MODELING TEXAS DRYLAND COTTON YIELDS, WITH APPLICATION TO CROP INSURANCE ACTUARIAL RATING

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Abstract

Texas dryland upland cotton yields have historically exhibited greater variation and more distributional irregularities than the yields of other crops, raising concerns that conventional parametric distribution models may generate biased or otherwise inaccurate crop insurance premium rate estimates. Here, we formulate and estimate regime-switching models for Texas dryland cotton yields in which the distribution of yield is conditioned on local drought conditions. Our results indicate that drought-conditioned regime-switching models provide a better fit to Texas county-level dryland cotton yields than conventional parametric distribution models. They do not, however, generate significantly different Group Risk Plan crop insurance premium rate estimates.

Key words: cotton, yield distribution, regime-switching, crop insurance, group risk plan, actuarial rating, adverse selection.

JEL Classifications: Q10, Q14, Q18

The modeling of crop yield distributions continues to receive considerable attention in the academic crop insurance and agricultural risk management literature. The importance of properly modeling yield distributions stems in part from the dramatic growth in participation in the U.S. crop insurance program after the enactments of the 1994 Crop Insurance Reform Act and the 2000 Agricultural Risk Protection Act (Goodwin, Vandeveer and Deal; Glauber). In 2004, total coverage under the program reached $46.6 billion, an increase of 67% over 1998 levels.

Accurate assessment of yield distributions, particularly their lower tails, is necessary for precise computation of crop insurance premium rates. Inaccurate rates can lead to adverse selection, in which producers whose rates are low relative to expected indemnities participate in greater proportion than producers whose rates are high relative to expected indemnities. Adverse selection raises the ratio of indemnities paid to the premiums collected, undermining the actuarial performance of the federal crop insurance and reinsurance program (Skees and Reed; Miranda; Goodwin).

Numerous studies have highlighted the challenges associated with the statistical modeling of crop yields for the rating of crop insurance (Day; Gallagher; Taylor; Goodwin and Ker; Just and Weninger; Ker and Goodwin; Ramirez, Misra and Field; Ker and Coble; Atwood, Shaik and Watts; Sherrick et al.). Most published studies have developed statistical models of yields for crops and regions in which yield variation is relatively regular and for which crop abandonment is relatively rare (e.g., Iowa corn). In most of these studies, standard parametric distribution methods are applicable and the debate centers on the appropriateness of one standard distributional form versus another

(e.g., the normal versus the beta distribution) (Day; Gallagher; Taylor; Just and Weninger; Ramirez, Misra and Field; Atwood, Shaik and Watts; Sherrick et al.).

However, very little attention has been given to the modeling of yield distributions for crops and regions in which yields exhibit highly irregular behavior. Of particular interest are crops and regions that exhibit high post-planting abandonment rates in years of unfavorable weather. In such regions, near-zero individual and aggregate yields are observed with some frequency, making common unimodal continuous probability distributions inadequate for explaining yield variation. The correct choice of distributional form for the yields of such crops remains an unsettled but important question.

In this paper, we undertake a statistical case study of Texas dryland upland cotton, which in recent years has exhibited poor actuarial performance under the U.S. crop insurance program. During the 1989-2004 period, indemnities paid to Texas cotton producers exceeded premiums collected in every year but 1994 (see Figure 1) and the typical insured Texas cotton producer received a $2.79 of indemnity per dollar of premium paid. During this period, Federal subsidies and premium discounts to Texas cotton producers averaged $116 millions per year, accounting for 12% of total subsidies provided by the federal crop insurance program nationally (Risk Management Agency). Even when federal premium subsidies were taken into account, indemnities paid to Texas cotton producers exceeded premiums collected in eleven of sixteen years between 1989 and 2004.

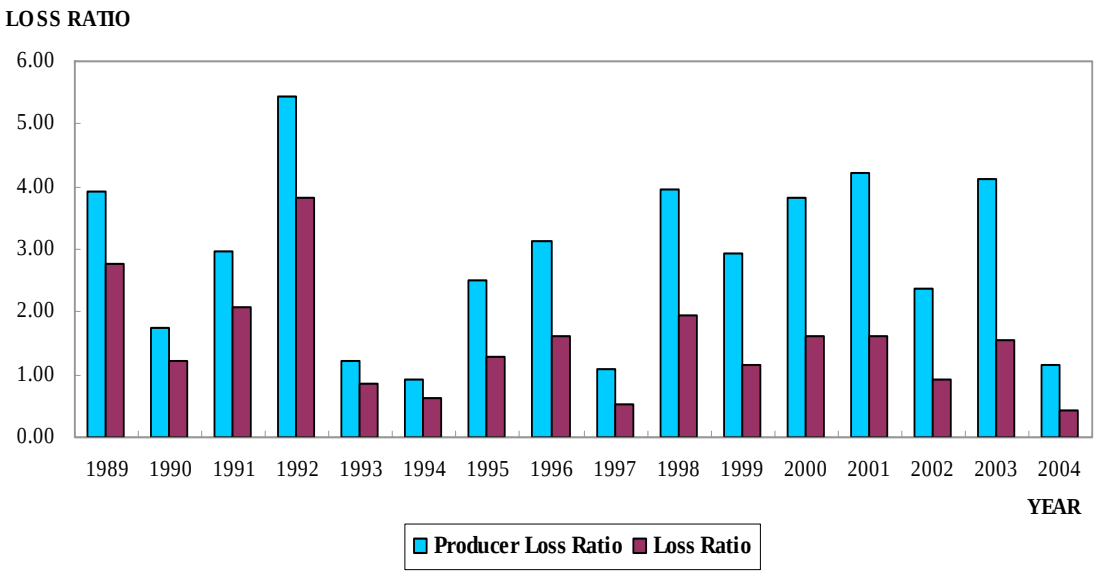

Figure 1. Producer Loss Ratio (Indemnities Divided by Producer-Paid Premiums) vs. Loss Ratio (Indemnities Divided by Total Premium, Including Federal Subsidies) for Texas Dryland Upland Cotton, 1989-2004

Texas dryland cotton yields exhibit greater variation and irregularities than yields of other major crops. For example, between 1972 and 2004, the average coefficient of variation of Texas county-level cotton yields was 38%, as compared to 19% for Iowa corn yields. In addition, Texas cotton acreage abandonment rates averaged around 13%, as compared to 4% for Iowa corn. Thus, the conventional parametric distributions that may be used to successfully model Iowa corn yields may not provide sufficient flexibility to accurately capture the idiosyncrasies of Texas cotton yields.

