On the Revelation of Asymmetric Information of the Private Insurance Companies in the U.S. Crop Insurance Program

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1 Introduction

In the U.S. crop insurance program three rather than two economic interests are served: the federal government through the United States Department of Agriculture's Risk Management Agency (RMA); the producers or farmers; and the private insurance companies. The RMA sets or approves the premium rates and provides subsidies to producers. The insurance companies sell policies and conduct claim adjustments. In return, RMA compensates them for these administrative and operating expenses (termed A&O). The underwriting gain/loss, which is defined as total premiums less total claims or indemnity payments, are shared between the insurance companies and the RMA according to the provisions set out in the Standard Reinsurance Agreement (SRA).

Very little has appeared in the literature on private insurance companies and their involvement in arguably one of the cornerstone programs of U.S. farm policy. For exceptions see Miranda and Glauber (1997), Ker (1999), Ker and McGowan (2000), and Ker (2001). Figure 1 illustrates the breakdown of government program costs or outlays since 1981 into producer subsidies, indemnities less premium, A&O reimbursement to insurance companies, and underwriting gains accrued by insurance companies. There are a number of interesting features: (i) producer subsidies increased dramatically in 1995 (result of the 1994 Federal Crop Insurance Act) and again in 2001 (result of the 2000 Agricultural Risk Protection Act); (ii) indemnities less premium are quite volatile; (iii) insurance companies A&O has increased with increases in total premium; and (iv) underwriting gains accruing to insurance companies have increased dramatically since 1994. Note that not only have total government costs increased dramatically but payments to insurance companies have tended to increase at a higher rate suggesting that they have been successful at accruing public rents. In fact, rents accruing to insurance companies are close to rivaling those accruing to producers.

One of the major premises of a publicly subsidized crop insurance program is the desire to eliminate ad-hoc disaster or emergency aid. Of course, ad-hoc aid continues along side crop insurance to be a prominent part of domestic farm policy. Reasons may vary but it is generally accepted

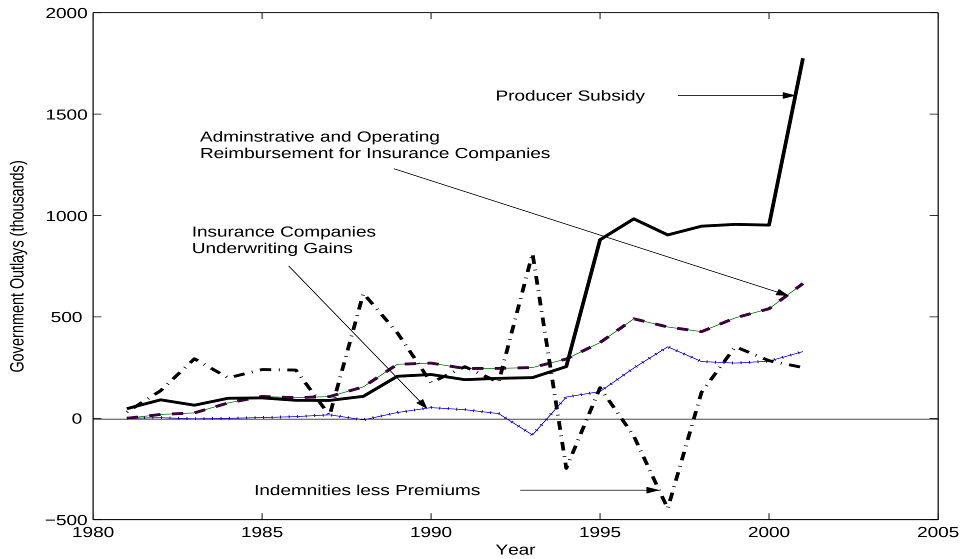

Figure 1: Government Outlays for U.S. Crop Insurance Program

that if there exists sufficiently high uninsured losses, it is politically efficient for politicians to trade financial support for political rents. To eliminate ad-hoc aid, it is conjectured that participation must be sufficiently high – thus uninsured losses are sufficiently low – such that providing ad-hoc aid is politically inefficient. This was noted by Secretary Bergland in testifying before the Senate Committee on Agriculture, Nutrition, and Forestry in 1978 where he stated "If less than 60 to 70 percent of the farmers are protected, it is likely that a sense of sympathy will prompt the system to provide protection for those who did not participate. Reaching the target level of participation would require both a well developed program and the termination of other programs that would provide protection thereby competing with the new system." (Bergland quoted in Wright and Hewitt, 1994.)

While the current approach to decrease total uninsured losses is greater subsidization at higher coverage levels (as evidenced in figure 1), in 1980 insurance companies were elicited for assistance. It was believed, correctly so, that decreased producer transaction costs via better established delivery channels would lead to significantly higher participation. Intermediaries are often used to carry out public policy when gains in efficiency are expected. In the crop insurance setting, efficiency gains were expected through two avenues. First, the better established delivery channels of insurance companies could reach a greater number of producers for a given cost. Second, the exploitation of informational asymmetries could increase the accuracy of rates thereby decreasing adverse selection activities. However, intermediaries also represent a new group of rent seekers that have the potential to decrease overall program efficiency.

Numerous policy questions arise: (i) do insurance companies reveal asymmetric information to RMA via their allocation decisions; (ii) are private insurance companies efficiently allocating (retain and cede decisions) their book of business with respect to the SRA; (iii) would producer demand be increased greater through government delivery and increased subsidies; (iv) is monitoring of insurance companies rather than sharing in the underwriting gains/losses of the program more efficient; (v) is the political equilibrium stable such that future gains may not be recoverable from utilizing asymmetric information; and (vi) does this degree of support to the private insurance companies represent in itself a political equilibrium. There is much room for research on these important issues.

In this manuscript we focus on the first policy question but offer discussion on all in our concluding section. In light of ARPA and the new subsidy structure, producer participation will continue to increase markedly and shift to higher coverage levels. As a result, total premium dollars will continue to increase significantly and hence the premium dollars being averted to private insurance companies will also increase significantly. We feel that research on these important policy questions is particularly pertinent in the context of current farm policy which continues to increase monetary resources for the crop insurance program.

