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Activity Specification and Input Risk Aversion in Risk Programming Models

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Musser *et al.*, present an intriguing study of how risk aversion may be confounded with constraint omission in explaining enterprise diversification with mathematical programming models. In particular, they compare an insufficiently constrained expected value-variance (E-V) model to a more completely constrained linear programming model to examine conditions under which the two models may yield comparable primal optimal solutions. Musser *et al.*, suggest that researchers' propensity to devote considerable attention to risk specifications has generated significant opportunity costs in the form of incomplete specification of appropriate technical constraints in past E-V studies. In order to evaluate the appropriateness of casting risk aversion in the traditional nonsymmetric quadratic E-V programming model, they suggest that researchers should first specify a full set of appropriate constraints before assessing the plausibility of risk specifications. More generally, the call by Musser *et al.*, for careful specification of constraints as a necessary condition for evaluating risk aversion in programming models may be characterized as part of the problem of choosing the "correct" specification of the mathematical programming model. Similar specification searches in econometrics have received much attention recently (Leamer; Hausman). Musser *et al.*, are to be lauded for emphasizing the importance of complete and appropriate specification of constraints in mathematical programming models.

In this paper, the mathematical results of Musser *et al.*, are extended by explicitly recognizing risk aversion in input use. The symmetric quadratic programming specification of the E-V problem serves as the basis for indicating how risk aversion in input supplies may be confounded with activity specification. This result regarding risk aversion in input use and activity specification is completely analogous to the confounding of risk aversion in returns or revenues with constraint specification in explaining activity diversification at the enterprise level. One implication of the new mathematical result is that researchers' inattention to modeling risk aversion in input supplies unnecessarily limits specification searches among mathematical programming models. A second implication of the mathematical result is that specification searches in mathematical programming models should compare optimal solutions and comparative static results from alternative programming models. Using the two alternative models from Musser *et al.*, as an illustrative example, comparative static comparisons indicate different crop diversification patterns for parametric changes in output prices even when the primal optimal solutions for nonsymmetric E-V and linear programming models are similar.

Symmetric Quadratic Programming

Comparisons of optimal solution values derived from an inadequately constrained E-V model—a nonsymmetric quadratic problem—with a fully constrained LP model effectively ignore the plausibility of stochastic input supplies in farm enterprises. Also implicit in the E-V specification is that risk aversion matters only as regards revenues; risk aversion in the use of inputs is precluded. Builders of E-V models appear not to have deemed risk aversion on the input side as important as risk aversion with respect to variation in revenues. In fact, since the inception of E-V models with Freund's formulation, a review of the literature finds relatively few empirical applications of E-V models which include risk aversion with respect to inputs (Kramer *et al.*; McSweeny and Kramer, 1986).

The E-V formulation for risk aversion is sufficiently flexible to handle risk aversion with respect to both revenues and input supply. Paris (1979*a,b*) has specified a symmetric formulation of the E-V problem as the following primal problem,

(1) Maximize $$c'x - \alpha/2\, x'Vx - \alpha/2\, y'Wy$$

subject to: $$Ax - \alpha W y \leq b$$

$$x \geq 0, y \geq 0$$

where c is a n-element vector of expected value of revenues for activities, x is a conformable vector of activities, V is a (n x n) matrix of variances and covariances of revenues for activities, y is a m-element vector of shadow prices for inputs, W is a conformable matrix of variances and covariances of input supplies, A is a (m x n) constraint matrix, b is an m-element vector of expected input supplies, and α is the risk aversion parameter.[1] If one assumes that the risk aversion parameter is different from zero, then the traditional E-V, nonsymmetric version of (1) requires that W be a null matrix and b a vector of constant input supplies.[2]

The symmetric E-V model in (1) embodies the assumption that the covariance between input supplies and revenues is zero. Paris (1979*b*), generalized the formulation in (1) to include non-zero covariances between input supplies and output prices. The information requirements for such a formulation may be more demanding as an additional (n x m) matrix of covariances must be estimated or calculated. But from a computational standpoint, the complementary pivot method guarantees solutions for well behaved problems (Cottle and Dantzig; Lemke). However, as McSweeny and Kramer (1986) note, the generalized mean-variance formulation with non-zero covariances between input supplies and revenues does not preserve the theoretically attractive expected utility interpretation of the model.

