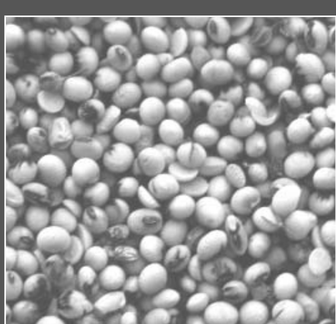
Bulletin 1109

August 2001



Potential of Multicrop Revenue Insurance to Serve the Needs of Mississippi Crop Producers

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This research was partially supported by the Risk Management Agency of the USDA and funded under cooperative agreement 98-COOP-2-6903. Bulletin 1109 was published by the Office of Agricultural Communications, a unit of the Division of Agriculture, Forestry, and Veterinary Medicine at Mississippi State University. August, 2001

Summary

The introduction of revenue insurance products that insure against both price and yield shortfalls has prompted consideration of a number of other variants on the traditional yield insurance concept. This study addressed the potential to develop actuarially sound insurance rates for a product subsuming the revenue risk from multiple crop enterprises. In this study, we developed a nonparametric approach that extends previous nonparametric rating models by accounting for the added complexity of cross-commodity correlations. This model was empirically applied to Sunflower County, Mississippi, where both cotton and soybeans are produced. Additionally, we illustrated going beyond the two-crop scenario with a three-crop combination of cotton, soybeans, and wheat. The empirical applications confirmed a substantial reduction in risk and insurance premium rates resulting from combined crop revenue coverage. Finally, the risk reduction effectiveness of these insurance designs was evaluated for a representative farm scenario.

Keywords: Crop insurance, risk, bootstrapping, revenue insurance.

Potential for Multicrop Revenue Insurance to Serve the Needs of Mississippi Crop Producers

Multiple-Crop Revenue Insurance

Multicrop revenue insurance is a further extension of the well-received crop insurance pilot programs providing revenue insurance. The 1996 elimination of deficiency payments increased producers' exposure to price risk. At the same time deficiency payments were eliminated, revenue insurance was made available providing both yield risk and price risk protection. Crop Revenue Coverage (CRC) was introduced in 1996. It pays for losses below the revenue guarantee at a preseason price or harvest price, whichever is higher. CRC has become increasingly available, as it was offered in 36 states in 1999. Two alternative revenue insurance plans have also been developed: Income Protection (IP) and Revenue Assurance (RA). IP has been piloted in several states. Arkansas and North Carolina soybeans, North Carolina corn, Texas sorghum, and a limited application of Alabama and Georgia cotton are the Southern pilot programs. RA has been offered in several northern states, as well as in Arkansas and Tennessee for corn and soybeans. Basic IP and RA pay an indemnity when the actual and appraised yield multiplied by the harvest price is less than the revenue guarantee. However, RA now has a harvest price option that provides coverage similar to CRC. The success of revenue insurance suggests that producers have an interest in subsuming multiple risks in a single insurance package. However, of these revenue insurance products, only CRC has been offered in Mississippi.

An extension of revenue insurance, which combines price and yield risk protection, is to aggregate across the portfolio of crops grown on the farm. RA, which recognizes the diversification effect from insuring more than one crop, does offer a multiple-crop option. Premiums are therefore adjusted for producers who insure corn and soybeans as a single unit. The maximum coverage also increases to 80% under the multiple-crop option.

Another pilot insurance design is Adjusted Gross Revenue Insurance (AGR), which provides coverage for gross revenue of producers growing crops without Multiple Peril Crop Insurance programs. The five pilot areas for AGR in 1999 were counties in Florida, Michigan, Maine, Massachusetts, and New Hampshire. AGR uses five years of Schedule F tax records to establish coverage, premium rates, and indemnities. (Prices are established according to projected prices, and yield guarantees are based on individual APH yields.) This product emphasizes multiple crops and provides producers with discounts for diversification.

The Southern experience with crop insurance also lends itself to the development of multiple-crop revenue insurance. The Southern situation is one of high premiums resulting from high risks and, some believe, a history of moral hazard, adverse selection, and product design problems. Relative to other regions, the Midsouth's historical experience with crop insurance has been a poor one, with low participation and large losses on insured policies (Barnett and Coble). This problem results from differences in the level of risk across producers as well as a lack of experience to set actuarially sound rates. These rates are also high due to past insurance losses and program abuse (Barnett, Coble, and Spurlock).

Therefore, an insurance program that takes into account the reduced risk from insuring multiple crops would seem relevant to the South. Given the historically high premiums that characterize this region, a policy recognizing the risk benefits of diversification could provide producers with protection at a lower premium rate. Further, this study was conducted in such a way that single crop revenue designs may also be investigated and compared with the more familiar yield insurance designs.

A review of cotton insurance rates conducted in 1999 resulted in large downward adjustments in the base MPCI yield insurance rates for 2000. Most Midsouth cotton yield insurance rates were reduced by approximately 50%, while no significant changes were made to the rates for other crops such as soybeans, rice, and corn. This makes the yield insurance product more attractive to cotton producers, but it also affects the potential for revenue insurance products. Historically, the CRC rating process has relied upon the yield insurance rates for the yield component of the CRC revenue risk. However, because the CRC product is privately developed and rated, the private company has the latitude to not follow the changes in cotton yield insurance rates. Instead, the company made an across-the-board 10% reduction in the yield component of the CRC rate. Before the cotton yield insurance rate changes, CRC cotton rates averaged 30-40% higher than yield insurance rates. With these rate changes, CRC will generally be in the neighborhood of 100% higher than yield insurance rates. Thus, Mississippi cotton producers are now likely to perceive the one revenue insurance product available to them (CRC) as cost-prohibitive. In contrast, some locations, such as portions of Iowa, have three or more comparably priced alternative revenue insurance products available.

