Evaluation of Alternative Risk Specifications in Farm Programming Models

Stephen A. Ford, Beth Pride Ford, and Thomas H. Spreen

The use of alternative probability density functions to specify risk in farm programming models is explored and compared to a traditional specification using historical data. A method is described that compares risk efficient crop mixes using stochastic dominance techniques to examine impacts of different risk specifications on farm plans. Results indicate that a traditional method using historical farm data is as efficient for risk averse producers as two other methods of incorporating risk in farm programming models when evaluated using second degree stochastic dominance. Stochastic dominance with respect to a function further discriminates among the distributions, indicating that a density function based on the historic forecasting accuracy of the futures market results in a more risk-efficient crop mix for highly risk averse producers. Results also illustrate the need to validate alternative risk specifications perceived as improvements to traditional methods.

The management of risk is an important issue in the study of decision-making in agriculture. Sources of risk in farm planning arise through uncertainty in farm level prices and yields. Traditional modelling efforts have been based on historical data which may not accurately reflect the risk faced by farmers in farm planning decisions for a single, specific year when market conditions are known. It seems logical, then, that the prescriptive use of risk programming models for crop planning decisions should incorporate risk specifications that are conditional on current, rather than historical, market information.

The objective of this paper is to evaluate alternative methods of incorporating risk in farm programming models to determine if the use of a particular method results in a more efficient production plan. The alternative risk specification methods considered in this paper are based on historical, futures, and futures options data, respectively. Previous research compares the efficiency of alternative risk specifications only through general descriptive discussions of the resulting crop mixes. These models have relied on "improved" techniques of risk specification which lead to solutions that are different from those of other techniques, and are therefore better (McCarl and Apland). Rather than rely on this approach, it is proposed that stochastic dominance techniques be used to evaluate the relative robustness of crop mixes resulting from alternative methods of incorporating risk in farm programming models. These techniques are demonstrated for a simple MOTAD farm planning model in the following sections.

The authors are, respectively, Assistant Professor and Project Assistant, Department of Agricultural Economics and Rural Sociology, The Pennsylvania State University and Professor, Food and Resource Economics Department, University of Florida. The authors wish to acknowledge the helpful comments of Wesley N. Musser and three anonymous reviewers.

Evaluation of the Robustness of Different Risk Specifications

A method is needed to discriminate between farm plans resulting from programming models using alternative risk specifications. Let R_H represent a risk specification based on historical information and let X be the solution vector of optimal crop activities obtained from the programming model. Then let $X(R_H)$ represent the distribution of net returns from crop plan X. Similarly, let R_C represent a risk specification based on conditional or current information and let Y be the resulting optimal crop mix from the programming model. Let $Y(R_C)$ be the distribution of net returns from crop plan Y. The risk efficiency of crop plans X and Y can be compared through their distributions of returns, $X(R_H)$ and $Y(R_C)$, using stochastic dominance analysis. Stochastic dominance is well-defined in the literature (King and Robison, 1981) and requires only mild assumptions about agent preferences. First degree stochastic dominance requires only that agents prefer more to less. Second degree stochastic dominance additionally requires that agents be risk averse. Stochastic dominance with respect to a function (Meyer, 1977) further evaluates risky outcomes at different intervals of risk aversion. However, care must be taken in a comparison of the distributions of returns, $X(R_H)$ and $Y(R_C)$. Because the crop plans, X and Y, are determined based on different risk specifications, they should be compared under the same risk specification distribution, R^*, to avoid bias in the comparison; e.g., $X(R^*)$ should be compared to $Y(R^*)$.

The appropriateness of using stochastic dominance techniques to evaluate MOTAD solutions is a cause of some concern (Robison). King and Robison (1984) have shown that conflicting ordering can arise between MOTAD and stochastic dominance. More recently, however, Meyer and Rasche have shown that the inconsistent ordering is likely of the order that would be provided by sampling error in specifying a probability distribution to represent risky outcomes; a concern shared by Buccola regarding the consistency of mean absolute deviation models with expected utility (Johnson and Boehlje, 1981 and 1982). Meyer and Rasche concluded that mean-standard deviation rankings can be consistent with expected utility rankings beyond the strict location-scale conditions usually necessary for consistent rankings between these two approaches (Meyer, 1987).

Because MOTAD is a close approximation to mean-standard deviation models (Thomson and Hazell; Boisvert and McCarl) and stochastic dominance analysis requires only mild assumptions about agent preferences, it seems reasonable to use these techniques to evaluate choice of risk specification in programming models. However, a strict theoretical link has not been made. Consequently, MOTAD results are compared to resulting mean-standard deviation rankings for consistency, and the location and scale condition (Meyer, 1987) is examined for consistency with expected utility.