The remainder of the manuscript proceeds as follows. The second section provides a terse review of the U.S. crop insurance program and ARPA as a backdrop. The third section details the Standard Reinsurance Agreement (SRA). The fourth section discusses the data and outlines the econometric methods. The fifth section presents the results while the final section focuses on the corresponding policy implications.

2 U.S. Crop Insurance Program

Federally regulated crop insurance programs have been a prominent part of U.S. agricultural policy since the 1930s. In 2002, the estimated number of crop insurance policies exceeded 1.25 million with total liabilities exceeding $37 billion. Traditional crop insurance schemes offered farmers the opportunity to insure against yield losses resulting from nearly all risks, including such things as drought, fire, flood, hail, and pests. For example, if the farmer's expected wheat yield is 30 bushels per acre ($y^e = 30$), a policy purchased at the 70% coverage level ($\lambda = 0.7$) insures against a realization below 21 bushels per acre (0.7×30 bushels per acre = 21 bushels per acre). If the farmer realized a yield of 16 bushels per acre, they would receive an indemnity payment for the insured value of 5 bushels per acre.

A variety of crop insurance plans and a number of new pilot programs are currently under development. Standard crop yield insurance, termed 'Multiple Peril Crop Insurance', pays an indemnity at a predetermined price to replace yield losses. Group-risk yield insurance, termed 'Group Risk Plan', is based upon the county's yield. Insured farmers collect an indemnity when their county's average yield falls below a yield guarantee, regardless of the farmers' actual yields. Three farm-level revenue insurance programs are available for a limited number of crops and regions: 'Crop Revenue Coverage'; 'Income Protection'; and 'Revenue Assurance'. These programs guarantee a minimum level of crop revenue and pay an indemnity if revenues fall beneath the guarantee. The recently developed 'Group Risk Income Plan', a variation of the Group Risk Plan, insures county revenues rather than yields.

Figure 1 illustrates that companies are a major participant in the U.S. crop insurance program and warrant attention, particularly now. ARPA increases the prominence of the crop insurance program in farm policy. The additional cost of this legislation is estimated to be \$8.2 billion over a 5-year period approximately doubling the federal budget on crop insurance programs to \$16.1 billion. ARPA has mandated the expansion of crop insurance in three important dimensions: expanded product coverage including for example livestock products; expanded geographical availability for existing crops; and increasing producer demand by doubling subsidies from approximately 30% to 60% of the estimated actuarially fair premium rate. Finally, the current form of the SRA will remain in effect through the 2004 reinsurance year. All legislative actions suggest crop insurance will remain one of the predominant policy instruments to funnel resources to agricultural producers. As a result, significant public resources will flow to private insurance companies.

3 The Standard Reinsurance Agreement (SRA)

The involvement of the private insurance companies in the U.S. crop insurance program is defined by the SRA. As mentioned, insurance companies sell policies and conduct claim adjustments and in return, RMA compensates them for these administrative and operating expenses. The underwriting gain/loss, which is defined as total premiums less total claims or indemnity payments, are shared, asymmetrically, between the insurance companies. Both the provisions by which the underwriting gains and losses are shared and the reimbursement for A&O expenses are set out in the SRA.[1]

3.1 Provisions of Sharing the Underwriting Gains/Losses

This section is summarized largely from Ker (2001) where the reader is directed for a deeper discussion. Section II.A.2 of the 1998 SRA states that an insurance company *"...must offer all approved plans of insurance for all approved crops in any State in which it writes an eligible crop insurance contract and must accept and approve all applications from all eligible producers."* An eligible farmer will not be denied access to an available, federally subsidized, crop insurance product. Therefore, an insurance company wishing to conduct business in a state cannot discriminate among farmers, crops, or insurance products in that state. An unusual situation arises; the responsibility for pricing the crop policies lies with the RMA but the insurance company must accept some liability for each policy they write and cannot choose which policy they will or will not write.

To elicit the participation of insurance companies, two mechanisms are required that emulate a private market. First, given that insurance companies do not set premium rates, there needs to be a mechanism by which they can cede the liability, or the majority thereof, of an undesirable policy. In a private market, the insurance company would not write a policy deemed undesirable. Second, a mechanism providing an adequate return to the insurance company's capital and a level of protection against ruin (bankruptcy) is needed. Premium rates in a private market reflect a return to capital and a loading factor guarding against ruin. RMA set premium rates do not reflect a return to capital but include a loading factor. The SRA provides these two mechanisms which, in effect, emulate a private market from the perspective of the insurance company. In so doing, the SRA also provides a vehicle by which an insurance company can exploit informational asymmetries by adverse selecting against the RMA.

Under the SRA, insurance companies cannot cede or retain the total underwriting gain/loss of a policy but must place each into one of three funds: assigned risk; developmental; or commercial. For each state in which the insurance company does business, there is a separate assigned risk fund, developmental fund, and commercial fund. The structure of the risk sharing is identical but

[1] The reader is directed to Ker (2001) and Skees (2001) for a discussion of the A&O expense reimbursement and it's economic implications.

the parameters that dictate the amount of sharing vary greatly across funds. For each fund, the underwriting gain/loss the insurance company retains is equal to the total underwriting gain/loss for the fund multiplied by two parameters. Formally,

$$\Omega^k_{IC} = \Omega^k \cdot \mu^k_1 \cdot \mu^k_2 \tag{1}$$

where Ω^k_{IC} denotes the underwriting gain/loss retained by the insurance company for fund k, Ω^k denotes the underwriting gain/loss for fund k, μ^k_1 is the first parameter for fund k, and μ^k_2 is the second parameter for fund k. The underwriting gain/loss retained by the RMA may be defined as:

$$\Omega^k_{RMA} = \Omega^k \cdot (1 - \mu^k_1 \cdot \mu^k_2) \tag{2}$$

where Ω^k_{RMA} denotes the underwriting gain/loss retained by the RMA.