Examples of Multiple Crop Coverage

Multiple-crop revenue insurance, as defined for this study, would provide an insurance guarantee that insures against shortfalls in the aggregate gross revenue of multiple crops. Thus, the equation may be written:

$$\text{Indemnity} = \text{MAX}\left[L\sum_{i=1}^{n} a_i \overline{P}_i \overline{Y}_i - \sum_{i=1}^{n} a_i P_i Y_i,\ 0\right]$$

where P and Y are, respectively, price and yield. The i subscript denotes the individual crops and the acreage in crop i is represented by a_i. Pre-sign-up futures market expectation of harvest-time price is $\overline{P}_i$. The expected farm yield for crop i is denoted by $\overline{Y}_i$ and assumed to be derived from standard approved production history (APH) calculations. The realized harvest month futures price is P_i, while the actual yield of the crop is denoted by Y_i. L represents the coverage level percentage chosen by the producer. The sum of $a_i \overline{P}_i \overline{Y}_i$ multiplied by L is the insured revenue for the crops covered by the policy, while the sum of $a_i P_i Y_i$ is the actual revenue produced by the insured crops. An indemnity is paid if the total revenue coverage level is greater than the total actual revenue. We would note that this insurance design does not include other government program payments. In particular, one might consider including loan deficiency payments. This has some intuitive appeal, but it has not been done in any existing crop revenue insurance design.

The following examples illustrate several scenarios of revenue insurance coverage for multiple commodities, in this case corn, soybeans, and cotton. This is illustrated in example A of Table 1. The combined expected total revenue is found by summing the expected total revenue across all crops. The liability is found by multiplying the coverage level — 75% for these examples — by the combined expected total revenue. For the following four examples, coverage is $210,600.

Table 1 shows examples of how multicrop revenue insurance would work. In example B, per-acre yields are below their expected levels, while prices are assumed for illustrative purposes to equal their expected values. Thus, the total revenue from each crop is less than expected, resulting in a total combined revenue shortfall of more than $40,000. However, since the realized revenue is well above the 75% coverage level, no indemnity is paid.

Example C is similar, except in this case prices are also lower than expected. Again, the revenue from each crop is substantially lower than expected. Yet, the combined total revenue remains above the 75% coverage level, and again, no indemnity payment is made.

Example D has one difference from example C: the soybean yield per acre is only 40% of expected yield. This causes the actual total revenue for soybeans to be $6,000 — a third of what was expected. Despite the low returns from soybeans, revenue from the other two crops causes actual combined total revenue to equal $211,000 — just above the level that would trigger an indemnity. This example illustrates the lower risk of combining crops from an insurer's perspective; although total revenue received from soybeans was much lower than expected, the total revenue received from all crops was still more than 75% of what was expected, hence no indemnities are paid.

The final example (E) also has prices and yields that are lower than expected, but this time yields per acre are reduced even further from the first two examples. Each crop's expected revenue is well below its expected level, resulting in combined total revenue that is less than the 75% coverage level. This triggers an indemnity payment, which is found by taking total revenue at the 75% coverage level — $210,600 — and subtracting the actual combined total revenue — $175,000 in this example. The difference is the resulting indemnity payment of $35,600.

Table 1. Examples of how multicrop revenue insurance would indemnify producers.

Crop	Acres planted	Price	Yield	Revenue
	no.	*$*	*bu/A*	*$*
Example A – Revenue guarantee.				
Corn	200	2.20	120	52,800
Soybeans	100	6.00	30	18,000
Cotton	500	0.60	700	210,000
Total Revenue				**280,800**
75% Coverage				**210,600**
Example B – Actual yields lower than expected yields with no indemnity payment.				
Corn	200	2.20	100	44,000
Soybeans	100	6.00	20	12,000
Cotton	500	0.60	600	180,000
Total Revenue				**236,000**
75% Coverage				**210,600**
Total Indemnity				**0**
Example C – Actual prices and yields lower than expected with no indemnity payment.				
Corn	200	2.00	100	40,000
Soybeans	100	5.00	20	10,000
Cotton	500	0.55	600	165,000
Total Revenue				**215,000**
75% Coverage				**210,600**
Total Indemnity				**0**
Example D – Actual prices and yields lower than expected with no indemnity payment.				
Corn	200	2.00	100	40,000
Soybeans	100	5.00	12	6,000
Cotton	500	0.55	600	165,000
Total Revenue				**211,000**
75% Coverage				**210,600**
Total Indemnity				**0**
Example E – Actual prices and yields lower than expected with indemnity payment.				
Corn	200	2.00	75	30,000
Soybeans	100	5.00	15	7,500
Cotton	500	0.55	500	137,500
Total Revenue				**175,000**
75% Coverage				**210,600**
Total Indemnity				**35,600**

Modeling and Rating Issues

Central to rating a multicrop revenue insurance policy is capturing the variability of each random variable subsumed in the policy and the correct correlation between these random variables. With revenue insurance, this requires measuring yield variability and price variability, as well as the correlation between the two. As one generalizes to a multicrop context, there is an increase in the number of random variables. Price and yield variability for each crop are added. Further, the number of correlations between random variables expands at an exponential rate. Another essential factor that must be addressed is the appropriate structure of the farm-county yield relationship for each crop. It is quite plausible that idiosyncratic factors that affect one crop on a farm are likely to affect another crop on that same farm. For example, if there was flooding on a farm's cotton acreage, it is untenable to assume that there cannot be a higher probability that there is flooding on that farm's soybean acres as well.

Beyond inclusion of the appropriate random variation within the multicrop context, there are essentially two approaches to modeling such a product. One can take a nonparametric approach, which emulates the IP rate-setting method, or one can take a parametric approach, which emulates the RA rate-setting method. There are tradeoffs between these two approaches. Parametric assumptions can add information to estimation, which gives a more efficient estimate of the distribution. However, incorrect assumptions about the parametric family from which the random variable is drawn can lead to biased and inconsistent estimates. Nonparametric approaches make no such assumption. However, they can be shown less efficient if the underlying distribution is known. Given the multitude of crops and regions to which the rate setting model may potentially be applied, we chose a nonparametric approach in the belief that this is a more flexible estimator capable of addressing a variety of different empirical data.

It was our objective in this analysis to develop an approach that can be generalized beyond the two-crop case and facilitate combining a larger number of crops. There is inherently additional complexity with multiple crops. However, we do believe decisions can be made in model development that make the model more tractable and allow for a generalization that is more straightforward than other approaches. Modeling multicrop revenue insurance will be a highly data-intensive procedure. Our results were derived for Sunflower County, Mississippi. The data for the study include historical Sunflower County yields and MPCI farm yield histories from Sunflower and neighboring counties. Price data include historical futures price data from the Chicago Board of Trade and the New York Futures Exchange. Details of the simulation model used to rate multicrop revenue insurance are reported in Appendix A. Further information regarding the data used is reported in Appendix B.

