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Weather-Based Adverse Selection and the U.S. Crop Insurance Program: The Private Insurance Company Perspective

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Surprisingly, investigations of adverse selection have focused only on farmers. Conversely, this article investigates if insurance companies, not farmers, can generate excess rents from adverse selection activities. Current political forces fashioning crop insurance as the cornerstone of U.S. agricultural policy make our analysis particularly topical. Focusing on El Niño/La Niña and winter wheat in Texas, we simulate out-of-sample reinsurance decisions during the 1978 through 1997 crop years while reflecting the realities imposed by the risk-sharing arrangement between the insurance companies and the federal government. The simulations indicate that economically and statistically significant excess rents may be garnered by insurance companies through weather-based adverse selection.

Key words: adverse selection, crop insurance, El Niño/La Niña, Standard Reinsurance Agreement

Introduction

A wealth of theoretical literature investigating the economics of adverse selection under various scenarios exists. Empirical studies of adverse selection also abound. With respect to the U.S. crop insurance program, see Coble et al.; Luo, Skees, and Marchant; Goodwin; and Quiggin, Karagiannis, and Stanton. The U.S. crop insurance program is unique among insurance schemes in that three rather than two economic interests are served. The federal government through the U.S. Department of Agriculture's (USDA's) Risk Management Agency (RMA), the private insurance companies, and the farmers all have vested interests. The marketing of crop insurance policies began transferring from the government to insurance companies in 1980, with the hopes of increasing farmer participation. While the pricing or rating of these crop insurance policies remains the responsibility of the RMA, insurance companies receive compensation for administrative expenses and share, asymmetrically, the underwriting gains and losses of the policies.[1] The Standard Reinsurance Agreement (SRA) stipulates the terms for sharing these underwriting gains and losses between the insurance companies and the RMA.[2]

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[1] The underwriting gain/loss for a set of policies is the total premium less the total indemnity payments.

[2] See Ker for a review of the Standard Reinsurance Agreement.

The above empirical investigations have considered only adverse selection by farmers. To the best of the authors' knowledge, adverse selection by insurance companies, a more probable scenario, has yet to be investigated.[3] This study addresses the question: Can insurance companies generate "excess" rents from weather-based adverse selection?[4] This question, and hence our analysis, is particularly topical in light of the increased prominence of the crop insurance program in the overall U.S. agricultural policy agenda.

The actuarially fair premium rate (denoted π) for a yield insurance contract or policy that guarantees a percentage (denoted λ) of the expected yield (denoted y^e) is defined as:

$$\pi = P(Y < \lambda y^e)(\lambda y^e - E(Y \mid y < \lambda y^e)), \tag{1}$$

where $0 \leq \lambda \leq 1$ is the coverage level, the expectation operator (E) and probability measure (P) are taken with respect to the conditional yield density $f_Y(y \mid I)$, and I is the information set known at time of rating. Equation (1) defines the premium rate (π) as the probability of a loss times the expected loss given a loss occurs (the unconditional expected loss).[5]

We denote the insurance company's information set as I_{IC} and the RMA's information set as I_{RMA}. Standard economic theory suggests that if I_{RMA} is a subset of I_{IC}, the insurance company may generate excess rents from adverse selection. With the U.S. crop insurance program, the RMA estimates premium rates well in advance (in some instances two years), while the decision of insurance companies to retain or cede a given policy may be made as late as 30 days after its closing sale date. Clearly, I_{RMA} is a subset of I_{IC}.

To estimate the extent of excess rents garnered through weather-based adverse selection, we undertake an empirical case study using Texas winter wheat and El Niño/La Niña weather events. For this case study, $I_{RMA} = (y_1, y_2, \ldots, y_T)$, while $I_{IC} = (y_1, y_2, \ldots, y_T; s_1, s_2, \ldots, s_T, s_{T+1})$. The sequence $(y_1, \ldots, y_T)$ denotes yield realizations for years 1 to T, and $(s_1, s_2, \ldots, s_T, s_{T+1})$ denotes realizations from the random variable representing El Niño/La Niña for years 1 to $T + 1$. We simulate, out-of-sample, reinsurance decisions during the 1978 through 1997 crop years given the differing information sets. Resulting "pseudo" loss ratios for the program, the RMA, and the insurance company subject to the constraints of the 1998 SRA are recovered.[6]

Although the convoluted sharing of the underwriting gains and losses of the policies presents complexities, any relevant empirical analysis must reflect the realities imposed by the SRA. As such, the following section presents a terse overview of the U.S. crop insurance program as a backdrop for the subsequent discussion of the SRA. The next section outlines the data and motivates the chosen empirical application. The chosen econometric methods are then detailed and justified, followed by a delineation of the simulation and a review of our findings. In the final section we discuss the policy implications. Technical details are relegated to the appendices.

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[3] We use the term "adverse selection" loosely throughout the article.

[4] By design, the SRA enables the insurance company to recover a return to capital. Our discussion focuses on the inflated returns, or "excess" rents.

[5] Generally, the premium rate is quoted as the ratio of unconditional expected loss to total liability. Our analysis revolves around the unconditional expected loss, so we define this as the premium rate. Additionally, we ignore the price guarantee and deal with bushels/acre; we present our results in terms of loss ratios, which are independent of the price guarantee assuming each policy has the same price guarantee.

[6] The loss ratio equals total claims divided by total premiums. Under the SRA, the loss ratio for the insurance company and the RMA cannot be calculated. We construct a new measure, termed "pseudo" loss ratio, as the ratio of total annual underwriting losses to total annual underwriting gains. See appendix A for a thorough examination.

The U.S. Crop Insurance Program and the SRA

Federally regulated crop insurance programs have been a prominent part of U.S. agricultural policy since the 1930s. In 1998, more than 1.75 million crop insurance policies were purchased. These policies carried a total liability in excess of $27.9 billion. In the past, crop insurance schemes offered farmers the opportunity to insure against yield losses resulting from nearly all risks, including drought, fire, flood, hail, and pests. For example, if the farmer's expected wheat yield is 30 bushels/acre ($y^e = 30$), a policy purchased at the 70% coverage level ($\lambda = 0.7$) insures against a realization below 21 bushels/acre (0.7 × 30 bushels/acre = 21 bushels/acre). If the farmer realized a yield of 16 bushels/acre, then an indemnity payment for the insured value of 5 bushels/acre would be made.

A variety of crop insurance plans and a number of new pilot programs are 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 the county average yield falls beneath a yield guarantee, regardless of the farmer's actual yields. Three farm-level revenue insurance programs are available for a limited, but quickly expanding, 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 (Goodwin and Ker). The recently developed Group Risk Income Plan, a variation of the Group Risk Plan, insures county revenues rather than yields (Baquet and Skees).

Producer Adverse Selection and the U.S. Crop Insurance Program

As mentioned, empirical investigations to date have considered only adverse selection by farmers. With respect to weather-based adverse selection, Luo, Skees, and Marchant found farmers could gain; conversely, Coble et al. found farmers did not consider preseason weather information in crop insurance decisions. As farmers and insurance companies have almost identical information sets, if farmers engaged in weather-based adverse selection, the advantage to the insurance companies is negated because their insurance pool would only consist of policies with an expected loss.

Given the importance of the latter finding to our analysis, we feel it necessary to explain why farmers do not exploit weather-based informational asymmetries while insurance companies will. Producer premium subsidies, risk aversion, and technical capabilities all play a part. For illustrative purposes, denote $\hat{\pi}_f$ as the derived premium rate from the estimated conditional yield density $\hat{f}_Y(y \mid I_f)$, where I_f is the farmer's information set. Since the information set of the farmer equals that of the insurance company, $\hat{f}_Y(y \mid I_f) = \hat{f}_Y(y \mid I_{IC})$ and $\hat{\pi}_f = \hat{\pi}_{IC}$. Denote $\hat{\pi}_{RMA}$, the price of the policy, as the RMA-derived rate from the estimated conditional yield density $\hat{f}_Y(y \mid I_{RMA})$. If $\hat{\pi}_f > \hat{\pi}_{RMA}$, a non-risk loving farmer will purchase the policy. Alternatively, if $\hat{\pi}_f < \hat{\pi}_{RMA}$, the farmer may still purchase the policy. First, the farmer premium subsidy (denoted τ) is of an order of magnitude such that $\hat{\pi}_f < (\hat{\pi}_{RMA} - \tau)$ generally.[7] Second, a risk-averse farmer would purchase the policy if expected utility remained greater in the insured state despite $\hat{\pi}_f > (\hat{\pi}_{RMA} - \tau)$. Finally, the inherent technical abilities of the farmer may be such that, by default, they set $\hat{\pi}_f = \hat{\pi}_{RMA}$. As Rubinstein notes, "Decision makers are not equally capable of analyzing a situation even when the information available to all of them is the same. The differences in their economic success can be attributed to these differences" (p. 3). In contrast to farmers, insurance companies will process all available weather information, will be less risk averse, and will not receive a deterministic subsidy. Therefore, it is most probable that insurance companies will engage in weather-based adverse selection activities while farmers will not.

Standard Reinsurance Agreement (SRA)

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. This creates an unusual situation because the responsibility for pricing the crop policies lies with the RMA, but the insurance company must accept some liability for each policy it writes and cannot choose which policy it will or will not write.

Why would insurance companies be involved in such a risk-sharing arrangement? To elicit their participation, two mechanisms are required that, necessarily, emulate a private market from their perspective. 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 adversely 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 policy into one of three funds: (*a*) assigned risk, (*b*) developmental, or (*c*) commercial. For each state in which the insurance company does business, there is a separate assigned risk fund, developmental fund, and commercial fund. While the structure of risk sharing is identical, 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.

