A PRODUCER-LEVEL CROSS-HEDGE FOR ROUGH RICE USING WHEAT FUTURES

Thomas P. Zacharias, Mark D. Lange, William J. Gleason, and Harlon D. Traylor

Abstract

This study explores the potential of routine preharvest cross-hedging of rough rice using wheat futures contract prices. A numerical simulation approach combined with risk efficiency analysis evaluates a wide range of cross-hedging alternatives. Results establish that farm-level cross-hedging can be considered a viable marketing alternative.

Key words: rice, wheat, futures pricing, cross-hedging, risk-efficiency, yield risk.

Rice producers in Louisiana and other states face price-risk problems similar to other grain crop producers in terms of input and commodity price variability. However, they are limited in their market planning because no viable futures market exists for rice from which to base forward contract pricing or hedging. Although a rice futures contract currently exists on the Chicago Board of Trade, the current volume of trading appears inadequate to sustain the liquidity needed for this purpose. Previous efforts in the early 1980s to establish a rice futures market on the New Orleans Commodity Exchange and on the Mid-America Commodity Exchange were both suspended after some months of trading.

For agricultural commodities that have futures markets, producers can use direct hedging as a risk-management tool. Direct hedging involves establishing a position in the futures market opposite to that of the cash position held, the primary objective being to reduce absolute price risk by exchanging it for basis risk (i.e., the difference between cash and future prices). The central hypothesis of this study is that even though there is no viable futures market for rice, producers in Louisiana may be able to reduce price-risk exposure through cross-hedging cash rice with wheat, a commodity having an established futures market.

Cross-hedging has been analyzed and used as an inventory management and pricing tool in the processing sector of agriculture (Elam et al.; Hayenga and DiPietre; Miller; Miller and Luke). However, few studies have analyzed the use of cross-hedging as a marketing option at the farm level. Blake and Catlett examine the use of corn futures contracts to cross-hedge alfalfa hay. Berck considers cross-hedging alfalfa and barley using wheat futures as an option in examining the simultaneous choice of cropping patterns and hedging alternatives.

This study examines the potential for farm-level cross-hedging of rough rice in Louisiana using futures prices established on the Chicago Board of Trade for the September soft red winter wheat contract. The Chicago market was selected primarily due to its trade volume since a potential danger in cross-hedging is that actual delivery is not possible. Four selected preharvest cross-hedging dates are compared with harvest pricing of rice. Comparison of the cross-hedge decision with harvest pricing (the most naive marketing strategy) serves as a basis for determining the potential feasibility of cross-hedging in relation to other marketing strategies such as a storage program. The applicability of cross-hedging to the farm situation is further tested by incorporating yield risk and futures transactions costs into the analysis.

PREVIOUS EFFORTS IN CROSS-HEDGE MODELING

Cross-hedging is the pricing of a cash commodity position by using futures for different commodities (Hieronymus, p. 236). Simple cross-hedging uses futures of one commodity to offset a cash position, and multiple cross-hedging uses two or more different com-

Thomas P. Zacharias is an Assistant Professor, Mark D. Lange is an Associate Professor, William J. Gleason was a Graduate Research Assistant, and Harlon D. Traylor is a Professor, Department of Agricultural Economics and Agribusiness, Louisiana Agricultural Experiment Station, Louisiana State University Agricultural Center, Baton Rouge, LA 70803.

modities (Elam et al.). The analysis presented here concerns itself only with simple cross-hedging.

Cross-hedging is more complicated than direct hedging. Difficulties arise both in selecting the appropriate futures contracts as cross-hedging vehicles and in determining the appropriate size of the futures position to be established. The most complete theoretical treatment of cross-hedging appears in Anderson and Danthine. Anderson and Danthine suggest that cross-hedging vehicles should be futures for a related commodity. Their basic model can be used to simultaneously determine the optimal futures position and optimal level of production in a mean-variance framework. The major limitation of their work is the failure to incorporate yield uncertainty.

