) role in the determination of the fitted $y_i$ values. Increasing the neighborhood of points influencing the fitted values increases the overall smoothness of the smoothed points.

Fitted values for each target value are estimated using a first-order polynomial (or a linear function) for the defined neighborhood using weighted least squares. Choosing a polynomial of degree 1 is appropriate because it strikes a balance between computational ease and the need for flexibility to reproduce patterns in the data (Cleveland, 1979). Thus, the $\beta_i$'s are chosen to minimize:

$$\sum_m w_m(x_i)(y_m - \beta_0 - \beta_1 x_m)^2 \tag{14}$$

Note that the $\beta(x_i)$ values are estimated for each target $x_i$.

**Figure 3. Bias-corrected Akaike Information Criterion (AIC) at different bandwidths**

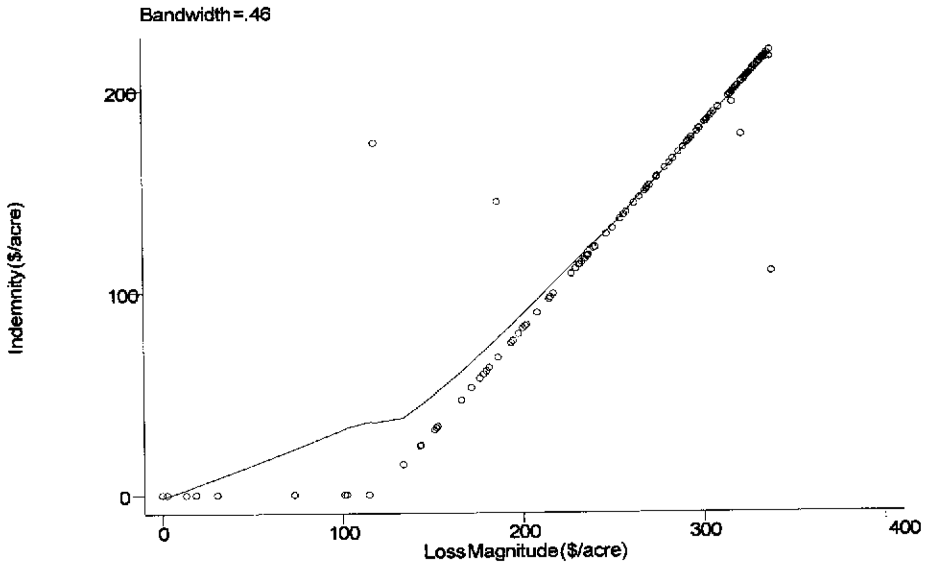


Fitted values for $(y_i, x_i)$ are computed from the β vector that minimizes equation (10) and corresponding regression residuals are also computed. The model is made 'robust' by using computed residuals to reweigh values in the neighborhood of the target values. New weighted least square values are estimated and the procedure iterated to estimate the LOESS fitted values. Outliers have smaller robustness weights and do not play a large role in the estimation of fitted values. In summary, LOESS is a nonparametric curve fitting method that starts off with a local polynomial least squares fit and then attempts to make the estimate more robust by using weights from the local neighborhood around the observation point. This procedure gives us a graphical indemnification profile that allows us to evaluate whether the crop insurance data coincides with the costly state verification or costly state falsification model.

## 4. Results and discussion

The estimated indemnification profile and the scatterplot of the data suggests that there seems to be no payments for losses below the threshold level ($118.26/acre) and losses above the threshold level seems to be fully indemnified (Figure 4). At the chosen bandwidth level (46 per cent), the estimated indemnification profile above the threshold level is very close to 45 degrees. This suggests full indemnification at levels above $m$. Furthermore, the scatterplot shows that loss magnitudes less than m received zero indemnities. This finding supports the costly state verification paradigm more than the costly state falsification paradigm.