Empirical applications of the symmetric quadratic programming model to risk problems have treated stochastic input supplies which may not be directly controlled by the producer. Kramer *et al.*, for example, include the means and covariances of available field hours—the number of hours in which field operations can be performed because weather is favorable—as the stochastic input supply in a model considering alternative soil conservation practices. Stochastic input supplies need not be limited to variability in weather phenomenon. Accessibility to the services rendered by many potentially limiting inputs is not guaranteed despite the producer having at least indirect control over the availability of the input. In U.S. agriculture, for example, labor supplies for hand harvesting of fruits and vegetables are clearly stochastic variables for many producers. Even for mechanized operations, the flow of services rendered by durable inputs may be conceived of as stochastic because of unforeseen breakdowns of equipment. Similarly, agricultural production in less developed countries may be characterized by stochastic input supplies: fertilizer and credit may be available only sporadically; hired labor availability may vary greatly depending upon weather and labor demands in surrounding areas; and, infrequently maintained durable inputs such as irrigation pumps and tractors may be subject to breakdowns. Thus the apparent preference in the literature for modeling risk as (i) a nonsymmetric quadratic programming problem in terms of output prices, yields, or in combination as revenues or (ii) as a symmetric quadratic progamming problem with stochastic input supplies which the decision maker cannot directly control would appear to be overly restrictive.

If specification searches in mathematical programming models are to be exhaustive, then as many maintained hypotheses as are plausible should be subjected to testing or, less ambitiously, to validation (McCarl and Apland). Thus the untested hypotheses that $W = 0$ and $\alpha = 0$ implicit in the nonsymmetric E-V specification also deserve scrutiny just as the full specification of constraints in any programming model deserve the researcher's scrutiny. To use an analogy from hypothesis testing, the power of a hypothesis test in assessing the validity of the null hypothesis may vary significantly depending upon the specific alternative hypothesis being considered. In mathematical programming, the comparison of a fully constrained LP model (the null hypothesis) to a fully constrained nonsymmetric E-V model (the alternative hypothesis) may have low power relative to another alternative hypothesis such as the fully constrained symmetric E-V model. A more general assessment of the validity of risk aversion formulations would encompass all possible special cases of the most general model to evaluate the importance of risk aversion with respect to both output prices and input supplies.

One may legitimately ask what is to be gained by considering the more general symmetric quadratic E-V model instead of its nonsymmetric special case. One reason for considering the more general symmetric E-V model is that an implication analogous to the confounding of output risk aversion and constraint specification may be demonstrated: activity specification and input risk aversion may be confounded. To see how input risk aversion and activity specification may be confounded, consider for illustrative purposes the following two models:

(2) Model A:

$$\begin{aligned} &\text{Maximize} && c_1'x_1 + c_2'x_2 \\ &\text{subject to:} && A_1x_1 + A_2x_2 \le b \\ &&& x_1 \ge 0,\ x_2 \ge 0 \end{aligned}$$

and (3) Model B:

$$\begin{aligned} &\text{Maximize} && c_1'x_1 - \alpha/2\, x_1'Vx_1 - \alpha/2\, y'Wy \\ &\text{subject to:} && A_1x_1 - \alpha Wy \le b \\ &&& x_1 \ge 0,\ y \ge 0 \end{aligned}$$

where the vector of activities is partitioned arbitrarily into two vectors, x_1 and x_2, with n_1 and n_2 elements, respectively. The constraint matrix of Model A is also partitioned conformably with submatrices A_1 and A_2. Model B is a special case of (1) where only a subset of the primal activities are included.