As an alternative to Anderson and Danthine, one can consider Rolfo's hedging model which was also derived using the mean-variance framework. While Rolfo addresses the issue of yield uncertainty, he does not consider the determination of the optimal level of output. Moreover, Rolfo does not explicitly state that his model could be used for cross-hedging, that is, taking a position in a futures market for a related commodity to offset a portion of the risk confronting the cash commodity of interest. However, Rolfo's model is a sufficiently general model to accommodate the cross-hedge decision, and we will use his results to discuss the optimal cross-hedging level assuming the production decision to be separable.[1]

With these points in mind, the net revenue associated with a single cross-hedge can be written as

$$(1)\ \tilde{\pi} = \tilde{p}_c \tilde{y} + (p_0^f - \tilde{p}_1^f)\, x,$$

where $\tilde{\pi}$ is expected net revenue, $\tilde{p}_c$ is expected spot price at harvest of the cash commodity, $\tilde{y}$ is expected output, p_0^f is the futures price of the commodity used to open the cross-hedge, $\tilde{p}_1^f$ is the expected futures price of that commodity, and x is the futures position taken. A short (long) futures position is indicated for x greater than (less than) zero. Within the context of mean-variance analysis, the following utility maximization problem can be considered,

$$(2)\ \max_{x} U(\tilde{\pi}) = E[\pi] - \tfrac{1}{2}\phi V[\pi],$$

where $E[\pi]$ and $V[\pi]$ are the expected value and variance, respectively, of the net revenue relation shown in equation (1) and ϕ is the decision maker's risk aversion parameter. Differentiation of equation (2) with respect to x yields the optimal cross-hedging level. This optimal cross-hedging level, denoted x^*, is conditional upon the futures price used to open the cross-hedge and the specification of the random variables in equation (1).

For comparative purposes we will present two possible derivations of x^* and then compare these results with those of Anderson and Danthine for the case of nonstochastic production. Determination of the optimal futures position or hedge is found by differentiating equation (2) with respect to x. This yields Rolfo's equation (1),

$$(3)\ x^* = \frac{p_0^f - \tilde{p}_1^f}{\phi V[p_1^f]} + \frac{C[p_c y, p_1^f]}{V[p_1^f]},$$

where C [•] is the covariance term. Rolfo's optimal hedge can be easily extended for the case of nonindependence under multivariate normality using the results of Bohrnstedt and Goldberger. This result is shown in equation (4),

$$(4)\ x^* = \frac{p_0^f - \tilde{p}_1^f}{\phi V[p_1^f]} + \frac{\tilde{p}_c C[y, p_1^f] + \tilde{y}\, C[p_c, p_1^f]}{V[p_1^f]}.$$

For the case of deterministic production (the Anderson and Danthine result), the optimal cross-hedge position can be written

$$(5)\ x^* = \frac{p_0^f - \tilde{p}_1^f}{\phi V[p_1^f]} + \frac{y C[p_c, p_1^f]}{V(p_1^f]}.$$

The first term in equations (3) - (5) is referred to as the pure speculative component, and the latter term is the pure hedge position (Anderson and Danthine). Notice that the optimal cross-hedging level would vary across decision makers depending on ϕ if the futures price quotation is biased. Moreover, the optimal cross-hedge is dependent upon the properties of the random variables in equations (3) - (5).

[1]Separability of production is assumed for two reasons. First, rice is primarily produced under the provisions of the current farm bill. Thus, farm acreage is to some extent fixed, and only deviations from expected yield need be considered. Second, Anderson and Danthine determine the optimal level of output assuming a well-behaved, twice-differentiable cost curve. Estimation of an empirical cost curve with such properties was beyond the scope of this study.

In the next section, we will develop a more generalized procedure for evaluating the cross-hedge decision. This procedure extends previous efforts by considering a wider class of decision makers in terms of their risk preferences. In addition the problems of futures transactions costs and lumpiness with the cross-hedge decision are explicitly treated.

A MORE GENERAL PROCEDURE FOR EVALUATING THE CROSS-HEDGE DECISION

Cross-hedging studies to date have predominantly employed some form of mean-variance analysis in evaluating the risk-efficiency of the cross-hedge decision (Anderson and Danthine; Fryar and Garland; Elam et al.). The mean-variance criterion in its most fundamental form can be stated in the following manner. For any two outcome distributions, A and B, with means E_A and E_B, and variances V_A and V_B, distribution A dominates B under the mean-variance criterion if $E_A \geq E_B$ and $V_A \leq V_B$ and if one of the two inequalities is strict.