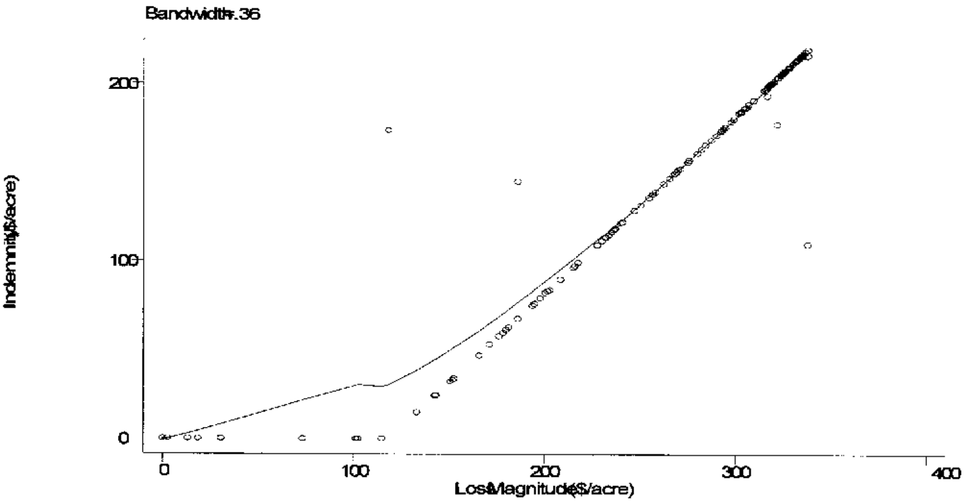
**Figure 4. Smoothed indemnification profile and scatter plot of indemnity vs. actual loss magnitude [bandwidth = 0.46; APH = 545; deductible = $118.26].**



To verify the sensitivity of our estimated profile to changes in the choice of the bandwidth, we also ran the LOESS estimation procedure at $\alpha$ = 36 per cent and $\alpha$ = 56 per cent. The estimated indemnification profile at $\alpha$ = 36per cent and $\alpha$ = 56 per cent is still very similar to the estimated profile at the 'optimal' bandwidth based on the BAIC (Figure 5A and 5B). Thus, the profile is robust to small deviations from the bandwidth chosen using the BAIC.

**Figure 5. Smoothed indemnification profile and scatter plot of indemnity vs. actual loss magnitude:**

**(A) Bandwith = 0.36**




**(B) Bandwidth = 0.56**

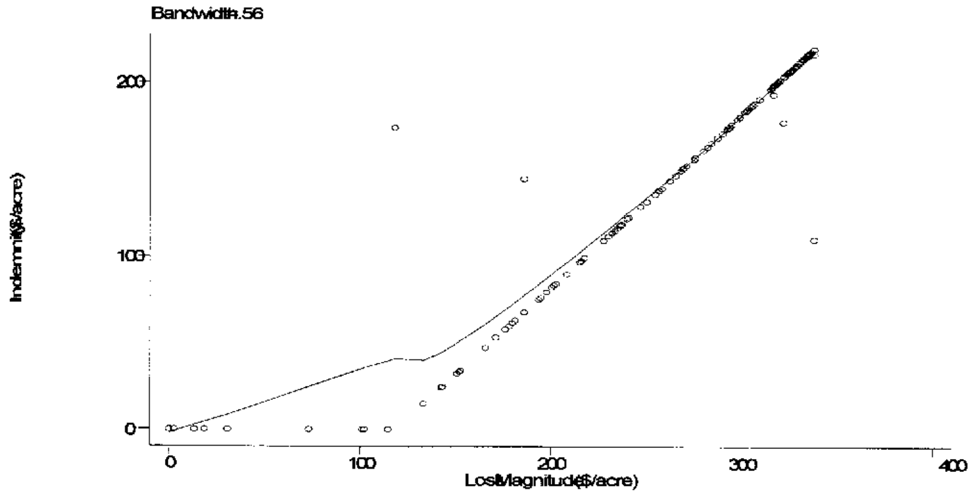
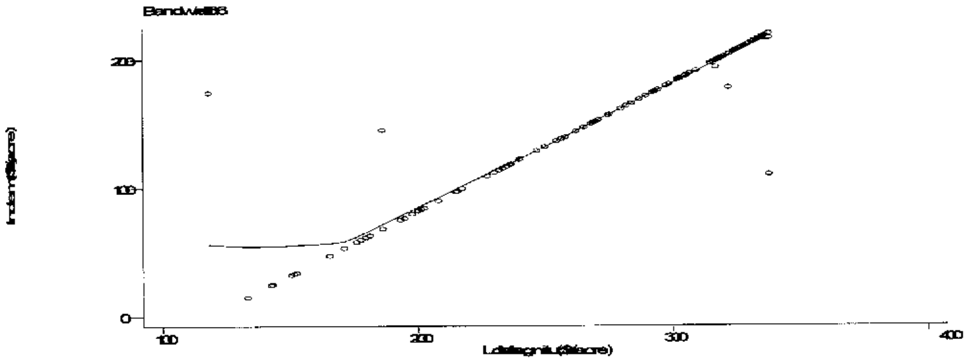
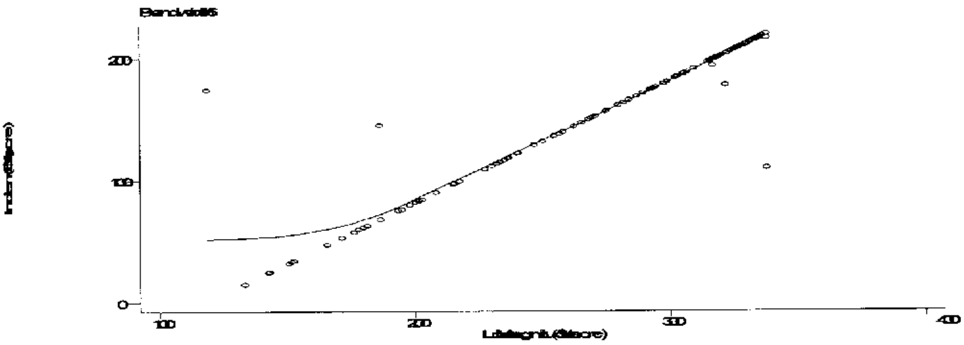