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[7] See Goodwin for an exposition of the farmer premium subsidy structure.

Formally,

(2) $$\Omega_{IC}^k = \Omega^k \times \mu_1^k \times \mu_2^k,$$

where Ω_{IC}^k denotes the underwriting gain/loss retained by the insurance company for fund k, Ω^k denotes the underwriting gain/loss for fund k, μ_1^k is the first parameter for fund k, and μ_2^k is the second parameter for fund k. The underwriting gain/loss retained by the RMA must be:

(3) $$\Omega_{RMA}^k = \Omega^k \times (1 - \mu_1^k \times \mu_2^k),$$

where Ω_{RMA}^k denotes the underwriting gain/loss retained by the RMA. The first parameter, μ_1^k, represents an ex ante choice variable for the insurance company. For $k \equiv$ assigned risk fund, the company must choose μ_1^k such that $\mu_1^k \in [0.2, 1.0]$. For $k \equiv$ developmental fund, $\mu_1^k \in [0.35, 1.0]$, while for $k \equiv$ commercial fund, $\mu_1^k \in [0.5, 1.0]$. The insurance company must choose μ_1^k by July 1 of the preceding crop year. The second parameter, μ_2^k, is not a fixed scalar, but a function of the ex post fund loss ratio.

Graphing the relationship between μ_2^k and the loss ratio for the three funds, the two required mechanisms of the SRA become self-evident (figure 1). First, policies the insurance company deems undesirable may be placed in the assigned risk fund where negligible underwriting gain/loss is retained. Second, insurance companies retain a larger share of the underwriting gains than losses for each fund, which thus provides a return to their capital (see Ker, and Miranda and Glauber for in-depth analyses of the SRA). The ability to allocate policies among the three funds provides a means by which insurance companies can exploit informational asymmetries and engage in adverse selection.

Data

Recall, the objective of this study is to estimate the extent to which weather-based adverse selection by insurance companies can generate excess rents. Texas winter wheat and El Niño/La Niña is the chosen application for the following reasons. First, if insurance companies engage in weather-based adverse selection, this might be their starting point. Loosely speaking, the *forecastability* of El Niño/La Niña has been widely publicized in the climatology literature as well as the popular literature. Additionally, El Niño/La Niña data are easily accessible, and the proximity of Texas to the Gulf of Mexico and the dependence of winter wheat on rainfall suggest that wheat yields in Texas may be influenced by El Niño/La Niña. Finally, this application represents a lower bound in that conditioning on local weather variables rather than a global weather variable will lead to more pronounced effects.

El Niño / La Niña

An indication of forthcoming weather and climate patterns can often be seen months in advance through oceanic and atmospheric anomalies. El Niño/Southern Oscillation (ENSO) refers to a fluctuating ocean-atmospheric phenomenon observed in the area of the equatorial Pacific Ocean. Every few years ENSO reaches an extreme state, La Niña [El Niño], which is characterized by abnormally cold [warm] surface waters in the eastern

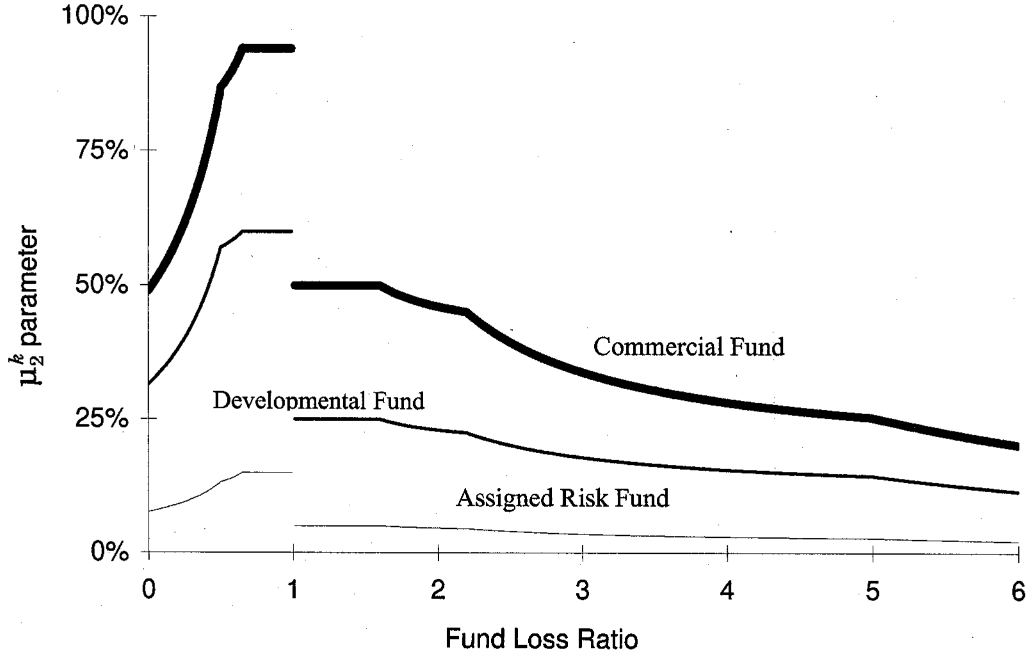

Figure 1. Relationship between μ_2^k and fund loss ratio for the three funds

and central equatorial region and high [low] overlaying surface air pressure over the southern Pacific Ocean. The different phases of ENSO have been linked to weather and climate anomalies throughout much of the globe including the U.S. and the state of Texas (Ropelewski and Halpert 1986, 1989; Kiladis and Diaz).

An intensification of convection over the western tropical Pacific and subsidence over the eastern Pacific characterizes La Niña.[8] This leads to a weakening and often northerly displacement of the jet stream and storm track over west and central North America.[9] A decrease in moisture flow across the southwestern U.S. and a decrease in the meridional migration of air masses across the North American continent often occur.[10] Thus warm and dry conditions, which tend to be detrimental to wheat production, often prevail in Texas. Conversely, El Niño, characterized by an enhancement of the subtropical jet stream resulting in increased moisture flow across the southern U.S. and the Gulf of Mexico, is typically beneficial to Texas wheat production.

Unfortunately, the climatology literature has varying definitions of what constitutes an El Niño event and a La Niña event. In addition, each El Niño event and La Niña event is unique. Extreme fluctuations in sea surface temperatures (SSTs) define El Niño and La Niña events. We use the underlying SST data as opposed to indicator variables (i.e., a phase-based approach).[11] Monthly SST data over the period of consideration for

[8] Convection is the process whereby rising moist air results in cloud formation.

[9] The jet stream refers to a band of high-speed upper atmosphere westerly winds that form along the boundary separating cold northern from warm southern air masses.

[10] Meridional airflows are those traveling in the North-South plane.

[11] McGowan and Ker find that using indicator variables as opposed to the underlying SST data results in a statistically significant loss in explanatory power.

the Niño3 region of the Pacific Ocean were obtained from the U.S. Department of Commerce/National Oceanic and Atmospheric Administration, Climate Prediction Center. The Niño3 is a critical region of the Pacific commonly observed to indicate changes in ENSO. In most empirical work in the climatology literature, SST data are averaged over a three-month season. The closing date for wheat policies in Texas is September 30, and insurance companies are afforded an additional 30 days to make decisions regarding reinsurance. Although SST anomalies typically peak in the season of November-December-January (which make this the best indicator of year-to-year ENSO variation and coincidentally most highly correlated with wheat yields), this information will not be available to the insurance companies prior to the reinsurance deadline. As such, the July-August-September SSTs are used.

Texas Wheat Yields

Mean yields at the county level for winter wheat during the 1956–97 period were obtained from the USDA's National Agricultural Statistics Service. We considered the top 55 producing counties, which constituted approximately 86% of the wheat acres for 1997. In 1997, Texas planted 6,300,000 acres of wheat, ranking it fourth nationally with about 9% of the total wheat-producing land in the U.S. We use yield per acre harvested to avoid contamination from wheat planted for grazing which goes unharvested.[12] Individual farm data (rather than county level) would be ideal as the majority of crop policies are sold at the individual farm or subfarm level. However, a credible analysis cannot be conducted because of insufficient farm-level data (4–10 years), and thus we resign ourselves to the county-level yield data. Of some advantage is that insurance companies tend to make reinsurance decisions at the county rather than producer level.

Econometric Methods

We model the technology component or temporal process of yields in the same fashion as done by the RMA for the county yield-based insurance program (Group Risk Plan), given county rather than individual yield data must be used. RMA estimates a one-knot linear spline with once iterated least squares while windsorizing outliers (determined based on estimates from the first iterations) in the second iteration (Skees, Black, and Barnett). The one-knot linear spline is specified as:

$$y_t = \alpha + \beta_1\Big(t \times I_{(0,\delta)}(t) + \delta(1 - I_{(0,\delta)}(t))\Big) + \beta_2\Big((1 - I_{(0,\delta)}(t))(t - \delta)\Big) + \epsilon_t, \tag{4}$$

where δ is the knot, t is the year, and $I(\cdot)$ is the indicator function.