More importantly, it is not the model solutions or the specific risk programming method that are being evaluated in this research so much as the robustness of these solutions to different risk specifications. The comparisons of these solutions can also be viewed as an analysis of optimal and near-optimal solutions which can also have value in farm management applications (Schurle and Erven) or as an analysis of diversified portfolios developed for comparison with stochastic dominance (McCarl, et al.). If the choice of risk specification is uncertain but a particular crop mix is robust across all reasonable specifications, more confidence can be ascribed to a prescription using that risk management strategy.

Risk Specification Issues

The problem of proper risk specification received much attention through the 1980s. Risk specifications in farm programming models are usually based upon expected net returns and higher moments characterizing the net returns distribution. If the primary objective of risk-programming analysis is descriptive in nature (ex post), then a risk specification based upon historical data may correctly capture the risk faced by a producer. Objective probability distributions derived from historical data have traditionally been used in programming models (Musser, Mapp, and Barry; Boisvert and McCarl). However, Young (1984) notes that there are no well-defined procedures for correctly estimating parameters of objective probability distributions, including distributions of net returns used in risk programming models.

Another use of risk programming analysis, however, is as a tool in production planning. Often, objective distributions based on historical data are used to determine the optimal cropping patterns producers could use to manage risk in the long run. This approach assumes that future returns are distributed the same as historical returns. However, producers follow agricultural commodity markets and have subjective price expectations based on information in addition to historical prices (Young, 1980). A risk specification based upon subjective probability distributions derived from current or conditional market information may better reflect the risk faced by a producer than a specification based upon historical or unconditional data. Current market information available to a producer might include carryover inventories, prices for futures contracts, and premiums for commodity options at specified strike prices.

While previous research has called for the use of subjective probability distributions in risk programming models (Adams, Menkhaus, and Woolery; Anderson, Dillon, and Hardaker; Lins and Sonka; Mapp and Helmers; Musser, Mapp, and Barry), the use of subjective probability distributions of outcomes offers its own set of problems. Farmers may not have fully defined subjective probabilities because of incomplete knowledge of current and past events. Further, there is no guarantee that the subjective probability elicited is an accurate specification of the risk actually faced on the farm, or that it would lead to risk-efficient farm plans. It must still be determined whether current or conditional information better describes the risk faced by a producer than does information derived from historical data.

A second issue that has received attention concerns the sensitivity of optimal solutions to model specification in the form of technical and resource constraints in general, and risk specification in particular. Many of the authors cited above describe the sensitivity of results to the length of time series used to specify the probability distribution of outcomes, detrending methods, and the adjustment of prices to real levels. Although the sensitivity of programming models to alternative specifications is not unique to risk analysis, solution results used to describe farm decision-making behavior or to prescribe farm strategies may be inaccurate. Meyer and Rasche point out the sampling error that is inherent in the specification of risk in such models. The sensitivity of optimal solutions to the risk specification and the constraint matrix formulation implies that the model solutions may not reflect the true risk faced by the farm. Consequently, optimal farm plans resulting from model solutions may not clearly dominate other "sub-optimal" or "near-optimal" plans.

Empirical Framework

Three MOTAD models (Hazell) were developed to evaluate the use of different risk specifications. The models were used to identify optimal crop mixes for 1989 given historical price and yield observations and futures market information at that time. Planning for 1989 offers an excellent test of different probability distributions for net returns because of the effect of the 1988 drought on expected commodity prices. The three models differ only in the coefficients used for net returns for crop activities in the objective function and in the coefficients used in the deviation constraints. The alternative risk specifications are based upon historical price and yield data and two methods which incorporate conditional information into the farm model. The two conditional methods use empirical distributions derived from futures market information. Thus, the conditional methods use information which is not included in the historical data. The approaches using futures market information can also be thought of as "collective" subjective probability approaches because they reflect market expectations.

The MOTAD farm planning models follow the approach found in Anderson, et al., where expected returns over variable costs are maximized subject to resource constraints and a constraint on total negative deviations from net revenue. The mathematical formulation of the model is:

$$(1) \qquad \max \sum_{j=1}^{3} c_j x_j - rL - \sum_{i=1}^{12} p w_i$$

subject to

$$(2) \qquad \sum_{j=1}^{3} d_{jt} x_j + y_t \geq 0 \qquad t = 1, \ldots, 15$$

$$(3) \qquad \sum_{t=1}^{15} y_t \leq \lambda \qquad \lambda = 0 \rightarrow \lambda_{\max}$$

$$(4) \qquad \sum_{j=1}^{3} a_{ij} x_j - w_i \leq g_i \qquad i = 1, \ldots, 12$$

$$(5) \qquad \sum_{j=1}^{3} x_j - L \leq L_E$$

$$(6) \qquad x_j, L, w_i, y_t \geq 0$$

where

- c_j = expected returns over variable costs for three crop activities
- x_j = number of acres of crop activity j
- r = rental price of land
- L = acres rented
- p = wage rate for hired labor
- w_i = labor hired in month i
- d_{jt} = deviation of activity j returns in year t from expected returns
- y_t = negative deviation in year t
- λ = level of negative deviations summed over 15 years ($t = 1, \ldots, 15$)
- a_{ij} = labor required by activity j in month i
- g_i = owner labor available in month i
- L_E = owned acres of land.