The first parameter, μ^k_1, represents an *ex ante* choice variable for the insurance company with respect to the commercial and developmental funds. For $k \equiv$ assigned risk fund, $\mu^k_1 = 0.2$. For $k \equiv$ developmental fund, $\mu^k_1 \in [0.35, 1.0]$ while for $k \equiv$ commercial fund, $\mu^k_1 \in [0.5, 1.0]$. They must choose μ^k_1 by July 1 of the preceding crop year.

The second parameter, μ^k_2, is not a fixed scalar but a function of the fund loss ratio. Figure 2 illustrates the relationship between the fund loss ratio and the percent of premium retained.[2] The fund loss ratio is defined as the ratio of total claims to total premiums. A loss ratio greater than one results when total claims exceed total premiums and thus corresponds to an underwriting loss. Conversely, a loss ratio less than one results when total premiums exceed total claims and thus corresponds to an underwriting gain.

Figure 2 illustrates aspects of the three funds (for the boundary values of μ_1) that pertain directly to our empirical analysis: (i) insurance companies minimize their exposure to the underwriting gains and losses for those policies in the assigned risk fund; and (ii) insurance companies maximize their exposure to the underwriting gains and losses for those policies in the commercial fund. Therefore, rational behavior would indicate that policies the insurance companies expect to yield underwriting gains would be placed in the commercial fund while policies the insurance companies expect to yield underwriting losses would be placed in the assigned risk fund. Very little can be determined about policies placed in the developmental fund. If $\mu^k_1 = 0.35$ (minimum) this fund resembles the assigned risk fund while if $\mu^k_1 = 1.00$ (maximum) this fund resembles the commercial

[2]See Ker (2001) for the exact μ^k_2's (table 3) and an alternative graphical representation (figure 1).

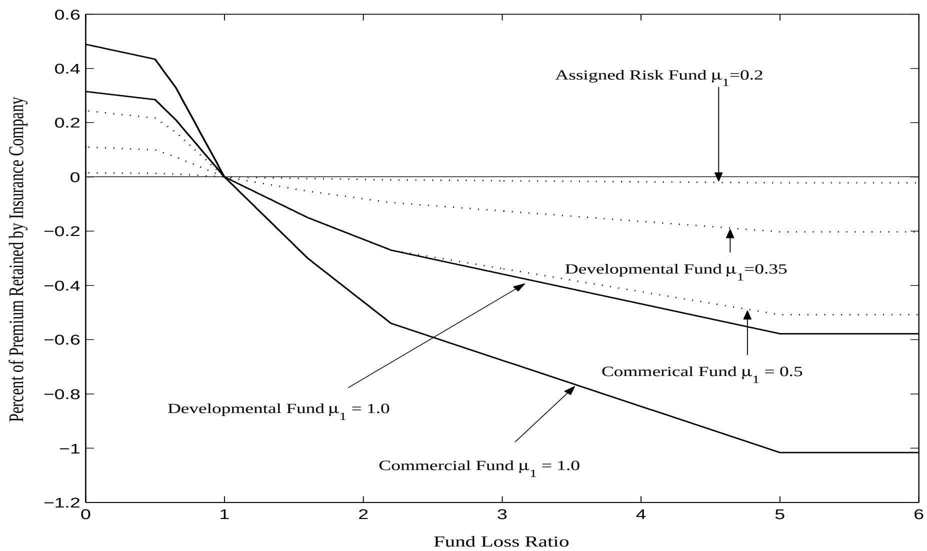

Figure 2: Percent of Premium Retained by Insurance Company Relative to Fund Loss Ratio

fund. Therefore, without knowledge of μ_1^k for the developmental fund we can not determine the expectations of the insurance companies regarding those policies.

Two final points of significance need discussed. First, there exists separate assigned risk funds, developmental funds, and commercial funds for "catastrophic policies", "revenue policies", and "other policies" which is comprised of MPCI/APH policies and GRP policies (GRP policies make up a negligible fraction of the total policies). We focus our attention on the three fund allocations for the "other policies" because insurance companies have significantly less experience and historical information with the "revenue policies" and "catastrophic policies" and thus their fund allocations may not be as efficient. Also note that while these funds are not aggregated across types of policies they are aggregated across crops. Second, insurance companies face a constraint, at the state level, on the maximum percent of premium in their book of business that can be placed in the assigned risk fund. These maximums, which vary quite significantly by state, are located in Table 1. While this may inhibit the insurance companies ability to cede unwanted policies, by choosing $\mu_1^k = 0.35$ for the developmental fund they can make it resemble the assigned risk fund and there are no such percent of premium restrictions on the developmental fund.

While the involvement of the private insurance company was initially justified to increase participation through better established delivery channels, this does not necessarily explain why insurance

Table 1: Maximum Percent of Premium in Assigned Risk Fund by State

State	Percent	State	Percent	State	Percent
Alabama	50%	Louisiana	50%	Ohio	25%
Alaska	75%	Maine	75%	Oklahoma	50%
Arizona	55%	Maryland	20%	Oregon	30%
Arkansas	50%	Massachusetts	45%	Pennsylvania	25%
California	20%	Michigan	50%	Rhode Island	75%
Colorado	20%	Minnesota	20%	South Carolina	55%
Connecticut	35%	Mississippi	50%	South Dakota	30%
Delaware	30%	Missouri	20%	Tennessee	35%
Florida	40%	Montana	75%	Texas	75%
Georgia	75%	Nebraska	20%	Utah	75%
Hawaii	10%	Nevada	75%	Vermont	15%
Idaho	45%	New Hampshire	10%	Virginia	30%
Illinois	20%	New Jersey	50%	Washington	30%
Indiana	20%	New Mexico	55%	West Virginia	75%
Iowa	15%	New York	40%	Wisconsin	35%
Kansas	20%	North Carolina	20%	Wyoming	35%
Kentucky	25%	North Dakota	45%		