Unfortunately, employing the one-knot linear spline when we include SST in the model may lead to problems. Although the climatology literature has historically assumed a linear relationship between yields and SST, McGowan and Ker found statistically significant nonlinearities. Thus nonparametric methods are used to estimate the SST component. However, the use of nonparametric methods presents a minor

[12] This differs from convention because we ignore fields that were planted but abandoned due to crop failure. We felt that grains planted for grazing constituted a more serious contamination of the data.

problem if the one-knot linear spline does not adequately approximate the temporal process.[13] In such a case, the nonparametric estimate of the SST component may be contaminated. To circumvent this potential problem, we undertake a two-stage approach where we initially estimate the generalized additive model, $y_t = m_1(t) + m_2(s) + e_t$. Note that the temporal process is initially being estimated nonparametrically rather than by the one-knot linear spline. By doing this, the estimate, $\hat{m}_2(s)$, is not biased by the potentially inappropriate use of the one-knot linear spline. Given $\hat{m}_2(s)$, we estimate a one-knot linear spline denoted $h(t)$ in the second stage.[14] Formally, in stage one we estimate:

$$(5) \qquad y_t - \bar{y} = m_1(t) + m_2(s) + e_t,$$

while in stage two we estimate:

$$(6) \qquad y_t - \bar{y} - \hat{m}_2(s) = \alpha_1\Big((t \cdot I_{(0,\eta)}(t)) + \eta(1 - I_{(0,\eta)}(t))\Big) + \alpha_2\Big((1 - I_{(0,\eta)}(t))(t - \eta)\Big) + \nu_t,$$

where η is the knot. Estimating the generalized additive model is somewhat technical, and thus the discussion is relegated to appendix B. We discuss the choices of nonparametric method below, but reference Ker and Coble for discussion of the employed methodology.

Choice of Nonparametric Methods

There exist many types of smoothing or nonparametric regression methods (e.g., kernel smoothing, local regression, spline smoothing, super smoothing). We employed the Isotonic Robust Super Smoother detailed in Ker and Coble. The Isotonic Robust Super Smoother uses an *m*-estimator line super smoother which is isotonized. We chose to smooth with a line rather than the traditional Nadaraya-Watson kernel to avoid end-point bias as our interest lies in the extremes of SSTs (La Niña and El Niño regions). We employed a robust criterion rather than least squares because mean yields over the spatial area of interest are generally considered nonnormal due to spatial dependence. Finally, we isotonized the smoothed estimates to belong to the class of nondecreasing functions, given economic and agronomic theory suggest that both $m_1(t)$ and $m_2(s)$ should be nondecreasing.

Figure 2 depicts the nonparametric estimate of the temporal process, while figure 3 depicts the nonparametric estimate of the SST component, both for Coleman County.[15] Figure 2 also illustrates the estimated one-knot linear splines for both the RMA and the insurance company. The two-stage estimation procedure tends to mimic the one-knot linear splines (not surprising, given independence of technology and SST). Figure 3 pictorially suggests that SST is significant. The statistical significance of $m_2(s)$ is tested

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[13] Moss and Shonkwiler point out that technological innovations and the adoption of those innovations are random events. Ker and Coble conjectured that the technology component of yields would be erratic but nondecreasing.

[14] In a generalized additive model, we assume $m_1(t) \in \mathcal{H}$, where $\mathcal{H}$ is a Hilbert space. Since $h(t) \in \mathcal{H}$, it is a restriction placed on $\hat{m}_1(t)$ and will be consistently estimated in the two-stage process.

[15] Coleman County was chosen as it is representative of the 55 Texas counties.

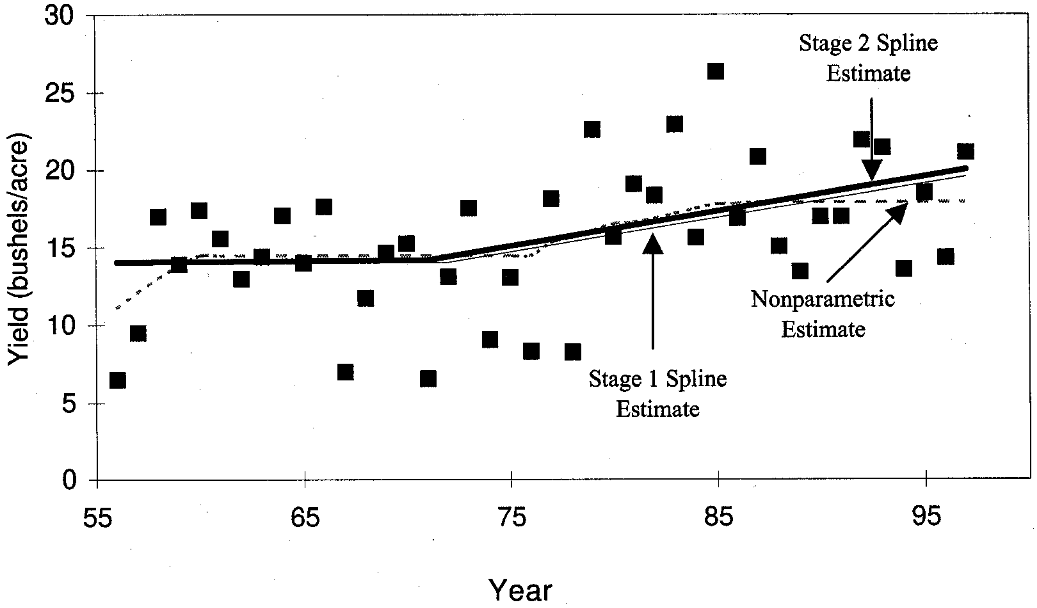

Figure 2. Estimated technology effect for Coleman County

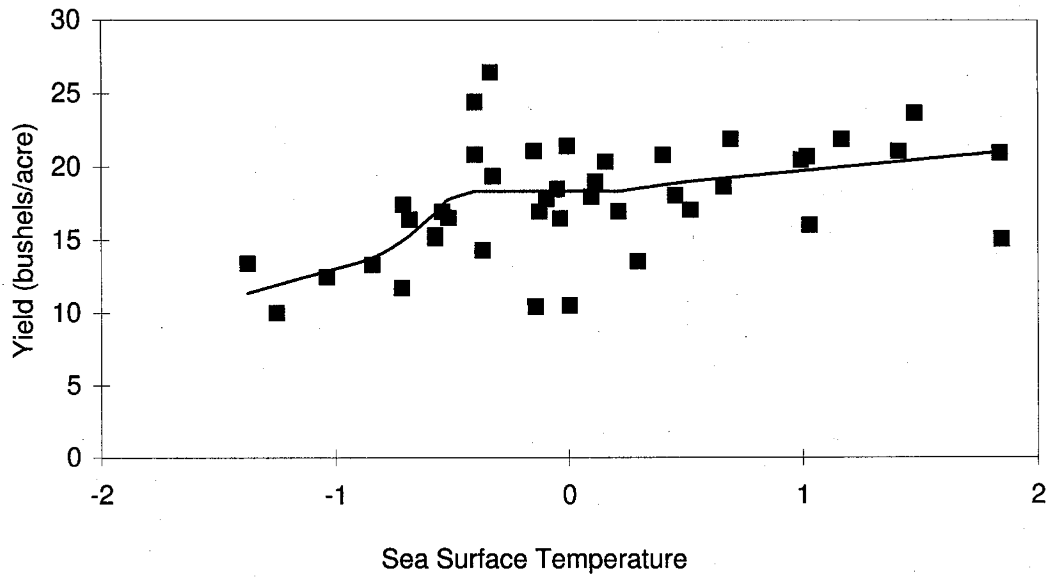

Figure 3. Estimated sea surface temperature effect for Coleman County

using approximate randomization tests.[16] In 50 of the 55 counties, SST was found to be significant at the 90% confidence level. The five counties where SST was insignificant are located in the panhandle of Texas, which is further inland and contains a much greater portion of irrigated land (dry conditions brought on by low SSTs have significantly less impact on irrigated yields). Figure 3 suggests that at low SSTs [La Niña] mean yields tend to be significantly lower, while at high SSTs [El Niño] mean yields tend to be mildly higher. Our finding is consistent with both climatological and agronomic theory.

Recovering the Conditional Yield Densities and Premium Rates

The conditional yield densities can be estimated given the predicted yields and the estimated residuals from the models of the previous subsection. Subsequently, the estimated premium rates are derived by inputting the estimated conditional yield densities into equation (1). Denote the sequence $(\hat{\epsilon}_1, \hat{\epsilon}_2, \ldots, \hat{\epsilon}_T)$ as the estimated residuals from the RMA model [equation (4)] and the sequence $(\hat{v}_1, \hat{v}_2, \ldots, \hat{v}_T)$ as the estimated residuals from the insurance company model [equation (6)]. Also, denote the fitted yield values from the RMA model as $(\hat{y}_1, \hat{y}_2, \ldots, \hat{y}_T)$ and the fitted yield values from the insurance company model as $(\tilde{y}_1, \tilde{y}_2, \ldots, \tilde{y}_T)$. Therefore, a sequence of asymptotically independent and identically distributed realizations from $f_Y(y \mid I_{RMA})$ is recovered in the following manner:[17]

$$(7) \qquad y_{T+1,t} = \left(\frac{\hat{\epsilon}_t}{\hat{y}_t} \right) \times \hat{y}_{T+1} + \hat{y}_{T+1} \qquad \forall\, t = 1, \ldots, T.$$

Similarly, a sequence of asymptotically independent and identically distributed realizations from $f_Y(y \mid I_{IC})$ is recovered in the following manner:

$$(8) \qquad y_{T+1,t} = \left(\frac{\hat{v}_t}{\tilde{y}_t} \right) \times \tilde{y}_{T+1} + \tilde{y}_{T+1} \qquad \forall\, t = 1, \ldots, T.$$

Adaptive kernel density estimation methods are employed using these sequences as inputs to recover estimates of $\hat{f}_Y(y \mid I_{RMA})$ and $\hat{f}_Y(y \mid I_{IC})$. These methods have been employed in Ker and Coble and in Ker and Goodwin to address potential nonnormalities. The interested reader is directed to either of these sources for a thorough review of the methodology.