The models were solved for five risk levels: $\lambda = 50{,}000$, $\lambda = 100{,}000$, $\lambda = 150{,}000$, $\lambda = 200{,}000$, and $\lambda = 999{,}999$ (unconstrained).

The model farm is a hypothetical north Florida crop farm. The model formulation is simplified in order to clearly illustrate results of the analysis. It is assumed that the farm consists of 600 acres of nonirrigated cropland. An additional 500 acres can be rented for $20 per acre. Up to 320 hours of labor can be hired each month for $5 per hour in addition to the owner's available labor. Corn, soybeans, and cotton can be grown on the farm. No government program participation is assumed in the farm model. When farmers participate in government farm programs, the resource allocation problem among crops may become trivial since farmers are generally locked into planting their ASCS crop bases. The exclusion of farm program participation from consideration in the farm model should not unduly bias the analysis as it reflects the situation in North Florida where there are generally low levels of participation in these programs (Ford and Hewitt). Also, the primary purpose of this research is to explore the choice and relative performance of alternative risk specifications rather than the adoption of specific cropping plans. However, if future agricultural legislation continues to move toward a market-oriented agricultural sector, resource allocation and farm planning problems for those farmers participating in farm programs may become more important.

Historical MOTAD Specification

The historical MOTAD specification defines expected net returns for crop j in the objective function (c_j) for the planning year as the fifteen-year average of historical gross returns from that crop activity less expected variable costs of production for the planning year:

$$(7) \qquad c_j = 1/15 \left[\sum_{t=1}^{15} p_{jt} y_{jt} \right] - E[vc_j]$$

where p_{jt} and y_{jt} are the historical price and yield, respectively, for crop j in year t. $E[vc_j]$ is the expected variable production cost per acre for crop j for the planning year. Expected variable production costs were taken from 1989 extension planning budgets for North Florida field crops (Hewitt). Expected variable costs of production were used rather than historical costs because of the prescriptive focus of the analysis. Price and yield data over the period from 1974 to 1988 were collected from a farm in North Florida for corn, soybeans, and cotton. Crop yields were detrended by regressing yields on a constant and a linear trend, with the only statistically significant trend occurring in cotton yields. Therefore, detrended yields for cotton and actual yields for corn and soybeans were used in the MOTAD model. Historical prices were not detrended. The deviation for year t (d_{jt}) in the historical MOTAD model is defined as the difference between the historical realized gross return and the fifteen-year average historical gross return:

$$(8) \qquad d_{jt} = p_{jt} y_{jt} - 1/15 \left[\sum_{t=1}^{15} p_{jt} y_{jt} \right].$$

Futures MOTAD Specification

The futures MOTAD specification differs from the historical specification only through how expected net returns in the objective function and the deviations are specified. Crop prices used in calculating c_j and d_{jt} for the futures specification were based on market information at planning, as opposed to historical prices used in the historical specification. Futures prices in the planning month for contracts nearest harvest are the local market's expected cash price at harvest when adjusted for expected basis. The planning month for this model is assumed to be February of the planning year. The futures contract months are September, November, and December for corn, soybeans, and cotton, respectively.

Harvest period futures prices at a planning date do not reflect cash prices received at harvest with certainty. One measure of the accuracy of futures prices as price forecasts is an evaluation of their performance over time. Therefore, a fifteen-year series of differences between the cash price received at harvest in year t and the futures price from the first Tuesday of the preceding February in year t was calculated using the farm level data from 1974–88. These differences can be thought of as the risk context in which to place the futures prices used for planning in February, 1989. The resulting distribution of these differences can be thought of as the distribution of the historic forecasting accuracy of the futures market; the "collective" subjective probability distribution of the market.

The differences were added to the futures prices for corn, soybeans, and cotton in the planning month (February, 1989) to generate a distribution of fifteen observations around the futures prices for the respective commodities. This relationship can be expressed as $(p_{jt} - F_{jt}) + F_j^* = p_{jt}^*$ where p_{jt} is the harvest price of commodity j observed in year t, F_{jt} is the harvest futures price at planning for crop j in year t, F_j^* is the 1989 harvest futures price at planning, and p_{jt}^* defines the distribution of prices based on historic differences of futures and realized prices.

