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An Evaluation of Selected Decision Models: A Case of Crop Choice in Northern Thailand

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ABSTRACT

This research examines the predictability of a profit maximization model, an expected value-variance utility maximization (E-V) model, and two versions of the target-MOTAD model for modeling risky agricultural production decisions. Model solutions were translated into expected value and variance of farm income for analysis. Direct comparison and chi-square analysis of actual and predicted expected income distributions were used in the analyses. It was concluded that the utility maximization and cash-cost target-MOTAD models predicted distributions of farm income better than the variable-cost target-MOTAD and profit maximization models.

Key Words: decision models, expected utility maximization, farm income, profit maximization, target-MOTAD.

The role of risk in agricultural behavioral and decision models is generally recognized today, but applied researchers do not agree on the appropriate methodology for incorporating risk in decision-making models. The purpose of this study is to evaluate alternative decision models that incorporate risk. Profit maximization, the risk-neutral model, is included for completeness. Determination of the more appropriate model in terms of predicting farmers' choices will allow policy makers to more effectively formulate programs to achieve specific objectives.

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Importance of Risk

Studies of farmers' economic rationality in developing countries using Cobb-Douglas production functions and cross-section data have concluded that farmers act as profit maximizers within their technological and institutional constraints (Hopper; Yotopolus). This approach has been criticized because methodologies explicitly incorporating risk considerations are probably a more realistic basis for making policy recommendations directed at modernization of traditional agriculture (Dillon and Anderson). Wolgin concluded that traditional (profit maximization) tests of economic efficiency in agriculture are generally misspecified if farmers are making decisions in the presence of risk.

The omission of risk in farm-level decision models of traditional agriculture may lead to results that bear little if any semblance to farmers' actual behavior. Agricultural decision models not including risk considerations may overestimate output levels of risky crops and fail to recognize the importance of diversification in traditional agricultural production systems (Wolgin). Ignoring risk may also lead to overvaluation of some inputs and incorrect prediction of technology choices (Hazell).

Empirical applications of behavioral models and theoretical considerations indicate the importance of incorporating risk into analysis of farmers' decision making. Risk from environmental, market, and policy factors will always exist in agricultural decision making (Mapp et al.) and it is an important consideration in agricultural decision making (Anderson, Dillon, and Hardaker; Roumasset; Barry).

Decision-Making Models Incorporating Risk

Risk concepts, and hence risk models, are classified into three major categories: (*a*) those requiring no probability information, (*b*) safety first, and (*c*) expected utility maximization (Young).

The class of models requiring no probability information is commonly referred to as game theoretic. These types of models assume that decision makers have no objective information or subjective feelings about the probabilities associated with alternate outcomes, or that they totally ignore whatever information they may have. The theoretical weaknesses and practical limitations of game-theoretic models have been well established (Halter and Dean; Young).

Safety-first models of decision making under risk have considerable appeal, both from theoretical and practical perspectives, and are often specified as lexicographic. Safety-first models specify that a decision maker first chooses those actions that will satisfy some preference for safety. A profit- or utility-oriented objective function is followed after satisfying the safety goal. Target-MOTAD (mean of the absolute deviations) models are frequently used to represent the safety-first class of preferences (Robison et al.; Young).

Expected utility maximization models are theoretically appealing. A polynomial function of the probability distribution moments is commonly used to depict risk in these models (Anderson, Dillon, and Hardaker). However, the question of how many moments are required to reflect the true nature of risk remains unanswered. One practice in empirical studies has been to assume that the true nature of risk can be represented by the variance of the probability distribution, and hence, a quadratic utility function. This specification is referred to as the E-V (expected value-variance) model. Using this simplified quadratic formulation, the variance is an unambiguous, single-dimensional index of risk—a characteristic many applied researchers find appealing (Young).

