Ind. Jn. of Agri. Econ.
Vol. 61, No. 2, April-June 2006

Measuring and Incorporating Farmers' Personal Beliefs and Preferences about Uncertain Events in Decision Analysis: A Stochastic Programming Experiment

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I

INTRODUCTION

The existence and importance of risk in agricultural production is well recognised. Farmers are confronted by important stochastic variations in both the prices and yields of their products as well as a range of other risks. These uncertainties add complexity to their decision-making. However, decisions must be made, and farmers must make the "best" decisions they can given their skills and knowledge, objectives and beliefs, and the technical, social and economic environment in which they work (Anderson *et al.,* 1977; Hardaker *et al.,* 2004; Torkamani, 2005).

The concept of subjective probability is at the core of methods of rational choice under uncertainty. A subjective probability distribution is based upon the decision maker's personal opinion about the occurrence of risky prospects. It reflects the degree of personal strength of belief about the likelihood of uncertain events, and it is applicable to both unique and repetitive events (Dillon, 1971; Hardaker *et al.*, 2004; Torkamani, 2005). So, it is rational to consider the idea of subjective probability as a component for decision-making under uncertainty (Anderson *et al.*, 1977).

The main purpose of this paper is to report the results of an experiment in Iran to elicit farmers' personal beliefs of crop yields and prices and, also, their preference functions. The specific objectives of this paper are (a) to review some methods of eliciting subjective probabilities and the major direct approaches to study the risk attitudes of the farmers, and (b) to compare the most commonly used utility functional forms, and (c) to incorporate the personal probability distributions of prices and yields in the estimation of net income for individual crops on each farm. The discrete stochastic programming (DSP) model was then used to predict farmers' behaviour. To examine the importance of incorporating farmers' beliefs and

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The author would like to acknowledge the valuable comments and suggestions of J.B. Hardaker on an earlier draft of the paper.

preferences in farmers' cropping decisions, models of utility maximisation were then compared with the risk neutral solutions. Based on these findings the conclusions are drawn in the final section of the paper.

1.1. Assessment of Subjective Probabilities

There are several methods for eliciting the probabilities such as the visual impact method, the judgmental fractile method, and the triangular distribution method (Anderson *et al.*, 1977; Grisley and Kellogg, 1983; Norris and Kramer, 1990; Hardaker *et al.*, 2004). In the visual impact method, the subject is given a visual aid in quantifying his or her subjective beliefs about some uncertain event. With this method the possible range of the uncertain variable might be divided into a convenient number of mutually independent and collectively exhaustive intervals. A reasonable number of counters is then given to the farmer to allocate among the intervals as a representation of his or her relative degrees of belief about the uncertain outcome falling in each category. This allocation may be revised until the farmer is satisfied with the displayed distribution. The ratios of the observed class frequencies to the total number of counters give the probabilities of various intervals. The distribution curve then can be plotted in a cumulative form for the uncertain variable.

The judgmental fractile method involves direct assessments of a decision maker's cumulative distribution function (CDF) by successively obtaining equally likely probability intervals. This method starts with assessing two extreme fractiles at probability levels zero and one respectively. Next the value $f_{0.5}$ (i.e., 0.5 fractile) is determined such that it is equally likely that the value of the variable x is less than or greater than $f_{0.5}$. The procedure continues in a similar way, by sub-dividing previously determined intervals into equally likely parts, to find several other fractile values such as $f_{0.25}$, $f_{0.75}$ and $f_{0.125}$. A smooth CDF then can be drawn through the elicited points. However, implementation of such a technique in the case of illiterate farmers may be difficult and time consuming as eliciting fractile values like $f_{0.125}$ and $f_{0.25}$ requires careful questions and considerable crosschecking.

In the triangular distribution method, only three values of an uncertain variable (i.e., lowest, highest and mode or most likely value) are needed to estimate the probability distribution function (PDF). The PDF for the triangular distribution can be calculated as

$$f(x) = 2(x - a)/(c - a)(m - a) \quad \text{for} \quad a \leq x \leq m$$

and

$$f(x) = 2(x - c)/(c - a)(m - c) \quad \text{for} \quad m \leq x \leq c$$

where x = the value of a risky prospect;

a = the lowest possible value of x;

m = the mode (i.e., the most likely value) of x; and

c = the highest possible value of x.