Although the mean-variance criterion is easy to use and its results are readily interpretable, proper application of the criterion is somewhat restrictive in that only the first two moments of the outcome distribution are employed. The criterion is only relevant if outcome distributions are normal or the decision maker possesses a quadratic utility function. This latter condition implies that the decision maker is increasingly risk averse with respect to wealth, that is, the decision maker becomes more risk averse as his/her wealth increases.

As an alternative to mean-variance analysis, three stochastic dominance criteria will be used in this study to determine the risk-efficient set of cross-hedging alternatives. Stochastic dominance orders risky alternatives for groups of decision-makers possessing similar risk attitudes toward wealth. The criteria used in this paper are first-, second-, and third-degree stochastic dominance (FSD, SSD, and TSD, respectively).

The FSD criterion orders risky alternatives by requiring the cumulative probability distribution of the dominant strategy to be less than or equal to that of the dominated strategy at all monetary outcome levels. The FSD criterion is based on the assumption that decision makers prefer more to less. FSD results hold for all decision makers regardless of risk preference. The SSD criterion orders among the FSD set by requiring that the accumulated area under the cumulative distribution function of the dominant strategy be less than or equal to that of the dominated strategy at all monetary outcome levels. The SSD criterion is based on the assumption that decision makers are risk averse in relation to wealth. Thus, SSD results hold for the class of all risk-averse decision makers. Lastly, the TSD criterion orders among the SSD efficient set by requiring that the cumulative area under the SSD function of the dominant strategy be less than or equal to that of the dominated strategy at all outcome levels. Under TSD, it is assumed that decision makers are decreasingly risk averse with respect to wealth. Notice that any strategy (inefficient alternative) eliminated by FSD is eliminated from further consideration in SSD, and consequently for TSD from SSD.

Results for the risk-neutral and maximin decision makers will also be presented along with the stochastic dominance and mean-variance risk efficiency results. Risk-neutral results are determined using the criterion of expected value maximization. Using the maximin rule, a decision maker selects the worst monetary payoffs from the set of available alternatives across all states of nature. Within this set of minimum values, the decision maker then selects the alternative with the highest monetary payoff. Discussions of the risk criteria presented in this paper can be found in several sources (Anderson et al.; Boehlje and Eidman; Zentner et al.).

In addition to the restrictive assumptions associated with mean-variance analysis, cross-hedging studies (other than Elam et al.) have not adequately treated the problems of lumpiness and futures transactions costs. Lumpiness basically refers to the difference in the desired level of the futures commitment in relation to the actual amount that must be committed in advance due to the standardization of quantities traded on the futures market. These latter two aspects of the cross-hedge decision can be incorporated within the stochastic dominance framework. Equation (1) can be modified as follows,

$$(6)\ \tilde{\pi} = \tilde{p}_c \tilde{y} + (p_0{}^f - \tilde{p}_1{}^f)x - c(x),$$

where c(x) are commission and margin costs as a function of the futures position taken. In the mean-variance framework, x was treated as a continuous variable, while in equation (6), x is an integer variable and depicts the lumpy nature of the cross-hedge decision problem. In contrast to the analytical results presented in the previous section, alternative integer levels of x can be numerically simulated.

Alternative opening dates will also be considered in this paper in order to determine the sensitivity of the effect of timing on the placement of the preharvest cross-hedge decision. Stochastic dominance is then applied to the simulation results to obtain the set of risk-efficient cross-hedge alternatives. This procedure improves upon current cross-hedging methodology by evaluating a wider range of cross-hedge alternatives and explicitly treats the problems of futures transactions costs and lumpiness along with the timing of the cross-hedge decision.

DATA AND SIMULATION ASPECTS

The baseline data used in the analysis are selected to allow initiating the cross-hedge at various stages of the preharvest period. The futures offsetting date of August 15 corresponds to the rice harvesting period and allows closing of the September futures position well before the delivery month for wheat.