An alternative approach to decision analysis is stochastic dominance. This methodology entails the search for an efficient set of decisions in the sense that they are undominated and hence are admissible as potential solutions. The hope is that the undominated set of decisions will be small or closely confined. The undominated set will tend to be smaller if more is known (or assumed) about preferences (Anderson, Dillon, and Hardaker, p. 281). Stochastic dominance is not considered in this study because it relates the whole probability distribution to the decision variables. This can be a very demanding task unless rather specific families of distributions are used. In addition, the use of stochastic dominance entails the abandonment of the quest for optimal decisions (Anderson, Dillon, and Hardaker, p. 177).

Models Used in This Study

The primary concern of the present study is to shed some light on the ability of alternative decision models that incorporate risk to predict the actual behavior of risk-averse farmers. The expected utility and safety-first classes of models were represented in this study. A profit maximization model was also included in the analysis as a point of reference. Profit maximization assumes a linear utility function (the dispersion of the expected returns is not a factor in farmers' choices). A game-theoretic model was not included in the analysis because it has been demonstrated by others that these types of models are lacking from theoretical and practical perspectives (Young). Stochastic dominance was not included because it does not give a predicted optimum farm plan.

The E-V model is used to represent the utility maximization class of models. It is possible to use a portfolio choice model to explain whole-farm planning under uncertainty (Markowitz). The portfolio model utilizes a trade-off between a measure of expected return and variance as a measure of risk to explain portfolio choice. An efficient set of farm plans can be calculated by minimizing variance of expected returns for predetermined levels of expected returns using the following quadratic programming model.

$$\text{Minimize:} \quad V = \Sigma_i \Sigma_j \sigma_{ij} X_i X_j$$

$$\text{Subject to:} \quad \Sigma_j A_{kj} X_j \leq b_k \qquad \forall\, k,$$

$$\Sigma_j C_j X_j = \alpha,$$

where V is variance of total expected income; C_j is expected gross margin per unit of crop j; X_j denotes units (area) of crop j; σ_{ij} is variance when $i = j$, and covariance otherwise; A_{kj} is resource k requirement for one unit of crop j; b_k is amount of resource k available; and α is the expected income parameter (varied parametrically to determine efficient frontier).

All parameters except the variances, covariance, and α are standard for programming models. The parameter α is varied parametrically to find an efficient frontier in terms of expected returns and associated variances of expected income. The model is composed of expected returns, C_j, and their variance-covariance matrix, σ_{ij}s. The strength-of-conviction technique was employed to estimate subjective probability distributions that were used to indicate the risk associated with choice alternatives for each farmer (Debrah and Hall). The efficient frontier is used in conjunction with a utility function to determine the optimal farm plan (Robison and Brake).

The preference functions required to find the optimal solution in expected value-variance space were derived using the modified von Neumann-Morgenstern approach function (Anderson, Dillon, and Hardaker). The use of quadratic functional form allows classification of farmers into risk-averse and risk-preferring categories based on the sign of the coefficient of the squared term. This approach has been used for Australian pastoralists (Francisco and Anderson), Malaysian fruit growers (Mohayidin), and Nepalese rice farmers (Anderson and Hamal). It is recognized that this approach does have potential bias. Instrument and interviewer bias are two of the major sources (Roumasset; Binswanger; Robison). Direct elicitation was used despite these potential pitfalls because of time and resource constraints. Instrument bias was reduced by pre-testing the questionnaire, and interviewer bias across observations was minimized because one individual conducted all the interviews.

Farm decision makers frequently associate risk with the failure to attain some given target return (Roumasset; Patrick et al.). Target-MOTAD models belong to the class of safety-first models that represent risk as the absolute value of negative deviations from some target level of return (Fishburn). The target-MOTAD model (Tauer) was specified as follows:

$$\text{Maximize:} \quad Z = \Sigma_j C_j X_j$$

$$\text{Subject to:} \quad \Sigma_j A_{kj} X_j \leq b_k \qquad \forall\, k,$$

$$T - \Sigma_j C_{tj} X_j - N_t \leq 0 \qquad \forall\, t,$$

$$\Sigma_t P_t N_t = \delta,$$

$$X_j, N_t \geq 0 \qquad \forall\, j, t,$$

where Z is total expected income, C_j is expected gross margin per unit of crop j, X_j denotes units (area) of crop j, A_{kj} is resource k requirement for one unit of crop j, b_k is amount of resource k available, T is target income level, N_t is deviation below target for state of nature t, P_t is probability of state of nature t, and δ is the risk constant parameterized from zero to a large value.