RATING MODEL RESULTS

The rate simulation model used in this analysis is a nonparametric bootstrapping model, which is commonly used in crop insurance rate simulation exercises. The Income Protection revenue insurance product is rated in a similar framework, but it does not allow for multiple crops. A crop insurance rating procedure must be capable of generating rates for individuals with a variety of characteristics that may influence rates. In particular, adjusting rates for individuals with differing levels of expected yield is a component of all the individual-level insurance designs currently offered. When moving beyond single-crop insurance to multicrop insurance, the riskiness of a policy is also conditional on the proportions of different crops in the portfolio. Our rating procedure was designed to account for both factors.

We also followed the rating innovation introduced by the designers of IP, which recognized that estimating the mean yield of a farm from a short yield history (10 years or less is used in U.S. crop insurance) resulted in an estimate with potentially large estimation error. Because county yields are available for a longer period than farm yields, additional information can be brought into the estimation of the farm's expected yield by combining it with the county yield. The rating procedure used in this study incorporates a county adjusted regional (CAR) yield factor that adjusts rates to account for the possibility that the APH for a farm may be based on 10 or fewer years that are not representative of the expectation derived from more years of data. For example, if the APH yield history contains three years where county yield was observed to be 10% below expectations, then an adjustment is made to reflect that this farm's APH yield is probably biased downward by poor growing conditions that occurred in those years.

Table 2 shows a rate table for a representative Sunflower County, Mississippi, multicrop revenue product for a combined cotton/soybean policy. The example has an APH on cotton and soybeans at the central R-span on both crops (an R-span is a yield range

Table 2. Sample Sunflower County, Mississippi, multicrop revenue insurance rates as a percentage of liability for cotton-soybean combined policy.[1]

Coverage level	Premium rates at various CAR yield percentages for cotton and soybeans [2]								
	0.8/0.8	0.8/1.0	0.8/1.2	1.0/0.8	1.0/1.0	1.0/1.2	1.2/0.8	1.2/1.0	1.2/1.2
Only soybeans planted									
50%	2.30	3.49	5.24	2.34	3.74	5.34	2.38	3.35	5.13
55%	2.77	4.25	6.63	2.79	4.42	6.77	2.76	4.31	6.52
60%	3.18	5.18	8.33	3.31	5.38	8.21	3.21	5.21	8.32
65%	3.68	6.18	10.10	3.78	6.44	10.24	3.84	6.43	10.33
70%	4.41	7.65	12.27	4.56	7.64	12.15	4.47	7.79	12.26
75%	5.19	9.19	14.66	5.23	9.12	14.66	5.24	9.05	14.53
50% cotton, 50% soybeans planted									
50%	0.82	1.06	1.23	1.52	1.70	1.99	2.31	2.67	2.97
55%	1.12	1.34	1.65	1.88	2.27	2.72	3.21	3.65	4.16
60%	1.49	1.83	2.24	2.60	3.11	3.58	4.09	4.84	5.68
65%	1.88	2.37	2.79	3.51	3.89	4.73	5.47	6.36	7.42
70%	2.46	2.95	3.54	4.32	5.17	6.06	7.06	7.99	9.59
75%	3.11	3.82	4.37	5.39	6.57	7.69	8.92	10.30	11.82
Only cotton planted									
50%	2.09	2.09	2.07	3.22	3.33	3.31	5.08	4.93	5.04
55%	2.33	2.36	2.51	4.00	4.11	4.06	6.52	6.47	6.48
60%	2.96	3.05	2.87	5.09	5.09	4.88	8.35	8.15	8.21
65%	3.51	3.56	3.55	6.28	6.26	6.09	10.20	10.34	10.07
70%	4.27	4.19	4.29	7.58	7.56	7.51	12.59	12.46	12.52
75%	5.00	5.15	5.06	9.22	9.23	9.11	15.07	15.08	15.01

[1]This analysis assumes a cotton approved production history (APH) of 667 pounds per acre and a soybean APH of 22.95 bushels per acre.
[2]These columns express premium rates at various combinations of county adjusted regional (CAR) yield percentages for cotton and soybeans. In each combination of CAR percentages, the first number represents cotton, while the second number represents soybeans. For example, the 0.8/1.0 column represents a situation in which cotton yield is at 80% of APH, but soybean yield is at 100% of APH. Premium rate is expressed as a percent of crop liability.

used in crop insurance to categorize the average yield of an insurance unit relative to historical average yields in the county). The generalization to the two-crop case results in a more complex rate table than with a single-crop model. There is an additional complexity in this table in that we have adopted the IP adjustment for indexing APH rates to the observed county experience in the years where the APH is available. This factor resulted in the various combinations of cotton and soybean CAR percentages presented in Table 2.

Table 2 illustrates premium rates in three multicrop revenue policy scenarios: (1) a farm planted 100% to soybeans; (2) a farm planted 50% to cotton and 50% to soybeans; and (3) a farm planted 100% to cotton. Premium rates are expressed as percentages of the crop liability. The first column of Table 2 indicates coverage levels ranging from 50% to 75% in 5% increments. The combinations of CAR percentages, which are presented above the second through the tenth columns of rate data in Table 2, reflect cotton and soybean APH adjustments. For example, the column heading of 0.8/0.8 reflects a situation in which the approved production histories on the policies for both cotton and soybeans are 80% of the expected yield for the farm. Likewise, the 1.0/1.0 combination of cotton/soybean CAR percentages indicates a situation where the APH on both cotton and soybeans is exactly at the expected yield for the farm. The APH is identical in all scenarios: for cotton, expected yield is 667.89 pounds per acre; for soybeans, 22.95 bushels per acre.

As expected, premium rates increase as coverage level increases from 50% to 75%. Rates also increase as CAR percentages increase, reflecting the fact that a CAR percentage greater than 1.0 implies overinsurance relative to the expected yield for the farm. Thus, the 1.2/1.2 combination of CAR percentages results in the highest premium rates. Comparisons of the rates under the three planting scenarios can be made. The first and third scenarios present rate tables for one-crop revenue insurance — the first covering soybeans and the third covering cotton. For comparison, the second scenario presents rates for a 50/50 combination of cotton and soybeans. For example, under the 1.0/1.0 CAR percentages at the 75% coverage level, the one-crop soybean revenue insurance rate is 9.12% of liability; the one-crop cotton rate is 9.23%. Both are considerably higher than the combined 50/50 rate of 6.57% of liability. Thus, an obvious reduction in the premium rate results from blending two crops together.