The Kuhn-Tucker conditions for optimal values of x_1, x_2, and y in the two models are:

(4) Model A:

$$\begin{aligned} c_1 - A_1'y &\le 0 \\ x_1(c_1 - A_1'y) &= 0 \\ x_1 &\ge 0 \\[1em] c_2 - A_2'y &\le 0 \\ x_2(c_2 - A_2'y) &= 0 \\ x_2 &\ge 0 \\[1em] A_1x_1 + A_2x_2 - b &\le 0 \\ y(A_1x_1 + A_2x_2 - b) &= 0 \\ y &\ge 0 \end{aligned}$$

and (5) Model B:

$$\begin{aligned} c_1 - A_1'y - \alpha Vx_1 &\le 0 \\ x_1(c_1 - A_1'y - \alpha Vx_1) &= 0 \\ x_1 &\ge 0 \\[1em] A_1x_1 - \alpha Wy - b &\le 0 \\ y(A_1x_1 - \alpha Wy - b) &= 0 \\ y &\ge 0 \end{aligned}$$

If the x_2 activities are nonbasic and input risk aversion is not present ($x_2 = 0$ and $\alpha = 0$), the last set of Kuhn-Tucker conditions for each of the two problems is identical. Alternatively, in the case that $A_2x_2 = -\alpha W y$, the primal optimal conditions would be identical for the two problems. These two cases represent the symmetric results corresponding to the nonsymmetric result shown with the Kuhn-Tucker conditions by Musser *et al.* (p. 148).

The scalar counterparts of the primal constraints may also be analyzed, as Musser *et al.*, do in the case of the nonsymmetric dual constraints, to understand in more detail the similarities between the two primal constraints,

(6) Model A:

$$b_i = \sum_{j=1}^{n_1} x_{1j} a_{1ij} + \sum_{k=1}^{n_2} x_{2k} a_{2ik}$$

and

(7) Model B:

$$b_i = \sum_{j=1}^{n_1} x_{1j} a_{1ij} - \alpha \sum_{p=1}^{m} y_p w_{ip}$$

where b_i, $x1_j$, $x2_j$, a_{1ij}, a_{2ij}, y_p, and w_{ip} are elements of b, x_1, x_2, A_1, A_2, y, and W, respectively. For the constraints to be binding, the right-hand sides of (6) and (7) must be equal. Three cases exist in which the right-hand sides of (6) and (7) would be equal: (i) the entire subset of x_2 variables is nonbasic and the decision-maker is risk neutral (all x_{2k} and α equal zero); (ii) the last summation term in (6) is equal to the negative of the last summation term in (7); and, (iii) particular empirical values of all the parameters take on values such that x_{1j} values are not the same in each constraint but both constraints hold with equality.

The physical and economic interpretation of the two constraints provide insight into the similarities between the two constraints. Without loss of generality, the linear programming constraint (6) can be interpreted for x_{1j} and x_{2j} as outputs with a_{1ij} and a_{2ij} as the required use of the i^{th} input in the production of a unit of the j^{th} output in each subset of activities. Accordingly, the linear programming constraint simply states that all uses of the i^{th} input cannot exceed the amount available of that input. The primal constraint for the symmetric E-V model (7) indicates that expected input supply b_i must equal or exceed the input use for the first n_1 activities adjusted by the opportunity costs of using stochastic inputs. The last term in equation (7) may be positive or negative depending upon the signs and relative magnitudes of the individual covariances, w_{ip}, so that the input use could be greater or smaller than under riskless conditions (Paris, 1979a).[3] In the particular case of interest here, $\sum_p y_p w_{ip}$ must be negative so that the risk-adjusted input use under the optimal solution to symmetric E-V model (3) is exactly equal to input use under the optimal solution to the linear programming model (2) with augmented activities. The relationship between the two constraints indicates that risk-adjustment in input use in (7) may substitute for full specification of activities as in (6). Thus the specification of extraneous activities may compensate for the omission of risk aversion in input use.

The existence of a symmetric set of mathematical results in which the effects of activities may be confounded with input risk aversion should not be surprising because of the nature of the saddle point problem. The Lagrangean function derived from the original primal specification of the programming problem is directly related to the dual and primal problems so that the Kuhn-Tucker conditions are optimal conditions both for the primal and dual problems. Accordingly, the characterization by Musser *et al.*, of an insufficiently constrained nonsymmetric quadratic programming problem and a more fully constrained linear programming problem could be restated as two different dual problems with different sets of dual activities,

(9) Model A:

$$\begin{aligned} &\text{Minimize} && b_1' y_1 + b_2' y_2 \\ &\text{subject to:} && A_1' y_1 + A_2' y_2 \geq c \\ & && y_1 \geq 0, \quad y_2 \geq 0 \end{aligned}$$

and (10) Model B:

$$\begin{aligned} &\text{Minimize} && b_1' y_1 + \alpha/2\, x' Vx \\ &\text{subject to:} && A_1' y_1 + \alpha Vx \geq c \\ & && y_1 \geq 0, \quad x \geq 0 \end{aligned}$$