Figures 4 and 5 compare estimates of the conditional yield densities of both the RMA and the insurance company for Coleman County. Figure 4 considers a La Niña year (1989), while figure 5 considers a regular (non El Niño/La Niña) year (1991). In figure 4, $\hat{f}_Y(y \mid I_{IC})$ is located on the lower tail of $\hat{f}_Y(y \mid I_{RMA})$ and has much smaller variance, both expected for a low SST [La Niña] year. Conditioning on a low SST produces a downward location shift and reduces the variance because of the heteroskedasticity correction. Simply conditioning on SST also played a part in reducing the variance. In figure 5, there

[16] A brief explanation of approximate randomization tests can be found in the "Simulation Analysis" section that follows. The interested reader is directed to Kennedy for a thorough discussion.

[17] Both raw and standardized residuals were tested for heteroskedasticity using Goldfeld-Quandt's nonparametric peak test (Goldfeld and Quandt). The test results indicated the standardized residuals should be used.

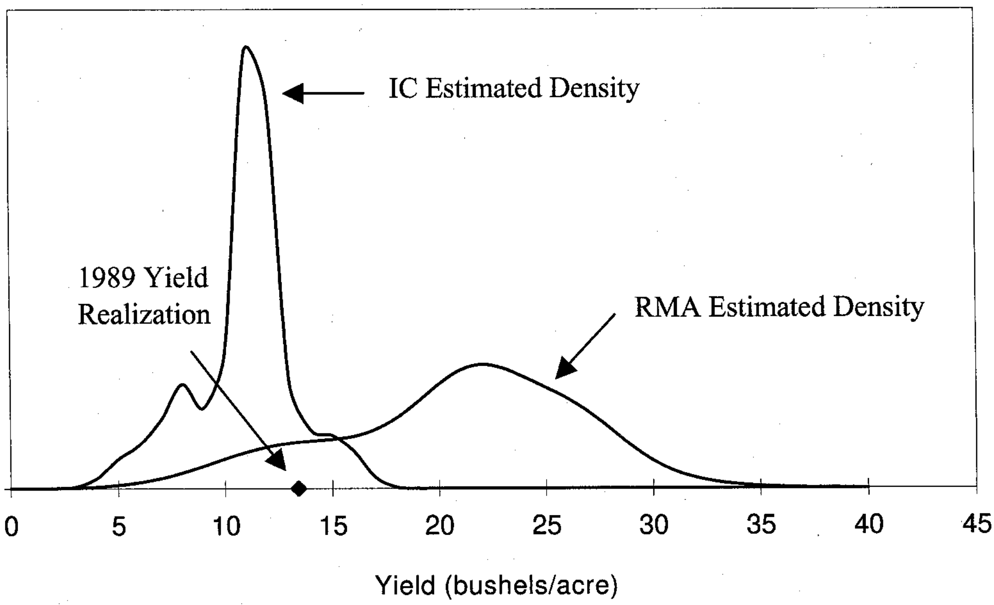

Figure 4. Estimated conditional yield densities for Coleman County: La Niña event (1989)

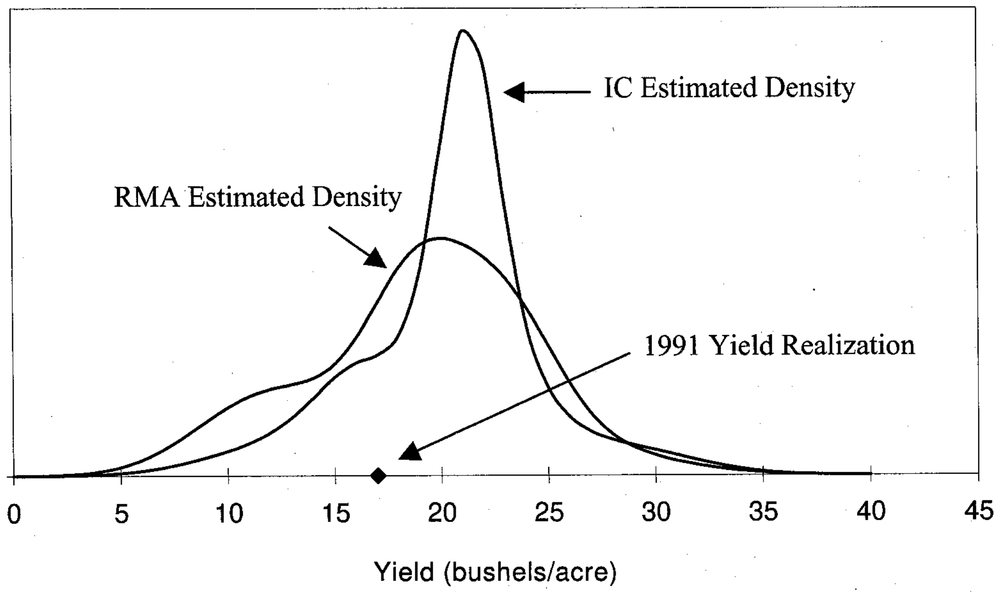

Figure 5. Estimated conditional yield densities for Coleman County: Regular year (1991)

is very little location shift although the variance is marginally smaller from conditioning on SST, both expected for a regular year.

For a given coverage level, say λ, the RMA calculates the premium rate according to equation (1), where y^e comes from equation (4) and the expectation and probability measure are taken with respect to $\hat{f}_Y(y\,|\,I_{RMA})$. Conversely, the insurance company calculates the premium rate for the policy based on y^e, also from equation (4), but the expectation and probability measure are taken with respect to $\hat{f}_Y(y\,|\,I_{IC})$. For example, consider the 1989 premium rates for the conditional yield densities in figure 4, where $I_{RMA} = (y_{56}, \ldots, y_{88})$ while $I_{IC} = (y_{56}, \ldots, y_{88}; s_{56}, \ldots, s_{88}, s_{89})$. The RMA recovers $y^e = 20.77$ bushels/acre. Assuming the 70% coverage level, the yield guarantee is 14.54 bushels/acre (λy^e). According to $\hat{f}_Y(y\,|\,I_{RMA})$, the probability of a loss is 0.169 and the expected loss, given a loss has occurred, is 3.39 bushels/acre. Therefore, RMA estimates the unconditional expected loss or premium rate for the policy at 0.57 bushels/acre (0.169 × 3.39). Conversely, the insurance company estimates the probability of a loss for the policy and the expected loss, given a loss has occurred, using $\hat{f}_Y(y\,|\,I_{IC})$. The insurance company estimates the probability of a loss at 0.921 and the expected loss, given a loss has occurred, at 3.94 bushels/acre for a policy with a yield guarantee of 14.54 bushels/acre. The insurance company estimates the unconditional loss or premium rate to be 3.63 bushels/acre (0.921 × 3.94), almost an order of magnitude larger than the RMA premium rate.

Simulation Analysis

Given estimated premium rates from the previous section for both the RMA and the insurance companies, we simulate, out-of-sample, fund allocation decisions for the 55 counties during the 1978 through 1997 crop years and calculate the pseudo loss ratios for the program, the RMA, and the insurance company. Note the insurance company bases its fund allocation decisions on its estimate of the conditional yield density, $\hat{f}_Y(y\,|\,I_{IC})$, and the price of the policy, $\hat{\pi}_{RMA}$. For example, consider county j and year t, where $I_{RMA} = (y_{56}, \ldots, y_{t-1})$ and $I_{IC} = (y_{56}, \ldots, y_{t-1}; s_{56}, \ldots, s_{t-1}, s_t)$. Given I_{RMA}, we estimate the parameters of the one-knot linear spline model [equation (4)] from which y^e is recovered. We use the resulting estimated residuals $(\hat{\epsilon}_{56}, \ldots, \hat{\epsilon}_{t-1})$ to estimate $f_Y(y\,|\,I_{RMA})$ from which the premium rate for county j in year t, $\hat{\pi}_{RMA}$, is derived. Conversely, we estimate the parameters of equation (6) using I_{IC}. We use the resulting estimated residuals $(\hat{v}_{56}, \ldots, \hat{v}_{t-1})$ to estimate $f_Y(y\,|\,I_{IC})$. Given $\hat{f}_Y(y\,|\,I_{IC})$ and $\hat{\pi}_{RMA}$, the insurance company makes an allocation decision based on the strategies discussed below. This procedure, including the estimation, is repeated for each of the 20 years for each of the 55 counties as I_{RMA} and I_{IC} are updated every year.

Fund Allocation Decision

Recall, under the SRA, the insurance company must place each policy into one of three funds: assigned risk, developmental, or commercial. The optimal strategy for allocating policies among funds is not analytically tractable because of dimensionality problems (see appendix C). As a result, we (as must the insurance company) consider "sub-optimal," dimension-reducing strategies. In the first strategy, the insurance company places policies deemed desirable ($\hat{\pi}_{IC} < \hat{\pi}_{RMA}$) in the commercial fund and policies deemed undesirable ($\hat{\pi}_{IC} > \hat{\pi}_{RMA}$) in the assigned risk fund. This strategy, detailed in appendix C, assumes the yield of a policy and the loss ratio for the fund in which it is placed are independent, and henceforth we denote this the "independent" strategy. The second strategy, also detailed in appendix C, assumes the yield of a given policy and the loss ratio for the fund in which it is placed are completely dependent. We denote this the "dependent" strategy. The insurance company assigns each policy to the fund that maximizes expected underwriting gain subject to the dependence assumption. Both strategies reduce a large dimensional problem into a single dimension.