Tables 3 and 4 provide additional insight to the Sunflower County, Mississippi, cotton/soybean example by quantifying two effects of a multicrop policy. Table 3 compares multicrop rates with single-crop insurance rates. At each coverage level, this table presents a ratio of the 50/50-cotton/soybean rate relative to the 100% soybean rate and to the 100% cotton rate. Because soybean rates are slightly higher, the ratios tend to be lower for soybeans than for cotton. The table shows that the 50/50 combined cotton/soybean policy rate is never more than 72% of the single-crop rate. This indicates the large effect on rates from combining the two crops. The second interesting effect is that the percentage relationship of the 50/50 rate to the single-crop rate declines as coverage level declines. We suggest that the less variable combined-revenue distribution results in rates that decline more rapidly as coverage level is reduced as compared with either individual crop revenue.

Table 3. Multicrop revenue insurance rates compared with single-crop revenue insurance rates in Sunflower County, Mississippi.

Coverage level	50/50 cotton/soybean multicrop rate as a percentage of 100% soybean rate	50/50 cotton/soybean multicrop rate as a percentage of 100% cotton rate
50%	45%	51%
55%	51%	55%
60%	58%	61%
65%	60%	62%
70%	68%	68%
75%	72%	71%

Table 4. Multicrop revenue insurance rates compared with MPCI rates in Sunflower County, Mississippi.				
Coverage level	100% soybean multicrop rate as a pct. of MPCI soybean rate	100% cotton multicrop rate as a pct. of MPCI cotton rate	50/50 cotton/soybean multicrop rate as a pct. of MPCI soybean rate	50/50 cotton/soybean multicrop rate as a pct. of MPCI cotton rate
50%	31%	37%	14%	19%
55%	33%	42%	17%	23%
60%	36%	47%	21%	29%
65%	38%	50%	23%	31%
70%	37%	50%	25%	34%
75%	35%	48%	25%	34%

Table 4 compares various coverage levels of multicrop revenue insurance rates with the 1999 MPCI rates for soybeans and cotton. Differences between the 100% soybean rate and the MPCI soybean rate largely stem from two factors: revenue is insured instead of yield; and an aggregation across crops occurs in the multicrop revenue insurance product. Further, the multicrop design does not allow unit breakout as allowed with MPCI. In this instance, the rate for the 100% soybean multicrop product never exceeds 38% of the MPCI yield rate. The other issue to note here is that this is a simulation-based approach to rate setting and that the underlying yield variability in the simulation model may not be consistent with the MPCI yield insurance rates. For example, prevented planting and replant provisions are probably not well reflected in this approach. Similar results are seen in the comparison of the 100% cotton revenue rate with the 1999 MPCI cotton rate. Here, the ratios are slightly higher, but they never exceed 50%. However, the most dramatic reductions in insurance rates are seen when the 50/50-soybean/cotton multicrop combination is compared with 1999 MPCI rates for soybeans and cotton. For example, for a 50% coverage policy, the multicrop rate is 14% of the MPCI soybean rate. In all the coverage levels examined, the 50/50-soybean/cotton rate never exceeds 34% of the MPCI cotton rate.

Three-Crop Analysis

To investigate further generalizations of multicrop revenue insurance to a larger number of crops, an empirical example for the Sunflower County, Mississippi, case was constructed, which added winter wheat to the mix. The addition of winter wheat introduces a third crop planted and harvested at a significantly different time than cotton and soybeans. Therefore, it is quite plausible that the yield for wheat would be much less correlated with the other two crops than cotton and soybeans are with each other. Table 5 supports this assumption with the computed correlations among the three crop yields. This correlation matrix was calculated from county-level yield deviations from trend. Cotton and soybeans, because of similar growing seasons, were correlated at a 0.5 level. However, wheat is less correlated with cotton (correlation = 0.26) and even less correlated with soybeans (correlation = 0.15). Therefore, including wheat should significantly lower insurance rates given the low correlation between wheat and the other crop yields.

Figure 1 shows the premium rate for Sunflower County, Mississippi, 75% multicrop insurance for a

Table 5. Correlation of Sunflower County, Mississippi, crop yields.

	Cotton	Soybeans	Wheat
Cotton	1.00		
Soybeans	0.50	1.00	
Wheat	0.26	0.15	1

farm with the average APH yield in the county. The darker bars in the figure reflect the premium rate for three crops (cotton, soybeans, and wheat), and each bar reflects different combinations of acreage among the three crops. The rate for two-crop (cotton and soybeans) insurance is included in the lighter bar. Interestingly, wheat is a riskier crop than cotton and soybeans. The first three sets of columns in Figure 1 represent insuring 100% of cotton, soybeans, and wheat. It becomes immediately obvious that wheat insurance rates are approximately 15%, while the higher of the other two crops, cotton, has a premium rate at approximately 9%. Although a diversification effect does result in lower rates at the various combinations of acreage, this effect is dampened by the fact that wheat rates are extremely high.

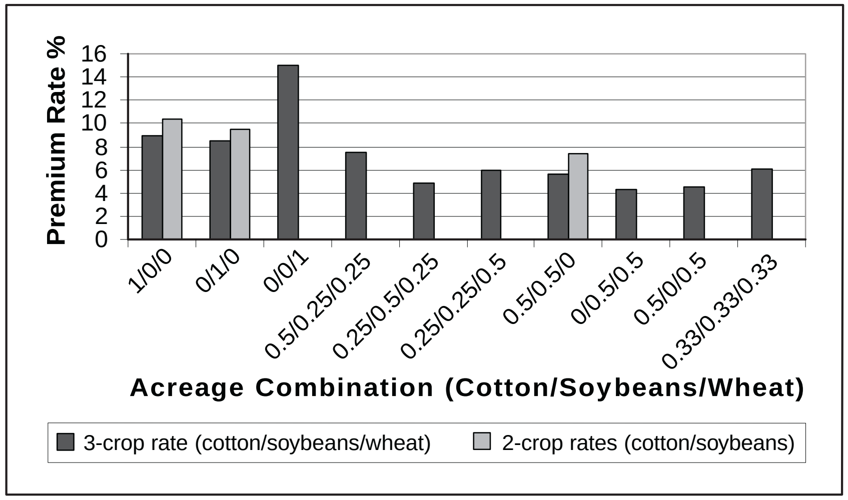

Figure 1. Comparison of three-crop and two-crop multicrop insurance rates at 75% coverage for average APH yields (Sunflower County, Mississippi).