Source: 1999 SRA

companies share in the underwriting gains and losses rather than just receive an A&O reimbursement. There are three possible reasons. The first is RMA wishes to share the risk with the private market. This is unlikely because RMA can self-insure without cost while in order to share underwriting gains and losses with the private market they must pay a risk premium. The second reason is so that the insurance companies are incentive compatible with RMA when conducting claim adjustments. That is, because the insurance companies must share, to some extent, the underwriting losses there is less exposure to fraudulent claims. However, in so doing, RMA must offer a vehicle for companies to adverse select. In essence, RMA has traded moral hazard for adverse selection with respect to insurance companies. It is unlikely that the cost of monitoring insurance companies claim adjustments would be in the order of magnitude of the necessary risk premium that RMA pays to insurance companies. The final reason for having insurance companies involved in the underwriting gains and losses is to design a contract that would reveal relevant asymmetric information to RMA regarding premium rates. This information could then be used to improve the accuracy of premium rates. The allocation of the policies to the three funds does reveal the expectations of the insurance companies with respect to the profitability of those policies. The key question, and the one studied here, is whether those expectations/allocations reveal unknown information.

4 Data and Methodology

Recall we wish to test whether relevant asymmetric information is revealed, with respect to rating policies (premium rates), in the fund allocations of private insurance companies. This hypothesis can be tested by predicting whether policies are profitable or not. If a policy is correctly expected to be profitable (premium exceeds expected indemnities), this would suggest that the premium rate needs to decrease. Conversely, if a policy is correctly expected to be unprofitable (premium less than expected indemnities), this would suggest that the premium rate needs to increase. Specifically, we can test whether our percent of correct predictions increases significantly when we include the insurance companies fund allocations as explanatory variables.

Our independent variable is whether a set of policies returned a profit or not. If total premium is greater than indemnities we define $Y = 1$. Conversely, if total premium is less than indemnities we set $Y = 0$. Our first model is:

$$Y = F(X\beta) + \epsilon \tag{3}$$

where X is information available to RMA such as historical loss ratio, crop dummies, state maximums on the assigned risk fund, and liability changes. $F(\cdot)$ is termed the link function and $X\beta$ is termed the index. Our second model is:

$$Y = F(X\beta + \text{ insurance company fund allocations} * \gamma) + \epsilon \tag{4}$$

where the set of explanatory variables now includes the insurance company fund allocations.[3]

[3]Our dependent variable is based on whether a set of policies returned a profit or not rather than the level of profit. As argued in Ker and McGowan (independent strategy), this is the decision that the insurance company faces. Under their "independent strategy" which assumes the loss ratio of a given policy is independent of the loss ratio for that fund, (most probable situation), the insurance company only needs to consider whether the policy is expected to return an underwriting gain or loss. Recall, insurance companies maximize their share of the underwriting gains/losses with the commercial fund and minimizes their share with the assigned risk fund. If the loss ratio of the policy is independent of the fund loss ratio, then the insurance company maximizes their total underwriting gain/loss by maximizing the size of the commercial fund. This of course is maximized by only allocating those policies with expected underwriting gain in the commercial fund. Those with expected underwriting loss are allocated to the assigned risk fund. Therefore, given this allocation rule the most that can be ascertained from their actual allocations is whether a policy is expected, by the insurance company, to return an underwriting gain or an underwriting loss, not the expected magnitude.

4.1 Data

Our data is comprised of the total premium, indemnities, liability, and number of policies, in each of the three funds by crop-county-year combination. We have data on Corn, Cotton, Soybeans, and Wheat for the reinsurance years 1998, 1999, 2000, and 2001. We remove combinations with less than \$500,000 in liability leaving 7,400 crop-county-year combinations.

We have three caveats regarding our data that require discussion. First, our data is aggregated to the county level; we do not have policy specific fund allocation decisions. We feel this is not problematic because anecdotal evidence (discussion with companies as well as looking at their fund allocations) suggests that insurance companies tend to allocate by crop-county combinations rather than individual policies. Second, the data is aggregated across coverage level. Again, insurance companies tend to allocate by crop-county combinations and do not consider coverage levels because of the lack of information at coverage levels differing from the 65% coverage level.[4] Third, our data is aggregated across insurance companies. While we would prefer company specific fund allocations and requested such, we were only able to obtain aggregated data.

4.2 Econometric Methodology

For estimation, we consider the parametric probit model along with the semiparametric single-index model estimators of Ichimura (1993) and Ergün and Ker (2003). Single-index models for binary data have the general form of

$$P(y = 1|x) = F(x\beta) \tag{5}$$

where F is an unknown function (not necessarily a distribution function). If F is the normal (logistic) distribution function, we have the probit (logit) model. If it is the identity function, we have the linear probability model. If the (normal or logistic) distributional assumption is not correct, the maximum likelihood estimates of coefficients and probability estimates will be inconsistent (see Ruud(1983) for an exception on the slope coefficient estimates). Choice of a probit or a logit model, almost a standard in the literature, is usually based on estimation convenience rather than any justification of distributional assumptions. These sometimes unrealistic assumptions may lead to erroneous results and implications. Furthermore, since these models are used with cross-section

[4]We do have more concern here in that premium rates at higher coverage levels tend to be biased upwards in high premium rate areas. However, it is likely that by eliminating those combinations with less than \$500,000 in liability we have mitigated the problem; participation in high rate areas tends to be weak.

data sets, heteroscedasticity is usually a real concern. Unlike linear models where one only loses efficiency, the maximum likelihood estimators of probit and logit models are inconsistent if the error distribution is heteroscedastic (see Yatchew and Griliches (1984)). Single-index models, on the other hand, can accommodate certain forms of heteroscedasticity (general but known form and unknown form if the distribution of the error term depends on x only through the index, i.e., the index restriction).[5] Optimization based estimation methods have been developed for single-index models without making distributional assumptions and thus avoiding misspecification. These include Ichimura, Klein and Spady (1993), and Ergün and Ker. The first of these estimators is based on minimizing a least-squares loss function and the last two are based on maximizing a profile likelihood function. These last two estimators are specifically for binary-choice model estimation. Ichimura and Klein and Spady show $\sqrt{n}$ convergence and asymptotic normality of their estimators and give a consistent covariance estimator. Ergün and Ker show the convergence of their estimator. The simulation results in Ergün and Ker favor the Ichimura estimator over Klein and Spady, therefore we only estimate the Ichimura estimator along with the estimator of Ergün and Ker.