A set of fifteen correlated prices and yields were drawn for each commodity from the distributions created from the futures prices and the same yield distributions used in the historical MOTAD model. The simulated draws were based on correlations among the harvest and futures price deviations and observed yields for the 1974–1988 period. The simulated draws of prices and yields were then used to calculate expected net returns in the objective function as

$$c_j = 1/15 \left[\sum_{t=1}^{15} p_{jt}^* y_{jt}^* \right] - E[vc_j], \tag{9}$$

where p_{jt}^* and y_{jt}^* are the simulated price and yield draws, respectively, for crop j and observation t. Deviations used in the constraint matrix were calculated using

$$d_{jt} = p_{jt}^* y_{jt}^* - 1/15 \left[\sum_{t=1}^{15} p_{jt}^* y_{jt}^* \right]. \tag{10}$$

Options MOTAD Specification

The options MOTAD specification uses futures options premiums in calculating net returns distributions. Options premiums that the market is willing to pay at different strike prices indicate the perceived variability of expected prices (futures prices) at planning time. Thus, options premiums and strike prices generate information about expectations of price volatility (Black; Gardner), and can be used to construct non-parametric representations of commodity price distributions (King and Fackler). These non-parametric price distributions provide a measure of price risk consistent with that which is perceived by commodity markets.

The Agricultural Risk Management Simulator (ARMS) developed by King, et al. was used to develop price and yield distributions for 1989 from futures options market information. The options contracts used for corn, soybeans, and cotton harvest periods were the same as for the futures MOTAD model. Crop yields used were the same as in the historical and futures MOTAD specifications. Fifteen correlated prices and yields were drawn from the ARMS distributions for each crop to be consistent with the number of historical observations available. Correlations for the random draws were based on historical relationships. Gross returns for these fifteen "years" were calculated as if these prices and yields were actually observed. Expected net returns in the objective function were defined as the average simulated gross returns less expected variable costs of production for each crop activity:

$$c_j = 1/15 \left[\sum_{t=1}^{15} \hat{p}_{jt} \hat{y}_{jt} \right] - E[vc_j], \tag{11}$$

where $\hat{p}_{jt}$ and $\hat{y}_{jt}$ are the simulated draws from the options price and yield distributions for crop j and observation t. Deviations were specified in the options MOTAD model as:

$$d_{jt} = \hat{p}_{jt} \hat{y}_{jt} - 1/15 \left[\sum_{t=1}^{15} \hat{p}_{jt} \hat{y}_{jt} \right]. \tag{12}$$

The relative risk efficiency of the solutions to the three MOTAD specifications was analyzed using stochastic dominance analysis. The performance of each crop mix from the MOTAD solutions was evaluated under the three different risk specification distributions to gain insight into the choice of risk specification. The method used is described in more detail in a later section.

MOTAD Model Solutions

Solutions to the three MOTAD models at each risk level are presented in Table 1. As expected, the value of the objective function increased in all models as risk became less constraining. Soybean acreage remained relatively constant at all risk levels of the three models, while corn and cotton acreage changed substantially depending on the model used and the risk level. The strength of soybeans in the crop mix of each model is interesting, especially since soybean acreage had declined substantially in North Florida over the previous decade. High expected soybean prices may account for the strength of soybeans in the futures model and options model results, as would the weight of extremely high prices experienced in 1988 in the historical model. Corn and cotton acreage increased as risk constraints were relaxed in the historical model. In the futures model, corn acreage failed to enter the solution, while cotton acreage increased substantially as risk constraints were relaxed. However, corn acreage increased and cotton acreage declined to zero as risk decreased in the options model. The result for cotton in the options model is due primarily to a low expected return in the objective function of that model specification.

One can see that the choice of risk specification in these MOTAD models results in significantly different crop mixes. The model based on histori-

Table 1. Solution Results to Three MOTAD Models

	Risk Constraining Levels of Lambda				
	λ = 50,000	λ = 100,000	λ = 150,000	λ = 200,000	Unconstrained
	acres planted				
Model 1—Historical Specification					
Corn	21	147	153	216	476
Cotton	96	145	261	332	411
Soybeans	202	240	228	221	213
Total Acres	319	532	642	769	1100
Objective Function	$14,567	$22,777	$26,954	$28,883	$32,237
Model 2—Futures Specification					
Corn	0	0	0	0	0
Cotton	65	186	282	369	384
Soybeans	185	235	226	217	216
Total Acres	250	421	508	586	600
Objective Function	$14,586	$21,386	$23,307	$24,911	$25,186
Model 3—Options Specification					
Corn	117	399	597	795	846
Cotton	73	0	0	0	0
Soybeans	247	254	254	254	254
Total Acres	437	653	851	1049	1100
Objective Function	$25,998	$36,640	$41,255	$45,640	$46,709

cal data has resulting crop mixes that are diverse and have significant acreage in each crop. The results of the model based on a risk specification from the futures market include no corn acreage at all risk levels and a substantially lower total acreage planted. The results of the model using the options risk specification include no cotton except at the lowest risk level.