The sample values of risky prospect x can then be derived by applying a pseudo-randomly uniform variate over the interval zero to unity to the inverse CDF as follows:

$$x = a + [F(x)(c-a)(m-a)]^{0.5} \text{ for } a \leq x \leq m \text{ and}$$

$$x = c - [(1 - F(x)(c-a)(c-m)]^{0.5} \text{ for } m \leq x \leq c$$

where x, a, m, and c are as defined above and F(x) indicates the CDF of the triangular distribution (Anderson *et al.,* 1977; Hardaker *et al*., 2004). The mean and variance for a random variable following the triangular distribution can be estimated as follows (Johnson and Kotz, 1970; Anderson *et al.*, 1977; Hardaker *et al.*, 2004):

$$\text{Mean} = (a + m + c)/3$$

and

$$\text{Variance} = [(c - a)(c - a) + (m - a)(m - c)]/18$$

This procedure preserves the aspects of the stochastic dependency in the historical data, in particular, the correlations, as well as the general shape of the historical distribution.

The triangular distribution is easy to elicit and, is amenable to mathematical manipulation. Furthermore, it enables a simple graphical representation of both the PDF and CDF. While this method puts a severe restriction on the form of the probability distribution, it has been widely recommended and used (Cassidy *et al.*, 1970; Anderson *et al.,* 1977; Chee-Yoong, 1978; Young, 1983; Torkamani and Hardaker, 1996; Hardaker *et al.*, 2004). Young (1983) used this approach to elicit subjective probability distributions of crop yield from 272 farmers and found the procedure to be both easy and quick to administer. The results of this study were also consistent with the results of agronomic field trials in the study area.

The judgment fractile method is considered as a time-consuming and also a rather difficult approach. Of the other two, as Dillon and Perry (1977) and Sonka and Patrick (1984) indicated, the triangular distribution method is simple and practical, especially in the case of semi-traditional and illiterate farmers. Furthermore, the accuracy of the distribution can be checked by comparing a triangular CDF and an elicited judgmental CDF at several points (Anderson *et al.*, 1977; Hardaker *et al.*, 2004).

While the choice of the best technique for eliciting decision makers' degrees of belief is still inconclusive, the method should be logical, definite and consistent (Cassidy *et al*., 1970; Norris and Kramer, 1990; Hardaker *et al*., 2004). Given the above properties, the triangular distribution method seems to have the advantage over other elicitation methods (at least for continuous uncertain quantities). Thus, this method was judged to be more appropriate for use in this study.

1.2. Measuring Risk Preference

Let W be final wealth, consisting of initial wealth, w, plus the certainty equivalent (CE) of income in the current period, M, i.e.

$$W = w + M$$

Then for a utility function U(W) = U(w+M), Pratt (1964) defined a measure of absolute aversion as

$$R_A = - U''(W) / U'(W)$$

where U'(W) and U''(W) are the first and second derivatives of a Bernoullian utility function. The absolute risk aversion measure (R_A) traces the attitude of an individual to a risky prospect as wealth rises but the prospect remains the same. The index of absolute risk aversion is positive, zero, or negative for risk averse, risk neutral, and risk takers, respectively (Pratt, 1964; Arrow 1965).

Several techniques for designing interviews to elicit the preference functions of farmers are available. The most commonly used methods are the von Neumann-Morgenstern (N-M) model, the modified version of the N-M model or the Equally Likely Certainty Equivalent (ELCE) method, the Ramsey or the Equally Likely but Risky Outcome (ELRO) method (Anderson *et al.,* 1977; Robison *et al.,* 1984; Hardaker *et al.,* 2004) and the experimental approach (Binswanger, 1980).

The experimental method based on real money bets needs a large sum of money, which makes it infeasible for the present study. Besides, it only gives the interval of risk aversion. The ELRO approach overcomes the interviewing bias but is relatively difficult to handle. The ELCE model is designed to avoid bias due to probability preferences. The subject is confronted with two-state risky prospects with equal probability of 0.5 for each state. This method overcomes the criticism of bias due to probability preference (Hardaker *et al.,* 2004; Torkamani, 2005). Thus the ELCE interview technique with imaginary payoffs was used in the present study to elicit the utility functions of the farmers.