Another issue illustrated in this figure is the differences in the two-crop and three-crop premium rates computed by the model. A different sample of farm-county yield difference was collected to derive the farm-level deviations for the three-crop rate than was used for the two-crop (cotton and soybeans) design. This implied that we had to take the APH yield data and match within a year for the same farm. In the two-crop analysis, there were 276 observations of farm-level yield deviations from which we could draw. In the three-crop case, even with an expanded geographical region from which farm-level yield deviations are drawn, the sample declined. The sample size in the three-crop case is based on only 91 observations. Thus, it appears that there is an empirical dilemma in setting such rates that stems from the limited sample of farms with data for multiple crops.

Risk Reduction for Mississippi Producers

The risk reduction gains for Mississippi producers are also addressed in this analysis. Given the primary incentive to purchase insurance is to reduce risk, this analysis quantifies not only the change in expected returns due to purchasing insurance, it also estimates the value that a risk-averse producer would place on having less risk. The examples computed here are reliant on assumptions regarding the wealth and risk aversion of the producer. We have assumed 75% insurance coverage for all scenarios. While the magnitude of the results for different producers is highly conditional on these assumptions, the relative ranking of the benefits from the alternative designs is generally stable.

The risk benefits reported here are calculated from several thousand replications of the random possible outcomes for prices and yields. The final monetary outcome for each iteration is found by subtracting production costs (according to enterprise budgets for the Mississippi Delta) and premiums, and adding indemnities to market revenue. Premiums are calculated by the procedures previously discussed and are assumed actuarially fair. Ending wealth is used to find the value a risk-averse farm would place on each possible outcome. These values are referred to as certainty equivalents and may be considered as the risk-adjusted returns to insurance. Details of the certainty equivalent calculations are reported in Appendix C.

The use of multicrop revenue insurance, single-crop revenue insurance, and yield insurance was found to increase certainty equivalents for selected acreage combinations as compared with uninsured production. Table 6 illustrates the average percentage increase in certainty equivalents for these three instruments for seven selected acreage combinations. The results indicate that the average increase in certainty equivalents is greatest for multicrop and single-crop revenue insur-

Table 6. Average percentage increase in certainty equivalents from multicrop insurance relative to no insurance for selected acreage combinations.[1]

Percent of crop			Multicrop	One-crop	Yield
Cotton	Soybeans	Wheat	revenue ins.	revenue ins.	insurance
75.0	12.5	12.5	3.05%	3.98%	3.63%
12.5	75.0	12.5	21.15%	21.60%	20.40%
12.5	12.5	75.0	14.97%	14.78%	13.64%
50.0	25.0	25.0	10.23%	10.91%	10.09%
25.0	50.0	25.0	17.45%	17.66%	16.71%
25.0	25.0	50.0	14.31%	14.84%	14.00%
33.0	33.0	33.0	14.30%	14.96%	13.96%

[1]Assumes 75% coverage insurance.

ance, as would be expected. However, in many instances the increases are only marginal at best. The increases for multicrop and single-crop revenue insurance are approximately the same, and single-crop revenue is slightly higher for most combinations. This is because single-crop revenue insurance pays indemnities in some instances where multicrop revenue insurance does not, resulting in the greater risk reduction. Table 6 also shows that the increases are smallest where cotton makes up the largest acreage combination.

Figure 2 illustrates the revenues (market revenue plus insurance indemnities) per acre found for the three insurance designs discussed in the preceding paragraph. The three designs are compared with the distribution of uninsured revenue. As expected, each insurance product decreases the probability of the lowest revenues per acre, effectively truncating the lower end of the revenue distribution with no insurance. In the upper tail of the revenue distributions, the revenue distributions of the insurance designs lie slightly to the left of the revenue distribution with no insurance due to

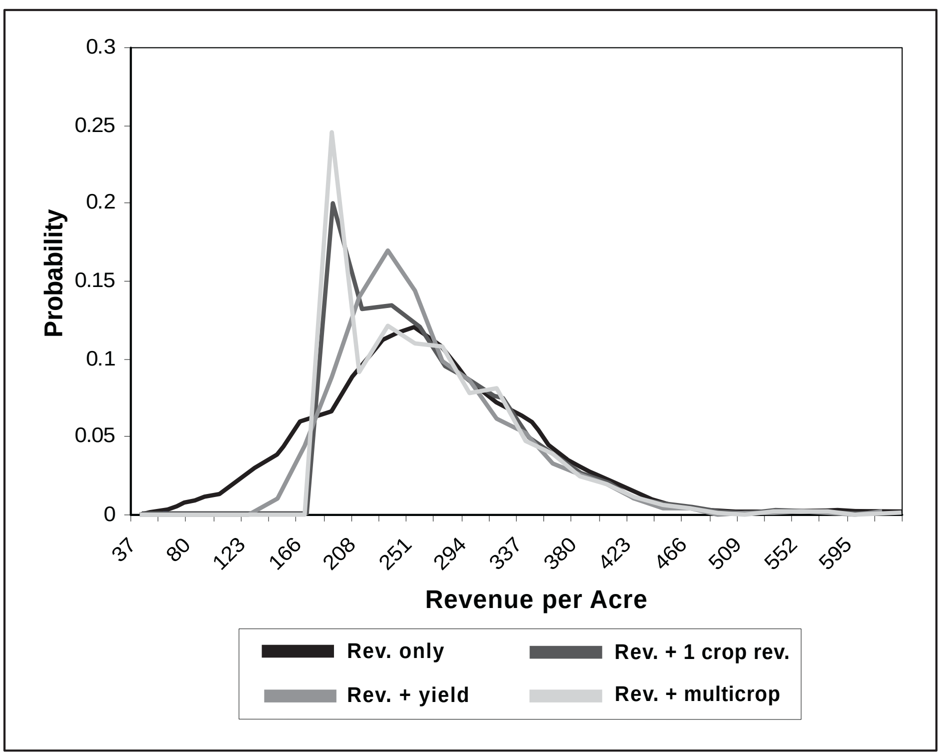

Figure 2. Comparison of the farm revenue distribution under alternative insurance designs.

the cost of a premium. The revenue insurance products do the best job of eliminating the lower end of the revenue distribution. Multicrop revenue insurance provides a smooth cutoff at 75% of expected revenue. The multicrop revenue insurance distribution has the lowest probability of low revenues. The single-crop revenue insurance pays out in some cases when the multicrop does not, because the trigger can be reached on an individual crop while not occurring over multiple crops.