In this paper, we compare the performance of alternative distributional models for Texas dryland cotton yields. In order to establish a baseline, we use historical county-level yield data to fit conventional parametric distributions that have been used or have

otherwise been proposed to rate crop insurance products: the normal, lognormal, and beta distributions. We then propose and estimate alternative regime-switching models in which the distribution of yield is conditioned on exogenous indicators of drought. We also examine the implications of the various distributional forms for the computation of actuarially fair Group Risk Plan (GRP) crop insurance premium rates.

The paper is organized as follows: in the next section, we discuss the Texas county-level dryland cotton yield data used in the analysis and the methods used to extract exogenous secular trends from the data. In the subsequent section, we fit the detrended yield data to common parametric distributional forms. In the following section, we introduce and estimate a pair of regime-switching models for detrended yields. In the final section, the implications of distributional assumptions for the computation of GRP fair premium rates are analyzed.

Detrending Yields

Our research employs 1972-2004 Texas upland cotton county-level yields published by the National Agricultural Statistics Service (NASS). Cotton production practices in Texas include irrigated and dryland (i.e., non-irrigated) cotton. Our analysis focuses on dryland cotton yields in forty-five Texas counties in which dryland practices are dominant. For each of these counties, thirty-three annual dryland cotton yield observations are utilized.

Secular trends in yields due to exogenous technical change pose a challenge for the modeling of yield distributions and for the rating of crop insurance products (Ker and Goodwin; Ker and Coble; Goodwin and Mahul; Ozaki et al.). Lack of sufficient data

compounds the problem, raising uncertainty about the exact form of the trend and the yield distribution (Goodwin and Mahul; Ozaki et al.).

We initially considered several detrending methods suggested in literature, including first- and higher-ordered polynomials (Atwood, Shaik and Watts; Sherrick et al.; Goodwin and Mahul; Oazki et al.) and autoregressive integrated moving average models (Goodwin and Ker; Ker and Goodwin). However, none of these methods proved satisfactory, due primarily to overfitting problems.

For the purposes of this study, we elected to use a bi-linear spline to model yields trends. In general, this detrending method generates higher R-square goodness-of-fit measures than the aforementioned methods. The bi-linear spline model allows up to two distinct linear trends in the data. In particular, the trend yield in period *t*, $\hat{y}_t$, is presumed to be a function of time:

$$(1) \qquad \hat{y}_t = f(t) = y^* + \beta_1 \min(0, t - t^*) + \beta_2 \max(0, t - t^*).$$

The breakpoint t^* between linear segments and the slopes β_1 and β_2 of the linear segments are endogenously determined and estimated by nonlinear least squares. The bi-linear spline model appeared to be free of the overfitting problems exhibited by more flexible models, but provided a necessary additional degree of flexibility not offered by a simple linear trend model. In this analysis, the breakpoint year for most counties occurs in the late 1980s.

Given the trend yields implied by the bi-linear spline model, detrended county-level Texas dryland cotton yields were computed by normalizing observed yields to 2004 equivalents as follows:

$$(2) \qquad y_t^d = y_t \times \frac{\hat{y}_{2004}}{\hat{y}_t}.$$

Here, y_t^d is the detrended yield in year *t*, y_t is the yield realized in year *t* and $\hat{y}_t$ is the fitted trend yield in year *t*.

Table 1 shows descriptive statistics for the detrended yields. Contrary to the findings of negative skewness in most studies involving other crops (Gallagher; Goodwin and Ker), our detrended Texas dryland cotton yields exhibit positive skewness in 35 of 45 counties, suggesting that probability is amassed at the lower tail of the yield distribution. Based on White's test, homoscedasticity could be rejected at a 5% significance level in only 6 of the 45 counties, indicating that heteroscedasticity is not a concern.

[Place Table 1 Approximately Here]

Parametric Distribution Models

In order to establish a baseline against which to evaluate the effectiveness of alternative distribution models for Texas county-level dryland cotton yields, we begin by fitting common parametric distributions to the detrended county-level yields. The three parametric distributions examined are the normal, lognormal, and beta distributions.

Common parametric distributions often present problems for the modeling of yield distributions and in the rating of crop insurance products. The beta distribution, for example, is very sensitive to assumptions about the maximum and minimum possible yield, often producing unreasonable "U-shapes" when the data exhibits substantial variation (Ker and Coble; Goodwin and Mahul). The lognormal distribution is often criticized for possessing positive skewness, a property generally believed not be exhibited by yield distributions.

Maximum likelihood estimates for the parameters and goodness-of-fit statistics for each of the three parametric distributions are presented in Table 2. To assess goodness-of-fit, we compute the Anderson-Darling statistic (A^2)

$$(3) \qquad A^2 = -n - (1/n)\sum_{i=1}^{n}(2i-1)\left[\ln\left(\hat{F}(y_i)\right) + \ln\left(1-\hat{F}(y_{n+1-i})\right)\right]$$

where $\hat{F}(y_i)$ is the fitted cumulative probability density of the specified distribution at a given observation and *n* is the sample size. The Anderson-Darling statistic allows one to test whether the data is generated by a specified distribution and its critical values depend upon the specific distribution that is tested[1]. An alternative to the chi-square and Kolmogorov-Smirnov *D* goodness-of-fit tests, the Anderson-Darling statistic A^2 places more weight on the tail of the distribution.

[Place Table 2 Approximately Here]

As seen in Table 2, the beta distribution is rejected at a 10% significance level for 12 of 45 counties while the normal distribution is rejected for 8 of 45 counties and the lognormal distribution is rejected for 34 of 45 counties. Based on the Anderson-Darling test, the parametric distributions may be ranked from best to worst fitting as follows: 1) normal distribution, 2) beta distribution and 3) lognormal distribution.

Figure 2 illustrates the estimated dryland cotton yield distributions for Howard County. In the figure, the histogram represents the historical detrended yields and the plotted curves represent the fitted parametric distributions. This figure suggests bi-modality of cotton yields for Howard County. This figure further suggests that parametric distributions provide a poor fit for the lower tails of the yield distribution.

[1] The parametric distributions were estimated using SAS, which automatically generates the critical values of the Anderson-Darling statistic.