We first undertake a simulation ignoring the realities of the SRA by assuming the insurance company may either retain or cede 100% of the potential underwriting gains/losses of each policy. We do this for two reasons. First, this simulation provides a backdrop for the results subject to the SRA. Second, both the loss ratio and pseudo loss ratio are calculable in this simulation, thereby allowing a heuristic comparison of the two measures. This simulation contrasts the SRA simulation where the insurance company allocates policies to one of the three funds and thus retains or cedes a portion, not all, of the potential underwriting gains/losses of each policy.

Simulation Results: Without SRA

Without the SRA, a risk-neutral insurance company will retain policies deemed desirable ($\hat{\pi}_{IC} < \hat{\pi}_{RMA}$) and cede policies deemed undesirable ($\hat{\pi}_{IC} > \hat{\pi}_{RMA}$). Denote Ξ as the universe set of 1,100 policies (55 counties × 20 years), $\mathscr{F}$ the set of policies the insurance company retains, and $\mathscr{F}^c$ the set of policies the insurance company cedes. The loss ratio for a set, say $\mathscr{F}$, is written as:

$$\text{(9)} \qquad Loss\ Ratio_{\mathscr{F}} = \frac{\sum_{j \in \mathscr{F}} \max(0, \lambda y_j^e - y_j) w_j}{\sum_{j \in \mathscr{F}} \hat{\pi}_{RMA,j} w_j},$$

where j is the policy, y_j is the realized yield associated with policy j, λ is the coverage level, y_j^e is the RMA expected yield associated with policy j, $\hat{\pi}_{RMA,j}$ is the RMA premium rate for policy j, and w_j is the weight or number of acres insured for policy j. Note, it is necessary to assume a weighting scheme to aggregate across counties. We weight counties by their average wheat acres insured between 1995 and 1998 rather than assuming uniform weights or weights proportional to their total wheat acres. We calculate the loss ratio for the program and the RMA by summing over Ξ and $\mathscr{F}^c$ in equation (9).

Tables 1 and 2 contain the simulation results for the 60%, 70%, and 80% coverage levels. Consistent with expectations, the insurance company retains greater than half the policies at all coverage levels, with the percentage decreasing as the coverage level increases (see table 1). Recall the RMA does not condition on SST, while the insurance company does. Therefore, the mean of $\hat{f}_Y(y \mid I_{IC})$ lies to the right (or left) of the mean of $\hat{f}_Y(y \mid I_{RMA})$ for approximately half the policies. Additionally, $\hat{f}_Y(y \mid I_{IC})$ will tend to have lower variance.[18] Hence, $\hat{\pi}_{IC}$ will tend to be less than $\hat{\pi}_{RMA}$ for greater than half the

[18] This does not hold almost surely given the heteroskedasticity adjustment. If the mean of $\hat{f}_Y(y \mid I_{IC})$ lies to the left of the mean of $\hat{f}_Y(y \mid I_{RMA})$, the variance is lower almost surely.

Table 1. Simulation Results: Retention and Allocation Rates

Coverage Level	Total Contracts	Without SRA (%)		With SRA (%)		
		Retained	Ceded	Assigned Risk	Develop-mental	Commercial
60%	1,100	88.27	11.73	n/a	n/a	n/a
70%	1,100	86.45	13.55	n/a	n/a	n/a
80%	1,100	79.64	20.36	n/a	n/a	n/a
Independent Strategy:						
60%	1,100	n/a	n/a	11.73	n/a	88.27
70%	1,100	n/a	n/a	13.55	n/a	86.45
80%	1,100	n/a	n/a	20.36	n/a	79.64
Dependent Strategy:						
60%	1,100	n/a	n/a	2.64	0.09	97.27
70%	1,100	n/a	n/a	2.91	0.36	96.73
80%	1,100	n/a	n/a	3.91	0.91	95.18

Table 2. Simulation Results: Loss Ratios

Coverage Level	Program Loss Ratio	RMA Loss Ratio	Insurance Co. Loss Ratio	p-Value
Without SRA: Pure Loss Ratio				
60%	0.90	3.36	0.63	0.000
70%	1.14	2.59	0.92	0.000
80%	1.35	1.92	1.20	0.004
Without SRA: Pseudo Loss Ratio				
60%	0.85	6.08	0.45	0.000
70%	1.29	4.13	0.84	0.000
80%	1.94	3.30	1.51	0.008
With SRA: Independent Strategy/Pseudo Loss Ratio				
60%	0.85	1.40	0.29	0.001
70%	1.29	2.07	0.51	0.004
80%	1.94	2.86	0.95	0.017
With SRA: Dependent Strategy/Pseudo Loss Ratio				
60%	0.85	1.29	0.45	0.008
70%	1.29	2.22	0.57	0.004
80%	1.94	3.13	0.97	0.001

policies, with increasing tendency at lower coverage levels, as variance decreases are most pronounced in the tails of the density. This is consistent with the simulation results as evidenced by the percentages retained at the three coverage levels.

Table 2 summarizes the program, RMA, and insurance company loss ratios for the simulation. The RMA loss ratio is greater while the insurance company loss ratio is lower than the program loss ratio for all coverage levels. The difference between the insurance company loss ratio and program loss ratio represents economically significant gains to weather-based adverse selection activities. We use approximate randomization tests to recover the statistical significance. These tests simulate the distribution of a desired statistic under the null when the null distribution is unknown. Approximate randomization tests are very intuitive, and although just surfacing in the econometrics literature, have been commonly employed in the statistical literature.

Our null is that the insurance company loss ratio is not lower from incorporating SSTs into its reinsurance decisions. That is, SSTs are uninformative, in which case $\hat{f}_Y(y \mid I_{IC}) = \hat{f}_Y(y \mid I_{RMA})$. Under this null, the insurance company estimates every policy to have zero expected gain since $\hat{\pi}_{IC} = \hat{\pi}_{RMA}$, and thus it is indifferent to retaining or ceding every policy. To retrieve a realization from the null distribution, the insurance company randomly retains a policy with probability ρ, where ρ is set equal to the percentage of policies retained in the original simulation (table 2). For example, $\rho = 0.883$ for the 60% coverage level. Note, we randomize over which policies are retained, not over the number of policies retained given the null leads to indifference. We compare the insurance company loss ratio from the analysis (denoted τ^*) to 1,000 simulated loss ratios under the null $\{\tau_1, \tau_2, \ldots, \tau_{1,000}\}$. The p-value for the test equals the percentage of $\tau_i \leq \tau^*$ (see table 2). The tests indicate the insurance company loss ratios are statistically lower, for all coverage levels, when retention decisions are conditioned on SST. Therefore, in the absence of the SRA, insurance companies can generate economically and statistically significant excess rents from weather-based adverse selection.

We also calculated the pseudo loss ratios for this simulation in order to make comparisons to the standard loss ratios. As expected (see result 1, appendix A), if the loss ratio is [<, =, >] one, the pseudo loss ratio is [<, =, >] one. Also, as the loss ratio departs from one, the magnitude of the departure is inflated when using the pseudo loss ratio (see result 2, appendix A). Most important, and not surprising, our findings do not differ markedly between the pseudo loss ratio and the standard loss ratio.

Simulation Results: With SRA

Table 1 reports the percentage of policies the insurance company places in each fund given the constraints of the SRA. For the independent strategy, the policies in the commercial fund are identical to the policies retained under the non-SRA simulation. Similarly, the policies in the assigned risk fund are identical to the policies ceded under the non-SRA simulation. This was expected as both simulations have identical decision criteria. The commercial fund contains significantly more policies for the dependent strategy—a strategy which tends to inflate the implicit subsidies underlying each fund—and the commercial fund tends to yield the largest dollar subsidy.

Table 2 presents the pseudo loss ratios for both strategies. Not surprisingly, insurance company pseudo loss ratios are lower for the SRA simulation relative to the non-SRA simulation. The insurance company pseudo loss ratios under the non-SRA simulation only reflect gains from weather-based adverse selection, while under the SRA simulation they reflect gains from weather-based adverse selection *and* the implicit subsidies. Also not surprisingly, the insurance company pseudo loss ratios are lower for the independent strategy relative to the dependent strategy. Under the dependent strategy, a policy with an expected loss may be placed in the commercial fund if the implicit subsidy, as estimated under the dependence assumption, is sufficient such that a combined expected gain results. Conversely, the insurance company places policies with an expected loss in the assigned risk fund for the independent strategy.

Why would the insurance company follow the dependent strategy if the independent strategy leads to a higher expected return? An insurance company may follow such a strategy because the total profits of the fund may be larger under the dependent strategy. Consider two funds where the first has premiums totaling $3 million and claims totaling $1 million, while the second has premiums totaling $10 million and claims totaling $5 million. Although the loss ratio of the first fund is lower than the loss ratio of the second fund (0.333 < 0.5), the profits are greater in the second fund ($5 million versus $2 million). Note, the policies placed in the commercial fund under the independent strategy must be a subset of the policies placed in the commercial fund under the dependent strategy. Therefore, although the loss ratio under the independent strategy will tend to be lower, total profits may be higher under the dependent strategy.

Testing the significance of these results (table 2) parallels the non-SRA simulation; approximate randomization tests are performed in the same manner but the probabilities are fixed by fund. That is, for the commercial fund using the dependent strategy at the 70% coverage level, the probability is 96.73%. These tests indicate that if the insurance company incorporates SST when allocating its policies among the three funds, the company can realize economically and statistically significant lower pseudo loss ratios. Therefore, despite the implicit subsidies underlying the SRA, statistically and economically significant excess rents may be garnered by insurance companies through weather-based adverse selection.