Conclusions

This research project investigated the empirical feasibility of designing a multicrop revenue insurance rate-setting approach that insured total revenue from more than one crop. Several challenges were confronted in this research. The first challenge was finding a fundamentally sound approach to combining random variables for both price and yield on multiple crops and to do so in a model that is estimable and tractable as one increases the number of crops.

We believe that the nonparametric approach, which we have taken, allows simplicity of construction that makes the expansion to multiple crops feasible. It also maintains a rigorous relationship between random variables such that valid estimates of the joint revenue across commodities for a single farm can be made. We see the primary limitation to this method stemming from limited data where observations on yield from the same farm for the different commodities are needed. As one expands the number of commodities to be insured, the intersection among commodities will become smaller. This appears to be a particular limitation in regions such as the Midsouth where crop insurance participation is much less prevalent.

A second issue is the difficulty of constructing rate tables. We were able to construct rate tables for a two-crop case readily. However, the additional dimension of a third crop appears to preclude reasonable rate table construction. Thus, it appears that once one goes beyond two crops, a software-base rating mechanism would be required.

The construction of our model required a number of fundamental assumptions. For example, trend estimation, the farm yield sample, the relationship between farm yield and the county were all assumed to conform to particular assumptions as we constructed this model. These issues need to be investigated further. As always, the issue of the representativeness of the APH yield history remains an issue. However, making a similar argument to that of Atwood, Baquet, and Watts, some of these problems may be precluded when the contract design maintains an enterprise level of aggregation. Extending the multicrop design to include optional units — which in MPCI allows subdivision of the insured acreage — will either require crude assumptions in rate setting or an extremely complex model as compared with our approach.

Finally, there is a need for further investigation of the underwriting issues associated with designing such a product. Differences in sign-up time and harvest dates of crops can, in our opinion, be either beneficial or problematic from an underwriter's point of view. A producer who insured wheat, cotton, and soybeans might know the actual wheat revenues before even planting the other two crops. The fact that wheat was insured in the combination policy could potentially induce moral hazard on the second set of crops. If the wheat revenue was very low, then there may be a disincentive to effectively manage the spring-planted crops and vice-versa. Double cropping of wheat and soybeans is not examined here but would probably add to this problem.

Another key underwriting issue that relates back to the actuarial issues is the fact that the development of this model and the rating approach requires knowledge of the acres of each crop that are being planted. A staggered planting scenario — such as combining wheat with cotton and soybeans in Mississippi — creates a situation where it is very possible that after the insurance is purchased, and for legitimate economic reasons, producers decide they want to alter the acreage allocation between cotton and soybeans. However, such reallocation would have an effect on the appropriate premium rate. This issue may be problematic when trying to insure staggered seasoned crops under the multicrop design.

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Appendix A

A Detailed Description of the Multicrop Revenue Insurance Rating Model

This appendix explains the rating procedure proposed for the multicrop revenue insurance product. Our terminology will follow that used by Atwood, Baquet, and Watts (ABW) in designing the Income Protection (IP) product. This convention is followed because both rating systems are nonparametric bootstrapping procedures. The extension to the multicrop case requires specification of each crop and the relevant joint distributions. We propose that this should be done primarily through pairing regression residuals and inclusion of cross price effects as will be shown below. First, the simulation of aggregate and then disaggregate yield is described. Then, the structure of the joint yield simulation is explained. Next, the relationship between price and yield is modeled. Finally, the full revenue simulation model is explained.

Regional Yield Trend and Variability

In this model, as in all revenue insurance models of which we are aware, long time series of yields are generally available only at the aggregate level. Capturing the information contained in a long time series is critical to appropriately assessing the probability of random weather events. However, aggregation of less than perfectly correlated yields inherently dampens variability in the aggregate measure. Thus, we follow ABW and Miranda in estimating farm-level yield variability by combining relatively short farm-level yield series with longer aggregate yield series.

The construction of the aggregate yield component of the model begins with estimation of yield trend to create a mean-stationary sample of aggregate yield variation. Time trend is assumed to reflect changes in production technology that may vary across crops. We separately estimate the trend for each crop but allow that the residuals may not be independent.

Following the ABW approach, regional yield trend is estimated as

$$(1) \qquad R_t = a_1^R + g(t) + e_t^R$$

Regional yield in year t, R_t, is expressed as a function of the intercept, a_1^R, and time that is generally represented by the function g(t) and may vary by region. Residual deviations from trend are denoted as e_t^R. The R superscript identifies these parameters with the regional yield. Because of potential heteroscedasticity in the residuals, the Glesjser test is estimated as

$$(2) \qquad |e_t^R| = b_1^R + b_2^R\, t + u_t^R$$

where the absolute value of e_t^R is regressed against time. If a significant relationship with time is found, the errors from (1) are scaled by the ratio of predicted errors in the forecast year (1998) to the predicted value for year t.

$$(2a) \qquad e_{t,97}^R = \; e_t^R * (b_1^R + b_2^R\, 1998) / (b_1^R + b_2^R\, t)$$

Given that trend g(t) is estimated at a regional level and assumed identical for all counties in the region, county intercept adjustments may be estimated as

$$(3) \qquad C_t = a_1^C + g(t) + u_t^C$$

where C_t is county yield in year t, a_1^C is the intercept and u_t^C represents the county-specific residuals. In either a linear or a nonlinear case, a_1^C can be estimated as the mean deviation of actual county yield from predicted as shown in

$$(3a) \qquad a_1^C = 1/T_c \sum\nolimits^{T_c}_{t=1} (C_t - g(t))$$

Given the estimate of a_1^C, ABW specify a county adjusted regional yield (CAR) denoted here as R_t^C. Equation (4) provides a predicted county yield and the residual is used to bootstrap county yield variability. Note that e_t^R is taken from (2a) above.

$$R_t^C = a_1^C + g(t) + e_t^R \quad (4)$$

After investigating alternative trend estimators, we could not reject the linear trend estimator for the Mississippi cotton, soybean, and wheat data. The resulting trend estimates resulting from ordinary least squares (OLS) and generalized least squares (GLS) procedures are reported in Appendix Table A-1. Tests for heteroscedasticity are found significant and GLS procedures are used in the soybean model. The cotton and wheat trends are estimated with OLS.