The choice of risk specification obviously greatly affects recommendations of crop mix given current market conditions. As expected, the specification based on historical data alone results in a diverse crop mix reflecting first and second moments of the historical patterns of yields and prices. Essentially, the crop mix is designed to account for the average risk for these crops. The optimal crop mixes from the futures and options specifications, however, reflect the market signals faced by producers. The risk specifications were conditional on the current market conditions at that time. No corn is planted under the futures specification reflecting the relative high prices of cotton and soybeans, but also the relative historic predictive accuracy of futures market prices for these three commodities. The current market confidence in futures predictions, however, leads to a crop mix in the options specifications that excludes cotton in favor of corn. The market is more sure, as reflected by options premiums, about future corn prices than future cotton prices, or alternatively, the market is more sure about low cotton prices.

The solution crop mixes are very different for each λ level and it is unclear which crop mix is advisable under the market conditions facing the producer. For example, at λ = 100,000, the optimal crop mix under the historic specification consists of 532 acres of which 240 acres are in soybeans with the remaining acreage split between corn and cotton. Under the futures specification at that risk level, only 421 acres are planted with 235 in soybeans and the remainder in cotton. No corn is planted. When the options specification is used, the solution consists of 653 total acres of which 254 are planted in soybeans and 399 acres are planted in corn. No cotton is planted under this specification. The differences in the alternatives offered by these different risk specifications are not minor.

The question remains as to which strategy would be optimal for the crop year in question. Consequently, the individual crop mix solutions are not as interesting as the proper choice of risk specification. Such a determination of an appropriate specification of the future risk faced by producers would then lead to a prescribed crop mix. The crop mixes at any specific risk level must be compared under common assumptions about risk since they were derived using different assumptions about the proper way to specify risk in the planning year.

Empirical Evaluation of Solution Robustness

After obtaining solutions for the three MOTAD models at five different risk levels (a total of fifteen crop mixes), stochastic dominance techniques were used to evaluate the robustness of solution crop mixes to alternative risk specifications. To correctly compare the efficiency of alternative solutions (at each risk level), total net returns for the optimal crop plans were calculated using prices and yields drawn from the distributions used for each risk specification method (historical, futures, options). Otherwise, results would be biased in favor of one of the three methods. Thus, a new set of 100 correlated price and yield draws for each crop was taken from each of the risk specification distributions (historical, futures, and options) and used to calculate net returns for each crop mix solution. A total of forty-five net returns distributions (each with 100 observations) were calculated (three crop mix solutions × five risk levels × three risk specification distributions). The resulting distributions of net returns for each crop mix solution were then compared to solutions from the other risk specifications at the same level of risk (λ) using first and second degree stochastic dominance. Further evaluation of the risk-efficiency of the solutions was performed using stochastic dominance with respect to a function (Meyer, 1977; King and Robison, 1981).

Crop mixes from each of the three MOTAD models at each risk level were evaluated in a series of fifteen, three-way comparisons (five risk levels and three simulated sets of price and yield distributions). For example, the optimal crop mixes resulting from the three MOTAD models at a risk level of λ = 100,000 were compared using stochastic dominance. A distribution of net returns was first developed for each crop mix by drawing a set of 100 "observed" prices and yields for each crop from the historical risk specification distribution (King; King, et al.; Bosch and Johnson). The dominant set of crop mixes was then determined for the three MOTAD models at the specified risk level. Next, the three crop mixes were compared at the specified risk level under the futures risk specification distribution, and then the options risk specification distribution. In this way, no crop mix would have an advantage over the others because of the choice of risk specification.

First degree stochastic dominance analysis of the solution crop mixes evaluated under the three risk specification distributions did not discriminate among the crop mixes at each risk level. Second degree stochastic dominance analysis also showed little discrimination among the crop mixes. Results of this analysis are presented in Table 2. When net returns for each of the 15 crop mixes were calculated with draws from the historical price and yield distributions, second degree stochastic dominance did not discriminate among the crop mixes derived from the three MOTAD specifications at the highest risk constrained level. For less constraining levels of allowable risk, the crop mixes from the options MOTAD specification were dominated by those from the historic and futures specifications. The crop mix from the futures MOTAD specification was dominant at the unconstrained level when evaluated using prices and yields from the historic distribution.