Two target income levels, T, were used in this study. They were farm cash cost and farm variable cost of production. Cash cost was defined as the expected annual monetary obligation associated with farm production. Variable cost was defined as cash cost plus imputed value of nonpurchased variable inputs. Both of these safety-first concepts are related to short-run survival, which appeared to be an important consideration among the farmers in the study. Other researchers have defined the target income level as some form of annual debt servicing plus estimated living expenses (Rawlins and Bernardo; Prevatt et al.). However, most of the food is produced on the farm in developing countries.

Optimal farm plans were determined by varying δ. The optimal farm plan corresponds to the lowest possible value of δ, or the smallest sum of the negative deviations from the target income level. If the level of δ associated with the optimal farm plan is zero, the optimal solution meets a strict safety-first criterion.

Finally, risk-neutral behavior was considered in the analysis for completeness. A profit maximization model was used for this case. It can be considered a simplification of either the E-V model or the target-MOTAD model. The profit maximizing programming model was specified as follows:

$$\text{Maximize:} \quad Z = C_j X_j$$

$$\text{Subject to:} \quad \Sigma_j A_{kj} X_j \leq b_k \quad \forall\, k,$$

$$\Sigma_j \geq 0 \quad \forall\, j,$$

where Z is total expected income, C_j is expected gross margin per unit of crop j, X_j denotes units (area) of crop j, A_{kj} is resource k requirement for one unit of crop j, and b_k is amount of resource k available.

Comparison of Farm Plans

A common denominator had to be used to compare the optimal farm plans derived from the E-V, target-MOTAD, and profit maximization models to the observed farm plans. Crop activity levels, X_js, were ruled out as the common denominator for presentation of the results since some were equal to zero in some predicted or actual farm plans. Zero-valued observations would have eliminated the possibility of using the chi-square goodness-of-fit test to determine which model best predicted farmer behavior. The optimal plans of each model were translated into expected value and variance of farm income because the income distribution is probably the best single characteristic of a farm plan (Lin, Dean, and Moore). This involved translating crop activity levels from the target-MOTAD and the profit maximizing models into expected incomes and variances. The expected incomes came directly from these models. The variances of the expected incomes were calculated as follows (Elton and Gruber):

$$V = \Sigma_i\, \sigma_i^2 X_i^2 + \Sigma_i\, \Sigma_j\, \sigma_{ij} X_i X_j,$$

where σ_i^2 is variance of crop i, and σ_{ij} denotes covariance between crops i and j, $i \neq j$.

The testing procedure used here follows that of Lin, Dean, and Moore in their study of decision making among California farmers. The chi-square goodness-of-fit test was used to judge if the income distributions of actual farm plans were significantly different from those predicted by the behavioral models. Before calculating chi-square values, the variances of the income distributions were converted to standard errors to provide equivalent units of measurement in the two dimensions of the income distributions. Chi-square values with one degree of freedom for each observation were calculated as follows:

$$\chi^2 = \Sigma_i \frac{(f_{io} - f_{ie})^2}{f_{ie}},$$

where i is expected value and standard deviation, f_o is the observed income distribution, and f_e is the income distribution of the predicted farm plan.

The calculated chi-square values were subsequently compared across models. This provided a joint test of which model more closely predicted actual behavior as measured by expected income and its standard deviation. The chi-square values were also used for pair-wise comparison of the alternative decision models.

The Research Setting

Growth in Thailand's agricultural production has been impressive over the past two decades.

