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 behavior conforms to the theoretical predictions of two *ex post* moral hazard models – costly state verification and costly state falsification. A nonparametric regression technique is used to estimate the crop insurance indemnification profile for non-irrigated cotton in Texas. The results suggest that indemnification behavior in crop insurance is more in line with the costly state falsification paradigm. Thus, crop insurers seem to indemnify based on the assumption that it is not easy to verify actual *ex post* loss magnitude and eliminate the asymmetric information held by the insured farmers.

Keywords: Crop Insurance; Costly State Verification; Costly State Falsification; *Ex post* Moral Hazard; Fraud; Indemnification Behavior

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Introduction

There is a substantial agricultural economic literature about moral hazard in crop insurance.[1] 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.

The theoretical literature on *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 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.

On the other hand, in the costly state falsification paradigm attributed to Lacker and Weinberg, 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 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 their modeling efforts. 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 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 behavior in the crop insurance markets. Only Crocker and Tennyson, 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 behavior conforms to the theoretical predictions of the two *ex post* moral hazard models. We first review the economically optimal contract design and the corresponding theoretical predictions, 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 behavior. The remaining sections proceeds as follows. The next section reviews the theoretical predictions from both models. The data and empirical methods are discussed in section three. The last two sections discuss the results and conclusions of the paper.

Theory

Costly State Verification

The costly state verification paradigm is attributed to the work of Townsend and has been examined in an insurance context by Dionne and Viala, Kaplow, and Bond and Crocker. The theoretical predictions elucidated here are based on the work of Bond and Crocker and is 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 π. 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 γ. Moreover, it is assumed that the farmers cannot take actions that have the effect of manipulating the monitoring cost γ. 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:

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

The profit of the insurer can also be written as:

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

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:

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

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 contact 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 (see theorem 1) and a proof is also expressed within a crop insurance context in Hyde and Vercammen. Note also that as the cost of monitoring γ 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).

Costly State Falsification

The costly state falsification paradigm was first attributed to Lacker and Weinberg but has been recently extended by Crocker and Morgan. We follow the format of Crocker and Morgan 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 $x = \in [\underline{x}, \bar{x}]$, 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.[2] 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:

(4) $$W - x + r - s(x - y)$$

where r is the indemnity payment. Letting π 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:

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

The insurance contract $C \equiv \{r, y, p)$, in this case, 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:

(6) $$\Pi(A, M) \equiv p - \pi \int_{\underline{x}}^{\bar{x}} r(x) f(x) dx.$$

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:

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

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

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 are 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 ($\bar{x}$) possible losses engage in some claims falsification. Formal proof of this theoretical prediction is seen in Crocker and Morgan (theorem 3).

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.

Data and Empirical Methods

This study utilizes MPCI data from the Risk Management Agency (RMA) of the U.S. Department of Agriculture (USDA) for reinsurance year 2000. In the spirit of homogeneity, only MPCI policies for non-irrigated cotton production in Texas are considered for analysis. To further assure a relatively similar claiming environment, cotton farmers with 55 percent coverage and above are the only ones considered in the analysis (non-catastrophic policies). The RMA data set contains information about the indemnity payments and the liabilities of insured farmers at the crop unit level. Thus, the analysis here is at the crop unit level. The liability figure is the dollar amount of insurance protection outstanding. This results to 28,984 observations with liabilities amounting to $222,438,910 and indemnities amounting to $182,617,520. The mean liability and indemnity for the whole sample are $7,674 and $6,300, respectively. The distribution of liabilities and indemnities are reported in Table 1.

The theoretical predictions in the previous section provide testable hypotheses about the indemnification behavior 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. Furthermore, all claims above that level should be fully insured so that the indemnity paid should equal the amount claimed (or in this case the liability amount). 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 claimed amount should be less than one. Therefore, these are the two hypotheses that we wish to empirically test using the crop insurance data set.

Given these two hypotheses, we are interested in the empirical relationship between the indemnities paid and the claimed amount or liability amount. Note that the amount of liability is used in the analysis instead of the claim amount because claim amount information is not available. Using the liability figures instead of the claim amount implicitly assumes that the farmer always claims the full amount of the liability when he submits a claim for a particular crop unit. Since the level of aggregation is at the crop unit level, this assumption is reasonable. Hence, we can still test the theoretical prediction above using the indemnity and liability variables.