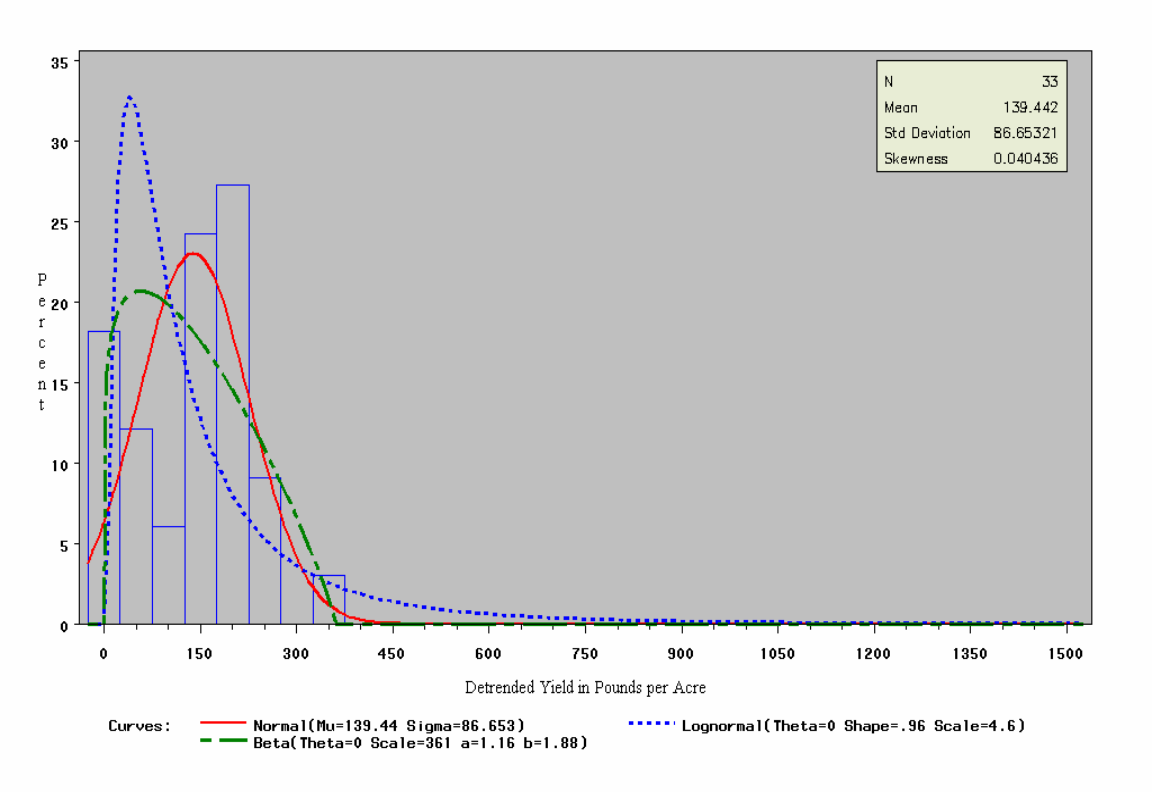

Figure 2. Fitted Parametric Distributions for Dryland Upland Cotton Yields in Howard County, Texas

Regime-Switching Models

To address suspected misspecification problems associated with conventional parametric distributions, we estimate an alternative regime-switching model that is an extension of Quandt's λ and Goldfeld and Quandt's *D* mixture models. The basic idea underlying this approach is that the probability distribution of the yield may be conditioned on exogenous environmental conditions or regimes. Under different regimes, the parameters of the conditional yield distribution may differ.

Specifically, we posit that the probability distribution of the yield depends upon whether drought conditions exist. The yield y_t is drawn from a normal distribution with

mean μ_1 and variance σ_1^2 if drought condition exists, or from a normal distribution with mean μ_2 and variance σ_2^2, otherwise. Whether drought conditions exist depends upon a pair of exogenous random variables, one observable and the other unobservable. In particular, we assume that a drought occurs if, and only if, $z_t + \tilde{\varepsilon}_t < z^*$ where z_t is an observable index of drought conditions during the critical month of the growing season, z^* is an unknown critical threshold to be estimated, and $\tilde{\varepsilon}_t$ is an unobserved error term, assumed to be an i.i.d. normal random variable with zero mean and variance $\sigma_{\tilde{\varepsilon}}^2$.

Under this assumption, the log likelihood of observing yield y_t in year *t*, conditional on contemporaneously observed drought index z_t, is

$$(4) \qquad l\left(\mu_1, \mu_2, \sigma_1^2, \sigma_2^2, z^*, \sigma_{\tilde{\varepsilon}} \middle| y_t, z_t\right)$$

$$= \sum_{t=1}^{T} \log\left[F\left(z^* - z_t; 0, \sigma_{\tilde{\varepsilon}}\right) f\left(y_t; \mu_1, \sigma_1^2\right) + F\left(z_t - z^*; 0, \sigma_{\tilde{\varepsilon}}\right) f\left(y_t; \mu_2, \sigma_2^2\right)\right]$$

where *F* and *f* are, respectively, the cumulative distribution function and the probability density function of a standard normal variable.

We consider two alternative indices of drought conditions, both of which are published by the National Climatic Data Center (NCDC): 1) average rainfall throughout the climate division in which the county is located and 2) the Palmer Drought Severity Index for the climate division in which the county is located. In all cases, the values of the indices during the critical third month of the cotton growing season are used to assess drought conditions. Since the month in which cotton is planted in Texas varies across geographic region, ranging from February in South Texas to June in the Plains Region, the critical third month depends upon where the county is located.

A challenge arises in computing estimates for the regime switching model due to the high irregularity of the likelihood function. In order to rule out globally suboptimal local optima, an extensive grid search was conducted in both z^* and $\sigma_{\tilde{\varepsilon}}$. Maximum likelihood estimates for the two regime-switching models are reported in Tables 3 and 4. Hereafter the two regime-switching models are referred to as the "rainfall index" and the "Palmer index" regime-switching models. In the two regime-switching models, the maximum likelihood estimates for $\sigma_{\tilde{\varepsilon}}$ are zero in some counties, which implies the two regimes are perfectly discriminated by the observed index variable.

One would expect to observe lower yields if drought condition exists; i.e. $\mu_1 < \mu_2$. However, the possibility that μ_1 exceeds μ_2 cannot be completely ruled out. This is the case, for example, for Refugio County for both regime-switching models and for Hill County for the Palmer index regime-switching model. In practice, a low yield can arise not only with extreme drought but also with extreme moisture. The critical thresholds, z^*, in the counties where $\mu_1 < \mu_2$ in Tables 3 and 4 are very high, indicating that in these counties, yields are drawn from a distribution associated with very high rainfall.