However, much of this growth has been accomplished by increasing the cultivated area rather than per unit of land productivity. For instance, rice production increased from 15,068,000 metric tons (1976–77) to 20,601,000 metric tons (1989–90), representing an increase of approximately 35%. Most of this growth was directly attributable to a 20% increase in land area during the same period. Production per unit of land, on the other hand, only increased about 13% over this period. The growth in agricultural production over this time frame coincides with the goal of the government to increase agricultural production, but the introduction of new lands into agricultural production cannot continue indefinitely. The latest crop year survey (1990–91) indicates that only 28% of the forest lands remain undeveloped (Thailand Ministry of Agriculture and Cooperatives).

Recognizing the dwindling supply of undeveloped lands and the importance of achieving optimal use of land resources, the Farming Systems Research Institute (FSRI) was founded in Thailand in 1982. The FSRI has conducted multi-location testing to determine the feasibility of alternative agro-economic systems to increase and stabilize production and incomes of farmers in rainfed production areas.

A mung bean/rice rotation has been considered a "mature technology"[1] to increase and stabilize production and incomes in rainfed areas since 1986. The government of Thailand has attempted to encourage adoption of this "mature technology." Programs including increased information through extension and cost reduction, such as seed exchange activities, have been implemented. However, widespread adoption of the mung bean/rice rotation system has not occurred. Adoption of the mung bean/rice rotation system of production is sporadic, even within a small geographic area. This case is a good example of farmers having similar production environments and access to technology and information to increase expected income. Some farmers choose to adopt the technology while others do not.

Study Areas

The study sites chosen were in the Maejai and Dokkhamtai Districts of Phayao Province in northern Thailand. The mung bean/rice rotation technology was introduced in 1986, and has been actively promoted by the government since that time in both districts. The two sites are within the purview of the same FSRI researcher who could help identify farmers for the sample. The districts have somewhat different physical production environments. These might have an impact on farmers' decisions regarding the adoption of the mung bean/rice rotation technology. The Maejai District is classified as a medium stable production area, while the Dokkhamtai District is classified as a less stable production area by the FSRI.

Both districts have adequate rainfall and soil moisture during the main cropping season, followed by a definite dry season of at least two months. The dry season is more pronounced in the Dokkhamtai District. The Maejai District has slightly more rainfall on average and better soil moisture retention, resulting in a higher productivity classification (Pathanothai).

Sample and Data

Purposive sampling was used in this study. Although it is not as preferred as some other sampling procedures, standard texts in sampling recognize purposive sampling as a valid technique under the right conditions. However, the method is not amenable to the development of sampling theory. Having an expert select a number of "typical" units (purposive sampling) may be the best technique available when the population is heterogeneous and the researcher is able to select only a small sample (Cochran; Kish). An FSRI researcher's exper-

[1] The FSRI has conducted tests for the mung bean/rice rotation cropping alternative in northern Thailand and found it to be biologically feasible in the area. The technology comes in a package that includes improved seed varieties, seed treatment (rhizobium and insecticide), and recommended cultural practices. The technology has also been deemed economically preferable to the traditional cropping system based on partial enterprise budgeting (Suppapanya, p. 114).

Table 1. Average Expected Gross Return and Variances from Crop Production

	Maejai District		Dokkhamtai District	
Crop	Gross Margin	Variance	Gross Margin	Variance
	(Baht*/Hectare)			
Rice	11,022	1,373,962	9,880	1,084,237
Corn	—	—	6,589	286,137
Paddy Mung Bean/Rice	11,022	1,373,962	9,880	1,084,237
Upland Mung Bean	—	—	4,767	633,962
Garlic	29,554	26,837,594	30,294	18,318,008
Ginger	46,724	93,948,154	—	—

* Baht = basic monetary unit of Thailand.

tise was used to identify the typical observations for the purposive sample.

