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Evaluating Crop and Revenue Insurance Products as Risk Management Tools for Texas Cotton Producers

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This paper develops and illustrates the application of a procedure to evaluate and compare the cost effectiveness of alternative crop insurance products for cotton in terms of their effect on expected producer net returns and the variation of net returns. Farm unit–level cotton yields and state-level price distributions are estimated by a multivariate nonnormal parametric modeling procedure and used to simulate the net returns to alternative crop insurance products over a 10-year planning horizon. The ranking of alternative insurance products using third-degree stochastic dominance is presented for Texas cotton producers.

Key Words: cotton, crop insurance, multivariate nonnormal parametric modeling, stochastic dominance

JEL Classifications: C5, Q1

Cotton production contributed an average of $5.27 billion/yr. to the U.S. economy from 1988 through 1994 (National Agricultural Statistics Service). More than 14.5 million acres of cotton were planted in the U.S. in 1999, with over 13 million acres harvested and about 16 million bales of cotton produced. Texas accounted for about 42% of planted acres, approximately 39% of harvested acres, and over 31% of total U.S. cotton production in 1999 (Texas Agricultural Statistics Service 2000). Cotton production, like many other agricultural enterprises, is inherently risky. Cotton producers are subject to unpredictable, random shocks, such as adverse weather, pest infestations, and other natural disasters, such as drought and flooding. Supply uncertainties, coupled with an inelastic demand for agricultural products generally lead to a more volatile price than those commonly experienced in other sectors of the economy (Goodwin and Smith).

Cotton producers in the U.S. have traditionally relied on the federal government for protection from price and yield variability. This protection came in the form of a federal crop insurance program, *ad hoc* disaster payments, and deficiency payments. However, the uncertainty and short-term nature of farm programs and the need for a longer term risk management strategy makes the evaluation of the efficacy of risk management options available to producers to help become better managers of paramount importance. Some of the risk management alternatives currently being scrutinized are forward contracting, hedging with futures and options, and crop and revenue in-

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surance. Crop and revenue insurance, the focus of this research, has received considerable attention in recent times (Coble, Heifner, and Zuniga; Duncan and Myers; Hennessy, Babcock, and Hays; Miranda and Glauber; Vercammen; Wang et al.), including increasing pressure for a complete reform because of low participation, poor actuarial performance, and the existence of *ad hoc* disaster payments (Skees et al.). The objective of this study was to develop and illustrate the application of an empirical procedure to evaluate and compare the cost effectiveness of alternative crop and revenue insurance products from a producer's perspective. For the purpose of illustration, multiple-peril crop insurance (MPCI) products that guarantee yield and crop revenue coverage (CRC) products that guarantee revenue were chosen along with the catastrophic (CAT) coverage. CAT is a 50/55 policy that has yield coverage of 50% and a price election of 55%; it is subsidized by the Federal Crop Insurance Corporation (FCIC) for a $60 processing fee per crop per county. Both MPCI and CRC insurance products receive premium subsidies through the FCIC of the U.S. Department of Agriculture.

Methods and Procedures

Precise estimates of yield and price distributions are needed to evaluate the cost effectiveness of crop and revenue insurance products and their effect on the farmer's financial condition. Pooled, farm unit- and county-level yield data are used to estimate the probability distributions of irrigated and dryland cotton yields at the farm unit-level in three West Texas regions (the southern High Plains, the northern High Plains, and the northern Low Plains) covering 13 counties. Data for 57 dryland and 39 irrigated units were collected from the Texas Agricultural Extension Service (Fincham, personal communication) and included between 5 and 10 years of producers' history—the number of acres planted, the realized yield, the location of the farm, and the farming practice (irrigated or nonirrigated).

The time span of the available unit-level data was not enough to precisely identify the mean and variance trends and other critical features of the yield distributions. Therefore, county-level time series (Texas Agricultural Statistics Service 1970–1998) yield data were used to assist in the estimation of the unit-level yield distributions and their changes through time. State-level annual price data from 1934 to 1999 (National Agricultural Statistics Service), adjusted for inflation using the U.S. Producer Price Index with 1999 as the base year, were used to estimate the price distribution faced by Texas cotton producers.

Several crop price and yield distributions have been found to be substantially nonnormal, with means and variances that are shifting through time, location, or both (Gallagher 1986, 1987; Ramirez; Ramirez, Moss, and Boggess; Taylor). In addition, the conditional mean of certain crop price distributions has been shown to be autocorrelated through time (Ramirez; Ramirez and Somarriba). Because the modeling and simulation of empirical distributions that resemble the key statistical features of the actual price and yield distributions is essential for a realistic risk and return analysis (Ramirez, Misra, and Field), the procedures utilized attempt to correct or minimize the effects of the previously discussed sample deficiencies. In particular, a multivariate parametric model, developed by Ramirez and expanded by Ramirez and Somarriba and Ramirez, Misra, and Field, was used to estimate and simulate the yield and price distributions. This approach utilizes a multivariate, nonnormal distribution that can accurately and separately account for heteroscedasticity, distributional right or left skewness and kurtosis, and correlation among the variables of interest: irrigated and dryland cotton yields in this case. The Ramirez and Somarriba adaptation of the Ramirez model, which can also account for autocorrelation, was used to model and simulate the cotton price distribution.