**Figure 6. Smoothed indemnification profile and scatter plot of indemnity vs. actual loss magnitude [where loss magnitude is above the deductible]:**

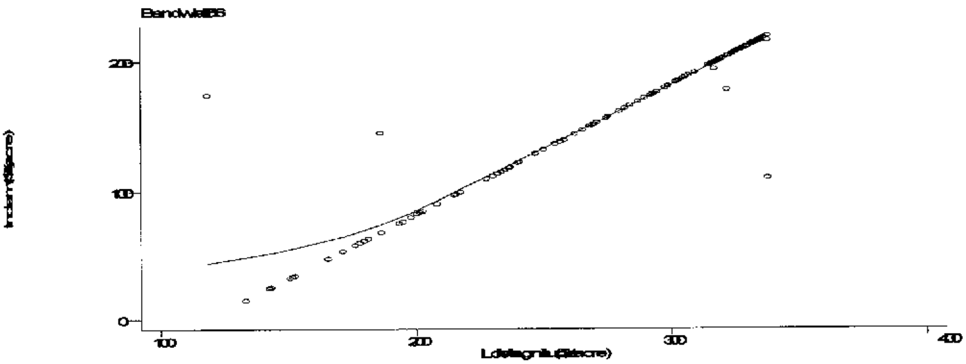
**(A) Bandwidth = 0.36**



**(B) Bandwidth = 0.46**



**(C) Bandwidth = 0.56**



In Figures 4 and 5, all the observations are included in the LOESS estimation of the profile, including the observations with zero indemnities. In Figure 6, we estimate the indemnity profile only for observations above the threshold level to remove the possible effects of the zero indemnity values in the estimation. This allows us to further explore if there is full indemnification above the threshold level. Bandwidth levels at 0.36, 0.46, and 0.56 are used for this LOESS estimation. In general, the estimated profiles still support the costly state verification paradigm. The estimated profiles in Figure 6 also show that there is a tendency for overpayment of losses at the lower loss magnitudes just above m. This behaviour may be due to the two cases of substantial overpayment at the lower loss levels. However, the estimated profiles still exhibit full indemnification at the higher loss levels even if there are two cases of underpayment at the higher loss levels. Therefore, Figure 6 suggests an indemnification behaviour of overpayments at the lower loss levels and full indemnification at the higher loss levels, for the monitoring region above the deductible. This type of indemnification behaviour is not supported by either the pure costly state verification paradigm or the pure costly state falsification paradigm discussed in the second section of this paper.[5] Nevertheless, the presence of full indemnification at the higher loss magnitudes and no indemnity payments below m more closely supports the costly state verification paradigm rather than the costly state falsification paradigm.

In summary, crop insurance indemnification behaviour appears to follow the theoretical predictions of the costly state verification paradigm. This result is consistent with Hyde and Vercammen (1997) where they argue that the costly state verification paradigm is more in line with actual crop insurance contract form. However, their result is only based on observed features of existing crop insurance contracts and not on actual indemnification behaviour. This paper shows that actual indemnities paid (based on RMA data) do indeed more closely follow the costly state verification paradigm. Based on this result, it seems that this paradigm is deemed by the federal crop insurance policy makers to be an optimal contract design to help mitigate fraud behaviour by insured crop producers.

## 5. Conclusions and policy implications

This paper explores whether actual crop insurance indemnity payments more closely conform to the theoretical predictions of either the costly state verification or the costly state falsification models. Using a nonparametric regression technique to estimate the crop insurance indemnification profile for non-irrigated cotton, we found that actual behaviour is more in line with the costly state verification paradigm than the costly state falsification paradigm.