Care must be taken when interpreting the results of a purposive sample since statistical inferences to an overall population are questionable. A total of 60 observations, 31 from Maejai and 29 from Dokkhamtai, were selected. This sample included 30 adopters and 30 nonadopters of the mung bean/rice rotation cropping alternative.

Production and financial situation, socioeconomic characteristics, and risk perceptions and attitudes of individual farmers were collected in the survey. (A detailed listing of information elicited from each surveyed household is provided in the appendix.) The individual farm production and financial data were used to determine the model parameters for each farmer. The data on risk perceptions and attitudes were used to specify the probabilities and the objective functions for the individual farmers.

Sample Descriptive Summary

The sample mean and variance of expected returns for each possible crop are presented by district in table 1. Ginger, which has the highest expected return, can be grown only in the Maejai District.

The socioeconomic characteristics of the sample farmers were similar in the two districts. A summary is presented in table 2. The average age (45 years), level of formal education (< 5 years), and household size (4.6 members) were the same in both districts. There was slightly more dispersion of age and household size in the Maejai District than the Dokkhamtai District. The average farm size was found to be 3.4 hectares in Maejai and 5.4 hectares in Dokkhamtai.

Forty-two of the farmers in the sample were classified as risk averse and 18 as risk preferrers based on the second-order coefficient of the quadratic utility function. Only the risk-averse farmers were included in the behavioral analysis.

Table 2. Sample Socioeconomic Characteristics

Characteristic	Maejai District (%)	Dokkhamtai District (%)
Age (years)		
< 30	9.7	3.4
30–39	22.6	17.2
40–49	32.3	58.6
50–59	19.4	17.2
> 59	16.1	3.4
Education (years school)		
< 5	77.4	82.8
5–7	9.7	10.3
> 7	12.9	6.9
Household Size		
< 4	35.5	10.3
4–5	35.5	75.9
> 5	29.0	13.7
Farm Size (hectares)		
< 1.8	16.1	6.9
1.9–4.0	58.1	37.9
4.1–6.5	16.1	31.0
6.6–8.9	6.5	13.8
> 8.9	3.2	10.3

Table 3. Expected Income from Actual Farm Plan vs. Predicted Farm Plans

	Model			
			Target-MOTAD	
Category	E-V Utility	Profit Maximization	Cash-Cost	Variable-Cost
	(No. of Farms)			
Maejai District				
Higher	17	20	17	14
Equal	2	2	2	2
Lower	3	0	3	6
Dokkhamtai District				
Higher	16	17	11	15
Equal	2	3	2	1
Lower	2	0	2	4
Combined Districts				
Higher	33	37	28	29
Equal	4	5	4	3
Lower	5	0	5	10

Note: The numbers in this table refer to the number of observations for which the expected income from the behavioral models are higher than, equal to, or lower than the expected income generated from the farm plan actually observed.

Results of the Analysis

Analysis results are presented by individual district as well as for the combined districts because of slight climatic and potential crop choice differences. However, overall conclusions and implications are similar for the individual and combined scenarios. Discussion focuses on the combined sample results since the differences between districts did not noticeably influence the predictability of models in most cases. However, the noticeable differences between districts are identified in the discussion.

Income distributions from the predicted farm plans were compared to the income distributions from the actual farm plan to judge the ability of the alternative models to predict actual farmer behavior. Table 3 provides a summary of the comparison of expected incomes from the predicted and actual farm plans. Predicted farm plans can result in expected incomes greater than, equal to, or less than the expected incomes from the actual farm plans. There is a tendency for all of the behavioral models to predict farm plans that yield higher expected incomes than do the farm plans actually implemented by farmers (table 3). The profit maximization model was the worst offender.

Table 4. Frequency of Models Judged "Best"

Model	Maejai District	Dokkhamtai District	Combined Districts
	(No. of Farms)		
E-V Utility	8	6	14
Profit Maximization	0	0	0
Cash-Cost Target-MOTAD	1	3	4
Variable-Cost Target-MOTAD	7	2	9
Total	16	11	27

Notes: "Best" is defined as the model predicting the farm plan with an income distribution nearest the income distribution of the observed actual farm plan as measured by the chi-square value. The total numbers are less than those shown in table 3 because ties are not reported.