Although it can be hypothesized that aggregate-level yields are negatively correlated with prices, sample correlation coefficients between county- and farm-level yields and prices, however, did not detect a statistically significant correlation. This could be because, as yield data are disaggregated, the yield-price

correlation likely becomes smaller in magnitude and harder to detect statistically. Thus, price and yield distributions were estimated independently for the purpose of this analysis.

In Ramirez's model,

$$(1) \quad E[Y_j] = F(X_j, B_j),$$

$$(2) \quad V[Y_j] = G(Z_j, \Sigma_j)^2 G(\Theta_j, \mu_j), \quad \Theta_j > 0, \quad -\infty < \mu_j < \infty,$$

where $F(\mathbf{X}_j, B_j)$ is a linear or nonlinear function controlling the mean of the distribution of Y_j through the parameter vector B_j and a set of independent variables $\mathbf{X}_j$, $G(Z_j, \Sigma_j)$ is another linear or nonlinear function controlling the standard deviation of the distribution of Y_j through the parameter vector Σ_j and a set of exogenous variables Z_j, $G(\Theta_j, \mu_j)$ is an exponential function of Θ_j and μ_j (the parameters that control the degree of nonnormality in the probability distribution), Y_j is the random variable of interest (cotton yield in this case), and j = D and I for dryland and irrigated yield distributions, respectively.

Equation (1) implies that the mean of the cotton yield distribution can be specified as a linear function of a set of independent variables and slope coefficients, as in the standard linear regression model estimated by ordinary least squares (OLS). Equation (2) states that the variance of the yield distribution is proportional to the value of the parametric function $G(Z_j, \Sigma_j)^2$. Therefore, both the mean and the variance of the yield distribution can be made variable across observations (time and space in this case) through $F(\mathbf{X}_j, B_j)$ and $G(Z_j, \Sigma_j)^2$. In regards to nonnormality, if $\Theta_j > 0$, Y_j has a kurtotic distribution, and if $\mu_j \neq 0$, Y_j has a skewed distribution. The sign of μ_j determines whether the distribution of Y_j is skewed to the left ($\mu_j < 0$) or right ($\mu_j > 0$).

The 13 counties considered in the study are combined into three groups on the basis of geographical location: (1) the southern High Plains, (2) the northern High Plains, and (3) the northern Low Plains. Two separate probability distribution models were estimated for irrigated and dryland cotton yields. In each of these models, the mean and variance of the yield distribution were estimated independently of each other, and of the distribution's skewness and kurtosis parameters, by the functions $F(\mathbf{X}_j, B_j)$ and $G(Z_j, \Sigma_j)$. The mean, $F(B_j, X_j)$, was specified as a third-degree polynomial function of time.

$$\begin{aligned}(3) \quad F(X_j, B_j) &= X_j B_j \\ &= B_{00} + B_{01}\text{NHP} + B_{02}\text{NLP} + B_{10}T \\ &\quad + B_{11}(T{*}\text{NHP}) + B_{12}(T{*}\text{NLP}) + B_2T^2 \\ &\quad + B_3T^3 + B_4AC + B_5AF,\end{aligned}$$

where T is a simple time trend variable starting at 1 in 1970, NHP = 1 if the yield observation was from a farm or county in the northern High Plains region and 0 otherwise, NLP = 1 if the observation was from a farm or county in the northern Low Plains region and 0 otherwise, AF is acres planted on the farm in deviations from the mean in the case of a farm-level yield observation and is 0 otherwise, and AC is acres planted in the county in deviations from the mean in the case of a county-level yield observation and is 0 otherwise. Equation (3) assumes that the mean of the farm- and county-level yield distributions was the same within each region, but it can vary across regions and through time.

The variance function was specified as

$$\begin{aligned}(4) \quad G(Z_j, \Sigma_j)^2 &= [Z_j\Sigma_j]^2 \\ &= [\sigma_{00} + \sigma_{01}\text{NHP} + \sigma_{02}\text{NLP} + \sigma_{0L}CL \\ &\quad + \sigma_{10}T + \sigma_{11}(T.{*}\text{NHP}) + \sigma_{12}(T.{*}\text{NLP}) \\ &\quad + \sigma_{1L}(T.{*}CL) + \sigma_2T^2 + \sigma_3AC \\ &\quad + \sigma_4AF]^2,\end{aligned}$$

where CL = 1 for county-level observations and 0 otherwise. Equation (4) allows for a different variance in the yield distribution across regions and levels (farm versus county). It also allows for the yield variance to change differently through time according to region and level. The acres planted at both the farm- and

county-unit levels were allowed to affect yield variability at each of these levels as well.

Each model assumes the same degrees of distributional skewness and kurtosis through time and across regions and levels (farm versus county). In principle, there is no reason to believe that the farm- and county-level distributions must have the same skewness and kurtosis, or that these should be identical across regions and time. The distributional shapes are allowed to change through time and across regions and levels by making their means and variances functions of these variables. Although Ramirez's methods could be expanded to make the third and fourth central moments of the yield distribution functions of time and regional- and aggregation-level dummies, because of the need for a relatively large number of observations required to estimate each higher order moment (i.e., skewness or kurtosis) parameter, this was deemed undesirable in this particular application.