[Place Table 3 Approximately Here]

[Place Table 4 Approximately Here]

In order to evaluate the adequacy of our regime-switching models, we limit the analysis to a comparison between the models and the normal distribution model, which was found previously to provide the best fit among conventional parametric distributions. Limiting the analysis to this comparison has the advantage that the normal distribution model may be viewed as a parametric restriction of the regime-switching model, allowing the comparison to be performed using the likelihood ratio test. The likelihood ratio

equals the maximum sample likelihood under the restriction of normality divided by the maximum sample likelihood without the restriction. The negative of twice the log of likelihood ratio is asymptotically a Chi-square statistic with 3 degrees of freedom under the null hypothesis that the yields are normally distributed.

Tables 3-4 present the likelihood ratio tests of the regime-switching models against the alternative of a normal distribution. At the 5% significance level, the normal distribution model may be rejected in favor of the rainfall index regime-switching model in 39 of 45 counties and in favor of the Palmer index regime-switching model in 37 of 45 counties. These results suggest that in most Texas counties, a regime-switching distribution explains the variation cotton yields significantly better than the normal distribution (see Figure 3 and 4).

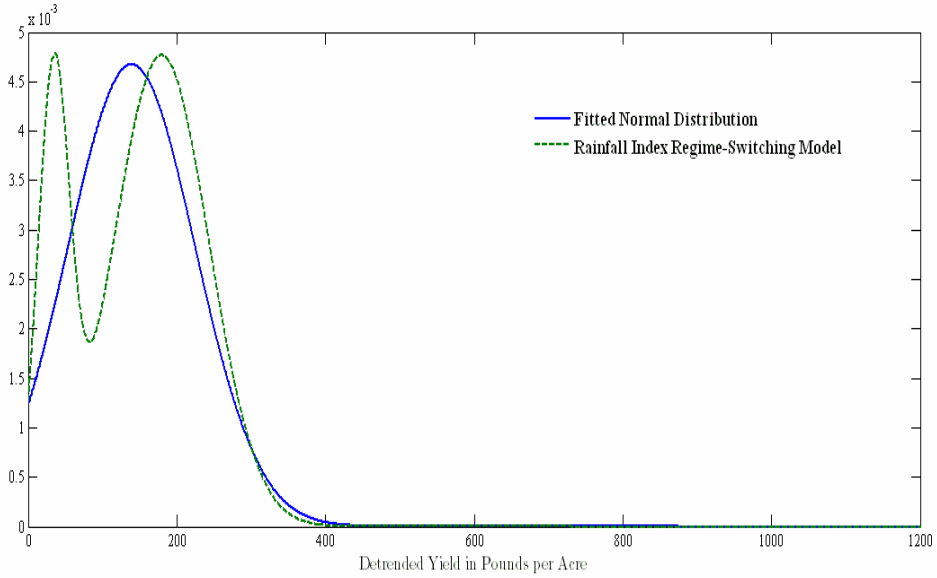

Figure 3. Fitted Distributions for Dryland Upland Cotton Yields in Howard County, Texas

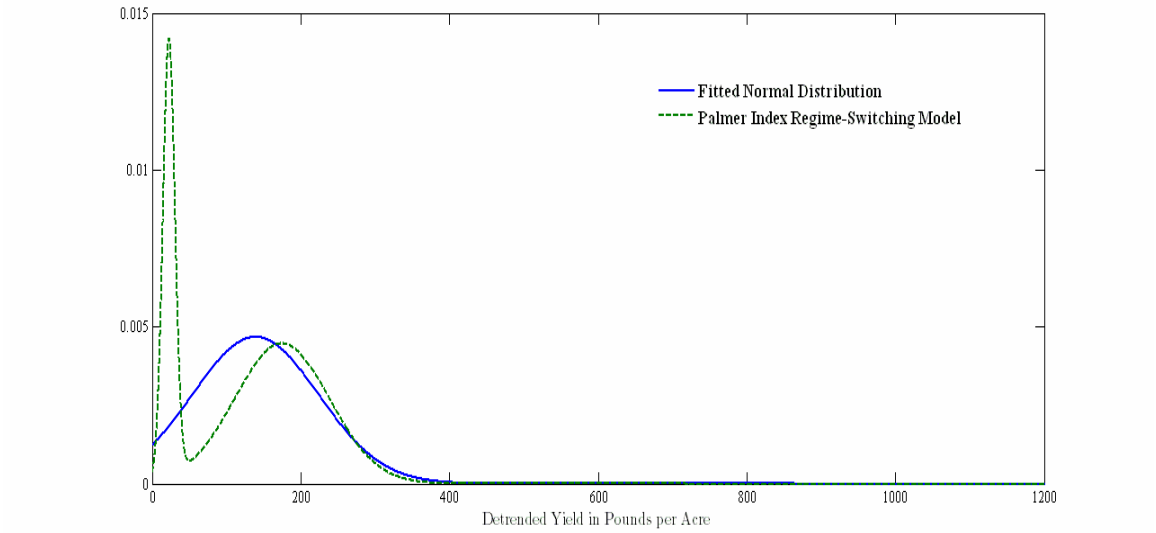

Figure 4. Fitted Distributions for Dryland Upland Cotton Yields in Howard County, Texas

Rating Crop Insurance Contract

Our research has been motivated in part by the need to compute accurate crop insurance rates, which depend largely upon how well the lower tail of the yield distribution is captured. Fair premium rates for Group Risk Plan (GRP) crop insurance computed using regime-switching models are now compared to the rates computed using normal and empirical distribution methods similar to those currently employed by the Risk Management Agency.

A GRP insurance contract pays an indemnity if and only if the realized county yield $\tilde{y}$ falls below a specified trigger yield, which is set equal to an elected coverage level α times the published expected area yield y^e. Specifically, per dollar of coverage,

$$(5) \qquad Indemnity = \max\left\{0, \frac{\alpha y^e - \tilde{y}}{\alpha y^e}\right\}.$$

Indemnities and premium rates are based on published National Agricultural Statistics Service county yield estimates. The expected county yield for Group Risk Plan set equal to the historical average NASS county yield, adjusted for secular trend.

Given a specific probability density function for county yields *f*, the fair premium rate, that is the expected indemnity per dollar of coverage, is computed as

$$(6) \qquad \pi = \frac{1}{\alpha y^e}\int_0^{\alpha y^e} \left(\alpha y^e - y\right) f\left(y\right) dy$$

RMA also applies geographic smoothing methods are applied to GRP premium rates, rendering a final premium rate for each county that is as a weighted average of the raw premium rates for the county and its neighbors (Skees, Black and Barnett).