There was no discrimination among the crop mixes from the three MOTAD specifications at any risk level when they were evaluated using price and yield draws from the futures distribution. Similarly, there was no discrimination among the

Table 2. Second Degree Stochastic Dominant Crop Mixes for Each Risk Specification (S indicates membership in the dominant set, N indicates that the crop mix is dominated)

		Risk Specification Distribution Used in MOTAD to Derive Optimal Crop Mix		
Risk Level	Distribution Used for Evaluation	Historical	Futures	Options
$50,000	Historical	S	S	S
	Futures	S	S	S
	Options	S	S	S
$100,000	Historical	S	S	N
	Futures	S	S	S
	Options	S	S	S
$150,000	Historical	S	S	N
	Futures	S	S	S
	Options	S	S	S
$200,000	Historical	S	S	N
	Futures	S	S	S
	Options	S	S	S
Unconstrained	Historical	N	S	N
	Futures	S	S	S
	Options	N	S	S

crop mixes at risk-constrained levels when they were evaluated under prices and yields drawn from the options distributions. Only the crop mix resulting from the historical MOTAD specification was dominated by the other two distributions at the unconstrained level when evaluated under the risk specification derived from the options markets.

The important and somewhat surprising result is the performance of the crop mixes derived using standard MOTAD methods and historical returns. The co-dominance of the crop mixes derived from the solution of the MOTAD model using historical data to reflect risk is contradictory to the argument that more explicit modelling of expectations in risk models would result in more efficient crop mixes. Note that the crop mixes from the futures MOTAD specification were in the second degree stochastic dominant set for each of the fifteen three-way comparisons and perhaps may be judged to be the appropriate method to specify risk. However, the crop mixes based on the historical MOTAD specification were also in the dominant sets when risk was constrained; these crop mixes were only dominated when risk was unconstrained.

The previous stochastic dominance results reflect the mildly discriminating nature of this type of analysis. Therefore, stochastic dominance with respect to a function was used to discriminate among all 15 crop mixes evaluated under each risk specification. The distributions of returns for each crop mix were compared over a range of absolute risk aversion coefficients representing producers who are risk averse (Boggess and Ritchie; Moss, et al.). The results of this analysis are presented in Table 3.

Stochastic dominance with respect to a function further discriminates among the distributions of returns for the crop mix solutions under different risk specifications. The dominant crop mixes presented in Table 3 indicate that there is still a wide variety of crop mixes among which mildly risk averse producers would be indifferent. In this case, several crop mix scenarios would be appropriate for mildly risk averse producers and there is no logical support for the use of one risk specification distribution over another for this group of producers. However, as the absolute risk aversion coefficient increases, the dominant set of crop mixes evaluated under each of the three risk specifications includes only the crop mix resulting from the futures specification at a risk level of $\lambda = 50{,}000$. Thus, the futures specification would be a more appropriate choice of distribution for modelling very risk averse producers.

Because there is no direct theory guaranteeing consistency among MOTAD and expected utility rankings, the consistency of the MOTAD and stochastic dominance results was evaluated. Means and standard deviations for the distributions arising from the MOTAD-generated crop mixes are presented in Table 4. The mean-standard deviation rankings of those crop mixes are consistent with those presented in Table 2 and 3.

To evaluate the consistency of MOTAD approximations to mean-standard deviation solutions with expected utility, the Kolmogorov-Smirnov (K-S)

Table 3. Risk Efficient Crop Mixes for Different Absolute Risk Aversion Coefficients Using Stochastic Dominance with Respect to a Function (x indicates membership in the dominant set)

Range of Absolute Risk Aversion Coefficients	Distribution Used for Evaluation	Risk Specification Used in MOTAD Models: Historical — Crop Mix from Risk Constraining Level in MOTAD Using the above Risk Specification (λ in 1000s)					Futures					Options				
		50	100	150	200	999	50	100	150	200	999	50	100	150	200	999
.0000–.0001	Historical		x	x	x			x			x	x				
	Futures		x	x	x	x						x	x	x	x	x
	Options		x									x	x			
.0001–.0002	Historical	x					x					x				
	Futures											x				
	Options		x									x	x			
.0002–.0003	Historical						x									
	Futures						x					x				
	Options						x									
.0003+	Historical						x									
	Futures						x									
	Options						x									

Table 4. Means and Standard Deviations of the Distributions Compared with Stochastic Dominance

		Risk Specification Distribution Used in MOTAD to Derive Optimal Crop Mix					
		Historical		Futures		Options	
Risk Level	Distribution Used for Evaluation	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
$50,000	Historical	14,462	8,352	12,174	5,961	17,892	12,495
	Futures	21,351	11,672	18,093	9,167	26,986	14,250
	Options	17,881	9,128	15,680	7,660	22,565	13,279
$100,000	Historical	20,654	16,754	18,405	14,284	20,446	27,656
	Futures	30,476	19,189	26,800	18,629	32,303	25,913
	Options	24,010	15,700	21,339	12,356	25,838	23,658
$150,000	Historical	22,531	24,643	20,539	22,204	19,731	29,005
	Futures	33,065	27,881	29,461	26,448	33,819	36,757
	Options	23,856	20,744	21,802	17,060	24,744	32,079
$200,000	Historical	22,623	32,292	22,336	29,769	18,783	50,511
	Futures	34,257	35,501	31,735	33,961	35,100	47,923
	Options	22,854	26,763	22,087	22,204	23,414	40,875
Unconstrained	Historical	21,171	48,367	22,648	31,773	18,494	53,462
	Futures	36,157	80,949	32,135	35,363	35,380	50,800
	Options	19,268	40,917	22,122	23,194	23,028	43,153