Separate irrigated and dryland yield distribution models were first estimated by maximizing the following univariate log likelihood function

$$(5) \qquad LL_j = \sum_{i=1}^{n} G_{ji} - \frac{1}{2}\sum_{i=1}^{n} H_{ji}^2,$$

where

$$G_{ji} = \ln[\theta_j(1 + R_{ji}^2)^{-1/2}/Z_{ji}\Sigma_j]$$

if Y_{ji} is nonnormally distributed and

$$G_{ji} = -\ln(Z_{ji}\Sigma_j)$$

if Y_{ji} is normally distributed;

$$R_{ji} = [\Theta_j(Y_{ji} - X_{ji}\beta_j)/Z_{ji}\Sigma_j] + F(\Theta_j, \mu_j);$$

$$H_{ji} = \{\ln[R_{ji}(1 + R_{ji}^2)^{1/2}]/\Theta_j\} - \mu_j$$

if Y_{ji} is nonnormally distributed and

$$H_{ji} = (Y_{ji} - X_{ji}\beta_j)/Z_{ji}\Sigma_j$$

if Y_{ji} is normally distributed;

$$F(\Theta_j, \mu_j) = [e(0.5\Theta_j^2)][e(\Theta_j\mu_j) - e(-\Theta_j\mu_j)]/2.$$

j = D and I indicate the irrigated and the dryland cotton yield models, respectively, Y_{ji} is the ith dryland or irrigated cotton yield observation, $X_{ji}B_j$ and $Z_{ji}\Sigma_j$ are the linear functions described above, and θ_j and μ_j are the parameters controlling the nonnormality of the yield distributions as discussed above.

Standard asymptotic t-tests and likelihood ratio tests were used to determine which variables should be dropped or combined to obtain final (restricted) univariate irrigated and dryland yield distribution models. These final models were then combined into a single (joint) model in order to estimate the correlation between the irrigated and dryland yield distributions. The parameters of the joint irrigated-dryland yield distribution model were estimated by maximizing the following bivariate log-likelihood function (Ramirez, Misra, and Field)

$$(6) \qquad BLL = \left\{\sum_{i=1}^{n}\sum_{j=\mathrm{I,D}} G_{ji} - 0.5\sum_{i=1}^{n_2}\sum_{j=\mathrm{I,D}} [\{H_{ji}*(\Omega^{-1})\}.*H_{ji}] - \sum_{i=n_2+1}^{n}\sum_{j=\mathrm{I,D}} H_{ji}^2 - \left[\frac{n_2}{2}\right]\ln|\Omega|\right\},$$

where BLL is the bivariate log-likelihood function, j = D for the dryland cotton, and j = I for the irrigated cotton yield observations; G_{ji} and H_{ji} are as defined in Equation (5); Ω is the irrigated-dryland correlation matrix with diagonal elements equal to one and a pair of nonzero, nondiagonal elements, $\rho_{12} = \rho_{21}$, to represent the correlation coefficient between Y_I and Y_D; * indicates a matrix multiplication; .* indicates an element-by-element matrix multiplication; n_2 is the number of irrigated and dryland yield observations that are "coupled" through time (690); and n is the total number of observations. The coupled data were used to estimate the correlation between dryland and irrigated yields. The data set consisted of yearly observations in which both dryland and irrigated yields were available at the county level. Because coupled data were not available at the unit level, it was assumed that the correlation coefficients at the farm and county levels were the same. The bivariate log-likelihood function linked the univariate log-likelihood functions for the irrigated and dryland

yield distribution models through the cross-distribution correlation matrix Ω. The joint yield distribution model, estimated by maximizing Equation (6), accounts for any potential nonnormality (kurtosis [θ_I and θ_D], right or left skewness [μ_I and μ_D], or both) and heteroscedasticity ($Z_I\Sigma_I$, $Z_D\Sigma_D$) and for the correlation among irrigated and dryland cotton yields (ρ_{12}). The mean of each of the two distributions was also allowed to shift according to X_IB_I and X_DB_D, respectively.

The procedure for estimating the cotton price distribution model was similar to that used to estimate the dryland and irrigated cotton yield distribution models, except that it accounted for autocorrelation. The mean function in the price distribution model was specified as

$$(7) \qquad F(X_{CP}, B_{CP}) = X_{CP}B_{CP} = B_0 + B_1T + B_2T^2,$$

and the variance function was specified as

$$(8) \qquad G(Z_{CP}, \Sigma_{CP})^2 = [Z_{CP}\Sigma_{CP}]^2 = [\sigma_0 + \sigma_1T + \sigma_2T^2]^2,$$

where $T = 1, \ldots, 65$, depending on the year that the observation was taken (1 = 1934, 65 = 1998). The price model is estimated by maximizing the univariate likelihood function in Equation (5), where, to account for autocorrelation, Y_{CP} is replaced by $Y_{CP}* = PY_{CP}$ and X_{CP} is replaced by $X_{CP}* = PX_{CP}$, Y_{CP} being the vector of original price data and the X_{CP} matrix containing the original data on the explanatory variables (time and time squared) believed to affect the mean of the price distribution. P is an $n \times n$ matrix used to transform autocorrelated random variables into independently distributed random variables. In the case of first-order autocorrelation, the element on the first row and column of P is $(1 - \rho^2)^{1/2}$, where ρ is the correlation coefficient between any two consecutive price observations. The rest of the elements in the principal diagonal of P are ones. All elements immediately below the principal diagonal are equal to $-\rho$, and the remaining elements of P are zero (Ramirez and Somarriba). Under the maximum likelihood procedure utilized, the autocorrelation coefficient ρ was estimated jointly with the other model parameters.