Table 5 provides a comparison of GRP rates at the 85% coverage level, for the 2006 crop year, computed using an empirical distribution model, a normal distribution model, a rainfall index regime-switching model, and a Palmer index regime-switching model. Among the 45 Texas counties examined, the regime-switching models appear to produce slightly higher GRP premium rates than the empirical and normal distribution models. As seen in Table 5, the average GRP premium rates across all 45 counties are 15.2 and 15.1 percent for the Palmer and rainfall index regime-switching models, respectively, and 14.6 and 14.7 for the empirical and normal distribution models, respectively.

However, the most striking feature of the results presented by Table 5 is that there appears to be very little difference among the GRP premium rates computed using alternative distributional forms. In order to assess formally whether the differences in computed premium rates are statistically significant, we employed nonparametric

bootstrapping techniques to compute estimates of the standard errors of the differences among the various computed premium rates. Given the estimated standard errors, we tested the differences between the rates generated by the empirical distribution and the rates generated by the normal distribution model, the rainfall index regime-switching model, and Palmer index regime-switching model. Of the 135 pairs of premium rate estimates compared, only 5 pairs were found to differ at the 5% level of significance (these are indicated by an asterisk in Table 5). Thus, we find no evidence that regime-switching models produce GRP premium rates that are significantly different from those computed using empirical or normal distribution models, suggesting that there is no compelling reason to use more complicated regime-switching models to compute Texas dryland cotton crop insurance premium rates.

[Place Table 5 Approximately Here]

Summary and Conclusions

In this paper, we have undertaken a statistical case study of Texas dryland cotton yields, which historically have exhibited greater variation and distributional irregularities than the yields of other crops grown in other parts of the country As a more flexible alternative to conventional unimodal parametric distribution models, we estimated regime-switching models in which the distribution of yield is conditioned on local drought conditions as measured by rainfall or the Palmer Drought Severity Index. A comparison of the fit provided by the various distributional forms based on likelihood ratio and Anderson-Darling goodness-of-fit tests indicated that regime-switching models

provide a significantly better fit to observed Texas dryland cotton yields than more conventional parametric models.

Our findings, however, indicate that the Group Risk Plan premium rates computed under alternative distributional assumptions do not systematically or significantly differ from one another. These findings suggest that although regime-switching models provide a more accurate description of Texas dryland county yield distributions than parametric distributions overall, they possess no clear advantage in describing the lower tail of the distribution, which is the only portion of the distribution that is relevant for crop insurance actuarial ratemaking. Thus, the empirical and normal distribution models commonly used in actuarial ratemaking appear to provide reasonable premium rate estimates and are thus arguably preferable to the regime-switching models examined here due to their simplicity.

Table 1. Summary Statistics for 1972-2004 Detrended Dryland Upland Cotton County-Level Yields, Selected Texas Counties (Yields Measured in Pounds per Acre)

COUNTY	Mean	Standard Deviation	Minimum	Maximum	Skewness	Kurtosis
ANDREWS	126.9	84.1	15.8	319.3	0.83	-0.23
BAILEY	153.6	106.6	14.2	436.4	0.81	0.47
BORDEN	189.7	115.4	11.7	482.6	0.30	-0.40
BRISCOE	163.9	82.7	45.3	354.9	0.56	-0.45
CAMERON	245.8	120.0	31.3	540.9	0.25	0.09
CHILDRESS	244.1	92.6	49.1	415.9	-0.02	-0.34
COCHRAN	179.9	129.4	7.3	488.0	0.88	0.34
COLLINGSWORTH	264.3	95.1	116.1	473.5	0.58	-0.20
CONCHO	241.7	115.9	4.3	585.4	0.54	1.35
COTTLE	199.8	80.6	36.9	376.4	-0.10	0.23
CROSBY	261.2	102.7	99.7	567.7	0.58	0.98
DAWSON	187.8	101.7	24.7	420.5	0.08	-0.70
DICKENS	274.8	114.9	77.4	638.8	0.89	2.25
DONLEY	260.2	97.3	86.8	454.5	0.07	-0.72
ELLIS	421.7	140.9	102.8	681.0	-0.13	-0.30
FISHER	233.3	117.3	6.1	431.2	0.05	-0.81
FLOYD	271.1	128.9	43.9	547.7	0.27	-0.43
GAINES	146.4	78.3	10.8	344.2	0.50	-0.07
GARZA	268.1	137.1	59.0	663.1	0.69	0.73
GLASSCOCK	83.1	52.3	12.9	256.6	1.15	2.25
HALE	294.9	143.9	37.7	590.1	0.36	-0.58
HALL	255.2	90.4	85.3	426.5	0.24	-0.74
HASKELL	250.8	109.2	24.4	457.5	-0.10	-0.45
HILL	489.7	159.6	215.0	845.1	0.67	0.09
HOCKLEY	211.6	108.3	7.3	512.4	0.83	0.75
HOWARD	139.4	86.7	13.3	344.1	0.04	-0.71
KNOX	247.1	104.7	28.3	489.4	-0.10	-0.01
LAMB	257.7	160.7	15.2	629.7	0.54	-0.51
LUBBOCK	265.6	125.1	53.3	629.7	0.53	0.74
LYNN	235.8	107.2	43.4	494.1	0.25	-0.05
MARTIN	143.3	90.6	8.1	293.7	-0.04	-1.39
MIDLAND	88.8	48.4	19.5	222.6	0.66	0.37
MITCHELL	219.4	126.2	2.5	450.8	-0.01	-0.72
MOTLEY	195.7	77.3	29.0	401.8	0.14	0.58
NAVARRO	426.4	133.2	200.4	740.8	0.65	0.31
NOLAN	206.2	106.6	14.1	394.5	-0.05	-0.81
PARMER	242.7	145.0	15.7	695.0	1.05	1.57
REFUGIO	593.5	220.9	77.7	1099.6	0.09	0.19
SAN PATRICIO	692.9	198.8	312.0	986.5	-0.27	-1.17
SWISHER	246.8	138.0	51.1	556.4	0.42	-0.51
TERRY	198.6	102.5	43.5	391.5	0.31	-0.86
TOM GREEN	191.8	82.6	7.7	475.2	0.93	3.57
WILLACY	397.1	172.1	40.3	824.8	-0.38	0.80
WILLIAMSON	509.8	119.9	220.2	748.5	0.03	-0.04
YOAKUM	137.6	87.1	3.7	335.6	0.46	-0.63

Table 2. Maximum Likelihood Estimates for Parametric Distributions Models of Detrended Dryland Upland Cotton County-Level Yields, Selected Texas Counties, 1972-2004