A nonparametric regression technique called locally weighted regression (LOESS), which is attributed to Cleveland, 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 liabilities. Furthermore, this nonparametric technique smoothes the data and is robust to potential outliers (Cleveland; Hardle). 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:

(8) $$y_i = g(x_i) + \varepsilon_i$$

where g is a smooth regression function and ε_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 claim or liability amount.

The "local" part of LOESS refers to a "k-nearest neighbor (K-NN)" type neighborhood. The K-NN is specified as a proportion α of the n data points to be used at each point of estimation. The proportion or "bandwidth" α used here is 5%. 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 kth nearest neighbor x_k. A weighted least squares linear regression is fit to the αn points. The weights $w_m(x_i)$ decrease as the distance from x_i increases:

(9) $$w_m(x_i) = W(d^{-1}(x_m - x_i))$$

where d^{-1} is the inverse of d, ($x_m - x_i$) is the distance of the mth 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 second-order polynomial for the defined neighborhood using weighted least squares. Thus, the $\beta(x_i)$'s are chosen to minimize:

(10) $$\sum_m w_m(x_i)(y_m - \beta_0 - \beta_1 x_m)^2 \ .$$

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

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 "robustified" by using computed residuals to reweigh values in the neighborhood of the target values. New weighted least square values are estimated and the procedure re-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.

Results and Discussion

The estimated indemnification profile for the whole crop insurance data suggests that bigger claims or liabilities tend to be underpaid (Figure 3). Furthermore, as the claim or liability amount increases, the degree of indemnity underpayment also increases. This finding supports the costly state falsification paradigm more than the costly state verification paradigm. As mentioned above, underpayment of large claims is more in line with the costly state falsification framework because it reduces incentives for falsification but still provides farmer income smoothing. Under the costly state verification framework, the theoretical prediction is that above a certain threshold there should be full indemnification because higher claims are most likely verified. Full indemnification of big losses is not evident in the crop insurance data examined here.

Furthermore, under the costly state verification paradigm, the indemnification profile should have a discontinuity at the lower bound of the monitoring region. Again, this is not evident in the estimated indemnification profile based on the crop insurance data for non-irrigated cotton in Texas. There appears to be a smooth and flatter indemnification profile present in the crop insurance program based on the LOESS procedure for estimating the indemnification profile. This conforms more to the theoretical predictions of the costly state falsification paradigm.

Another characteristic of the estimated indemnification profile in Figure 3 is that smaller claims or liabilities (≤ 25000) look to be fully indemnified. However, upon closer inspection of the smallest claims (≤ 1000), the visual evidence also shows a systematic indemnity underpayment (Figure 4). This feature of the estimated profile is neither supported by the costly state verification paradigm nor the costly state falsification paradigm. For costly state verification, a flat indemnification profile ($\bar{r}$) for claims lower than a certain threshold (*m*) should be the optimal behavior. For very low claims, $\bar{r}$ should be larger than the 45-degree line ($\bar{r}$ is higher than the value of the loss). This is not evident in the estimated indemnification profile of crop insurance for non-irrigated Texas cotton. For costly state falsification, there should also be overpayment of smaller claims, but this is also not evident in the estimated indemnification profile in Figures 3 and 4.

Given these findings, we investigate the presence of indemnity overpayment from the raw data. Figure 5 shows that there are crop units where the indemnity payments exceed the claimed amount. Note that majority of the indemnity overpayments are clustered towards the lower claims level. Furthermore, there appears to be no flat overpayment of indemnities consistent with the costly state verification. The variability of overpayment is also visually larger at the lower claims level as compared to the higher claims level. Therefore, the overpayment characteristics of the data at the lower claims level are more in line with the costly state falsification framework than the costly state verification framework.

In summary, the crop insurance indemnification behavior at higher claim levels and the existence of a majority of overpayments at the lower claim levels more closely support the theoretical predictions of the costly state falsification paradigm. This result seems to be different from Hyde and Vercammen where they argue that the costly state verification paradigm is more in line with actual crop insurance contract form. Their result is based on their observation in crop insurance contracts that indemnification occurs only for big losses (low yield states) and only if it is verified. However, from our results based on actual indemnities paid out, there are actual indemnity payments even for low loss states. Moreover, at the low loss states there is indemnity overpayment behavior that is more in line with costly state falsification. Thus, even if observed insurance contract form seem to support the costly state verification framework (as argued by Hyde and Vercammen), actual indemnification behavior from insurance coverage of non-irrigated Texas cotton more closely follow the theoretical predictions of the costly state falsification framework.