The estimated parameters for the price and bivariate yield distribution models were used to simulate 15,000 realizations from each of the estimated distributions. This simulation technique, developed by Ramirez, incorporates, when appropriate, the exogenous factors shifting the mean and variance of the yield and price distributions (time, location, etc.), autocorrelation, kurtosis, and right or left skewness; in this case, it took into account correlation between dryland and irrigated cotton yields.

To conduct the yield simulations, a 15,000 $\times$ 2 matrix (V) of random numbers generated from a standard normal distribution was multiplied by the Cholesky decomposition of Ω. Because dryland cotton yields were found to be nonnormally distributed, they were simulated using the following formula.

$$(9) \qquad Y_{Dit} = [Z_{Dt}\Sigma_D/\Theta_D] \times \{[(e^{\Theta_D(V_{Di}+\mu_D)} - e^{-\Theta_D(V_{Di}+\mu_D)})/2] - F(\Theta_D, \mu_D)\} + X_{Dt}B_D,$$

where $t = 25, \ldots, 40$ for the year 1995, . . . , 2009, $F(\Theta_D, \mu_D)$ is as defined in Equation (5), Θ_D and μ_D are the kurtosis and skewness parameter estimates for the dryland yield distribution, respectively, B_D and Σ_D are the estimates for the parameter vectors in the mean and variance functions [Equations (3) and (4)], respectively, and V_{Di} is the is the ith element of the first column of V, which corresponds to dryland cotton. $Z_{Dt}\Sigma_D$ and $X_{Dt}B_D$ vary according to Equations (3) and (4) as dryland cotton yields were simulated for different time periods and regions. Because it was concluded that irrigated cotton yields were normally distributed, their simulation involved the simple formula

$$(10) \qquad Y_{Iit} = (Z_{It}\Sigma_I).*V_{Ii} + X_{It}B_I,$$

where $t = 25, \ldots, 40$ for the years 1995, . . . , 2009 and V_{Ii} is the ith element of the second column of V, which corresponds to irrigated cotton. As in the nonnormally distributed dry-

land cotton yield simulation, $Z_{It}\Sigma_I$ and $X_{It}B_I$ vary according to Equations (3) and (4) as irrigated cotton yields were simulated for different time periods and regions. Because it was concluded that cotton prices were normally distributed, but autocorrelated, they were simulated using the following formula

$$(11)\quad CP_{F(T+t)} = (Z_{CP(T+t)}S_{CP}).*v + \{X_{CP(T+t)}B_{CP} + [\rho^t_{CP}(Y_{CP(T)} - X_{CP(T)}B_{CP})]\},$$

where v is a 15,000 × 1 vector of random numbers drawn from a standard normal distribution; F stands for a forecast; T is the observation during the final year in the data set (T = 64 for 1998); t is the number of years forecasted beyond the data set (t = 2, . . . , 11 for 2000–2009); Z_{CP}, Σ_{CP}, X_{CP}, and B_{CP} are as defined in Equations (7) and (8); and ρ_{CP} is the estimated autocorrelation coefficient. This simulation procedure incorporates autocorrelation into the conditional mean of the price distributions by multiplying the residual for the final observation ($Y_{CP(T)} - X_{CP(T)}B_{CP}$) by the cross-observation correlation coefficient (ρ_{CP}) raised to the power of t. A simulation model that does not account for autocorrelation would simulate the mean of the price distribution at its long-term trend ($X_{CP(T+t)}B_{CP}$), ignoring the presence of price cycles. If the last price observation is not near the long-term mean trend, the autocorrelated simulation procedure smooths the transition back to the long-term trend.

The draws from the yield and price distributions obtained from the simulations described above were used as the first component of empirical procedure to analyze the cost effectiveness of alternative crop insurance products in terms of their effect on expected producer net returns and the variation of net returns over a 10-year planning horizon. From the total revenue distributions, 15,000 draws per year were first calculated by multiplying the draws from the yield distribution by the draws from the price distribution

$$(12)\quad TR = SY.*SP,$$

where TR is an $n \times T$ matrix containing n = 15,000 total revenue realizations at T = 10 time periods (years 2000–2009), SY is an $n \times T$ matrix of simulated yields containing the n draws from the estimated yield distribution for the T time periods under analysis, SP is an $n \times T$ matrix of simulated prices containing the n random draws from the estimated price distribution for T time periods in the evaluation, and .* is the element-by-element matrix multiplication operator. Net revenues per planted acre were then calculated by subtracting production costs from and adding cottonseed revenues to the total revenues[1]

$$(13)\quad NR = TR - PC + SR,$$

where NR is an $n \times T$ matrix containing n net revenue realizations at T time periods, PC is an $n \times T$ matrix containing the production cost per planted acre less insurance and returns to management, and SR is an $n \times T$ matrix containing the seed revenues per planted acre associated with the n simulated yield realizations for the T time periods in the analysis. Production costs were derived by taking an average of 1996–1998 costs for each region as reported in the Texas Agricultural Extension Service's (TAEX) crop budgets and were assumed to remain constant for the study period. Cottonseed yields for each region were based on the simulated lint yields assuming the same ratio of seed to lint as the TAEX budgets. Cottonseed revenues were calculated using the average of the cottonseed price reported in TAEX budgets during the last 3 years.

Net returns per planted acre were then calculated by subtracting insurance premiums and adding indemnity payments, when applicable.

$$(14)\quad NRet = NR - IC + IR,$$

where $NRet$ is an $n \times T$ matrix of net returns,

[1] It is noted that other farm incomes that include government payments have not been taken into account in calculating total and net revenues per planted acre of cotton.