II

MATERIALS AND METHODS

The primary data on various aspects of farm economy were collected from a sample of farmers in Kavar district, in the Iranian province of Fars during the agricultural year 2002-03. In a stratified random sampling method, first, in order to prevail the uniformity of the sample, a uniform stratum of 110 farmers from Kavar district was established on the basis of soil and water quality, level of mechanisation, cropping pattern, type of cropping, assets-holding status, and a minimum education level of the farmers (ability to read and write). Data on crop production and other activities and items such as input-output coefficients, access to farm inputs and credit, as well as resource base information were collected through structured questionnaires by trained investigators. Also, data on farmers' risk attitudes and their subjective beliefs regarding crop yields and prices were recorded. Historical data on yield per hectare and prices of various crops pertaining to the period 1993 to 2002 were mainly taken from Kavar Rural Service Center, the Ministry of Agriculture, the Planning and Management Organisation and also the Annual Reports and Balance Sheets of the Central Bank of Iran.

Applying cluster analysis to classify the sample farms into homogenous groups is likely to eliminate or at least minimise aggregation bias (Buckwell and Hazell, 1972; Aldenderfer and Blashfield, 1984; Hazell and Norton, 1986). Thus statistical cluster analysis was used to divide the sample farms into homogenous size classes. After ranking the farms on the basis of their area, the median farm of each group was chosen, following Hazell and Norton (1986), as being representative, resulting in representative farms of the following sizes: small 3.5 ha, medium 6.5 ha, and large 13.5 ha. The degree of representativeness of these median farms was then tested by comparing the total net revenue (TNR) per ha of each selected farm to the average TNR per ha of the corresponding size class.

In this study, both farmers' subjective judgments and historical data on crop yields and prices were used as bases for the probability distributions used in the models. In order to preserve the aspects of stochastic dependency in the historical data, in particular, the correlations, as well as the general shape of the historical distributions, the following procedure was adopted. First, the historical data on crop yields and prices were detrended to remove the effects of inflation and technological change. Second, following Hardaker *et al.* (2004) and Torkamani (2005), a single elicitation method (i.e., the triangular distribution method) was used to elicit the marginal subjective probability distributions of crop yields and of prices for the sample farmers. Then the trend-corrected time-series data sets were reconstructed to have the same means and standard deviations as those obtained from the selected farmers.

The trend-corrected time-series data set was reconstructed by using the following formula:

$$Y_{sjk} = M_{sj} + [(Y_{djk} - M_{dj})/SD_{dj}]SD_{sj}$$

where Y_{sjk} is the subjectively adjusted values on crop yields or prices for crop j and state k;

M_{sj} is the mean of the subjective distribution for crop j;

Y_{djk} is detrended data for crop j and state k;

M_{dj} is the mean of detrended data for crop j;

SD_{dj} is the standard deviation of detrended data for crop j; and

SD_{sj} is the standard deviation of the subjective distribution for crop j.

This new set of data was estimated for the representative farms, based on the average of the subjective means and standard deviations. The adjusted data are treated in this study as a set of equally likely states of nature. The subjectively adjusted time-series data on yields and prices of different crops which are cultivated in the study region were introduced in the DSP models (Cocks, 1968; Rae, 1971a, b; Apland and Hauer, 1993; Torkamani and Hardaker, 1996; Hardaker *et al.*, 2004; Torkamani, 2005) to determine the optimum program for each representative farm.

Finally, in order to investigate the importance of incorporating risk aversion and subjective probability in farmers' decision, the farmers' existing cropping patterns were compared with the results of the models of expected utility maximisation and expected profit maximisation (i.e., models with a linear utility function which implies risk neutrality).