Note that we need a scale-location normalization for identification purposes in single-index models. Since the link function F is assumed to be completely unknown, the intercept term can not be identified as it can be subsumed in the definition of F. Also a scale normalization is needed for the same reason that it is imposed in parametric models (assuming the error term has unit variance). This scale normalization in the semiparametric models can be achieved by setting the coefficient of one (continuous) regressor equal to a constant.[6]

Semiparametric least squares (SLS) estimator of Ichimura minimizes

$$\frac{1}{n}\sum_{i=1}^{n}[y_i - \hat{F}(x_i b)]^2 \tag{6}$$

where $\hat{F}$ is the nonparametric estimator for the unknown link function and b is the β vector after location-scale normalization is imposed, i.e., $b \equiv (constant, \beta_2, \ldots, \beta_q)^T$ assuming the first regressor has a continuous distribution and q is the number of explanatory variables. Ichimura calls this model as semiparametric least squares (SLS) and shows that $\hat{\tilde{b}}$ is consistent and $\sqrt{n}(\hat{\tilde{b}} - \tilde{b}_0) \xrightarrow{d} N(0, \Omega_{SLS})$, where $\tilde{b}$ is b without its first component, and gives a consistent estimator of $\Omega_{SLS} = \Gamma^{-1}\Sigma\Gamma^{-1}$. Γ

[5]See the maximum score estimator of Manski (1975) and its smoothed version by Horowitz (1992) for estimators which can accommodate arbitrary forms of heteroscedasticity although at the cost of a rate of convergence slower than $\sqrt{n}$.

[6]An alternative scale normalization would be $||\beta|| = 1$ where $||\cdot||$ is the Euclidean norm.

and Σ can be consistently estimated by

$$\begin{aligned} \hat{\Gamma} &= \frac{1}{n}\sum_{i=1}^{n} \tilde{x}_i \tilde{x}_i^T \hat{F}'(x_i\hat{b})^2, \\ \hat{\Sigma} &= \frac{1}{n}\sum_{i=1}^{n} \tilde{x}_i \tilde{x}_i^T \hat{F}'(x_i\hat{b})^2 [y_i - \hat{F}(x_i\hat{b})]^2 \end{aligned} \tag{7}$$

where $\tilde{x}_i \equiv (x_{2i}, \ldots, x_{qi})$, $\hat{b} \equiv (1, \hat{\tilde{b}}^T)^T$, and $\hat{F}'$ is the derivative of $\hat{F}$. For $\hat{F}$, he uses the Nadaraya-Watson estimator

$$\hat{F}(z) = \frac{1}{nh\hat{p}(z)} \sum_{j \neq i} y_j K\left(\frac{z - x_j b}{h}\right) \tag{8}$$

where

$$\hat{p}(z) = \frac{1}{nh} \sum_{j \neq i} K\left(\frac{z - x_j b}{h}\right) \tag{9}$$

where K is the kernel function (usually a symmetric density function) and $h = h(n)$ is the smoothing parameter such that $h \to 0$ as $n \to \infty$.

In parametric probit and logit models, one maximizes the likelihood function

$$\sum_{i=1}^{n} (y_i \log[F(x_i\beta)] + (1 - y_i)\log[1 - F(x_i\beta)]) \tag{10}$$

where F is assumed to be the normal or logistic distribution function. The idea behind the estimators of Klein and Spady and Ergün and Ker is that they replace the unknown link function F by a suitable estimator. Unlike Klein and Spady estimator, however, which uses a completely nonparametric (Nadaraya-Watson) estimator, Ergün and Ker estimate F semiparametrically. Their estimator, which is based on the parametric start idea of Hjort and Glad (1995) and Glad (1996), introduce prior information about the shape of the link function in the form of a parametric function. Note that in binary-choice problems $E(y_i|x_i\beta) = F(x_i\beta)$. So for known β, the problem of estimating F can be achieved by nonparametric mean regression of y on $z = x\beta$. In fact this is exactly what the Klein and Spady estimator does. Ergün and Ker start with a parametric model for the link function F, say G which is a known function (for instance normal cdf) and multiply it with the correction function $r = F/G$ which is estimated nonparametrically. The idea is based on bias reduction: if the parametric start G is close to the true function F, the correction factor will be close to linear and thus smoother and easier to estimate than F itself (a constant can be estimated nonparametrically at the parametric rate). Hence the bias associated with nonparametric estimation of this correction factor would be less than the bias from direct nonparametric estimation of the unknown function. Note that the information that we start with is only related to the shape of the link function and not to the coefficient estimates. In this sense we are using a fixed start vis-à-vis Hjort and Glad (1995) and Glad (1996). Ergün and Ker use the Nadaraya-Watson estimator to estimate the correction factor, their proposed estimator replaces the unknown link function F in the likelihood function with

$$\hat{F}(x_i b) = \sum_{j \neq i} \left\{ y_j \frac{G(x_i b)}{G(x_j b)} \right\} K\left(\frac{x_i b - x_j b}{h}\right) \Big/ \sum_{j \neq i} K\left(\frac{x_i b - x_j b}{h}\right). \tag{11}$$

They show that the estimator which maximizes the resulting likelihood function is consistent. Note that in practice if, for some z_j, $G(z_j)$ is zero or near zero while $G(z_i)$ is not then the ratio $G(z_i)/G(z_j)$ blows up. Following the suggestions of Hjort and Glad (1995) and Glad (1996), we trim below 0.1 and above 10.[7]