The opening futures transactions dates are March 15, April 15, May 15, and June 15. Closing prices for each of these dates were recorded for an 11-year period, 1975–1985. The selected range of opening dates allows for futures pricing in the preplanting, planting, and growing stages of rice production.

Cash rough rice prices available in southwest Louisiana during mid to late August are utilized in computing realized net cross-hedging returns. These prices also serve as a "control" pricing method against which to compare net returns from cross-hedging. The prices were obtained from *Rice Market News* (USDA).

The effect of yield risk on cross-hedging returns is examined by simulating random crop yields over a hypothetical 10-year period using actual yield data. Two particular yield distributions were identified from a randomly selected group of rice producers in Jefferson Davis Parish in southwest Louisiana for the 10-year period 1975–1984. The first rice yield distribution possessed a relatively low mean yield of 32.30 cwt. per acre and a standard deviation of 2.16 cwt. per acre. The second yield distribution exhibited a high mean value of 44.67 cwt. per acre and high standard deviation of 6.63 cwt. per acre. These yield distributions and cash rough rice prices had correlation coefficients of approximately 0.2 and −0.2, respectively.

The method for evaluating the decision model proposed in this paper is a stochastic simulation analysis. Simply computing the returns implied by equation (6) for the historical period 1975–1984 and ranking the respective distributions would result in an *ex post* selection and is conceptually flawed. Proper simulation of equation (6) requires appropriately correlated simulated time series data. The procedure developed by Clements et al. for simulating a correlated time series of normally distributed random variables is employed in this study. This simulation procedure has been applied elsewhere in the literature (e.g., Wetzstein et al.; Ray and Richardson; and Bailey and Richardson). Data were stochastically simulated for a ten-year time series for rice yield distributions, cash rough rice price, August 15 futures price for September wheat, and September wheat futures prices for March 15, April 15, May 15, and June 15. Simulation of the net return distributions was based on a production level of 300 rice acres.

Commissions and opportunity costs on margin requirements were approximated in the following manner. Commission charges were assumed to be $80 for a 5,000 bushel contract for wheat on the Chicago Board of Trade and $55 for a 1,000 bushel contract for wheat on the Mid-America Exchange. Opportunity cost on the margin deposit was based on a level of 7.5 percent of contract value and a 10 percent annual interest rate weighted by the number of months of the contract period.

ECONOMETRIC ESTIMATION OF THE CROSS-HEDGE LEVEL: A DIGRESSION

Concern over the appropriate procedure for econometrically determining the optimal hedge ratio has been the subject of recent discussion. Witt et al. indicate that the concern surrounds the use of cash and futures price levels, price changes, or percentage changes in prices in regression analysis when estimating the minimum price risk hedge ratio. Within this context, Witt et al. also discuss the cross-hedging model of Anderson and Danthine. The authors then proceed to analyze the practical and theoretical differences among these procedures. Witt et al. state that there is no statistical basis for preferring a particular estimation procedure and that the estimation procedure is inherently linked to the decision maker's objective function and the form of the hedge. Although Witt et al. discuss the cross-hedge decision for the yield uncertainty case, their econometric analysis does not directly address this issue. The work of Rolfo does provide some guidance for the case of price and yield uncertainty.

Rolfo suggests that nominal revenue as a function of the futures price level is the appropriate specification for the anticipatory cross-hedge being evaluated in this paper. This regression model is stated as follows,

$$(7)\ \tilde{p}_c \tilde{y}_t = a + b\tilde{p}^f_t + e_t,$$

where $\tilde{p}_c \tilde{y}_t$ and $\tilde{p}^f_t$ are the producer's nominal revenue and wheat futures price, respectively, at the period when the hedge is to be lifted for year t; a and b are the intercept and slope parameters, respectively. The stochastic disturbance term is e_t. The estimated slope, $\hat{b}$, The regression model in equation (7) was estimated for the high-mean, high-variance and low-mean, low-variance yield distributions discussed in the previous section. The results are shown in Table 1. The estimated cross-hedge ratios indicate that approximately 18,000 bushels of wheat should be cross-hedged under the high-yield scenario while only 13,000 bushels should be cross-hedged for the low-yield situation. However, the estimated cross-hedge ratios for both yield distribution scenarios are not significantly different from zero at the 5 percent level.