The farmers' decision problems may be represented as mathematical programming problems with stochastic objective function coefficients and/or stochastic constraints. Stochastic programming has been developed to accommodate uncertainty in both the objective function and the constraint coefficients. Decision models may be classified as sequential or nonsequential (Hadley, 1962; Hardaker *et al.*, 1991; Dorward, 1999; Hardaker *et al.*, 2004). However, most practical problems involve embedded risk where farmers have the opportunity to make sequential decisions as a season progresses (Hardaker *et al.*, 1991; Dorward, 1999; Torkamani, 2005). DSP is an approximate method of dealing with sequential stochastic farm planning problems (Cocks, 1968; Ray, 1971a, b; Torkamani and Hardaker, 1996; Dorward, 1999; Hardaker *et al.*, 2004). The method can represent the sequential nature of the farming decision problem capturing uncertainty in both the resource constraints and objective function.

The DSP model of the study illustrating a two-stage (i.e., t=2) sequential decision problem is outlined below. It is assumed that the farmer's objective is to maximise the utility value of net revenue via a monotonic concave utility function. The DSP model can then be expressed as follows (Hardaker *et al.*, 2004):

maximize $E(U) = p'u(z_{tk})$
subject to: $A_1x_1 \leq b_1$
$-L_{1k}x_1 + A_{2k}x_{2k} \leq b_{2k}$
$c_{tk}x_{tk} - Iz_{tk} = f_k$
and $x_1, x_{tk} \geq 0, k = 1\ldots, n$

where U(.) is a monotonic and concave utility function. Note that U(.) is a monotonic and concave utility function.

p is a vector of state probabilities;
$u(z_{tk})$ is a vector of utility values of net revenue for state k;
A_1 is a matrix of technical coefficients of first-stage activities;
x_1 is a vector of first-stage activity levels or decisions;
b_1 is a vector of first-stage resource stocks (i.e., resource availabilities restricting the first-stage decisions);
L_{1k} is a matrix linking first and second-stage activities for state k (i.e., a matrix measuring yields and/or sales in terms of each activity for state k);
A_{2k} is a matrix representing the conversion of each product into sale and/or domestic consumption for state k;
x_{tk} is a vector of activities or decision variables given state k has occurred (i.e., it measures the sales and levels of domestic consumption);
b_{2k} is a composite vector constraining the second-stage decisions for state k;
c_{tk} is a vector of per unit activity net revenues for state k;
I is an identity matrix;
z_{tk} is a variable to measure the total farm revenue for state k; and
f_k is a vector of fixed costs for state k.

In the current study, data were available over a period of ten agricultural years (i.e., k=10). After subjective scaling, these were regarded as ten equally likely states of nature. The constraints and activities were therefore introduced to represent 10 states of nature. These state of nature together with the various sub-matrices of the main matrix represent the stochasticity natures of the model.

The model comprises the objective function, activities and constraints. The general objective of the programming models was maximisation of the expected utility of the farmer's total net revenue subject to satisfying the minimum required family food needs. As mentioned above, it was assumed that the utility function has an exponential functional form. The activities were grouped into production, selling, borrowing, purchasing and consumption activities. The objective function was maximised subject to several constraints such as land, labour availability in different periods, working capital, water availability, borrowing limit and subsistence requirement. Various states of nature and model coefficients may be regarded as exogenous and endogenous data, respectively. The DSP models were then solved by using the GAMS/MINOS non-linear maximisation option (Brooke *et al*., 1988).

A possible range was established for each individual farmer's annual cash income is based on past performances, as it was more convenient for the farmers to remember. The preference levels of 1 and 0 were assigned to the highest and lowest value of the above range, respectively. Each farmer was then asked to indicate the certain amount he or she would need to be indifferent between receiving this amount and a lottery with consequences of the highest and lowest values of the possible outcome each with probability of 0.5. The utility level of 0.5 was attached to this first certainty equivalent. The procedure was then repeated twice with the lowest and highest value and the above certainty equivalent respectively as the new possible ranges to find the second and third certainty equivalents. The preference levels of 0.25 and 0.75 were assigned to the second and third certainty equivalents, respectively. Consequently, the elicitation procedure yielded 5 points on the utility function of each farmer. A smooth curve through these points represents the preference function of each individual farmer. Finally, a 'check' question was asked in order to gauge the consistency of farmers' responses and, if necessary, the procedure repeated to achieve consistency.