Conclusions

This paper explores whether actual crop insurance indemnity payments more closely conforms 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 in Texas, we found that actual behavior is more in line with the costly state falsification paradigm than the costly state verification paradigm. Larger claims tend to be underpaid, while smaller claims tend to be overpaid. Moreover, the data do not indicate the presence of a discontinuity that is a part of the theoretical prediction in the costly state verification framework. The estimated profile is a flat and smooth function consistent with costly state falsification.

The results indicate that insurers seem to indemnify based on the assumption that it is not easy to verify actual loss magnitude and eliminate the informational asymmetry of the farmer. Intuitively, with the number of farmers and crop units involved in the crop insurance program it would be hard for insurers to verify and fully indemnify each and every loss above a certain threshold. The optional units provision of the crop insurance program, which allows a framer to divide his farm into several insurable units, makes it very difficult to monitor actual yield losses on the farm. For example, a farmer can shift bushels from one unit to the next and it is very difficult to verify which bushels came from which insurable unit. Furthermore, if farmers were able to collude with agents and adjusters to falsify the magnitude of losses then verification would even be more difficult.

Another aspect of the crop insurance program that supports the indemnity behavior in the costly state falsification paradigm is the difficulty in proving fraudulent claims and the constraints insurers have on imposing penalties on farmers found to falsify claims. Note that penalties for farmers that falsify claims are a part of the costly state verification paradigm because if a claim is verified to be fraudulent then there should be a corresponding punishment. Without penalties there is no incentive to truthfully reveal the magnitude of the loss. In the crop insurance program, penalties have been intensified in the Agricultural Risk Protection Act (ARPA) of 2000, but there is no definite menu of penalties for various offenses that is publicly circulated to insured farmers, adjusters, and agents. This uncertainty in terms of penalties also supports the costly state falsification framework in the crop insurance program.

Although crop insurance contract form can be argued to have some characteristics that follow costly state verification, as suggested by Hyde and Vercammen, the difficulty in verifying actual loss magnitudes and the constraints on imposing punishment makes it more attractive to follow the theoretical predictions of the costly state falsification paradigm as a means to deter *ex post* moral hazard. In terms of crop insurance program design, therefore, provisions that make it difficult to verify actual loss magnitudes (i.e. allowing optional units) should be reviewed carefully and probably be revised if the costly state verification paradigm is to be effective in controlling *ex post* moral hazard.

Footnotes

[1] Knight and Coble gives an excellent review of the crop insurance literature since 1980, including a review of the literature on moral hazard in crop insurance.

[2] 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).

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Table 1. Distribution of insurance liability and indemnity for cotton (Texas, 2000)

Range (dollars)	Liability (dollars)			
	Mean	St. Deviation	Frequency	Cumulative Percentage
0 to 50	29	13	100	0.35
51 to 100	79	15	161	0.90
101 to 500	304	115	1,919	7.52
501 to 1,000	738	143	2,360	15.66
1,001 to 5,000	2,703	1,133	11,273	54.56
5,001 to 10,000	7,225	1,434	6,228	76.05
10,001 to 25,000	15,049	4,011	5,424	94.76
25,001 to 50,000	33,485	6,801	1,229	99.00
50,001 to 100,000	64,579	13,135	256	99.88
100,001 to 400,000	156,439	67,310	34	100.00
Range	Indemnity (dollars)			
0 to 50	26	14	383	1.32
51 to 100	79	14	430	2.80
101 to 500	293	117	3,007	13.18
501 to 1,000	739	143	2,860	23.05
1,001 to 5,000	2,620	1,132	11,334	62.15
5,001 to 10,000	7,173	1,424	5,507	81.15
10,001 to 25,000	15,012	4,016	4,320	96.06
25,001 to 50,000	33,216	6,607	942	99.31
50,001 to 100,000	64,705	13,301	186	99.95
100,001 to 400,000	147,460	68,160	15	100.00