The use of these econometrically determined cross-hedging levels will be considered in the results section as a possible subset of the class of risk-efficient cross-hedging levels.

TABLE 1. ESTIMATED CROSS-HEDGE RATIOS USING ROLFO'S HEDGING MODEL, 1975–1984

	Yield Distribution Scenario	
	High-mean, High-variance	Low-mean, Low-variance
Intercept	56,473.19	41,375.41
(t-statistic)	(1.29)	(1.49)
Slope	17,709.82	12,832.83
(t-statistic)	(1.49)[a]	(1.70)[a]
R^2	.22	.27
D.W.	1.54	2.38
N	10	10

[a]Coefficient is not significant at the 5 percent level.

RISK-EFFICIENCY RESULTS

Results of the risk-efficiency analysis are presented in Tables 2 and 3. These tables summarize evaluations of simulated net returns realized from market strategies of cash sales at harvest in the absence of any cross-hedge position and cross-hedge positions ranging from 5,000 to 20,000 bushels of September wheat futures. The results presented in Table 2 reveal the efficient sets for the high-yield, high-variance scenario. For this particular set of simulated output, risk-neutral decision makers would prefer to cross-hedge 20,000 bushels of September wheat futures in mid-June. This same distribution possessed the highest minimum value among the set of cross-hedging alternatives and thus, is the maximin choice as well. Under the FSD rule, no alternatives could be eliminated from the efficient set. This result is not too surprising since it is usually the case that very few alternatives are eliminated using FSD (Anderson; King and Robison).

The SSD efficient set shown in Table 2 contains only the months of April and June along with cash sales at harvest. With the exception of cash sales at harvest, the mean-variance results are reasonably similar to SSD efficient set. The SSD results in Table 2 clearly demonstrate the importance of incorporating the integer nature of the cross-hedge decision and futures transactions costs. It is interesting to note that the SSD set does not contain either the April or June 19,000 bushel contract level which would require three 5,000 bushel contracts on the Chicago Board of Trade and four 1,000 bushel contracts on the Mid-America Exchange. Moreover, cross-hedging in June on the September contract was non-optimal for hedging levels between the 10,000 and 15,000 bushel levels which require individual 1,000 bushel contracts on the Mid-America Exchange.

The TSD efficient set consists of a 20,000 bushel cross-hedge in June and the April cross-hedging date for contracting levels between 10,000 and 16,000 bushels. Again, the importance of futures transactions costs should be stressed because a cross-hedging level of 18,000 bushels was implied by the regression results presented in the previous section. The 18,000 bushel cross-hedge level is optimal only in June under the SSD rule.

Risk-efficient sets for the low-yield, low-variance scenario are found in Table 3. In contrast to the results presented in Table 2, cross-hedging in June is no longer risk-efficient. Proceeding beyond the FSD rule, which is unable to discriminate among the alternatives, the optimal cross-hedging months for this scenario are March and April. Risk-neutral decision makers would cross-hedge 20,000 bushels of wheat in April while the maximin choice is to cross-hedge 15,000 bushels in March. These results further reinforce the notion that lumpiness of the contracting level is an issue in considering cross-hedging as a price risk reducing market tool.

The SSD and TSD results found in Table 3 are somewhat unusual. Under the SSD rule, cash sales at harvest are eliminated and the remainder of the SSD efficient set consists of the March and April cross-hedging dates for all cross-hedging levels irrespective of lumpiness and futures transactions costs. The mean-variance set includes only the April 20,000 bushel cross-hedge and all cross-hedging levels for March. In general, the net return distributions for the months of May and June were characterized by lower means and lower minimum values relative to the March and April return distributions. The TSD set consisted of only the 15,000 bushel cross-hedge in March. This was also the maximin choice. The minimum value of this distribution was $68,877.12 with a mean of $83,236.15 and standard deviation of $12,288.69.