The next step was to specify an appropriate mathematical expression for the utility function. There are a number of algebraic forms which can be fitted to the elicited data (Anderson *et al.*, 1977; Hardaker *et al.*, 2004). However, quadratic, cubic polynomials and exponential utility functions are the most popular and have been used in many previous empirical investigations (Zuhair *et al.*, 1992; Torkamani, 2005).

2.1. Quadratic Utility Function

The early researchers preferred the quadratic utility function:

$$U = a + bM + cM^2 \qquad b>0 , c < 0$$

where U is utility, M is referred to the monetary measure which comes from the sample farmers and a, b, and c are parameters. This functional form, when combined with a linear profit function, generates quadratic expected utility functions that are easily maximised with ordinary programming routines.

The absolute risk aversion coefficient (R_A) for quadratic utility function is:

$R_A = -2c/(b+ 2cM)$

This coefficient rises with increase in the monetary measure. In other words, an increase in wealth causes an increase of risk aversion, a conclusion that is not consistent with the usual expectation of risk averse behaviour.

2.2. Cubic Utility Function

Cubic utility function can be presented as:

$U= a + bM + cM^2 + dM^3$

where a, b, c, and d are parameters. The second derivative is given by 2c + 6dM, the sign of which depends on the sign and magnitude of the parameters c, d, and level of M. Thus increasing and decreasing marginal utility are both possible. The Arrow-Pratt absolute risk aversion coefficient for cubic utility function is:

$R_A = - \{(2c + 6dM) /(b+2cM +3dM^2)\}$

The R_A thus can be positive or negative depending on the parameter values and income at which equation of R_A is evaluated.

2.3. Exponential Utility Function

The exponential utility function for money has long attracted attention because it exhibits non-increasing (in fact constant) absolute risk aversion. Also, under certain conditions, it generates an expected utility function that can be maximised in a quadratic programming model.

The exponential utility function is:

$U = a - be^{-\lambda M}$ for a, b, $\lambda > 0$

where e is the base of natural logarithms. The second derivative of the function is:

$-\lambda^2 be^{-\lambda M} < 0$

which means the marginal utility of the function is diminishing. The Arrow-Pratt absolute risk aversion coefficient, R_A, is equal to λ, which is positive and constant. The exponential utility function, therefore, exhibits constant risk aversion over all levels of income, which can be argued to be its major limitations.

2.4. Utility Function Estimation

After elicitation of utilities for respondents, in order to specify the appropriate functional form, the above utility functions were estimated, based on the time and budget restrictions, for a sub-sample of 20 farmers, drawn randomly from the main sample, by non-linear least square method and related absolute risk aversion coefficients were determined. After testing and improving statistical aspects of data, the parameters of different non-linear utility functions were estimated by non-linear least square (NLS) method for the sub-sample of 20 farmers and used for calculating risk aversion coefficients. The results revealed that, in all cases, farmer utility indices have significant relationship with levels of farm income. However, a few of the parameters of utility functions were not significant statistically. For quadratic utility function this occurred twice (b and c parameters for farmer number 9, and c parameter for farmer number 11), and for cubic utility function one time (c and d parameter for number 9). For exponential utility function, λ was significant in all cases. Using estimated parameters, the absolute risk aversion coefficients obtained are presented in Table 1.

TABLE 1. ABSOLUTE RISK AVERSION COEFFICIENTS USING DIFFERENT UTILITY FUNCTIONS, (R_A) FOR THE SUB-SAMPLE OF 20 FARMERS[a]

Farmer No. (1)	Quadratic Utility Function (2)	Cubic Utility Function (3)	Exponential Utility Function (4)
1.	-0.000610	-0.029310	0.0001793
2.	-0.002200	-20.006090	0.0001316
3.	0.002328	0.003710	0.0000055
4.	0.001195	-0.00083	0.0002241
5.	0.002164	0.000740	0.0003110
6.	0.001423	0.001056	0.0001213
7.	0.000431	-0.00020	0.0001682
8.	0.004070	0.006227	0.0004640
9.	-0.003030	-0.002890	0.0001482
10.	0.002752	0.001096	0.0003183
11.	0.004241	0.004314	0.0003381
12.	0.003413	0.001182	0.0003220
13.	-0.003890	-0.001080	0.0000560
14.	0.002578	0.001789	0.0005786
15.	0.002237	0.000217	0.0003063
16.	0.001380	0.002545	0.0002940
17.	-0.014330	-0.002170	0.0001203
18.	0.001584	0.000596	0.0002033
19.	0.007712	0.004215	0.0003229
20.	0.003663	0.004066	0.0018930

[a] *Source*: Farm survey of the study.