In single-index models, the asymptotic distribution of the normalized and centered estimator does not depend on the smoothing parameter so, asymptotically, any sequence of smoothing parameters is going to give the same estimator as long as it satisfies certain conditions.[8] For this reason, in semiparametric single-index models, selection of the smoothing parameter has not been well studied. One exception is the paper by Härdle et al. (1993) where they show that SLS estimator of Ichimura can be expanded as $A(b)+B(h)$ and can be minimized simultaneously with respect to both b and h. This is like separately minimizing $A(b)$ with respect to b and $B(h)$ with respect to h. The end result is a $\sqrt{n}$-consistent estimator of b and an asymptotically optimal estimator of h in the sense that $\hat{h}/h_0 \to 1$ as $n \to \infty$ where h_0 is the optimal bandwidth for estimating F when b is known and is proportional to $n^{-1/5}$ as usual in nonparametrics (see Härdle et al. for technical details). We apply this idea to profile log-likelihood function as well as SLS objective function and hence we optimize the Ichimura and Ergün and Ker objective functions with respect to both b and h.[9] To our knowledge, this is the first paper which uses this idea in practice other than the original Härdle et al. paper. Note that in estimating F, we are excluding observation i so in a way we are "cross-validating" the objective functions.

[7]Note that in these semiparametric estimators, asymptotic theory requires trimming those observations for which the index $x\beta$ is arbitrarily close to the boundary of its support. Klein and Spady note that trimming appears to have little effect on their results. For the Ichimura and Ergün and Ker estimators knowledge of the distribution of the index is required which is unknown in practice. Other applied papers (Horowitz (1993), Gerfin (1996), Fernandez and Rodriguez-Poo (1997)) do not consider trimming. As Horowitz(1993,p.53) explains "...this amounts to assuming that the support of $x\beta$ is larger than that observed in the data."

[8]But in finite samples the performance of the estimators can be very sensitive to the choice of this smoothing parameter.

[9]The asymptotic optimality (in the sense just defined) of h obtained this way is established only for the Ichimura estimator. There is no study which finds a similar result to Härdle et al. for the profile log-likelihood functions.

In estimations, we use a normal density function truncated at plus and minus 3 standard deviations as our kernel for both of the single-index models. Note that Ergün and Ker do not provide a consistent covariance estimator. In the absence of this estimator, it would be ideal to bootstrap the standard errors. Unfortunately this is not feasible due to our sample size and the time that is required for optimization.[10] For this reason, we first experimented with the robust covariance estimator of White (1982) since the problem is likelihood based. This estimator requires second derivatives, however, and due to highly nonlinear nature of the problem, the numerical second derivatives from the optimizer were not reliable at all. Thus, we calculated the BHHH estimator using the analytical gradient. However, our empirical tests are based on out-of-sample forecast performance rather than within-sample standard errors.

5 Estimation Results

To test our hypothesis we randomly split our sample into an estimation sample and a prediction sample. We evaluate our hypothesis using out-of-sample methods rather than within-sample methods because (i) the insurance companies must make their allocation decisions out-of-sample; and (ii) out-of-sample tests minimize spurious results from over-fitting the data (particularly concerning for nonparametric methods which if applied inappropriately can be made to over fit the data).

The explanatory variables used in our analysis are crop dummies for Cotton, Soybeans, and Wheat, historical loss ratios (from 1981 to year prior to the corresponding crop year), ratio of current liability to the previous year liability, the maximum percent of premium allowed in the assigned risk fund for that state, percent of premium placed in the commercial fund, and the percent of premium placed in the assigned risk fund.

5.1 Revelation of Asymmetric Information

To test the hypothesis about the revelation of asymmetric information we estimate two sets of models. The difference between the first and second set of models is that the fund allocation explanatory variables are only included in the second set of models. The estimation results and predictive performances for the models without and with the fund allocation data are located in

[10] Note that during the optimization, at each iteration, a nonparametric estimation is required.

Tables 2 and 3 respectively (standard errors are in parentheses).

Table 2: Estimation Results and Predictive Performance without Fund Allocation Data

Parameter Estimate	Probit	Ichimura	Ergün and Ker
intercept	1.6902	0.0000*	0.0000*
	(0.0683)	n/a	n/a
d_{cotton}	-0.2374	-5.1377	3.9632
	(0.0881)	(0.0754)	(0.0146)
$d_{soybeans}$	-0.1077	3.1030	4.1033
	(0.0587)	(0.0630)	(0.0337)
d_{wheat}	-0.1067	-2.7825	0.8989
	(0.0715)	(0.0911)	(0.0224)
liability ratio	-0.0020	-0.0687	-0.2558
	(0.0078)	(0.0067)	(0.0013)
state risk	-1.6868	-6.8218	-2.1699
	(0.1533)	(0.1150)	(0.0013)
historical LR	-0.2521	-0.2521*	-0.2521*
	(0.0475)	n/a	n/a
h	n/a	0.3264	0.1089
Predictive Performance	74.66%	77.84%	78.34%

* - parameter is restricted as necessitated by estimation procedure

Note that d_{cotton} is the dummy variable for cotton, $d_{soybeans}$ is the dummy variable for soybeans, d_{wheat} is the dummy variable for wheat, liability ratio is the ratio of current years liability to the previous years liability, state risk is the percent of premium in the insurance companies book of business that is allowed in the assigned risk fund, historical LR is the historical loss ratio up to but not including that years insurance experience, commercial is the percent of premium placed in the commercial fund, and assigned is the percent of premium placed in the assigned risk fund. We do not include the percent of premium placed in the developmental fund as that would result in a singularity problem as the three percentages in the three funds always equals one. Recall the dependent variable is set equal to 1 if the set of policies resulted in a profit (premium greater than indemnities) and 0 if the set of policies resulted in a loss (premium less than indemnities). Finally, for the semiparametric and nonparametric estimators we restrict the intercept to 0 and the parameter estimate on the historical loss ratio to the probit estimate as is commonly done.[11]

We have no expectations about the signs of the dummy variables whereas we do have expecta-

[11] This parameter can be set to any finite constant.