Three caveats to our results deserve attention. First, the results represent a lower bound in that conditioning on local weather variables, which to an extent are determined by SST, necessarily leads to more pronounced results. Second, there exist bounds on the number of policies that may be placed in the assigned risk fund. For Texas, a maximum of 75% of the insurance company's total premium (in Texas) may be placed in the fund. In response, we repeated our analysis assuming the insurance company could only place policies in the developmental or commercial funds. That is, we assumed other policies from other crops in the state saturated their assigned risk fund. The results (available from the lead author) differed very little from the results presented. Third, winter wheat premium rates in Texas tend to be underestimated, which has led insurance companies to place most policies in the assigned risk fund. In attempting to rectify the underestimated rates, the RMA is constrained by bounds on changes in premium rates from one year to the next. In light of underestimated rates that currently exist, all simulations were repeated assuming the RMA rates were 70%, 80%, and 90% of the actuarially fair rates. Results from these simulations may also be obtained from the lead author. We chose to present the simulations using actuarially fair rates so that our results will not be dated by actions of the RMA to rectify the current problem.

Policy Implications

The objective of this analysis was to investigate if an insurance company could garner excess rents from weather-based adverse selection activities. Our investigation is particularly timely since political forces have fashioned crop insurance as the cornerstone of U.S. agricultural policy. We focused on Texas winter wheat and El Niño/La Niña weather events because we conjectured that if insurance companies were to engage in weather-based adverse selection, this might be their starting point given the forecastability of El Niño/La Niña, and data are easily accessible. We simulated, out-of-sample, reinsurance decisions during the 1978 through 1997 crop years and calculated pseudo loss ratios for the program, the RMA, and the insurance company. Although many complexities arose because of the convoluted sharing of the underwriting gains and losses of the policies, the empirical analyses reflected the realities imposed by the SRA. By design, the SRA enables the insurance company a return on its capital through the asymmetric sharing of the underwriting gains and losses. We focused on inflated returns or excess rents.

Our simulations indicated that statistically and economically significant excess rents may be garnered by an insurance company through weather-based adverse selection activities. Recall, however, that these results are unfortunately, but necessarily, conditioned on the use of county rather than individual farm yields. On the one hand, increased variability at the farm level will lessen the significance of the results, while on the other hand, conditioning on local climatic variables rather than sea surface temperatures should increase the significance of the results. Given that medium-term climatic forecasting is relatively new in the literature, there does not exist a sufficient number of years to empirically test whether insurance companies have adopted weather-based adverse selection strategies. Nonetheless, the economic and statistical significance of the results suggests that such behavior may become prevalent.

In addition to weather, other forms of asymmetric information exist on which an insurance company can adverse select. Given adverse selection is a zero-sum game, how can the RMA counter this? There is very little the RMA can do to reduce the informational asymmetries; to serve the farmers, the RMA must set rates well in advance, while an insurance company cannot make fund allocation decisions until after the closing sale date. Alternatively, the RMA could acknowledge, within the parameters of the SRA, that companies adverse select based on informational asymmetries. While insurance companies require a return on their capital, we illustrated that return may be significantly inflated through adverse selection based on informational asymmetries. The RMA could reduce the level of asymmetries in the sharing of the underwriting gains and losses so that the insurance company's return to capital, without the exploitation of asymmetric information, is insufficient. However, insurance companies that exploit the asymmetric information (for example, weather information) will recover a return equivalent to that of a private market with similar risks. In essence, the RMA could acknowledge that insurance companies exploit asymmetric information within their fund allocation decisions by altering the parameters of the SRA.

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Appendix A: Pseudo Loss Ratio

The purpose of this appendix is to outline the pseudo loss ratio referred to in the main text. In order to do so, it is necessary to define the following terms:

Q_{jt} ≡ indemnity paid for county j in time period t, which is $\max(0, \lambda y_{jt}^e - y_{jt})$;
$\hat{\pi}_{jt}$ ≡ RMA estimated premium rate for county j in time period t; and
w_j ≡ average number of acres insured over the 1995–98 period.

The loss ratio (LR) for the program over the 20-year period is defined as the ratio of total indemnities to total premiums and may be expressed as:

(A1)
$$LR = \frac{\sum_{t=78}^{97}\sum_{j=1}^{55} Q_{jt}w_j}{\sum_{t=78}^{97}\sum_{j=1}^{55} \hat{\pi}_{jt}w_j}.$$

We use 55 counties during the time period of the simulation, 1978 through 1997. As discussed in the main text, neither the RMA nor the insurance company accepts total liability of a policy under the SRA environment, and thus we are unable to associate the premium or indemnity of a policy with either. Therefore, the LR for the RMA and the insurance company cannot be calculated, although it still may be derived for the program overall. We construct a new measure, denoted "pseudo" loss ratio (PLR), which we define as the sum of annual underwriting losses divided by the sum of annual underwriting gains over the 20-year simulation period. First, consider the PLR of the program, which is expressed as:

(A2)
$$PLR = \frac{\sum_{t=78}^{97} \max\left(0, \sum_{j=1}^{55}(Q_{jt} - \hat{\pi}_{jt})w_j\right)}{\sum_{t=78}^{97} \max\left(0, \sum_{j=1}^{55}(\hat{\pi}_{jt} - Q_{jt})w_j\right)}.$$

The expression $\max(0, \Sigma_{j=1}^{55}(Q_{jt} - \hat{\pi}_{jt})w_j)$ represents underwriting losses if indemnities exceeded premiums, and zero otherwise for year t. Therefore, the sum over years represents net annual dollars paid over the 20-year period. Conversely, $\max(0, \Sigma_{j=1}^{55}(\hat{\pi}_{jt} - Q_{jt})w_j)$ represents underwriting gains if premiums exceeded indemnities, and zero otherwise for year t. Again, the sum over years represents net annual dollars received over the 20-year period.

The PLR mimics the LR in that both represent the ratio of dollars paid to dollars received. The LR, expressed in terms of premiums and indemnities, is the ratio of gross dollars paid to gross dollars received; the PLR, expressed in terms of underwriting gains and losses, is the ratio of net dollars paid to net dollars received.

We discuss two points (proven below) that bring credence to our PLR measure. First, if the LR is [<, =, >] one, the PLR should be and is [<, =, >] one. Intuitively, if total indemnities exceed total premiums over the 20 years (overall underwriting loss), in which case the LR is greater than one, then net annual underwriting losses must exceed net annual underwriting gains, in which case the PLR is greater than one. The converse follows the same reasoning. Second, if the LR is less [greater] than one, the PLR is less [greater] than the LR; this is a less intuitive result that relies on the fact that the difference between the denominator and numerator is identical for the LR and PLR, and both the numerator and denominator of the LR are greater than the numerator and denominator of the PLR, respectively.

■ RESULT 1. *If the LR is* [<, =, >] *one, the PLR is* [<, =, >] *one.*

Denote δ_t such that

$$\delta_t \equiv \begin{cases} 1 & \text{if } \sum_{j=1}^{55} Q_{jt}w_j > \sum_{j=1}^{55} \hat{\pi}_{jt}w_j \quad \text{(underwriting loss)}, \\ 0 & \text{otherwise} \quad \text{(underwriting gain)}. \end{cases}$$

Now, PLR can be rewritten as:

(A3)
$$PLR = \frac{\sum_{t=78}^{97} \delta_t \sum_{j=1}^{55} (Q_{jt} - \hat{\pi}_{jt}) w_j}{\sum_{t=78}^{97} (1 - \delta_t) \sum_{j=1}^{55} (\hat{\pi}_{jt} - Q_{jt}) w_j}.$$

By expanding and rearranging terms in the denominator,

(A4)
$$PLR = \frac{\sum_{t=78}^{97} \delta_t \sum_{j=1}^{55} (Q_{jt} - \hat{\pi}_{jt}) w_j}{\sum_{t=78}^{97} \delta_t \sum_{j=1}^{55} (Q_{jt} - \hat{\pi}_{jt}) w_j + \sum_{t=78}^{97} \sum_{j=1}^{55} (\hat{\pi}_{jt} - Q_{jt}) w_j}.$$

Now it may be seen that if LR [>, =, <] $1 \rightarrow \Sigma_{t=78}^{97} \Sigma_{j=1}^{55} (\hat{\pi}_{jt} - Q_{jt}) w_j$ [<, =, >] $0 \rightarrow PLR$ [>, =, <] 1. Alternatively, this may be seen by rearranging the expression of the LR in equation (A1):

(A5)
$$1 - LR = \frac{\sum_{t=78}^{97} \sum_{j=1}^{55} \hat{\pi}_{jt} w_j - \sum_{t=78}^{97} \sum_{j=1}^{55} Q_{jt} w_j}{\sum_{t=78}^{97} \sum_{j=1}^{55} \hat{\pi}_{jt} w_j}$$

(A6)
$$= \frac{\sum_{t=78}^{97} \sum_{j=1}^{55} (\hat{\pi}_{jt} - Q_{jt}) w_j}{\sum_{t=78}^{97} \sum_{j=1}^{55} \hat{\pi}_{jt} w_j}.$$

Thus, if LR [<, =, >] $1 \rightarrow 1 - LR$ [<, =, >] $0 \rightarrow \Sigma_{t=78}^{97} \Sigma_{j=1}^{55} (\hat{\pi}_{jt} - Q_{jt}) w_j$ [<, =, >] 0.