Appendix Table A-1. Regression results of trend estimator for Sunflower County, Mississippi, cotton and soybeans.

Variable	Soybean yield [1]		Cotton yield		Wheat yield	
	Parameter estimate	Pr > |t|	Parameter estimate	Pr > |t|	Parameter estimate	Pr > |t|
Intercept	20.51	<0.0001	532.02	<0.0001	23.6	<0.0001
Time	0.044	0.0426	3.095	0.135	0.155	0.048
R-square	0.972 [2]		0.057		0.099	
F-value	660.6		2.32		4.17	
Pr > F	<0.0001		0.135		0.048	

[1]Tests for heteroscedasticity indicated a GLS estimate should be used. Those parameters are reported.
[2]In the GLS procedure, R-square is redefined.

Farm Yield Deviations

After having constructed a model of county yield variation, the next step in rating is to capture the difference in farm and county yield. Note that there must be a statistical relationship between the county and farm yield due to the county yield being an aggregate subsuming the farm yield. Equation (5) computes the absolute deviation of farm yield, y_t^f, from yield R_t^c:

$$d_t^f = y_t^f - R_t^c \quad (5)$$

where d_t^f represents the absolute difference. This difference is computed for the subset of years where APH records are available. The APH records contain no more than 10 years of farm yields. A lower limit of six years of actual reported yields was imposed in selecting records for inclusion in this analysis. The average deviation for each farm is computed as

$$\bar{d}^f = 1/T_f \sum_{t=1}^{T} (y^f - R^c) \quad (6)$$

T_f is the years of actual farm yield available where $\bar{d}^f$ is the mean difference of the farm from the county, y^f is the yield for the farm, and R^C is the county yield calculated over the years where farm yields are available. This construct allows the decomposition of farm-level residual variability, e_t^f, as

$$e_t^f = d_t^f - \bar{d}^f = (y_t^f - \bar{y}^f) - (R_t^C - \bar{R}^C) \quad (7)$$

It is instructive to rewrite this equation as

$$y_t^f = \bar{y}^f + (R_t^C - \bar{R}^C) + e_t^f \quad (7a)$$

In this form, it can be compared to Miranda's (1991) model. Miranda's model is more general in that it adds a slope parameter as in (7b).

$$y_t^f = \bar{y}^f + B\,(R_t^C - \bar{R}^C) + e_t^f \quad (7b)$$

Thus, our approach has implicitly assumed that B = 1.

With both the aggregate and disaggregate yield variability estimated, we then generate bootstrap simulations of the farm yield through

$$y_s^f = R_s^C + \bar{d}^f + e_t^f \quad (7c)$$

where y_s^f is a simulated farm yield.

Multicrop Farm Yield Simulation

Having described the basic structure of the yield simulation in a single crop case, we now describe the approach used to generalize to the multicrop case. Our general model of yield variability in the multicrop case may be written as

$$y_{ti}^{f} = \bar{y}_{i}^{f} + B_{ii}(R_{ti}^{C} - \bar{R}_{i}^{C}) + B_{ij}(R_{tj}^{C} - \bar{R}_{j}^{C}) + e_{ti}^{f} \tag{8a}$$

$$y_{tj}^{f} = \bar{y}_{j}^{f} + B_{ji}(R_{ti}^{C} - \bar{R}_{i}^{C}) + B_{jj}(R_{tj}^{C} - \bar{R}_{j}^{C}) + e_{tj}^{f} \tag{8b}$$

where i and j identify different individual crops. The B_{ij} coefficient captures the relation of farm yield i with regional yield j. This specification generalizes equation 7b by allowing for interactions between the disaggregate yield of one crop and aggregate yield of another crop. However, our empirical analysis suggests these cross terms, B_{ij} and $B_{ji,}$ generally lack significance. What is expected, however, is that there will be a strong covariance among the residuals due to common weather events. In the bootstrapping model, e_{ti}^{f} and e_{tj}^{f} are jointly selected by a random draw t such that residuals for every i and j are always drawn from the same period. This is done to maintain the empirical covariance across crops. In the current model, e_{ti}^{f} and e_{tj}^{f} are taken from the matched records across crops for a single farm. That is, the APH records used came from those farms where the multiple crops were insured.

Price-Yield Relationships

The model estimates a historical relationship between future price changes between the preplanting sign-up period and harvest. This relationship was modeled as

$$\frac{P_{t}^{1}}{P_{t}^{0}} = a_{1}^{P} + a_{2}^{P}\left(\frac{R_{t}^{C}}{\hat{R}_{t}^{C}} - \frac{1}{T_{C}}\sum_{t=1}^{T_{C}}\frac{R_{t}^{C}}{\hat{R}_{t}^{C}}\right) + e_{t}^{P} \tag{9a}$$

P_{it}^{1}/P_{it}^{0} is the relative price change from period 0 (sign-up) to period 1 (harvest). The terms in parentheses reflect relative deviation of county yield in a particular year from expected county yield. The α's are parameters estimated with an OLS regression to capture interaction of price and yield. $\hat{R}_{t}^{C}$ denotes the predicted county yield for year t derived from the trend estimation.

Price realizations are generated through a modification of (9a), which normalizes the relative price deviations to one. This is done to adjust for the relatively short series of yield and prices data for estimation of this relationship. In a short time series, there is potential for the mean of the relative county yield deviations to differ from one.

$$P_{s}^{1} = P^{0}\left(1 + a_{2}^{P}\left(\frac{R_{t}^{C}}{\hat{R}_{t}^{C}} - 1\right) + e_{t}^{P}\right) \tag{9b}$$

Equation 9b shows this modification. For simulation purposes, this equation centers the simulated prices around the expected price. To generalize to the multicrop case the price equations also need to account for the interactions among crops. Equations (10a) and (10b) generalize equation (9a) to capture the correlation between prices and yields for multiple crops. Here, cross-commodity yield effects on price are likely to be insignificant but may reflect supply substitution effects among crops (i.e., if corn yield deviates from expectation the price of sorghum may fall).