IC is an $n \times T$ matrix containing the cost of insurance premiums, and *IR* is an $n \times T$ matrix containing revenues from insurance indemnity payments.

Insurance premiums were calculated using an average production history (*APH*), estimated base price, and 1999 premium rates and subsidy factors obtained from the USDA's FCIC–Risk Management Agency (FCIC-RMA). Regional rates were held constant across the planning horizon. The *APH* was calculated as a moving average of the previous 5 years' yields

$$(15) \quad APH_t = [SY_{(t-5)} + SY_{(t-4)} + SY_{(t-3)} + SY_{(t-2)} + SY_{(t-1)}]/5,$$

where APH_t is the $n \times 1$ vector of *APH*s calculated for time period *t*. Simulated yield vectors for the previous 5 years were needed to calculate the *APH* vector for time $t = 1$. Thus, a total of $T + 5$ $n \times 1$ yield realization vectors had to be simulated.

The base prices for MPCI insurance products, which are annually set by the FCIC based on expectations of the market price, were estimated by a distributed lag model, and the model was tested and corrected for first-order autocorrelation using the first-order autoregressive process [Equation (16)]. The estimated model was

$$(16) \quad BP_t = \underset{(0.0628)}{0.1134} + \underset{(0.0960)}{0.2093}*P_{t-1} + \underset{(0.0921)}{0.2751}*P_{t-2} + \underset{(0.0955)}{0.2449}*P_{t-3} \qquad R^2 = 0.88,$$

where BP_t is the base price at time *t*; P_{t-1}, P_{t-2}, and P_{t-3} are the market prices observed at time $t - 1$, $t - 2$, and $t - 3$, respectively; and the numbers in parentheses are the standard error estimates. Base prices for CRC insurance products, though determined by the FCIC as 95% of the average of December futures contract between January 15 and February 14, were also predicted for each of the 10 years in the planning horizon using Equation (16).

The premium rates are dependent on the *APH* and coverage level chosen. Indemnity payments were calculated for each simulated yield realization. For the MPCI product, the indemnity payment was calculated as

$$(17) \quad IR_{it} = [(APH_{it}*CL) - SY_{it}]*BP_t*PE,$$

where IR_{it} is the *i*th element of the $n \times 1$ *IR* vector for year *t*, *CL* is the chosen level of yield coverage, and *PE* is the chosen price coverage level. The indemnity was only calculated when the simulated yield fell below the guaranteed yield, or when $SY_{it} < (APH_{it}*\mathrm{CL})$. Otherwise, IR_{it} was set equal to zero. For the CRC insurance product, because the indemnity is based on the higher of the base price and market price at harvest, the indemnity payment was calculated as

$$(18) \quad IR_{it} = \{[APH_{it}*\max(BP_t, SP_{it})]*CL\} - (SY_{it}*SP_{it}),$$

where SP_{it} is the *i*th element of the $n \times 1$ vector of simulated prices for year *t*. The indemnity was only calculated if the simulated total revenue fell below the guaranteed level or when $(SY_{it}*SP_{it}) < \{[APH_{it}*\max(BP_t, SP_{it})]*CL\}$. Otherwise, IR_{it} was set equal to zero.

Simulated net returns under different crop and revenue insurance products were used to analyze the efficacy of the insurance products from the producers' perspective. The statistical measures used to compare insurance products and coverage levels were mean net returns, standard deviation, coefficient of variation of net returns, probability of receiving an indemnity payment, premiums paid and indemnity payments received over the 10-year planning horizon, and the difference between the indemnities received and premiums paid. A third-degree stochastic dominance analysis was also used to rank crop insurance products and coverage levels assuming that cotton producers are risk averse. Also, confidence premiums were calculated using a method developed by Mjelde and Cochran as a measure of a premium subsidy it would take in order to make a producer indifferent between a dominated scenario and the dominant scenario.

Table 1. Parameter Estimates for the Irrigated and Dryland Cotton Yield and the Texas Cotton Price Distribution Models

	Parameter Estimate		
Parameter	Final Irrigated Model	Final Dryland Model	Final Price Model
θ	—	0.2631	
μ	—	19.9886	
B_{00}	394.2706	265.3709	
B_{01}	—	—	
B_{02}	91.8765	51.4848	
B_{10}	−7.7264	−16.2232	
B_{11}	—	—	
B_{12}	−7.4253	—	
B_2	0.5814	1.7620	
B_3	—	−0.0460	
B_4	—	0.2747	
B_5	—	—	
σ_{00}	230.6986	185.3323	
σ_{01}	—	−51.5959	
σ_{02}	−47.0928	—	
σ_{0L}	−112.0892	−49.5568	
σ_{10}	—	—	
σ_{11}	1.8243	1.9146	
σ_{12}	—	−1.1149	
σ_{1L}	1.8542	—	
σ_2	−0.0149	—	
σ_3	−0.2137	—	
σ_4	—	−0.1366	
θ			—
μ			—
ρ			0.4431
B_0			0.7043
B_1			−0.0022
B_2			—
σ_0			0.1180
σ_1			−0.00067
σ_2			—

Notes: All parameters are as defined in Equations (1–4), (7), and (8) in the text. All parameters included in the final model are statistically significant at the 10% level, according to the two-tailed Student's t- and the single-parameter likelihood ratio test.