	NORMAL			LOGNORMAL			BETA			
COUNTY NAME	Mean	Std Dev	A-Sq	Shape	Scale	A-Sq	Scale	Alpha	Beta	A-Sq
ANDREWS	127	84	1.000*	0.73	4.61	0.258	335	1.23	1.85	0.736*
BAILEY	154	107	0.498	0.95	4.71	1.135*	458	1.09	2.06	0.373
BORDEN	190	115	0.494	0.87	4.97	1.234*	507	1.30	2.15	0.406
BRISCOE	164	83	0.527	0.56	4.96	0.369	373	1.90	2.32	0.459
CAMERON	246	120	0.462	0.68	5.34	1.801*	568	1.82	2.36	0.666*
CHILDRESS	244	93	0.192	0.48	5.41	0.931*	437	2.49	1.94	0.345
COCHRAN	180	129	0.730*	1.00	4.84	0.933*	512	0.96	1.65	0.529
COLLINGSWORTH	264	95	0.419	0.37	5.51	0.176	497	2.90	2.44	0.808*
CONCHO	242	116	0.272	0.84	5.29	2.484*	615	1.74	2.66	0.846*
COTTLE	200	81	0.486	0.55	5.18	1.905*	395	2.37	2.31	0.749*
CROSBY	261	103	0.361	0.42	5.48	0.665*	596	2.99	3.70	0.568
DAWSON	188	102	0.436	0.73	5.03	1.413*	442	1.57	2.12	0.419
DICKENS	275	115	0.715*	0.46	5.52	1.078*	671	2.68	3.70	1.085*
DONLEY	260	97	0.185	0.42	5.48	0.598	500	3.09	2.82	0.163
ELLIS	422	141	0.217	0.41	5.98	0.804*	715	3.10	2.14	0.329
FISHER	233	117	0.516	0.90	5.22	2.470*	453	1.33	1.28	0.514
FLOYD	271	129	0.173	0.60	5.46	0.766*	575	1.89	2.07	0.240
GAINES	146	78	0.308	0.70	4.80	0.797*	361	1.66	2.37	0.286
GARZA	268	137	0.320	0.60	5.44	0.678*	696	1.93	2.96	0.409
GLASSCOCK	83	52	0.593	0.71	4.21	0.486	269	1.48	3.09	0.528
HALE	295	144	0.480	0.62	5.54	0.742*	620	1.80	1.93	0.474
HALL	255	90	0.328	0.39	5.47	0.274	448	2.85	2.08	0.492
HASKELL	251	109	0.472	0.63	5.38	1.774*	480	1.97	1.82	0.495
HILL	490	160	0.908*	0.33	6.14	0.490	887	3.38	2.64	1.392*
HOCKLEY	212	108	0.743*	0.73	5.18	1.492*	538	1.75	2.62	0.826*
HOWARD	139	87	0.773*	0.96	4.61	2.246*	361	1.16	1.88	0.921*
KNOX	247	105	0.187	0.60	5.38	1.636*	514	2.24	2.42	0.397
LAMB	258	161	0.475	0.83	5.30	0.657*	661	1.28	1.93	0.200
LUBBOCK	266	125	0.326	0.55	5.45	0.892*	661	2.19	3.15	0.496
LYNN	236	107	0.232	0.56	5.33	1.019*	519	2.14	2.51	0.367
MARTIN	143	91	0.836*	0.99	4.63	1.653*	308	1.03	1.22	0.434
MIDLAND	89	48	0.415	0.62	4.32	0.635*	234	1.76	2.75	0.418
MITCHELL	219	126	0.242	1.17	5.03	2.763*	473	1.02	1.26	0.467
MOTLEY	196	77	0.214	0.51	5.17	1.214*	422	2.68	3.05	0.481
NAVARRO	426	133	0.472	0.32	6.01	0.236	778	3.67	2.91	0.990*
NOLAN	206	107	0.190	0.80	5.11	1.660*	414	1.41	1.44	0.166
PARMER	243	145	0.582	0.73	5.29	0.574	730	1.53	2.90	0.511
REFUGIO	594	221	0.248	0.50	6.29	1.177*	1155	2.77	2.60	0.456
SAN PATRICIO	693	199	0.613	0.32	6.50	0.890*	1036	3.69	1.81	0.400
SWISHER	247	138	0.418	0.68	5.32	0.945*	584	1.54	2.03	0.372
TERRY	199	102	0.453	0.61	5.13	0.698*	411	1.61	1.66	0.415
TOM GREEN	192	83	0.557	0.67	5.12	2.476*	499	2.21	3.45	1.349*
WILLACY	397	172	0.739*	0.74	5.81	3.613*	866	1.94	2.36	1.505*
WILLIAMSON	510	120	0.238	0.25	6.20	0.309	786	5.27	2.81	NA**
YOAKUM	138	87	0.444	0.95	4.63	1.001*	352	1.17	1.79	0.167

Notes: * Estimate is significant at the 10% level.

** SAS does not compute the Anderson-Darling statistic if the shape parameter estimate is greater than 5.

Table 3. Maximum Likelihood Estimates for Rainfall Index Regime-Switching Distribution Models of Detrended Dryland Upland Cotton County-Level Yields, Selected Texas Counties, 1972-2004