test was used to test the location and scale condition (Meyer and Rasche) for these distributions of returns. The 45 distributions were first normalized to have zero means and unit variances and then the K-S test was applied to determine whether the samples are identically distributed. Tests were performed for all combinations of the 15 distributions devaluated under each of the three expected price assumptions. The tests failed to reject the null hypotheses of identical distributions for any of the comparisons at the five percent significance level. Thus, the location and scale condition is satisfied, implying that the rankings of the MOTAD results are consistent with expected utility for this analysis.

Conclusions and Implications

The results presented suggest that the use of historical data to calculate risk measures in programming models works equally as well as or better than the methods using conditional information based on futures market prices investigated in this research. This conclusion is based on results of mildly discriminating second degree stochastic dominance criteria. Although this is not a very discriminating tool, it has been used to order crop mixes in other studies and is a common method to distinguish between risky prospects. It is acknowledged that the results presented in this research may hold only for a single case farm and only for the risk specifications examined under the market conditions at that time. However, if historical distributions perform as well as distributions using conditional information, then determining the correct methods to detrend data, explicitly incorporate risk, and adjust monetary measures to real terms may depend more on the performance of model results than on "sensible" methods.

Stochastic dominance with respect to a function, however, does discriminate among the solution crop mixes, particularly for the range of absolute risk aversion coefficients representing very risk averse producers. This ordering of crop mixes indicates that the risk specification based on the historical accuracy of futures market prices provides the most robust solution of the three specifications examined. In this case, a "sensible" method has been validated.

The extreme sensitivity of crop mix solutions to the choice of risk specification suggests that more research is necessary to determine exactly how current market risk can be incorporated into risk programming models. The important conclusions of this research, then, are the demonstrated need to incorporate market information into conditional probability distributions in risk models and to test the robustness of optimal crop mixes from risk programming solutions to different methods of risk specification. Research using stochastic dominance techniques frequently results in a set of efficient farm plans, not just a single plan. Researchers using risk programming methods need to recognize that model solutions under one set of assumptions may not be robust across alternative risk specifications. This is an important result, especially given the widely divergent optimal crop mixes that arose from the use of different risk specifications.

Additional care must be taken in the use of stochastic dominance in evaluating MOTAD model results. Until it is shown theoretically that MOTAD rankings are consistent with expected utility, procedures similar to those presented in this research must be used to evaluate whether MOTAD rankings are consistent with mean-standard deviation rankings and whether the location and scale condition is met.

Finally, the results of this research may have some impact on the application of risk programming models to individual farm situations in extension efforts. Different methods of specifying risk will have different information demands. Reliable on-farm historical data or county average data may be difficult to obtain. Alternatively, futures market information is often readily available to research and extension personnel. The methods of specifying conditional risk distributions illustrated in this research will be useful to those advising farm production decisions in a risky market environment.

References

Adams, R.M., D.J. Menkhaus, and B.A. Woolery. "Alternative Parameter Specification in E,V Analysis: Implications for Farm Level Decision Making." *Western Journal of Agricultural Economics* 5(1980):13–20.

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

Black, F. "The Pricing of Commodity Contracts." *Journal of Financial Economics* 3(1976):167–79.

Boggess, W.G., and J.T. Ritchie. "Economic and Risk Analysis of Irrigation Decisions in Humid Regions." *Journal of Production Agriculture* 1(1988):116–22.

Boisvert, R.N., and B. McCarl. "Agricultural Risk Modeling Using Mathematical Programming." Southern Cooperative Series, Bulletin No. 356, 1990.

Bosch, D., and C. Johnson. "An Evaluation of Risk Management Strategies for Dairy Farms." *Southern Journal of Agricultural Economics* 24(1992):173–82.

Buccola, S. "Minimizing Mean Absolute Deviations to Exactly Solve Expected Utility Problems: Comment." *American Journal of Agricultural Economics* 64(1982):789–91.

Ford, S., and T. Hewitt. "1989 Feed Grains Program." *Farm Management Newsletter*. Food and Resource Economics Department, University of Florida, 1989.

Gardner, B.L. "Commodity Options for Agriculture." *American Journal of Agricultural Economics* 59(1977):986–92.