Results

Yield and Price Distributions

Table 1 presents the final estimated yield and price distribution models. Single-parameter asymptotic t-tests were used to determine the statistical significance of the model parameters. All parameters that did not appear statistically significant at the 10% level were set equal to zero in the final models. Likelihood ratio tests were conducted to make sure that the restrictions imposed in the final models were statistically justified. The results indicate that dryland cotton yields in the northern High Plains, southern High Plains, and northern Low Plains are nonnormal, exhibiting a kurtotic and right-skewed distribution, whereas irrigated yields in those same regions appear to follow a normal distribution. The mean and variance of both distributions are changing through time and are affected by factors such as region and acres planted. This information is useful since actuarially fair premiums can only be calculated under a precise knowledge of the crop yield distributions.

For 1995, the predicted mean of the irrigated cotton yield distribution in the northern and southern High Plains was approximately 588 lbs./planted acre, whereas the predicted mean for the northern Low Plains was about 486 lbs./planted acre. The standard deviations of the irrigated cotton yield distributions in the southern High Plains, northern High Plains, and northern Low Plains were estimated at about 266, 219, and 172 lbs./planted acre, respectively. The means of the estimated dryland cotton yield distributions in 1995 were 228 lbs./planted acre for the northern and southern High Plains and 279 lbs./planted acre for the northern Low Plains. The standard deviations were 189 lbs./planted acre for the northern and southern High Plains and 159 lbs./planted acre for the northern Low Plains.

The mean of the yield distribution for each region was assumed to be the same at the farm and county levels, but different variances were estimated at each level. Farm- and county-level irrigated yield variability was found to be changing at different rates through time. The standard deviation of the estimated county-level irrigated cotton yield distribution for the year 1995 was about 75 lbs./acre less than the standard deviation of the estimated farm-level yield distribution for that year. Farm- and county-level dryland yield variability was found to be changing at the same rate through

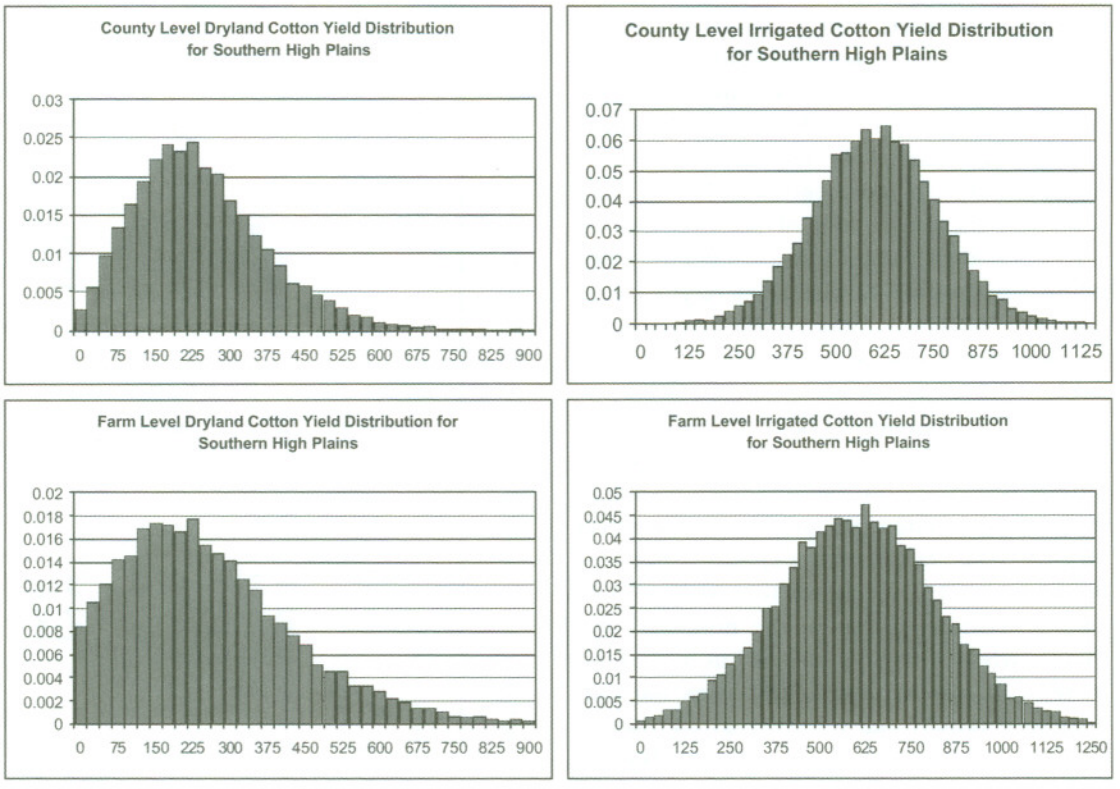

Figure 1. Comparison of 1995 Cotton Yield Distributions

time. The model indicates that from 1960 to 1998, the standard deviation of the farm-level dryland yield distribution was about 50 lbs./acre more than the standard deviation of the county-level yield distribution.

The simulated farm- and county-level dryland and irrigated cotton yield distributions for the southern High Plains in 1995 are presented in Figure 1. It should be noted that dryland yield right skewness is compatible with West Texas farmers' and researchers' intuition. Given normal rainfall conditions of 7–12 inches during the growing season, dryland cotton varieties can produce 100–400 lbs./acre. Under drought conditions (4–7 inches of rainfall), which can occur once or twice a decade, many farms achieve low, or even zero, yields. Extremely high yields (500–700 lbs./acre) can occur every 10–15 years as a result of very favorable temperatures and rainfall amounts exceeding 16 inches during the growing season. Therefore, right skewness of the dryland cotton yield distribution is derived from the right skewness of the rainfall distribution. It should also be noted that average dryland county-level yields were seldom below 75 lbs./planted acre, but farm-level yields have a much higher probability of falling between zero and 75 lbs./planted acre.