To extend the analysis, one behavioral model was judged a "best" predictor for each observation using the chi-square goodness-of-fit test. A summary of the number of cases in which each of the models was judged best is presented in table 4. The E-V model performed best in 14 out of 27 cases. This was followed by the variable-cost target-MOTAD model with a frequency of 9, the cash-cost target-MOTAD model with 4, and the profit maximization model with 0. None of the risk-averse farmers' behaviors could be adequately modeled using a profit maximization model. These results strongly indicate that across-the-board application of the profit maximization model is not advisable when modeling agricultural decision making.

A pair-wise comparison of the alternative models was made in an attempt to further clarify the desirability of the alternative models. The results are presented in table 5. The findings suggest that the E-V model is the best in predicting cropping patterns that give income distributions consistent with those of the observed cropping patterns. This model consis-

Table 5. Frequency of Pair-Wise Predictive Ability Comparisons

	More Successful Model[a]			
			Target-MOTAD	
Less Successful Model	E-V Utility	Profit Maximization	Cash-Cost	Variable-Cost
	No. of Observations (percent)[b]			
Maejai District (n = 22)				
E-V Utility	—	3 (14)	5 (23)	9 (41)
Profit Maximization	10 (45)	—	3 (14)	10 (45)
Cash-Cost Target-MOTAD	10 (45)	2 (09)	—	10 (45)
Variable-Cost Target-MOTAD	10 (45)	2 (09)	3 (14)	—
Dokkhamtai District (n = 20)				
E-V Utility	—	2 (10)	4 (20)	5 (25)
Profit Maximization	8 (40)	—	5 (25)	3 (15)
Cash-Cost Target-MOTAD	10 (50)	7 (35)	—	3 (15)
Variable-Cost Target-MOTAD	12 (60)	5 (25)	7 (35)	—
Combined Districts (n = 42)				
E-V Utility	—	5 (12)	8 (21)	14 (33)
Profit Maximization	18 (43)	—	8 (19)	13 (31)
Cash-Cost Target-MOTAD	20 (48)	9 (21)	—	17 (40)
Variable-Cost Target-MOTAD	22 (52)	7 (17)	10 (24)	—

[a] Based on the calculated chi-square value for predicted versus actual farm income distribution.
[b] Excludes those observations for which two or more of the models yielded identical optimal farm plans. Numbers in parentheses are percentages.

tently outperformed other models in the prediction of observed farm plans by more than 40% (individual and combined districts) when the models were compared pair-wise.

The E-V model predicted the observed expected income distribution better than the profit maximization, cash-cost target-MOTAD, and variable-cost target-MOTAD models in 43%, 48%, and 52% of the cases, respectively, in the combined districts. Further, this result is similar for each individual district.

The variable-cost target-MOTAD model was second, with better predictions than the E-V utility maximization, profit maximization, and cash-cost target-MOTAD models in 33%, 31%, and 40% of the cases, respectively, for the combined districts. The variable-cost target-MOTAD model predicted equivalent to the E-V model in the Maejai District. It did not predict nearly so well in the Dokkhamtai District, where predictability was more in line with that of the cash-cost target-MOTAD and profit maximization models. This may indicate that farmers in the two districts have different behavioral characteristics underlying their decision-making framework.

One difference that might influence farmer behavior is the production of ginger in the Maejai District, but not in the Dokkhamtai District. Ginger is a very high-value cash crop that requires substantial amounts of capital for purchased inputs. Farmers growing ginger often find it necessary to borrow the funds necessary to purchase the inputs. These farmers may indeed have a stronger safety-first component to their decision making in terms of production loan repayment capacity.

The profit maximization and cash-cost target-MOTAD models predicted poorly for both the combined and individual districts.