Hazell, P.B.R. "A Linear Alternative to Quadratic and Semivariance Programming for Farm Planning under Uncertainty." *American Journal of Agricultural Economics* 53(1971):384–90.

Hewitt, T. "1989 Crop Budgets for North Florida." Extension Mimeograph. Food and Resource Economics Department, University of Florida, 1989.

Johnson, D., and M. Boehlje. "Minimizing Mean Absolute Deviations to Exactly Solve Expected Utility Problems." *American Journal of Agricultural Economics* 63(1981):728–9.

Johnson, D., and M. Boehlje. "Minimizing Mean Absolute Deviations to Exactly Solve Expected Utility Problems: Reply." *American Journal of Agricultural Economics* 64(1982):791–3.

King, R. "Operational Techniques for Applied Decision Analysis under Uncertainty." Ph.D. dissertation, Michigan State University, 1979.

King, R.P., F.J. Benson, J.R. Black, and P.A. Held. "Agricultural Risk Management Simulator." Minnesota Extension Service AG-CS-257, University of Minnesota. 1989.

King, R.P., and P.L. Fackler. "Probabilistic Price Forecasts Based on Commodity Option Values." Department of Agricultural Economics P85-28, University of Minnesota. 1985.

King, R.P., and L.J. Robison. "An Interval Approach to Measuring Decision Maker Preferences." *American Journal of Agricultural Economics* 63(1981):510–20.

King, R.P., and L.J. Robison. "Risk Efficiency Models." *Risk Management in Agriculture*. P.J. Barry, ed., pp. 68–81. Ames: Iowa State University Press, 1984.

Lindgren, B.W. *Statistical Theory*. New York: MacMillan Publishing Co., Inc., 1976.

Lins, D., S. Gabriel, and S. Sonka. "An Analysis of the Risk Aversion of Farm Operators: An Asset Portfolio Approach." *Western Journal of Agricultural Economics* 6(1981):15–30.

Mapp, H.P., and G.A. Helmers. "Methods of Risk Analysis for Farm Firms." *Risk Management in Agriculture*. P.J. Barry, ed., pp. 116–128. Ames: Iowa State University Press, 1984.

McCarl, B.A., and J. Apland. "Validation of Linear Programming Models." *Southern Journal of Agricultural Economics* 18(1986):155–64.

McCarl, B., T. Knight, J. Wilson, and J. Hastie. "Stochastic Dominance over Potential Portfolios: Caution Regarding Covariance." *American Journal of Agricultural Economics* 69(1987):804–12.

Moss, C.B., S.A. Ford, and M. Castejon. "Effect of Debt Position on the Choice of Marketing Strategies for Florida Orange Growers: A Risk Efficiency Approach." *Southern Journal of Agricultural Economics* 23(1991):103–12.

Musser, W.N., H.P. Mapp, Jr., and P.J. Barry. "Applications 1: Risk Programming." *Risk Management in Agriculture*. P.J. Barry, ed., pp. 129–147. Ames: Iowa State University Press, 1984.

Meyer, J. "Second-Degree Stochastic Dominance with Respect to a Function." *International Economic Review* 13(1977):477–87.

Meyer, J. "Two Moment Decision Models and Expected Utility Maximization." *American Economic Review* 77(1987):421–30.

Meyer, J., and R. Rasche. "Sufficient Conditions for Expected Utility to Imply Mean-Standard Deviation Rankings: Empirical Evidence Concerning the Location and Scale Condition." *Economic Journal* 102(January 1992):91–106.

Robison, L. ''Expanding the Set of Expected Utility and Mean Standard Deviation Consistent Models'' *Risk Modeling in Agriculture: Retrospective and Prospective*. Program proceedings for the annual meeting of the Technical Committee of S-232. Iowa State University, August 1994.

Robison, L., and L. Lev. ''Distinguishing Between Indirect and Direct Outcome Variables to Predict Choices Under Risk or Why Woody Chip Went to the Air.'' *North Central Journal of Agricultural Economics* 8(January 1986):59–67.

Schurle, B., and B. Erven. ''Sensitivity of Efficient Frontiers Developed for Farm Enterprise Choice Decisions.'' *American Journal of Agricultural Economics* 61(August 1979): 506–11.

Thomson, K., and P. Hazell. ''Reliability of Using the Mean Absolute Deviation to Derive Efficient E-V Farm Plans.'' *American Journal of Agricultural Economics* 54(August 1972):503–6.

Young, D.L. ''Evaluating Procedures for Computing Objective Risk from Historical Time Series.'' in *Risk Analysis in Agriculture: Research and Educational Developments*. Department of Agricultural Economics AE-4492, University of Illinois. 1980.

Young, D.L. ''Risk Concepts and Measures for Decision Analysis.'' *Risk Management in Agriculture*. P.J. Barry, ed., pp. 31–42. Ames: Iowa State University Press. 1984.