The estimated price model (Table 1) suggests that cotton prices in Texas have been linearly declining in real terms (1998 dollars) by about one cent every 5 years. The model estimates that the mean of the price distribution in 1934 was around $0.70/lb. The standard deviation of the 1934 price distribution was estimated at about $0.12/lb. and slightly decreasing through time. The statistical tests discussed earlier suggest that cotton prices are normally distributed, but autocorrelated.

Analysis of Alternative Crop and Revenue Insurance Products

Utilizing the simulated yields and prices, net revenues for the alternative crop and revenue

insurance products were generated for the 2000–2009 planning horizon. Furthermore, insurance premiums and indemnities were summed across a 10-year horizon to determine whether the receipt of indemnity payments offset the cost of the premiums. Tables 2 and 3 present the mean sum of net revenues ($/acre/yr.) and the mean sum of indemnity-premium surplus (I-P Surplus; $/acre/yr.) for alternative insurance products for irrigated and dryland cotton management practices, respectively.

For irrigated cotton (Table 2), the CAT insurance option increased the mean sum of net returns over the no-insurance scenario for all three regions under consideration. However, all CRC insurance products appear to decrease producers' net revenue relative to the no-insurance option, except in the northern High Plains, where CRC 50 resulted in a marginal increase in net revenues. CAT was the only insurance option that returned an I-P surplus in all of the scenarios studied. The 50/100 and 60/100 options also returned a surplus in the northern High Plains. The 75/100 option returned an I-P deficit in all scenarios. The 50% CRC option for irrigated cotton returned a surplus in the NHP, whereas the 60% and the 75% options returned a deficit in all of the scenarios studied. These results indicate that, in terms of expected producer net returns, irrigated cotton producers in all regions considered are better off to purchase at least the catastrophic coverage. In NHP, however, 50/100 and 60/100 MPCI products were also cost effective. Of the CRC insurance products, the 50% CRC option was the only cost-effective product for producers in the NHP.

For dryland cotton management practice (Table 3), CAT, 50/100, and 60/100 insurance options increased the mean sum of net returns over the no-insurance scenario for all three regions under consideration. CRC 50 also increased producer net returns relative to the no-insurance option in all regions, and CRC 60 resulted in a marginal increase in net revenues in NHP. Similarly, CAT, 50/100, 60/100, and CRC 50 insurance options returned an I-P surplus in all of the scenarios studied. The CRC 60 option also returned a surplus in NHP. The

Table 2. Net Revenues ($/acre/yr.) and Indemnity-Premium (I-P) Surplus ($/acre/yr.) for Irrigated Cotton for Alternative Insurance Products and Under a No-Insurance Scenario

	No Insurance	CAT 50/55	MPCI 50/100	MPCI 60/100	MPCI 75/100	CRC 50	CRC 60	CRC 75
SHP								
Mean net revenues	−83.39	−80.57	−84.32	−86.47	−92.19	−86.53	−89.77	−104.34
I-P surplus	—	25.34	−7.74	−26.58	−121.39	−28.34	−57.84	−189.01
NHP								
Mean net revenues	−79.29	−73.96	−76.98	−78.92	−91.94	−78.81	−81.60	−97.75
I-P surplus	—	47.68	21.28	4.28	−110.94	4.04	−21.27	−166.19
NLP								
Mean net revenues	−163.82	−161.92	−164.92	−166.62	−174.58	−165.96	−167.97	−177.10
I-P surplus	—	17.09	−9.32	−24.29	−94.64	−19.40	−37.82	−120.43

Table 3. Net Revenues ($/acre/yr.) and Indemnity-Premium (I-P) Surplus ($/acre/yr.) for Dryland Cotton for Alternative Insurance Products and Under a No-Insurance Scenario

	No Insurance	MPCI				CRC		
		CAT 50/55	50/100	60/100	75/100	50	60	75
SHP								
Mean net revenues	−125.85	−119.27	−121.48	−124.92	−141.44	−123.22	−127.60	−147.08
I-P surplus	—	58.55	19.99	8.54	−138.04	23.35	−15.63	−188.94
NHP								
Mean net revenues	−100.53	−93.93	−94.78	−96.85	−109.97	−96.12	−98.99	−114.83
I-P surplus	—	58.67	51.23	32.90	−83.55	39.11	13.47	−127.50
NLP								
Mean net revenues	19.45	22.84	21.69	21.21	14.92	20.51	19.35	10.69
I-P surplus	—	30.19	19.99	15.78	−39.95	9.04	−1.64	−79.20

Table 4. Ranking of Alternative Crop Insurance Products and Confidence Premiums for Irrigated Cotton According to Stochastic Dominance

	Irrigated			
	MPCI		CRC	
Region	Ranking	Confidence Premium (%)	Ranking	Confidence Premium (%)
SHP	CAT	—	No Ins.	—
	No Ins.	—	50	28.33
	50/100	62.76	60	34.41
	60/100	59.05	75	49.70
	75/100	53.14		
NHP	CAT	—	50	—
	50/100	38.13	No Ins.	—
	60/100	31.26	60	13.12
	No Ins.	—	75	39.11
	75/100	46.44		
LHP	CAT	—	60	—
	50/100	57.59	50	1.49
	60/100	36.40	No Ins.	—
	No Ins.	—	75	19.15
	75/100	46.51		

75/100 and CRC 75 options, however, returned an I-P deficit in all scenarios. These results suggest that available crop and revenue insurance products are relatively more effective for dryland cotton management practice in all regions considered. Producers were found to be better off to purchase up to 60/100 MPCI products and CRC 50 in all regions. In NHP, the CRC 60 product was also cost effective.