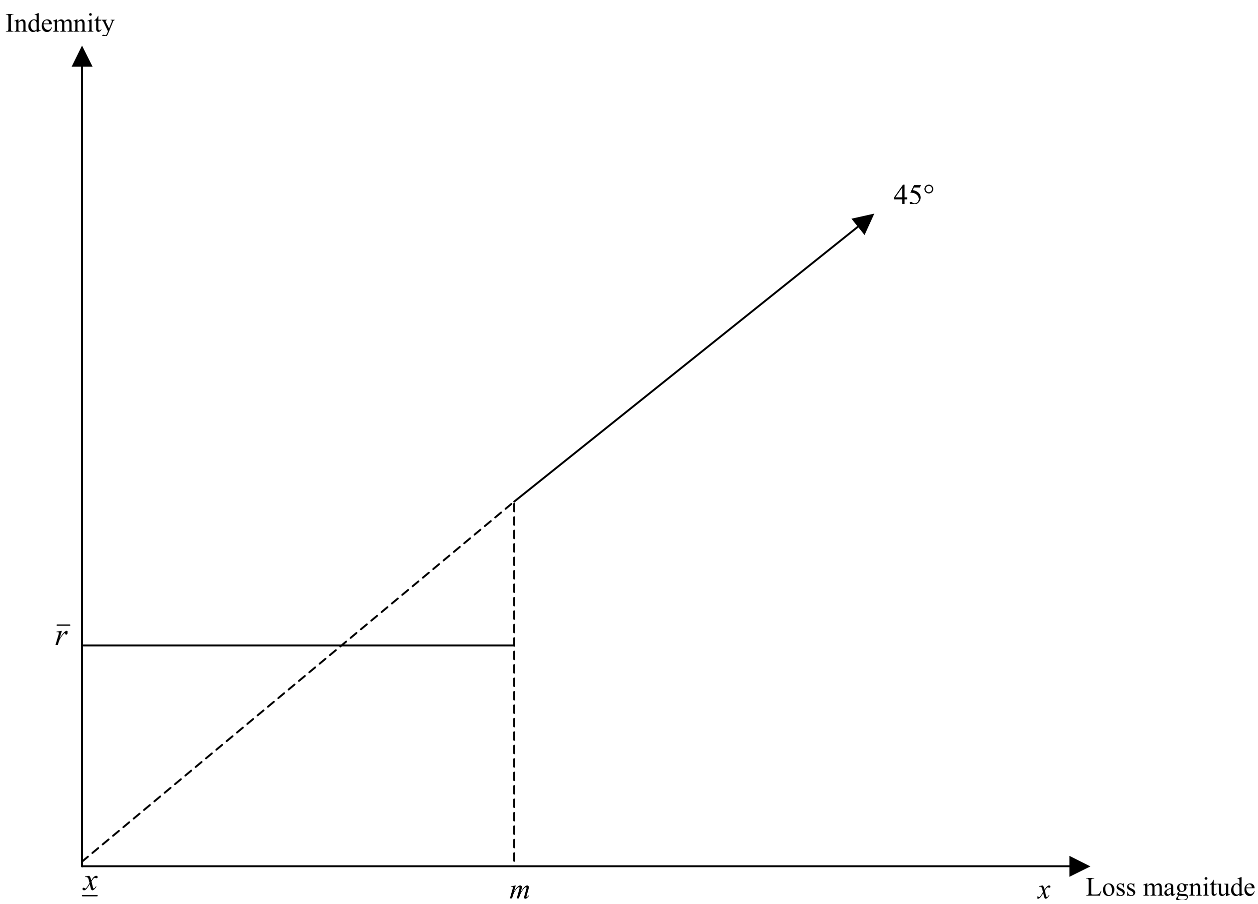

Figure 1. Optimal indemnification profile with costly state verification

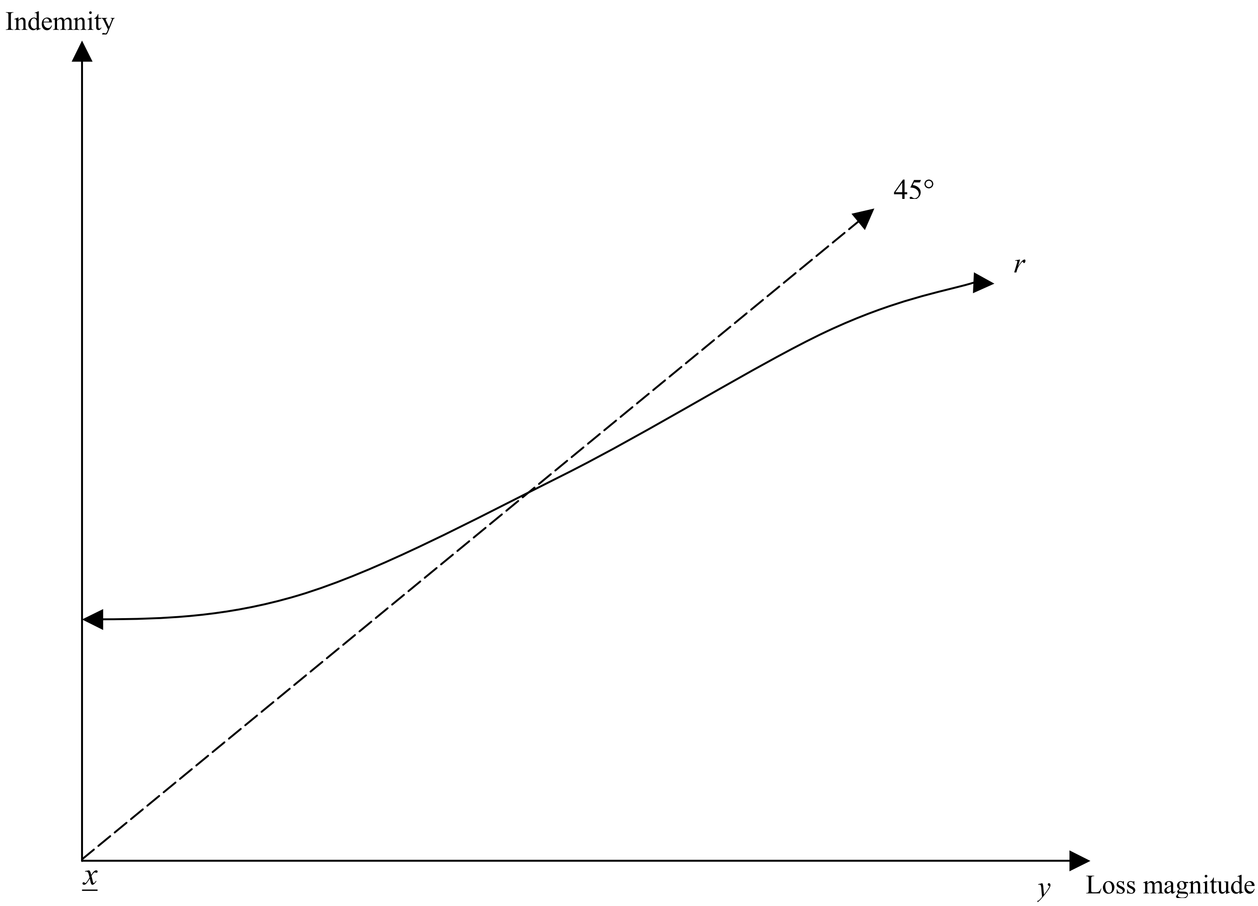