COUNTY NAME	μ_1	μ_2	σ_1	σ_2	z^*	$\sigma_{\tilde{\varepsilon}}$	Likelihood Ratio
ANDREWS	71	158	30	86	1.71	0.44	17.04*
BAILEY	61	178	30	104	1.13	0.78	7.78
BORDEN	77	267	43	75	1.38	1.22	17.04*
BRISCOE	100	203	32	77	1.71	1.31	9.57*
CAMERON	188	284	118	102	1.75	0.11	5.03
CHILDRESS	139	276	60	74	0.80	0.13	14.08*
COCHRAN	104	251	62	131	2.15	2.21	6.73
COLLINGSWORTH	190	313	46	84	1.38	0.62	11.61*
CONCHO	203	294	78	132	3.27	0.19	9.01*
COTTLE	98	230	54	58	0.80	0.18	17.18*
CROSBY	142	290	30	91	1.13	0.08	21.10*
DAWSON	59	226	21	81	1.13	0.76	17.73*
DICKENS	201	322	80	105	1.38	0.25	10.06*
DONLEY	192	303	66	87	1.38	0.11	11.02*
ELLIS	320	482	116	113	1.49	0.08	12.24*
FISHER	168	371	74	43	3.18	2.52	9.43*
FLOYD	213	327	84	136	2.15	0.16	10.65*
GAINES	104	186	59	71	2.15	0.00	11.40*
GARZA	105	304	49	120	0.80	0.00	18.44*
GLASSCOCK	41	106	18	49	1.71	1.24	9.25*
HALE	256	348	149	111	2.50	0.00	4.98
HALL	185	301	58	74	1.38	0.00	18.28*
HASKELL	170	301	89	85	1.38	0.27	11.72*
HILL	315	537	70	140	1.05	0.33	11.43*
HOCKLEY	131	232	26	110	1.13	0.13	16.30*
HOWARD	35	179	21	64	1.13	0.97	19.91*
KNOX	134	279	90	82	0.80	0.23	9.79*
LAMB	112	295	36	156	1.13	0.43	14.44*
LUBBOCK	166	290	55	123	1.13	0.15	10.05*
LYNN	149	283	71	90	1.71	0.33	12.69*
MARTIN	39	201	19	53	1.71	1.52	26.37*
MIDLAND	42	112	14	41	1.71	0.83	16.38*
MITCHELL	186	323	117	80	3.18	0.00	9.90*
MOTLEY	100	224	39	59	0.80	0.14	17.71*
NAVARRO	332	481	80	124	1.49	0.28	11.91*
NOLAN	130	294	70	62	1.90	0.85	14.60*
PARMER	122	276	28	144	1.13	0.97	8.51*
REFUGIO	601	588	158	253	3.77	0.00	3.35
SAN PATRICIO	676	706	136	229	3.77	0.00	4.17
SWISHER	69	292	14	114	1.13	1.14	14.97*
TERRY	73	236	19	84	1.13	1.14	13.53*
TOM GREEN	178	241	55	126	4.11	0.24	12.62*
WILLACY	361	447	202	91	2.54	0.00	10.83*
WILLIAMSON	434	552	58	122	1.49	0.11	12.34*
YOAKUM	71	176	41	81	1.71	0.72	10.35*

Note: Asterisk (*) denotes variables significant at the 5% level.

Table 4. Maximum Likelihood Estimates for Palmer Index Regime-Switching Distribution Models of Detrended Dryland Upland Cotton County-Level Yields, Selected Texas Counties, 1972-2004

COUNTY NAME	μ_1	μ_2	σ_1	σ_2	z^*	$\sigma_{\tilde{\varepsilon}}$	Likelihood Ratio
ANDREWS	68	194	30	72	0.91	3.72	16.66*
BAILEY	122	260	71	127	3.29	1.88	10.67*
BORDEN	59	252	30	81	-0.35	0.93	33.82*
BRISCOE	92	180	40	80	-1.74	0.00	9.63*
CAMERON	81	281	55	96	-2.06	1.05	12.61*
CHILDRESS	163	297	59	66	-0.35	0.80	20.26*
COCHRAN	130	341	80	117	3.29	2.57	12.10*
COLLINGSWORTH	225	317	55	108	1.42	0.32	13.99*
CONCHO	176	279	72	117	-1.00	0.04	8.12*
COTTLE	152	245	66	62	0.49	0.18	14.06*
CROSBY	132	288	18	90	-1.74	1.08	10.34*
DAWSON	58	234	21	72	-1.74	2.95	15.97*
DICKENS	230	341	77	125	1.42	0.45	11.76*
DONLEY	214	304	70	96	0.49	0.00	9.85*
ELLIS	266	456	106	120	-2.31	1.19	6.12
FISHER	136	297	69	94	-0.35	0.00	21.84*
FLOYD	236	319	93	149	0.91	0.00	7.25
GAINES	108	201	55	71	0.91	1.19	10.98*
GARZA	183	348	91	120	0.49	0.00	16.66*
GLASSCOCK	40	109	17	48	-0.96	3.95	10.23*
HALE	236	517	92	37	3.29	2.89	15.22*
HALL	172	309	41	68	-0.35	2.59	12.59*
HASKELL	167	305	83	84	-0.35	0.00	16.70*
HILL	492	481	175	38	2.96	0.59	8.10*
HOCKLEY	167	340	66	97	3.29	3.13	11.12*
HOWARD	23	175	8	64	-1.74	2.93	22.40*
KNOX	191	300	88	87	0.49	0.14	10.82*
LAMB	118	316	43	152	-1.74	3.57	8.53*
LUBBOCK	241	298	100	143	0.91	0.00	3.90
LYNN	187	306	79	99	0.91	1.09	10.08*
MARTIN	39	202	19	51	-0.96	2.76	28.81*
MIDLAND	35	107	10	41	-1.74	2.18	14.76*
MITCHELL	41	268	31	92	-2.11	1.10	22.78*
MOTLEY	163	243	63	68	1.42	0.09	10.36*
NAVARRO	283	457	62	121	-2.31	1.19	6.59
NOLAN	113	267	67	78	-0.35	0.00	23.72*
PARMER	171	304	66	161	0.14	3.15	7.44
REFUGIO	617	506	228	142	2.72	0.00	3.48
SAN PATRICIO	405	738	59	170	-2.01	1.34	7.68
SWISHER	178	402	87	92	3.29	5.68	4.01
TERRY	74	233	23	86	-1.74	0.84	17.01*
TOM GREEN	140	226	57	77	-1.00	0.00	11.57*
WILLACY	188	448	195	116	-2.06	0.22	18.02*
WILLIAMSON	362	543	76	99	-2.31	0.69	11.06*
YOAKUM	100	261	56	37	3.29	1.50	22.02*

Note: Asterisk (*) denotes variables significant at the 5% level.