Table 3: Estimation Results and Predictive Performance with Fund Allocation Data

Parameter Estimate	Probit	Ichimura	Ergün and Ker
intercept	1.3813	0.0000*	0.0000*
	(0.1426)	n/a	n/a
d_{cotton}	-0.2129	-0.1836	-0.2954
	(0.0885)	(0.0631)	(0.0286)
$d_{soybeans}$	-0.1083	-0.0728	1.6128
	(0.0589)	(0.0404)	(0.0183)
d_{wheat}	-0.0880	-0.1330	-0.1540
	(0.0718)	(0.0527)	(0.0256)
liability ratio	-0.0028	-0.0022	-0.0141
	(0.0078)	(0.0095)	(0.0040)
state risk	-1.6507	-2.9153	-1.9087
	(0.1545)	(0.1102)	(0.0382)
commercial	0.2854	0.1448	0.5151
	(0.1236)	(0.0445)	(0.0171)
assigned	-0.3957	-0.7199	-0.8445
	(0.2141)	(0.1147)	(0.0417)
historical LR	-0.1738	-0.1738*	-0.1738*
	(0.0523)	n/a	n/a
h	n/a	0.1025	0.0484
Predictive Performance	75.24%	79.63%	79.18%

* - parameter is restricted as necessitated by estimation procedure

tions about the signs of the other parameter estimates. First, the sign of liability ratio is negative as expected. If liability increases (decreases) significantly from one year to the next, this may suggest that producers perceive their return to that insurance contract to have increased (decreased) and thus the expected return for the insurance company may decrease (increase). The parameter estimate on state risk is negative (as expected) and significant. This indicates, quite interestingly, that policies in those states with higher bounds on the percent of premium allowed in the assigned risk fund are less likely to be profitable. It is interesting from a political economy perspective that these parameters were negotiated in the 1980s and yet they still provide an indicator as to the profitability of a current crop insurance contract. The parameter estimate on the historical loss ratio in the Probit models are negative and significant as expected; the higher the loss ratio the less likely the policies are profitable. The parameter on the percent of policies in the commercial fund is positive as expected. This suggests that policies the insurance company places in the commercial fund are more likely to be profitable. This is statistically significant in the both the Probit and nonparametric models. Finally, the parameter on the assigned variable is negative as expected suggesting that policies the insurance company places in the assigned risk fund are less likely to be profitable.

Our null hypothesis is that no private information is revealed in the fund allocation decisions. To test this we compare the percent of policies correctly predicted with and without the fund allocation explanatory variables. Specifically, the percent of policies correctly predicted should increase significantly when the fund allocation explanatory variables are included in the model. Our test may be formally written as:

$$H_o : \rho_f - \rho_{nf} \leq 0 \text{ versus } H_a : \rho_f - \rho_{nf} > 0. \tag{12}$$

where ρ_f corresponds to the percent of correct predictions from the model that includes the two fund variables while ρ_{nf} corresponds to the percent of correct predictions from the model that does not include the fund variables. Table 4 summarizes the empirical tests. Standard errors are calculated by bootstrapping the prediction sample and recovering the difference in the percent of correct predictions (500 bootstraps are used).

Table 4: Hypothesis Test Results

Test	Test Statistic	Standard Error
Asymmetric Information Tests		
Model 2 less Model 1 with Probit	0.0058	0.00169
Model 2 less Model 1 with Ichimura	0.0179	0.00576
Model 2 less Model 1 with Ergün and Ker	0.0084	0.00592
Probit versus Nonparametric Tests		
Ichimura less Probit - Model 1	0.0318	0.00557
Ergün and Ker less Probit - Model 1	0.0368	0.00506
Ichimura less Probit - Model 2	0.0439	0.00504
Ergün and Ker less Probit - Model 2	0.0394	0.00498

The out-of-sample tests results reveal - exception being the Ker and Ergün method - that predictive performance increases significantly when the fund allocations are included as explanatory variables indicating that there exists relevant asymmetric information. This coincides with the in-sample results which suggested that the fund allocations were significant at explaining profitable and nonprofitable sets of policies. Therefore, we reject the null that no relevant asymmetric information is revealed in the fund allocation data.

5.2 Testing the Parametric Probit Model

We undertake two tests, one formal and one informal, of the parametric Probit model. The first calculates the difference in the predictive performance of the nonparametric methods versus the Probit for both models 1 and 2 (see Table 4). These test results reject the Probit model in favor of the nonparametric methods. We could not reject either of the nonparametric models in favor of the other. A second less formal but pictorially pleasing test follows the graphical approach of Horowitz (1998, p.53). Figures 5 and 6 show nonparametric kernel estimates of dF/dz where $z = x\hat{\beta}_{probit}$, pointwise 95% bootstrap confidence interval, and the normal density function. Note that for a probit model, dF/dz would be the normal density function. In these nonparametric estimations, we used the standard normal density as our kernel. For bandwidth selection, we initially tried cross-validation for derivative estimation (see Härdle (1990, pp.160-161)). Numerical minimization of this objective function was not successful for the most part so after experimenting with CV, we chose the bandwidths accordingly. In both graphs, the derivative of the link function is clearly left skewed that can not be accommodated by the symmetric normal density. Pointwise confidence intervals are represented by the dotted lines. In both figures, the derivatives are bimodal which suggests that the true data generating processes may possibly be a mixture of two populations. Using a parametric probit model clearly misses these features of the data.

6 Conclusions and Policy Implications

Although the crop insurance program has garnered significant attention in the academic literature, surprisingly little has focused on the insurance companies and in particular, the SRA. However, the rents obtained by the crop insurance companies in return for their involvement are close to rivaling those obtained by producers. Consequently, more research is needed, both theoretically and empirically, focusing on the involvement of crop insurance companies.