Figure 2. Optimal indemnification profile with costly state falsification

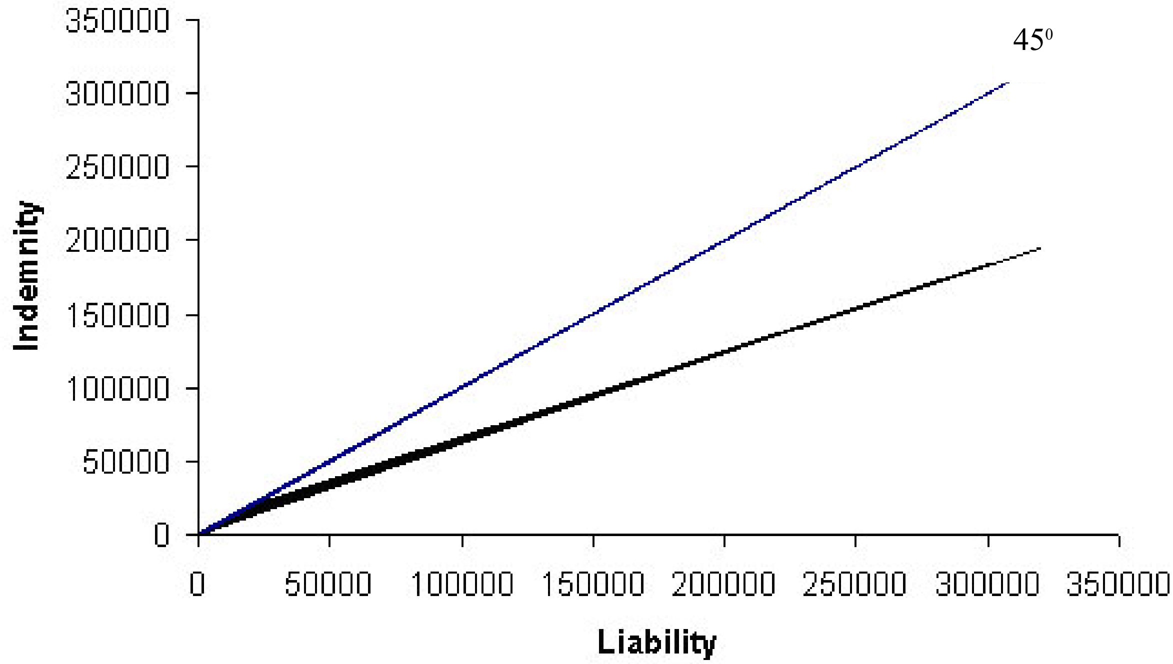