Table 5. Estimated Group Risk Plan Premiums as a Percent of Liability, Texas Dryland Upland Cotton, by County

COUNTY NAME	Empirical Distribution Model	Normal Distribution Model	Palmer Regime-Switching Model	Rainfall Regime-Switching Model
ANDREWS	22.1	22.6	22.0	21.6
BAILEY	23.1	24.0	21.5	24.9
BORDEN	22.1	20.2	27.3*	22.0
BRISCOE	15.1	15.6	15.6	15.2
CAMERON	14.4	14.8	18.5*	14.9
CHILDRESS	10.1	10.1	10.8	9.5
COCHRAN	23.9	25.2	22.7	23.8
COLLINGSWORTH	8.4	9.3	7.9	8.9
CONCHO	13.3	14.5	14.2	13.3
COTTLE	11.3	11.1	11.4	10.8
CROSBY	10.7	10.7	13.7*	11.0
DAWSON	19.2	17.2	20.7	18.4
DICKENS	10.3	11.8	10.6	11.7
DONLEY	10.5	9.9	9.4	9.8
ELLIS	8.1	8.2	8.5	8.6
FISHER	15.1	15.5	15.9	16.0
FLOYD	14.2	14.3	13.3	13.3
GAINES	17.1	16.9	16.0	16.8
GARZA	14.7	15.8	15.7	16.7
GLASSCOCK	20.1	21.1	21.4	22.0
HALE	14.4	14.8	14.6	15.0
HALL	9.1	9.0	9.7	9.1
HASKELL	11.9	12.5	13.0	13.3
HILL	6.4	7.9*	7.3	8.2
HOCKLEY	13.4	15.9	13.9	15.2
HOWARD	23.6	20.8	26.9	20.5
KNOX	12.2	12.0	12.2	11.6
LAMB	21.3	20.9	21.7	21.3
LUBBOCK	13.9	14.1	13.5	13.7
LYNN	13.4	13.4	12.6	13.6
MARTIN	24.7	21.3	25.6	27.4
MIDLAND	17.9	17.4	19.1	20.3
MITCHELL	19.3	18.7	20.0	19.3
MOTLEY	10.6	10.8	10.6	10.4
NAVARRO	6.3	7.3	7.5	7.0
NOLAN	16.8	16.1	17.0	17.1
PARMER	18.3	19.7	17.7	20.5
REFUGIO	9.3	9.8	9.5	9.6
SAN PATRICIO	7.5	6.3	8.7	5.9
SWISHER	17.5	18.0	16.8	24.8*
TERRY	16.6	16.1	17.9	18.5
TOM GREEN	10.1	12.3	12.1	10.3
WILLACY	12.5	12.4	12.3	12.5
WILLIAMSON	3.8	4.3	4.6	3.5
YOAKUM	21.9	21.3	21.4	21.0
AVERAGE	**14.6**	**14.7**	**15.2**	**15.1**

Note: An asterisk (*) indicates that the computed premium rate is statistically different from the empirical distribution premium rate at the 5% level

Footnotes

[1] The parametric distributions were estimated using SAS, which automatically generates the critical values of the Anderson-Darling statistic.

References

Atwood, J., S. Shaik and M. Watts. "Are Crop Yields Normally Distributed? A Reexamination." *American Journal of Agricultural Economics* 85(November 2003):888-901.

Day, R.H. "Probability Distributions of Field Crop Yields." *Journal of Farm Economics* 47(August 1965):713-741.

Gallagher, P. "U.S. Soybean Yields: Estimation and Forecasting with Nonsymmetric Disturbances." *American Journal of Agricultural Economics* 69(November 1987):796-803.

Glauber, J.W. "Crop Insurance Reconsidered." *American Journal of Agricultural Economics* 86 (December 2004):1179-1195.

Goldfeld, S.M. and R.E. Quandt. *Nonlinear Methods in Econometrics*. Amsterdam: North-Holland Publishing Co., 1972.

Goldfeld, S.M. and R.E. Quandt. "A Markov Model for Switching Regressions." *Journal of Econometrics* 1(1973):3-16.

Goodwin, B.K. "An Empirical Analysis of the Demand for Multiple Peril Crop Insurance." *American Journal of Agricultural Economics* 75(May 1993):425-434.

Goodwin, B.K. and A.P. Ker. "Nonparametric Estimation of Crop Yield Distributions: Implications for Rating Group-Risk Crop Insurance Contracts." *American Journal of Agricultural Economics* 80(February 1998):139-153.

Goodwin, B.K. and O. Mahul. "Risk Modeling Concepts Relating to the Design and Rating of Agricultural Insurance Contract." Working paper 3392, World Bank Policy Research, September 2004.

Goodwin, B.K., M.L. Vandeveer, and J.L. Deal. "An Empirical Analysis of Acreage Effects of Participation in the Federal Crop Insurance Program." *American Journal of Agricultural Economics* 86(November 2004):1058-1077.

Just, R.E. and Q. Weninger. "Are Crop Yields Normally Distributed?" *American Journal of Agricultural Economics* 81(May 1999):287-304.

Ker, A.P. and K.H. Coble. "Modeling Conditional Yield Densities." *American Journal of Agricultural Economics* 85(May 2003):291-304.

Ker, A.P. and B.K. Goodwin. "Nonparametric Estimation of Crop Insurance Rates Revisited." *American Journal of Agricultural Economics* 82(May 2000):463-478.

Miranda, M.J. "Area-Yield Crop Insurance Reconsidered." *American Journal of Agricultural Economics* 73(May 1991):233-242.

National Oceanic & Atmospheric Administration–National Climatic Data Center. Internet site: http://www.ncdc.noaa.gov/oa/climate/onlineprod/drought/xmgr.html (Accessed August 30, 2007).

Ozaki, V.A., S.K. Ghosh, B.K. Goodwin and R. Shirota. "Spatio-Temporal Modeling of Agricultural Yield Data with an Application to Pricing Crop Insurance Contracts." Paper presented at the conference of American Agricultural Economics Association Annual Meeting, Providence, Rhode Island, July 24-27, 2005.

Quandt, R.E., "A New Approach to Estimating Switching Regressions." *Journal of the American Statistical Association* 67(June 1972):306-310.

Ramirez, O.A., S. Misra and J. Field. "Crop-Yield Distributions Revisited." *American Journal of Agricultural Economics* 85(February 2003):108-120.

Sherrick, B.J., F.C. Zanini, G.D. Schnitkey, and S.H. Irwin. "Crop Insurance Valuation under Alternative Yield Distributions." *American Journal of Agricultural Economics* 86(May 2004):406-419.

Skees, J.R., J.R. Black, and B.J. Barnett. "Designing and Rating an Area Yield Crop Insurance Contract." *American Journal of Agricultural Economics* 79(May 1997):430-438.

Skees, J.R. and M.R. Reed. "Rate Making for Farm-Level Crop Insurance: Implication for Adverse Selection." *American Journal of Agricultural Economics* 68(August 1986):653-659.

Taylor, C.R. "Two Practical Procedures for Estimating Multivariate Nonnormal Probability Density Functions." *American Journal of Agricultural Economics* 72(February 1990):210-217.

U.S. Department of Agriculture–National Agricultural Statistics Service. Internet site: http://www.nass.usda.gov/index.asp (Accessed August 30, 2007)

U.S. Department of Agriculture–Risk Management Agency. Internet site: http://www.rma.usda.gov/ (Accessed August 30, 2007)