Potential price-yield relationships were modeled as

$$\frac{P_{it}^{1}}{P_{it}^{0}} = a_{i1}^{P} + a_{ii}^{P}\left(\frac{R_{it}^{C}}{\hat{R}_{it}^{C}} - \frac{1}{T_{C}}\sum_{t=1}^{T_{C}}\frac{R_{it}^{C}}{\hat{R}_{it}^{C}}\right) + a_{ij}^{P}\left(\frac{R_{jt}^{C}}{\hat{R}_{jt}^{C}} - \frac{1}{T_{C}}\sum_{t=1}^{T_{C}}\frac{R_{j}^{C}}{\hat{R}_{jt}^{C}}\right) + e_{it}^{P} \tag{10a}$$

(10b) $$\frac{P^1_{jt}}{P^0_{jt}} = a^P_{j1} + a^P_{jj}\left(\frac{R^C_{jt}}{\hat{R}^C_{jt}} - \frac{1}{T_C}\sum_{t=1}^{T_c}\frac{R^C_{jt}}{\hat{R}^C_{jt}}\right) + a^P_{ji}\left(\frac{R^C_{it}}{\hat{R}^C_{it}} - \frac{1}{T_C}\sum_{t=1}^{T_c}\frac{R^C_{i}}{\hat{R}^C_{it}}\right) + e^P_{jt}$$

The empirical estimates of this relationship are reported in Table A-2. They uniformly show a lack of significance for Sunflower County. Analysis not reported here indicates that these relationships may be significant in other regions of the country. As in the ABW approach, parameters and residuals from the model will be used to bootstrap price realizations. There are likely temporal correlations in price residuals due to common demand shocks and macroeconomic effects. Again, these relationships will be maintained through jointly drawing the t^{th} price residual for all crops. The actual price simulations follow from equation 9b.

(11a) $$P^1_{is} = P^0_{is}\left(1 + a^P_{ii}\left(\frac{R^C_{it}}{\hat{R}^C_{it}} - 1\right) + a^P_{ij}\left(\frac{R^C_{jt}}{\hat{R}^C_{jt}} - 1\right) + e^P_{it}\right)$$

(11b) $$P^1_{js} = P^0_{js}\left(1 + a^P_{jj}\left(\frac{R^C_{jt}}{\hat{R}^C_{jt}} - 1\right) + a^P_{ji}\left(\frac{R^C_{it}}{\hat{R}^C_{it}} - 1\right) + e^P_{jt}\right)$$

Appendix Table A-2. Regression results of relative price change on Sunflower County, Mississippi, relative yield deviations.

Variable	Soybean price ratio		Cotton price ratio		Wheat price ratio	
	Parameter estimate	Pr > |t|	Parameter estimate	Pr > |t|	Parameter estimate	Pr > |t|
Intercept	1.31	<0.000	0.953	0.005	0.921	0.001
Cotton yield ratio	-0.047	0.7934	-0.059	0.830	-0.017	0.938
Soybean yield ratio	-0.218	0.2548	0.268	0.348	0.111	0.618
Wheat yield ratio	-0.22		-0.124	0.615	-0.017	0.931
R-square	0.097		0.046		0.0127	
F-value	0.93		0.42		0.11	
Pr > F	0.44		0.74		0.95	

Multicrop Revenue Simulation

Given equations (8) and (11) simulated multicrop revenue is generated by bootstrapping to generate random price and yield with the appropriate correlation structure. The s^{th} simulated multicrop revenue is constructed as

(12) $$MRev_s^f = \sum_i A_i P_{is}^1 y_{is}^f$$

where $MRev_s^f$ is the sum of revenues across the multiple crops and A_i reflects the planted acres of the i^{th} crop. Indemnities are calculated as

(13) $$\text{Indemnity} = \text{Max}\left(0, L \sum_i A_i P_{tj}^0 \bar{y}_{is}^f - MRev_s^f\right)$$

where L is the insurance coverage level.

Estimates of actuarial fair rates are derived by bootstrapping 5,000 or more iterations, which result in a new observation on indemnity with each draw. Given each draw is equally likely, expected indemnity is the simple average of indemnity across all iterations.

Appendix B

Data Used to Construct Rate Models

The estimates of county yield variability are based on NASS county yield data for the period 1958-1997. Predicted yield for each year was derived using a spline trend estimator for each county and crop. This allows for changes in expected yield through time based largely on the assumption that technology such as seed genetics and production practices has evolved through time. The residual variation around the trend estimate largely captures variation in weather and other random events such as insect infestation.

The expected difference between farm and county yield, d_t^f, and the residual deviation of farm yield from county yield, e_t^f , are calculated from crop insurance yield history records for the year 1997. These records contain up to 10 years of yield history during the 1987-1996 crop years. Only records with at least six years of yield history were used. Furthermore, the individual crop records were matched by farm so that paired observations of cotton, soybeans, and wheat were retained. Then, the individual yields are matched with NASS county yield for the same year.

Estimation of the relationship between the relative price change from planting to harvest and the county yield deviations were conducted using data from 1968-1997. The regression models were estimated with ordinary least squares regression and reported in Table A-2.

Appendix C

Calculation of Risk Benefits Due to Insurance

The risk reduction gains for Mississippi producers are also addressed in this analysis. The results reported assume a beginning wealth of $500,000 and a relative risk aversion coefficient of 2. Ending wealth is found by subtracting production costs (according to enterprise budgets for the Mississippi Delta) and premiums, and adding indemnities to market revenue. Ending wealth is used to find expected utility using the constant relative risk aversion utility function:

(14a) $$E(U)_r = \sum_{S=1}^{S} \omega_S \frac{W_S^{1-r}}{1-r}, \ r \neq 1$$

or

(14b) $$E(U)_r = \sum_{S=1}^{S} \omega_S \ln(W_S), \ r = 1$$

where r = risk aversion coefficient, ω = the probability of an outcome, and W_s = ending wealth.

Certainty equivalents are calculated using the expected utility found in (14) by the following formula:

(15a) $$CE_{sr} = (1-r)E(U_{sr})^{\frac{1}{1-r}}, r \neq 1$$

or

(15b) $$CE_{sr} = e^{E(U_{sr})}, r = 1$$