III

RESULTS AND DISCUSSION

Table 1 shows the Arrow-Pratt risk aversion coefficients (R_A) using different utility functional forms for the sub-sample of 20 farmers. The quadratic utility function classified 15 farmers as risk-averse and 5 farmers as risk-preferring at the income mid-point. For risk-averse farmers, the R_A ranged from 0.007712 (farmer 19) to 0.000431 (farmer 7). For farmers classified as risk preferring, the R_A ranged from-0.00061 (farmer 1) to -0.01433 (farmer 17) at the midpoint of income.

The cubic utility function classified 13 farmers as risk-averse and 7 farmers as risk-preferring. The R_A for risk-averse farmers ranged from 0.006227 (farmer 8) to 0.000217 (farmer 15) and for risk-preferring farmers, the R_A ranged from -0.00020 (farmer 7) to -0.029310 (farmer 1) at the income midpoint.

The exponential classified all farmers as risk-averse which is consistent with expectations. The R_A for exponential utility function ranged from 0.001893 (farmer 20) to 0.0001203 (farmer 17). It has been demonstrated by Zuhair *et al.* (1992) that negative exponential utility functions can better predict farmers' behaviour than the cubic and quadratic utility functions. Negative exponential functions exhibit decreasing marginal utility with respect to income. Moreover, the function is defined by only R_A, which makes it easy to work with. This latter characteristic makes it particularly convenient in empirical work (Anderson and Dillon, 1992). Consequently, the farmers' utility functions were assumed to be negative exponential in form. By fitting the above function to each set of data points, the estimates of the risk aversion coefficient for each of the 110 sample farmers were obtained.

The R_A values ranged from 0.0000524 to 0.0004890, 0.0000332 to 0.0002186 and 0.0000103 to 0.0000981 for the small, medium and large farms, respectively (Table 2). Although further research is needed before the above results can be generalised, based on the technological and institutional constraints and also the risky nature of the environment within which decisions are made, it seems likely that the Iranian farmers would behave in a risk-averse way. Also, a close examination of risk aversion coefficient revealed that R_A, in general, declines with farm size, which is consistent with the expectations.

TABLE 2. PRATT ABSOLUTE RISK AVERSION COEFFICIENT, R_A, FOR DIFFERENT FARM SIZES[a]

	Farm size		
Risk aversion (1)	Small (2)	Medium (3)	Large (4)
Low	0.0000524	0.0000332	0.0000103
Medium	0.0001612	0.0000917	0.0000345
Large	0.0004890	0.0002186	0.0000981

[a] *Source*: Farm survey of the study.

Detailed cropping pattern of models of utility maximisation and expected profit maximisation are compared with the existing farm plans in Tables 3 to 5 for small, medium and large representative farms, respectively. As is evident from the tables, the major crops in the region are wheat, barley, corn, sugar beet and tomatoes. Wheat and barley crops are harvested by combine harvester. However, on most farms harvesting of sugar beet and tomatoes takes place manually without mechanisation. Weed control is a major concern in sugar beet production and manual weed control is the common practice.

TABLE 3. CROPPING PATTERNS FOR ALLOCATIVELY EFFICIENT FARM PLANS AND EXISTING SITUATION (SMALL FARM)[a]

Farm Plans (1)	Activity levels					ETNR[b] (1000 Rials) (7)
	Barley (ha) (2)	Maize (ha) (3)	Sugar beet (ha) (4)	Tomatoes (ha) (5)	Wheat (ha) (6)	
EFP[c]	0.75	0.50	1.00	0.00	1.00	6457.50
UMFP[d]	0.50	0.40	1.20	0.30	0.80	6851.25
PMFP[e]	0.15	0.40	1.15	0.75	0.80	7345.50

a - The small representative farm has 3.5 hectare of operated land.
b - ETNR stands for expected value of total net revenue.
c - EFP represents existing farm plan.
d - UMFP represents expected utility maximizing farm plan.
e - PMFP represents expected profit maximizing farm plan.