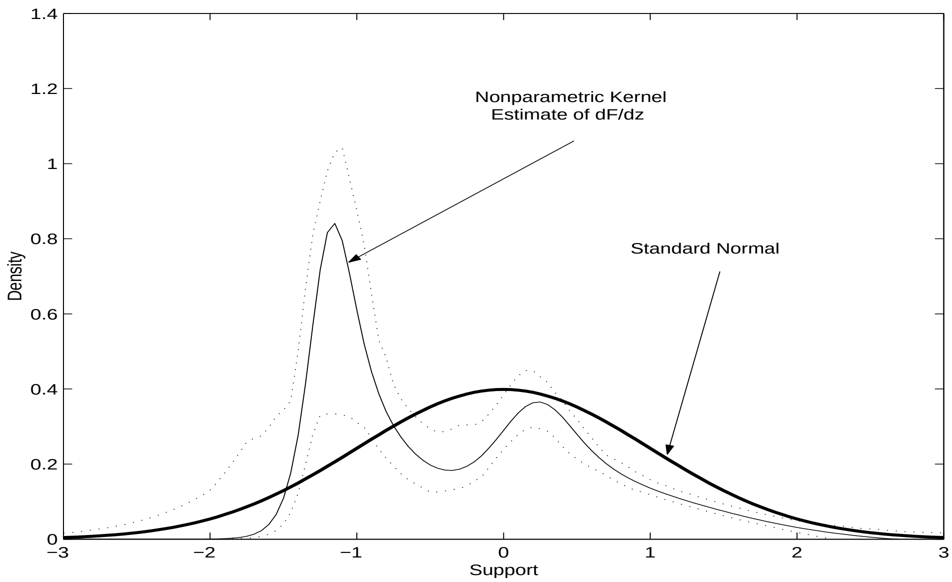

Figure 3: Test of Probit for the Data not Including Fund Allocations

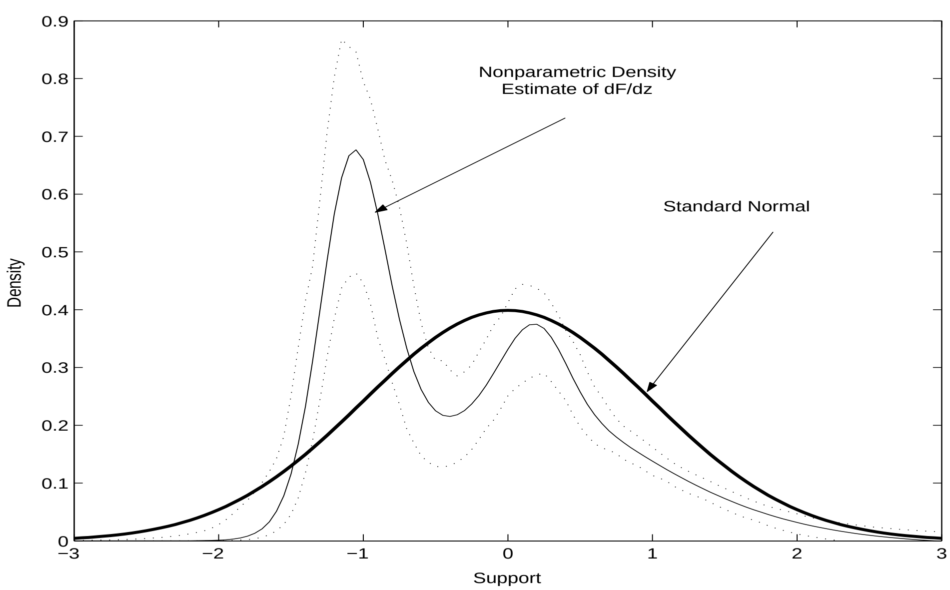

Figure 4: Test of the Probit for the Data Including Fund Allocations

This manuscript focused on whether insurance companies reveal asymmetric information through their fund allocation decisions. We have shown statistically that private insurance companies do possess relevant asymmetric information that may warrant their involvement in crop insurance program. However, the percentage increase in predictive performance is economically marginal in that the increased ranged from 0.58 percentage points with the Probit model to 1.79 percentage points with the Ichimura model. An important policy question is whether RMA would adjust premium rates given the revelation of new information. Past evidence suggests not in the sense that the state maximums on the assigned risk fund should not be statistically significant in our models. These state maximums, known by RMA, would not be significant if the rates incorporated this information - states with high maximums tend to yield less profitable contracts while states with low maximums tend to yield more profitable contracts.

Recall the arguments for involving the private insurance companies in the crop insurance program are: (i) lower delivery costs; (ii) increased efficiency due to the revelation of asymmetric information; and (iii) risk sharing. First, Ker (2001) suggests that delivery costs are not lower with private insurance companies. Second, we show here that the economic value of the asymmetric information is weak. Third, the government should not be risk sharing with private insurance companies as they can self-insure at no cost.

Why then are private insurance companies involved in this crop insurance program? We conjecture that they were initially involved to increase demand through lower transaction costs incurred by producers by the better established delivery channels of insurance companies. However, this increase in demand was obviously not sufficient to ward off ad-hoc disaster aid. In addition, we suspect that the savings brought about by a government delivered insurance program if funnelled back to producers through subsidies, would have a substantially greater impact on demand, particularly now that producers can sign-up for their insurance electronically. It appears to us that the private insurance companies have been active and successful in a political economy sense to not only survive but obtain significant rents. There is ample evidence of this in ARPA. For example, premium subsidies have caused a pronounced shift in demand to higher coverage levels. Therefore, the amount of A&O reimbursement has increased according to the increases in premium at these higher coverage levels. The percentage rate of A&O reimbursement should decline with the coverage level as there is both a fixed and variable cost component with A&O activities. However, this has not happened.

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