■ RESULT 2. *If the LR is less [greater] than one, the PLR is less [greater] than the LR.*

First, we express the numerator of the PLR from equation (A3) as:

(A7)
$$\sum_{t=78}^{97} \delta_t \sum_{j=1}^{55} (Q_{jt} - \hat{\pi}_{jt}) w_j = \sum_{t=78}^{97} \sum_{j=1}^{55} (Q_{jt} - \hat{\pi}_{jt}) w_j \delta_t$$

(A8)
$$= \sum_{t=78}^{97} \sum_{j=1}^{55} Q_{jt} w_j \delta_t - \sum_{t=78}^{97} \sum_{j=1}^{55} \hat{\pi}_{jt} w_j \delta_t$$

(A9)
$$\leq \sum_{t=78}^{97} \sum_{j=1}^{55} Q_{jt} w_j$$

because $\delta_t \leq 1 \; \forall \, t$, and $\Sigma_{t=78}^{97} \Sigma_{j=1}^{55} \hat{\pi}_{jt} w_j \delta_t \geq 0$. Similar reasoning illustrates that the denominator of the PLR is less than the denominator of the LR. Next, consider that the denominator less the numerator of the PLR as expressed in equation (A3) is:

(A10)
$$\sum_{t=78}^{97} \sum_{j=1}^{55} (\hat{\pi}_t - Q_{jt}) w_j = \sum_{t=78}^{97} \sum_{j=1}^{55} \hat{\pi}_{jt} w_j - \sum_{t=78}^{97} \sum_{j=1}^{55} Q_{jt} w_j,$$

which is the denominator less the numerator of the LR. To prove Result 2, we simplify matters by making the following notational changes:

$$PLR = \frac{\kappa_1}{\kappa_2},$$

where

$$\kappa_1 = \sum_{t=78}^{97} \delta_t \sum_{j=1}^{55} (Q_{jt} - \hat{\pi}_{jt}) w_j \quad \text{and} \quad \kappa_2 = \sum_{t=78}^{97} (1 - \delta_t) \sum_{j=1}^{55} (\hat{\pi}_{jt} - Q_{jt}) w_j;$$

and

$$LR = \frac{\zeta_1}{\zeta_2},$$

where

$$\zeta_1 = \sum_{t=78}^{97} \sum_{j=1}^{55} Q_{jt} w_j \quad \text{and} \quad \zeta_2 = \sum_{t=78}^{97} \sum_{j=1}^{55} \hat{\pi}_{jt} w_j.$$

We have shown that $\kappa_2 - \kappa_1 = \zeta_2 - \zeta_1$, $\kappa_1 \le \zeta_1$, and $\kappa_2 \le \zeta_2$. To prove Result 2, it is necessary to show the following:

$$\text{if } \frac{\zeta_1}{\zeta_2} > 1, \quad \text{then } \frac{\kappa_1}{\kappa_2} > \frac{\zeta_1}{\zeta_2};$$

$$\text{if } \frac{\zeta_1}{\zeta_2} < 1, \quad \text{then } \frac{\kappa_1}{\kappa_2} < \frac{\zeta_1}{\zeta_2}.$$

Consider that

(A11) $$\frac{\zeta_1}{\zeta_2} = \frac{\kappa_1 + (\zeta_1 - \kappa_1)}{\kappa_2 + (\zeta_2 - \kappa_2)},$$

where $(\zeta_1 - \kappa_1) = (\zeta_2 - \kappa_2) = \xi \ge 0$, and thus

(A12) $$\frac{\zeta_1}{\zeta_2} = \frac{\kappa_1 + \xi}{\kappa_2 + \xi}.$$

With a few lines of algebra and rearranging, we get

(A13) $$\frac{\zeta_1}{\zeta_2}\theta = \frac{\kappa_1}{\kappa_2},$$

where

$$\theta = \left(1 + \frac{\xi(\zeta_1 - \zeta_2)}{\zeta_1 \kappa_2}\right).$$

Therefore, if

$$\frac{\zeta_1}{\zeta_2} > 1 \rightarrow \theta > 1 \rightarrow \frac{\kappa_1}{\kappa_2} > \frac{\zeta_1}{\zeta_2}.$$

Conversely, if

$$\frac{\zeta_1}{\zeta_2} < 1 \rightarrow \theta < 1 \rightarrow \frac{\kappa_1}{\kappa_2} < \frac{\zeta_1}{\zeta_2}.$$

Unlike the LR, the PLR may be calculated in the SRA simulation by introducing the parameters of the SRA. Recall from the text discussion of the Standard Reinsurance Agreement, the underwriting gain/loss the insurance company retains is equal to the total underwriting gain/loss for the fund multiplied by two parameters:

(A14) $$\Omega_{IC}^k = \Omega^k \mu_1^k \mu_2^k,$$

where Ω_{IC}^k denotes the underwriting gain/loss retained by the insurance company for fund k, Ω^k denotes the underwriting gain loss for fund k, μ_1^k is the first parameter for fund k, and μ_2^k is the second parameter for fund k. The underwriting gain/loss retained by the RMA was defined as:

(A15) $$\Omega_{RMA}^k = \Omega^k (1 - \mu_1^k \mu_2^k),$$

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, whereas the second parameter (μ^k_2) is a function of the fund LR.

Unfortunately, it is necessary to introduce more notation. Define $\mathcal{F}^1_t$ as the set of policies the insurance company places in the assigned risk fund in year t, $\mathcal{F}^2_t$ as the set of policies the insurance company places in the developmental fund in year t, and finally $\mathcal{F}^3_t$ as the set of policies the insurance company places in the commercial fund in year t. Also, redefine δ_t such that

$$\delta^{IC}_t \equiv \begin{cases} 1 & \text{if } \sum_{i=1}^3 \sum_{j\in\mathcal{F}^k_t} Q_{jt} w_j \mu^k_{1t}\mu^k_{1t} > \\ & \quad \sum_{i=1}^3 \sum_{j\in\mathcal{F}^k_t} \hat{\pi}_{jt} w_j \mu^k_{1t}\mu^k_{1t} \qquad \text{(underwriting loss)}, \\ 0 & \text{otherwise} \qquad \text{(underwriting gain)}, \end{cases}$$

and thus the PLR for the insurance company is:

(A16) $$PLR_{IC} = \frac{\sum_{t=78}^{97} \delta^{IC}_t \sum_{k=1}^{3} \sum_{j\in\mathcal{F}^k_t} (Q_{jt} - \hat{\pi}_{jt}) w_j \mu^k_{1t}\mu^k_{2t}}{\sum_{t=78}^{97} (1 - \delta^{IC}_t) \sum_{k=1}^{3} \sum_{j\in\mathcal{F}^k_t} (\hat{\pi}_{jt} - Q_{jt}) w_j \mu^k_{1t}\mu^k_{2t}}.$$

Conversely, for the RMA we define:

$$\delta^{RMA}_t \equiv \begin{cases} 1 & \text{if } \sum_{k=1}^3 \sum_{j\in\mathcal{F}^k_t} Q_{jt} w_j (1 - \mu^k_{1t}\mu^k_{2t}) > \\ & \quad \sum_{k=1}^3 \sum_{j\in\mathcal{F}^k_t} \hat{\pi}_{jt} w_j (1 - \mu^k_{1t}\mu^k_{2t}) \qquad \text{(underwriting loss)}, \\ 0 & \text{otherwise} \qquad \text{(underwriting gain)}, \end{cases}$$

and thus the PLR for the RMA is:

(A17) $$PLR_{RMA} = \frac{\sum_{t=78}^{97} \delta^{RMA}_t \sum_{k=1}^{3} \sum_{j\in\mathcal{F}^k_t} (Q_{jt} - \hat{\pi}_{jt}) w_j (1 - \mu^k_{1t}\mu^k_{2t})}{\sum_{t=78}^{97} (1 - \delta^{RMA}_t) \sum_{k=1}^{3} \sum_{j\in\mathcal{F}^k_t} (\hat{\pi}_{jt} - Q_{jt}) w_j (1 - \mu^k_{1t}\mu^k_{2t})}.$$

Finally, because of the three funds, δ^{IC}_t and δ^{RMA}_t may simultaneously be 1, simultaneously be 0, or one may be 0 and the other 1.

Appendix B: Generalized Additive Models

Estimating an additive model finds the projection onto the closest linearly additive subspace of a generalized ρ-dimensional Hilbert space. The interested reader will find a thorough treatment of generalized additive models in Buja, Hastie, and Tibshirani. Define $\mathcal{H}_{add} = \mathcal{H}_t + \mathcal{H}_s$, which are closed subspaces of $\mathcal{H}_{y,t,s}$. We minimize

(A18) $$E(y - m(t, s))^2$$

subject to $m(t, s) = m_1(t) + m_2(s) \in \mathcal{H}_{add}$ as opposed to the looser restriction $m(t, sst) \in \mathcal{H}$. In a fully nonparametric setting where $m(t, sst) \in \mathcal{H}$, we have $m(t, sst) \in E(Y\,|\,t, s)$. Restricting the class of functions to $\mathcal{H}_{add}$ recovers the closest additive approximation to the function $E(Y\,|\,t, s)$. Ideally, $E(Y\,|\,t, s) \in \mathcal{H}_{add}$. Although the additive model is only consistent for a restricted class, the convergence of the unrestricted model decreases rapidly as the number of independent variables increases. The estimator $\hat{m}(X)$ is

$O(n^{-(2/4+d)})$, where d is the dimension of X (Härdle). In our case, $\hat{m}(t, s)$ is $O(n^{-1/3})$, whereas $\hat{m}_1(t)$ and $\hat{m}_2(s)$ can be estimated with the optimal one-dimensional rate $O(n^{-2/5})$ assuming $E(Y|t, s) \in \mathcal{H}_{add}$.