In summarizing the results of Tables 2 and 3, it is interesting that various cross-hedging strategies for April were found in the SSD efficient sets for both yield-distribution scenarios. It is also interesting to note that the risk-neutral and maximin choices were associated with only 5,000 bushel contracts. Lastly, the reader will observe that the hedging level suggested by regression analysis may or may not be a risk-efficient choice depending upon the decision criteria employed. Recall that an 18,000 bushel cross-hedge was appropriate for the high-mean yield distribution while a 13,000 bushel cross-hedge was appropriate for a low-mean yield distribution using the regression results presented in the previous section.

CONCLUSIONS

Prior to this paper, cross-hedging studies have been somewhat narrowly defined with respect to the risk-management implications of the cross-hedge decision. In general, these studies have evaluated the cross-hedge decision within the restrictive mean-variance framework or the econometric hedge-ratio estimation approach. These studies have also failed to adequately incorporate futures transactions costs in terms of the integer nature of the contracting level facing the decision maker. Although these approaches have a certain analytical appeal, it is unclear as to their practical application. In this paper a numerical simulation approach, in combination with risk-efficiency analysis, was used to evaluate a wider range of cross-hedging alternatives than had been previously considered. The analysis indicates that previous results represent a subset of the risk-efficient sets presented in this paper. Thus, a more general framework has been established.

The results of this paper further established that farm-level cross-hedging can be considered a viable marketing alternative. Fu-

TABLE 2. RISK-EFFICIENCY RESULTS: EFFICIENT SETS FOR THE PREHARVEST CROSS-HEDGE OF RICE WITH WHEAT FOR A HIGH-MEAN, HIGH-VARIANCE YIELD DISTRIBUTION

	Decision Criteria[a]					
Marketing Alternative	Risk Neutral	First Degree Dominant	Second Degree Dominant	Third Degree Dominant	Mean-Variance	Maximin
1 Cash Sales at Harvest		✓	✓			
2 10,000 Bushel Cross-Hedge		M,A,MY,J	A, J	A	A	
3 11,000 Bushel Cross-Hedge		"	A	A	A	
4 12,000 Bushel Cross-Hedge		"	A	A	A	
5 13,000 Bushel Cross-Hedge		"	A	A	A	
6 14,000 Bushel Cross-Hedge		"	A	A	A	
7 15,000 Bushel Cross-Hedge		"	A, J	A	A	
8 16,000 Bushel Cross-Hedge		"	A, J	A	A	
9 17,000 Bushel Cross-Hedge		"	J		J	
10 18,000 Bushel Cross-Hedge		"	J		J	
11 19,000 Bushel Cross-Hedge		"			J	
12 20,000 Bushel Cross-Hedge	J	"	J	J	J	J

[a]Symbols in table are defined as follows: M, A, MY, and J represent the establishment of short positions for the September wheat futures contract for the months of March, April, May, and June, respectively.

ture efforts could compare cross-hedging with various farmer-owned storage policies as well as allow for sequential and/or multiple cross-hedging at the farm-level.

TABLE 3. RISK-EFFICIENCY RESULTS: EFFICIENT SETS FOR THE PREHARVEST CROSS-HEDGE OF RICE WITH WHEAT FOR A LOW-MEAN, LOW-VARIANCE YIELD DISTRIBUTION

	Decision Criteria[a]					
Marketing Alternative	Risk Neutral	First Degree Dominant	Second Degree Dominant	Third Degree Dominant	Mean-Variance	Maxi-min
1 Cash Sales at Harvest		✓				
2 10,000 Bushel Cross-Hedge		M,A,MY,J	M, A		M	
3 11,000 Bushel Cross-Hedge		"	M, A		M	
4 12,000 Bushel Cross-Hedge		"	M, A		M	
5 13,000 Bushel Cross-Hedge		"	M, A		M	
6 14,000 Bushel Cross-Hedge		"	M, A		M	
7 15,000 Bushel Cross-Hedge		"	M, A	M	M	M
8 16,000 Bushel Cross-Hedge		"	M, A		M	
9 17,000 Bushel Cross-Hedge		"	M, A		M	
10 18,000 Bushel Cross-Hedge		"	M, A		M	
11 19,000 Bushel Cross-Hedge		"	M, A		M	
12 20,000 Bushel Cross-Hedge	A	"	M, A		M, A	

[a]Symbols in table are defined as follows: M, A, MY, and J represent the establishment of short positions for the September wheat futures contract for the months of March, April, May, and June, respectively.