TABLE 4. CROPPING PATTERNS FOR ALLOCATIVELY EFFICIENT FARM PLANS AND EXISTING SITUATION (MEDIUM FARM)[a]

Farm Plans (1)	Activity levels						ETNR[b] (1000 Rials) (8)
	Barley (ha) (2)	Maize (ha) (3)	Tomatoes (ha) (4)	Sugar beet (ha) (5)	Sunflower (ha) (6)	Wheat (ha) (7)	
EFP[c]	1.00	0.00	0.50	1.00	0.00	4.00	11530.00
UMFP[d]	0.35	0.50	1.05	1.20	1.00	2.30	12060.70
PMFP[e]	0.00	0.55	1.35	1.65	1.40	1.50	12830.50

a - The small representative farm has 6.5 hectares of operated land.
b - ETNR stands for expected value of total net revenue.
c - EFP represents existing farm plan.
d - UMFP represents expected utility maximizing farm plan.
e - PMFP represents expected profit maximizing farm plan.

It is evident from Tables 3 to 5 that the farmers' existing total net revenues are different from those of both utility maximisation and risk-neutral models. According to the data in the above tables, there is scope for increasing the existing total net revenues of the representative small, medium and large farms by as much as 393.75, 530.00 and 662.00 thousand Rials,[1] respectively, with the existing resources and

TABLE 5. CROPPING PATTERNS FOR ALLOCATIVELY EFFICIENT FARM PLANS AND EXISTING SITUATION (LARGE FARM)[a]

Farm Plans (1)	Activity levels Maize (ha) (2)	Tomatoes (ha) (3)	Sugar beet (ha) (4)	Sunflower (ha) (5)	Wheat (ha) (6)	ETNR[b] (1000 Rials) (7)
EFP[c]	2.00	1.40	3.00	2.00	5.00	22095.50
UMFP[d]	2.20	1.55	2.95	2.10	4.50	22757.50
PMFP[e]	2.35	1.85	3.10	2.20	3.95	23780.00

a - The small representative farm has 13.5 hectares of operated land.
b - ETNR stands for expected value of total net revenue.
c - EFP represents existing farm plan.
d - UMFP represents expected utility maximizing farm plan.
e - PMFP represents expected profit maximizing farm plan.

existing technology by re-allocating areas under different crops through adopting the utility maximisation models. The differences between the total net revenues of the existing situations and the utility maximisation models may be attributed to the possibility of increasing farmers' outcome through more efficiently allocating their resources. So, the risk-efficient plans are superior to the existing plans. However, the differences between the total net revenues of models of utility maximisation and profit maximisation plans, that disregards risk, indicate the impacts of farmers' risk aversion and expectations on their outcome. Thus, a farmer who wish to avert risk may adopt a plan that has less variability and lower total net return. However, as it can be seen, these differences are larger in the case of the representative small and medium farms compared with the representative large farm when they are calculated on per hectare basis. This demonstrates the importance of decision makers' risk aversion and also their expectations about uncertain events in the case of small and medium farms as compared to large farms.

Iran has a high proportion of small and medium size farms. About 87 per cent of the farms are below 10 hectares and these occupy around 63 per cent of the farm land. Thus, understanding of risk aversion and farmers' expectations is useful in proposing policies by the government. Also, the results indicated the existence of considerable allocative inefficiencies in the study area. Thus, measures that can reduce risk and change farmers' behaviour could lead to improvement in farming efficiency through the reallocation of the existing resources in an optimal manner, and of the rate of diffusion of new technologies. Besides, policy intervention is needed to improve information and reduce its cost to farmers. The policy implications include improving education and extension services and adoption of risk-mitigating strategies such as more reliable technologies or agricultural insurance, and providing more credit facilities. Extension agencies involved in the area could play more active role in preparing and advocating the risk efficient optimum farm plans. Adoption of optimum farm plans will help in augmenting the income even under the existing technology and with the existing resource base on the representative farms.

Received May 2005. *Revision accepted May 2006.*

NOTE

1. Rials 8300 = US$1.

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