Figure 3. Estimated indemnification profile using LOESS regression

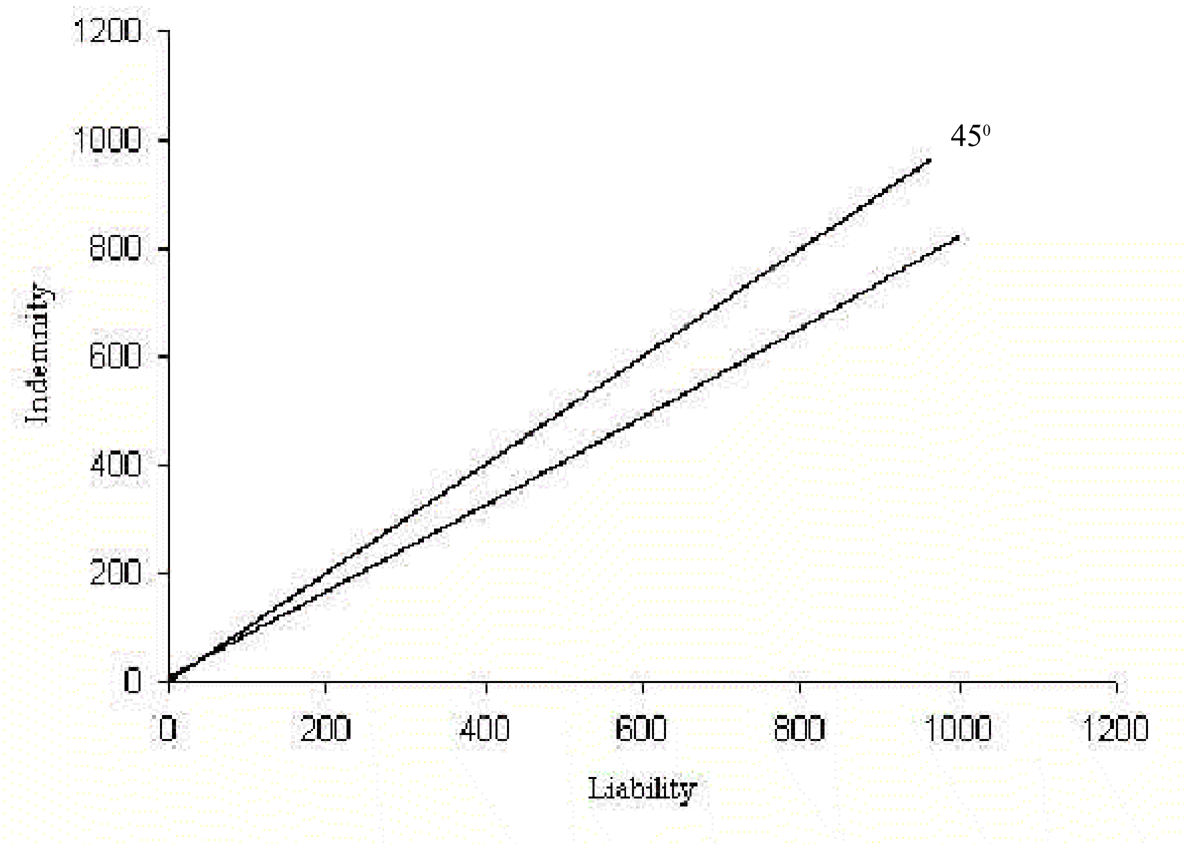

Figure 4. Estimated