REFERENCES

Anderson, J. R. "Risk Efficiency in the Interpretation of Agricultural Production Research." *Review of Marketing and Agricultural Economics*, 42,1(1974):131–84.

Anderson, J. R., J. L. Dillon, and B. Hardaker. *Agricultural Decision Analysis*. Ames: Iowa State University Press, 1977.

Anderson, R. W., and J. P. Danthine. "Cross Hedging." *J. Political Economy*, 89,6(1981):1182–96.

Bailey, D. V., and J. W. Richardson. "Analysis of Selected Marketing Strategies: A Whole-Farm Simulation Approach." *Amer. J. Agr. Econ.*, 67(1985):813–20.

Berck, P. "Portfolio Theory and the Demand for Futures: The Case of California Cotton." *Amer. J. Agr. Econ.*, 63,3(1981):466–74.

Blake, M. L., and L. Catlett. "Cross Hedging Hay Using Corn Futures: An Empirical Test." *Western J. Agr. Econ.*, 9,1(1984):127–34.

Boehlje, M. D., and V. R. Eidman. *Farm Management*. New York: John Wiley and Sons, 1984.

Bohrnstedt, G. W., and A. S. Goldberger. "On the Exact Covariance of Products of Random Variables." *J. Amer. Stat. Assoc.*, 64,328(1969):1439–42.

Clements, A. M., H. P. Mapp, and V. R. Eidman. "A Procedure for Correlating Events in Farm Firm Simulation Models." Agricultural Experiment Station Bulletin T-131, Oklahoma State University, 1971.

Elam, E. W., S. E. Miller, and S. H. Holder. "Cross-Hedging Rice Bran and Millfeed." *Rice Outlook and Situation*, (March 1984):14–18.

Fryar, E. O., and K. Garland. "The Feasibility of Crosshedging Rice with Corn, Wheat." *Ark. Farm Res.*, (July–August, 1986):11.

Hayenga, M. L., and D. D. DiPietre. "Cross-Hedging Wholesale Pork Products Using Live Hog Futures." *Amer. J. Agr. Econ.*, 64,4(1982):747–51.

Hieronymus, T. *Economics of Futures Trading for Commercial and Personal Profit*. New York: Commodity Research Bureau, Inc., 1981.

King, R., and L. Robison. "Risk Efficiency Models." *Risk Management in Agriculture*. Ed. Peter Barry. Ames: Iowa State University, 1984.

Miller, S. E. "Beef Price Hedging Opportunities for Food Service Institutions." *J. Food Dist. Res.*, 11,1(1980):29-34.

Miller, S. E., and D. R. Luke. "Alternative Techniques for Cross-Hedging Wholesale Beef Prices," *J. Futures Markets*, 2,2(1982):121-29.

Ray, D. E., and J. W. Richardson. "Detailed Description of Polysim." Agricultural Experiment Station Bulletin T-151, Oklahoma State University, 1978.

Rolfo, J. "Optimal Hedging Under Price and Quantity Uncertainty: The Case of a Cocoa Producer." *J. Political Economy*, 81,1(1980):100-16.

U.S. Department of Agriculture. *Rice Market News.* AMS. Little Rock, selected issues 1975-85.

Wetzstein, M. E., D. M. Edwards, W. N. Musser, and R. W. McClendon. "An Economic Simulation of Risk Efficiency Among Alternative Double-Crop Machinery Selection." Georgia Agricultural Experiment Station, Research Bulletin 342, 1986.

Witt, H. J., T. C. Schroeder, and M. L. Hayenga. "Comparison of Analytical Approaches for Estimating Hedge Ratios for Agricultural Commodities." *J. Futures Markets*, 7,2(1987):135-46.

Zentner, R. P., D. D. Greene, T. L. Hickenbotham, and V. R. Eidman. *Ordinary and Generalized Stochastic Dominance: A Primer.* Department of Agricultural and Applied Economics, Staff Paper P81-27. University of Minnesota, St. Paul, MN, September 1981.