The results indicate that insurers seem to indemnify based on the assumption that it is possible to verify actual loss magnitude and eliminate the informational asymmetry of the farmer. In crop insurance, losses are indeed verified through crop insurance loss adjusters. Given the existence of a way to verify losses, indemnification based on the costly state verification paradigm seems to be optimal to deter ex post moral hazard. However, the optimal indemnification predicted under the 'pure' costly state verification paradigm discussed here assumes that farmers cannot deceive the loss adjusters and adjusters always truthfully report the actual loss magnitudes (i.e. insured producers cannot manipulate monitoring costs to deceive adjusters). These assumptions are not necessarily true and, thus, may influence the applicability of using the optimal predictions of the 'pure' costly state verification model to deter ex post moral hazard in crop insurance.

For example, the optional unit provision of the crop insurance program, which allows a farmer to divide his farm into several insurable units, makes it very difficult for adjusters to verify actual yield losses on the farm. A farmer can easily shift bushels from one unit to the next and it is very difficult to verify which bushels truthfully came from which insurable unit. Furthermore, if farmers were able to collude with agents and adjusters to falsify the magnitude of losses then truthful verification would be impossible. There has been anecdotal evidence that these situations are present in crop insurance, which indicates that following the theoretical predictions of the 'pure' costly state verification model may not reduce incentives for fraud behaviour and, hence, may not be the optimal contract design to deter fraud.

These examples show that there may be room for further study of more appropriate contract forms or indemnification schedules when there is a possibility for insureds to manipulate the truthful verification of loss magnitudes, as is probably the case in crop insurance. Recent studies by Bond and Crocker (1997) and Picard (2000) have extended the costly state verification model to consider the possibility of manipulating monitoring costs by insureds. Indeed, the extension of Bond and Crocker (1997) may possibly support the behaviour of overpayment in the lower loss magnitudes (within the monitoring region) observed in our results. However, more in-depth study of existing extensions of the costly state verification model is still needed to ascertain which particular indemnification profile may be optimal for crop insurance. Moreover, studies of contract forms to deter collusion of insured producers and adjusters may also help in determining the optimal contract to deter fraud in crop insurance.

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## APPENDIX

**Table 1. Distribution of loss magnitude (x) and indemnity (y) for cotton, 2000**

| *Range* | *Loss Magnitude ($/acre)* | | | |
|---|---|---|---|---|
| | *Mean* | *St Dev* | *Frequency* | *Cumulative percentage, %* |
| <100 | 5.10 | 2.95 | 27 | 15.43 |
| 100 < x < 200 | 158.08 | 6.67 | 21 | 27.43 |
| 200 < x < 300 | 254.73 | 4.47 | 44 | 52.57 |
| 300 < x < 400 | 327.22 | 1.19 | 83 | 100.00 |
| *Range* | *Indemnity ($/acre)* | | | |
| <50 | 5.67 | 2.07 | 37 | 21.14 |
| 50 < y < 100 | 76.54 | 3.74 | 16 | 30.29 |
| 100 < y < 150 | 126.54 | 2.85 | 22 | 42.86 |
| 150 < y < 200 | 179.87 | 2.41 | 38 | 64.57 |
| 200 < y < 250 | 213.75 | 0.71 | 62 | 100.00 |

## ENDNOTES

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2. Knight and Coble (1997) give an excellent review of the crop insurance literature since 1980, including a review of the literature on moral hazard in crop insurance.

3. In this case, a farmer exerts effort to physically alter apparent yield and alter the magnitude of the loss. This can be done in a variety of ways such as feeding grain to stock, hiding grain off-farm, hiding grain in concealed on-farm storage, collude with adjusters to alter loss magnitude, and/or selling part of the production in the name of a relative (i.e. son-in-law, son).

4. The analysis here was also applied to data with other APH levels aside from the one reported in this paper. However, the reason for choosing the particular APH, price election, and coverage level combination reported in this paper is because it is the one with the highest number of observations. Note that the results of the analysis for other APH levels are similar to the results reported. These results are available from the author upon request.

5. Although this indemnification behaviour is not supported by the 'pure' costly state verification model, theoretical predictions of a special case of the costly state verifica-

tion paradigm somewhat follows the observed behaviour here. Bond and Crocker (1997) showed that full indemnification at the higher loss states within the monitoring region and overpayment at the lower loss states within the monitoring region may be an optimal contract when the insured can manipulate the costs of monitoring and when the insurer can observe the actual cost of monitoring. Note that in the 'pure' costly state verification model it is assumed that farmers cannot take actions that have the effect of manipulating the monitoring cost.

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