There does not exist any theoretical or empirical evidence in either the agronomy or climatology literature to suggest that $E(Y|t, s) \notin \mathcal{H}_{add}$. Casual observation suggests SST and the technology component of yields are uncorrelated; research and development expenditures determine the technology set and are independent of SST. Why was it necessary to estimate the insurance company model in two stages? Unless the realized SSTs produced orthogonality for certain columns of the projection matrix, $\hat{m}_2(s)$ would pick up some of the temporal process not adequately approximated by the one-knot linear spline (Buja, Hastie, and Tibshirani). We chose to avoid this minimal contamination so that the significance of SSTs in modeling yields is not biased upward, even slightly.

Recently, there has been a significant amount of theoretical literature on estimating the generalized additive model. Originally, backfitting procedures forwarded by Buja, Hastie, and Tibshirani were employed. Hastie and Tibshirani (1987, 1990) noted that these procedures worked fairly well in many empirical applications. The backfitting algorithm estimates each component holding the other fixed and then iterates until the estimates converge. The current estimate of $\hat{m}_2(s)$ is updated by smoothing the partial residuals $y_t - (\bar{y} + \hat{m}_1(t))$ against s.

Most recently, theoretical properties of backfitting methods have been investigated in Neilsen and Linton. Tjøstheim and Auestad, and Linton and Neilsen introduced an alternative approach using marginal integration with kernel smoothers. Finally, Fan, Härdle, and Mammen have provided an approach for direct estimation of low-dimensional additive models. Rather than the marginal integration approach, we employed backfitting procedures to estimate the components. In our application, where the components are independent, the backfitting algorithm converged very quickly (generally within 4–6 iterations) as expected; problems arise when the independent variables are correlated.

Appendix C: Insurance Company Allocation Decision

This appendix outlines the insurance company's allocation decision of policies among the three funds: assigned risk, developmental, and commercial. We first illustrate that the optimal strategy for allocating policies among funds is not analytically tractable because of dimensionality problems. Second, we detail the two (albeit suboptimal, but dimension-reducing) strategies, termed "independent" and "dependent." Both strategies reduce a large dimensional problem into a single dimension.

Optimal Strategy

In our case study, the insurance company has 55 policies to allocate among the three funds given the funds are cleared or settled each year. In reality, the insurance company has significantly more policies to allocate. The optimal strategy chooses the allocation scheme that maximizes expected profits among all possible allocation schemes. Two problems plague the optimal strategy. First, the number of possible allocation schemes to evaluate is unmanageable ($3^{55} = 1.74E + 26$). Second, there do not exist sufficient data to estimate expected profit for any allocation scheme. To illustrate, assume a particular allocation scheme yields sets $\mathcal{F}_1$, $\mathcal{F}_2$, and $\mathcal{F}_3$, where again $\mathcal{F}_1$ is the set of policies in the assigned risk fund, $\mathcal{F}_2$ is the set of policies in the developmental fund, and $\mathcal{F}_3$ is the set of policies in the commercial fund. The expected profit of this scheme is the sum of the expected profit for each fund. Recall from the main text that the insurance company's profit for fund k is

$$\Omega_{IC}^k = \sum_{j \in \mathcal{F}_k} (\hat{\pi}_j - Q_j)\mu_1^k \mu_2^k, \tag{A19}$$

where $\Sigma_{j \in \mathcal{F}_k}(\hat{\pi}_j - Q_j)$ denotes the underwriting gain/loss for fund k, μ_1^k is the first parameter for fund k, and μ_2^k is the second parameter for fund k. Also recall the first parameter (μ_1^k) represents an ex ante choice variable for the insurance company, while the second parameter (μ_2^k) is a function of the fund loss ratio (LR). That is,

$$\mu_2^k = g_k\left(\frac{\sum_{j\in\mathscr{F}_k} Q_j}{\sum_{j\in\mathscr{F}_k} \hat{\pi}_j}\right),$$

where g_k is depicted in figure 1. Thus, we need the joint density of $Q_j\,\forall j\in\mathscr{F}_k$ to recover the LR density. Note that $Q_j = \max(0, \lambda y_j^e - y_j)$, and thus has a mixed (discrete and continuous parts) density which may be recovered from a transformation of the density of y_j. Therefore, to recover the LR density, we require an estimate of the joint density of $y_j\,\forall j\in\mathscr{F}_k$. There exist insufficient data to estimate the ρ_k dimensional density, where ρ_k is the cardinality of $\mathscr{F}_k$. We overcome both problems by making dimension-reducing assumptions on the joint density of the yields.

Independent Strategy

Recall, the insurance company's profit from fund k is

(A20) $$\Omega_{IC}^k = \sum_{j\in\mathscr{F}_k} (\hat{\pi}_j - Q_j)\mu_1^k\mu_2^k,$$

and therefore the contribution to total profit of a particular policy, say j belonging to fund k, which we denote Γ_j^k, is

(A21) $$\Gamma_j^k = (\hat{\pi}_j - Q_j)\mu_1^k\mu_2^k.$$

By assuming y_j is independent of the fund LR (we discuss this assumption below), then

(A22) $$E(\Gamma_j^k) = \left(\hat{\pi}_j - E[Q_j]\right)\mu_1^k E[\mu_2^k],$$

where $E[Q_j]$, the expected indemnity, is, with respect to the insurance company, density $\hat{f}_{Y_j}(y_j|I_{IC})$. Therefore, if $(\hat{\pi}_j - E[Q_j]) > 0$, the insurance company believes the policy to be overpriced and maximizes $E[\Gamma_j^k]$ by placing the policy in the fund which maximizes $E[\mu_2^k]$. Conversely, if $(\hat{\pi}_j - E[Q_j]) < 0$, the insurance company believes the policy to be underpriced and maximizes $E[\Gamma_j^k]$ by placing the policy in the fund which minimizes $E[\mu_2^k]$. In general, to recover $E[\mu_2^k]$ for fund k, we need the joint density of the yields associated with the policies belonging to the fund. However, the support for the random variable $0.2\mu_2^1$, which is the insurance company's share of the assigned risk fund when $\mu_1^1 = 0.2$ is specified, does not intersect the support for the random variable μ_2^3, which is the insurance company's share of the commercial fund when $\mu_1^3 = 1.0$. That is, $E[0.2\mu_2^1] < E[\mu_2^3]$ almost surely.[19] Therefore, if policy j is overpriced (gains expected), then $E[\Gamma_j^k]$ is maximized when $k = 3$ (policy placed in the commercial fund) and the insurance company sets $\mu_1^3 = 1.0$ (recall from the main text that $\mu_1^3 \in [0.5, 1.0]$). Conversely, if policy j is underpriced (losses expected), then $E[\Gamma_j^k]$ is maximized when $k = 1$ (policy placed in the assigned risk fund) and the insurance company sets $\mu_1^1 = 0.2$ (recall that $\mu_1^1 \in [0.2, 1.0]$). The independence assumption leads to a strategy where policies estimated to be underpriced are placed in the assigned risk fund while policies estimated to be overpriced are placed in the commercial fund.

Dependent Strategy

The second strategy assumes the yield of a given policy and the loss ratio for the fund in which it is placed are perfectly dependent. Specifically, we assume that the loss ratio of policy j, denoted LR_j, equals the loss ratio (LR) of the fund almost surely. Again, recall that the contribution of policy j belonging to fund k to the total profit of the insurance company from fund k is:

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[19] Unfortunately, it cannot be said that $E[\mu_1^1\mu_2^1] < E[\mu_1^2\mu_2^2] < E[\mu_1^3\mu_2^3]$ almost surely, although by design this inequality generally holds.

(A23) $$\Gamma_j^k = (\hat{\pi}_j - Q_j)\mu_1^k \mu_2^k,$$

where $\mu_2^k = g_k\,(LR)$, but $LR = LR_j$ almost surely. Therefore, LR is a function of the indemnity payment Q_j. Since $Q_j = \max(0, \lambda y_j^e - y_j)$,

$$LR_j = \max\left(0, \frac{\lambda y_j^e - y_j}{\hat{\pi}_j}\right),$$

which is a mixed (discrete and continuous parts) density resulting from a univariate transformation of $\hat{f}_{Yj}(y_j | I_{IC})$.[20] Therefore, substituting Q_j and LR_j yields

(A24) $$E[\Gamma_j^k] = \int_0^\infty \left(\hat{\pi}_j - \max(0, \lambda y_j^e - y_j)\right)\mu_1^k \mu_2^k \left(\max\left(0, \frac{\lambda y_j^e - y_j}{\hat{\pi}_j}\right)\right) f_{Yj}\left(y_j | I_{IC}\right) dy_j.$$

Unlike the independent strategy, the dependent strategy takes into account the implicit subsidies brought about by the asymmetric sharing of the underwriting gains and losses. However, this strategy tends to overestimate the subsidy effect; mixing of indemnity payments across policies in the fund tends to lower the implicit subsidy.

As mentioned, the funds are cleared by state. That is, any policies sold in a state are placed in one of three funds. Consequently, an insurance company will have policies from not just different regions of a state in a particular fund, but from different crops as well. Therefore, in a state not dominated by one or two crops where Q_j is not very dependent across space and crop, the independent assumption would be realistic. However, in a state dominated by a few highly correlated crops, with respect to one another and space, the dependent assumption could be more realistic.

[20] The LR_j density has mass at support point 0 equal to $\int_{\lambda y^e}^\infty \hat{f}_{Yj}(y_j|I_{IC})\,dy_j$ and continuous part derived from the transformation

$$LR_j = \frac{\lambda y_j^e - y_j}{\hat{\pi}_j} \text{ from } \hat{f}_{Yj}(y_j|I_{IC}) \text{ for } \lambda y_j^e > y_j.$$