Limitations

This study has a number of limitations. These include number and selection of observations, elicitation methods, and limited scope. The sample was formulated as a purposive rather than probability sample. Although the techniques used for eliciting risk perceptions and attitudes are frequently used by researchers, they are not without limitations. The classification of decision makers into risk-averse and risk-preferring groups depends on the tenability of the methodology and assumptions required to derive the utility functions. Only risk-averse decision makers and a small number of models and variations thereof were considered in this analysis.

These limitations exist because of time and resource constraints. They are important considerations for any interpretations and conclusions based on the results presented above. The purposive sample framework makes statistical inferences regarding the population invalid.

Summary and Conclusions

Many alternative models have been developed in attempts to explain farmer decision making in a risky production environment. These modeling endeavors can be differentiated according to the risk concept embodied in the alternatives. Two basic risk concepts were considered in this study—safety first and expected utility maximization. The target-MOTAD model was used to represent the safety-first classification. Two different target levels, cash cost and variable cost, were used in the target-MOTAD model. The E-V model was used to represent the expected utility classification. A profit maximization model was included to represent the risk-neutral situation. The criterion for how well models explained farmer behavior was the difference between income distributions from the predicted and actual farm plans.

The technical production coefficients and resource constraints were derived through farmer interviews. The modified von Neumann-Morgenstern approach was used to elicit risk preferences of the decision makers. The strength-of-conviction technique was used to estimate the individual subjective probabilities. After determining optimal farm plans using each of the four models considered in this study for each farm observation, all solutions were translated into expected value and standard deviation of farm income for comparisons. A chi-square goodness-of-fit test was used to judge which model was the best predictor.

Little can be said about the adoption of the mung bean/rice rotation technology in northern Thailand due to the nature of the sample. However, the results do provide insights into the modeling of farmers' choices. This study supports previous evidence that risk should be explicitly taken into account. Some guidelines regarding the choice of decision models incorporating risk do appear valid.

The expected incomes from the farm plans predicted by all the models tended to be higher than the expected incomes from the observed farm plans. The E-V model was generally found to be a better predictor of observed farm income distribution than other models based on a chi-square goodness-of-fit test. This conclusion is in agreement with findings reported by other researchers (Lin, Dean, and Moore; Herath, Hardaker, and Anderson; Anderson and Hamal). The predictive ability of the E-V model was closely followed by the variable-cost target-MOTAD model. The profit maximization and cash-cost target-MOTAD models performed about equally poorly in predicting farm plans that yielded income distributions similar to those of the observed farm plans.

The selection of the target level in a target-MOTAD model appears to be crucial, and is definitely subjective. The present study focused on short-term survival. Other researchers have focused on debt servicing, have asked the decision maker to specify a target level, or have parametrically varied the target level. Target-MOTAD models do have considerable empirical appeal in modeling farmer decision making under risk. However, there are really no clear guidelines on the appropriate specification of the target level or levels for the model. Specific research is needed in this area.

Some form of risk consideration exists in farmers' decision-making processes, although the exact nature of the incorporation of risk by farmers is unclear at this point. It may be some form of expected utility maximization, safety-first criterion, or some combination of the two. Incorporation of risk into the decision-making process by farmers may vary across groups and individuals depending upon the technical and economic environment, and attitudes of the farmers. Both the E-V and target-MOTAD models have considerable theoretical and empirical appeal, and both need to be investigated more thoroughly as models of farmers' decision-making processes.

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Appendix

The information elicited from each interviewed household included the following:

(1) Socioeconomic characteristics: household size, education, age, and off-farm employment.
(2) Inventory of assets: land, water availability, livestock, and equipment.
(3) Information by crop: types and amounts of outputs and inputs including labor, and prices of outputs sold and inputs purchased.
(4) Decisionmaker's risk perception, including both yield and price factors.
(5) Decisionmaker's risk preferences.
(6) Income from off-farm employment.
(7) Household expenditures.
(8) Credit information: amount, interest, and terms of outstanding debts.