indemnification profile for smaller liabilities (≤1000)

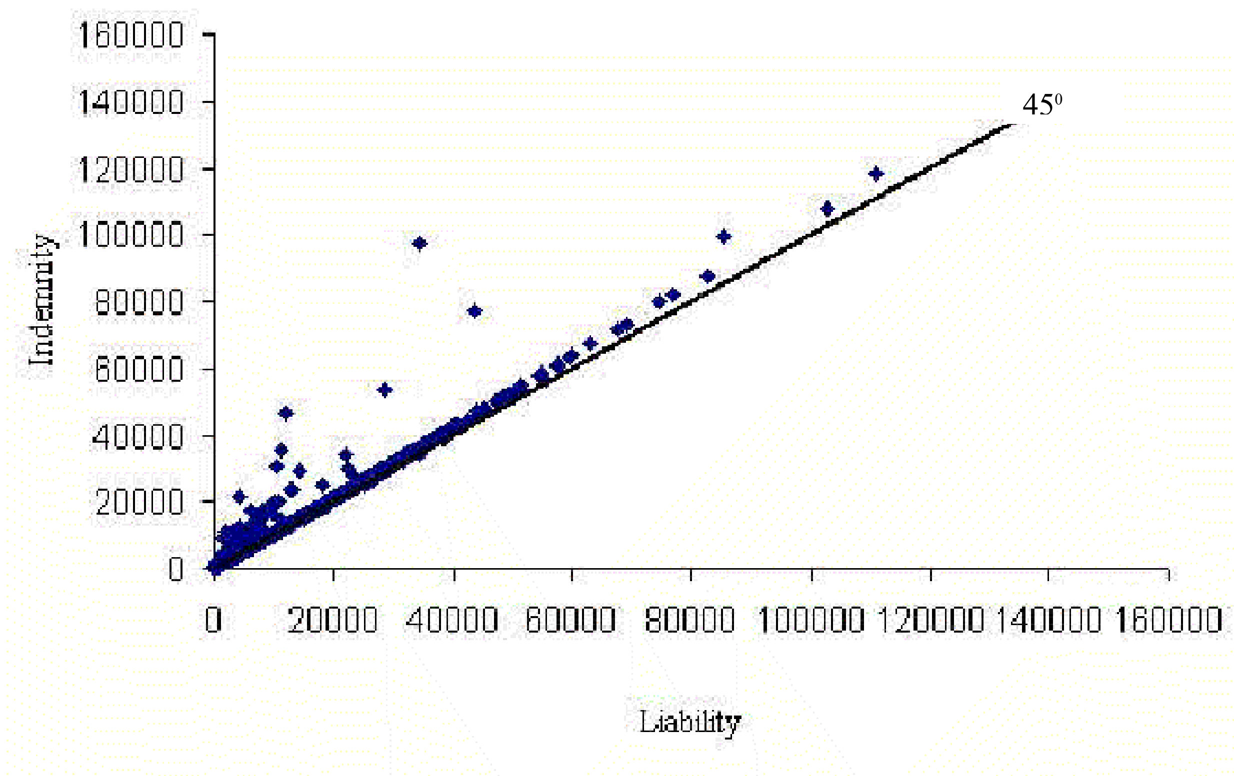

Figure 5. Scatterplot of indemnity overpayment