The stochastic dominance analysis for a risk-adverse irrigated producer indicates that the CAT is the overwhelmingly preferred MPCI option for all scenarios (Table 4). The ranking of the other MPCI options was consistently 50/100, 60/100, and 75/100. However, if no insurance is considered an option, it was found to be the second preferred option after CAT for irrigated cotton in the southern High Plains and was preferred over the 75/100 option in the northern High Plains and northern Low Plains. For dryland management

Table 5. Ranking of Alternative Crop Insurance Products and Confidence Premiums for Dryland Cotton According to Stochastic Dominance

	Dryland			
	MPCI		CRC	
Region	Ranking	Confidence Premium (%)	Ranking	Confidence Premium (%)
SHP	CAT	—	50	—
	50/100	21.84	No Ins.	—
	60/100	37.78	60	25.43
	No Ins.	—	75	45.36
	75/100	49.98		
NHP	CAT	—	50	—
	50/100	9.11	60	22.32
	60/100	27.89	No Ins.	—
	No Ins.	—	75	44.67
	75/100	47.09		
LHP	CAT	—	50	—
	50/100	34.00	No Ins	—
	60/100	24.80	60	12.43
	No Ins.	—	75	39.43
	75/100	42.23		

practice, the ranking of the other MPCI options (Table 5) was also consistently CAT, 50/100, 60/100, and 75/100 in all scenarios, and the no-insurance option always fared better than the 75/100 option.

In the case of the CRC insurance products for irrigated cotton (Table 4), the 50%, 60%, and 75% options ranked in that order in SHP and NHP. In NLP, CRC 60 was ranked higher that CRC 50, followed by CRC 75. The no-insurance option fared better than any of the CRC options in SHP. In the northern High Plains, the 50% option was preferred to no insurance, and in NLP, both CRC 50 and CRC 60 were preferred to no insurance. In the case of dryland cotton (Table 5), 50% CRC coverage ranked higher than no insurance for both the southern High Plains and northern Low Plains. In the northern High Plains, both the 50% and 60% CRC coverage levels fared better than the no-insurance option. In all scenarios considered, the no-insurance option ranked above the 75% CRC coverage level.

Tables 4 and 5 also present the confidence premiums expressed in percentage of subsidy it would take in order to make a producer indifferent between a dominated scenario and the dominant scenario. For irrigated cotton (Table 4), premium confidence results indicate that the amount of subsidy ranged from 38% to 63% for the 50/100 option. Subsidy levels for the 60/100 and 75/100 options ranged from 31% to 49% and from 46% to 53%, respectively. For CRC options, a range of subsidies from 1.5% to 50% were observed. Premium confidence for dryland cotton (Table 5) was generally lower than for that of the irrigated cotton. It is important to note that confidence premiums varied considerably across regions and production practices, perhaps implying that premium rates, to be actuarially fair, might have to be adjusted by varying amounts across regions for irrigated and dryland cotton.

Conclusions

The current study compares crop and revenue insurance products for selected regions in Texas using farm unit–level data. The main contribution of this study is the development of a comprehensive empirical procedure for evaluating and comparing the cost effectiveness of alternative crop and revenue insurance products.

An important aspect of the procedure is that the cotton yield and price distributions are estimated using an econometric technique that can accurately and separately account for the changing means and variances through time and location, right or left skewness, kurtosis, and the correlation among the irrigated and dryland cotton yield distributions. Results indicate that the probability distribution of dryland cotton yields in the southern Plains of Texas is right-skewed and kurtotic. Because of the right-skewness, assuming a normal distribution would likely overestimate the probability of low yields and underestimate the probability of high yields (Ramirez, Misra, and Field). If the probability of low cotton yields is being overestimated, certain crop and

revenue insurance products might appear efficient in a simulation analysis like the one conducted in this study, because they would be triggered by low yields. Also, the calculation of probabilistic statements about net returns from alternative crop and revenue insurance products would likely be biased because of the assumption of yield distribution normality. Clearly, when comparing various crop and revenue insurance products, it is important to accurately estimate the underlying yield and price distributions used for the analyses.

Although the illustration of the empirical procedure, in this study, is limited to 13 counties of three west Texas regions and seven alternative insurance products, its potential for wider adaptability should be recognized. The illustration suggests that 1999 premium rates (after subsidies) were too high for most buy-up insurance products for Texas cotton producers. One reason that insurance premiums appear high for higher levels of insurance could be adverse selection. Adverse selection results from a skewed participation rate toward the high-risk producers, increasing the risk of the insurance pool and indemnity payments. Actuarially fair premiums should not only result in increased producer participation but also might minimize the amount of adverse selection and lower the overall risk of the insurance pool. However, given premium confidences were found to vary considerably across region and production practices, an extensive evaluation of the current rating policy and setting mechanism might need to be undertaken on the basis of sound actuarial sciences.

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