Note that no loss of information occurs with the specification of these two alternative models as dual problems. In fact, the source of the confounding—the dual constraints—is seen more immediately than in the primal specifications. Thus the potential for confounding dual activities with input risk aversion, when comparing a symmetric quadratic programming model with insufficient activities and a linear programming model with more activities, follows directly from the primal-dual relationships for the saddle point problem.

The potential confounding of input risk aversion and activity specification suggests a conclusion paralleling that made by Musser *et al.*: the importance of risk in programming models should be evaluated based on fully specified constraints and activities in all models. With such well specified models, the possibility of confounding (input) risk aversion with omitted constraints (activities) would be mitigated. Instead of judging a priori that risk aversion in input supply is inconsequential, the symmetric E-V formulation could be specified to examine the plausibility of the nonsymmetric E-V and linear programming special cases.

Specification Searches in Symmetric QP Models

The foregoing results suggest that the symmetric specification of the E-V problem incorporating input supply and output price variability provides a more general model for assessing the importance of risk. Examination of the Kuhn-Tucker conditions for the symmetric specification, for example, yields a new result entirely analogous to the constraint omission and risk aversion relationship demonstrated by Musser *et al.*; namely, specification of extraneous activities in linear programming models may compensate for the omission of risk aversion in input use. The significance of the potential confounding of risk aversion with constraint and activity specification has not been analyzed in empirical studies.

A specification search to determine the correct or most plausible empirical specification of the general symmetric E-V model can be framed conceptually as a series of nested hypothesis tests.[4] The special cases of the symmetric E-V model become apparent by examining the linear complementarity problem,

(11)
$$w = q + Mz,\ w \geq 0$$
$$w'z = 0$$
$$w = \begin{bmatrix} v \\ u \end{bmatrix}\ q = \begin{bmatrix} b \\ -c \end{bmatrix}\ M = \begin{bmatrix} \alpha V & -A \\ A' & \alpha W \end{bmatrix}\ z = \begin{bmatrix} y \\ x \end{bmatrix}$$

where v and u are conformable vectors of primal and dual slack variables and all other variables are defined as before. The nested cases of the symmetric E-V model are easily seen. If W = 0, equation (11) becomes the traditional nonsymmetric E-V specification. The symmetric E-V model collapses to the linear programming model with (i) $\alpha = 0$ or (ii) V = 0 and W = 0 (or both). Hence the specification tests for evaluating the validity of risk aversion in both output prices and input supplies may be performed by testing or validating whether α, V, and W are different from zero. Although V and W may not be null matrices, if α is zero then revenue and input supply variability are of no consequence in the linear complementarity problem. Hence, a sufficient condition for determining whether the nonsymmetric E-V (linear programming) problem is the correct specification is that α equals zero.

Classical statistical hypothesis tests for subsets of the parameters in the linear complementarity problem (11) may be feasible but the probability distributions of the parameters are not readily determined. Methods similar to those employed by Collender might be used to determine either confidence intervals for the E-V frontier or hypothesis tests for the risk aversion coefficients.

An alternative strategy for attempting to determine whether risk aversion parameters are different from zero would make use of the comparative statics properties in addition to the optimal solutions of alternative models. Recall that the confounding of risk aversion with constraint specification occurs for optimal solution values of the primal variables because the corresponding dual constraints are nearly identical. The analogous confounding of input risk aversion with activity specification would occur in the optimal solution values of the dual variables because the primal constraints (6) and (7) are nearly identical. Although in both cases of revenue and input risk aversion two alternative models may have nearly identical optimal solutions, the comparative statics of the two models may be markedly different. Hence, additional information for assessing the importance of risk aversion may be gained by examining departures from or perturbations around the optimal solution values.

For positive economic analysis, the comparative statics of the alternative models may be as important as the optimal solution values. Hence, parametric changes in (i) output prices or expected revenues and (ii) input quantities or expected input supplies may provide important information for discriminating among alternative model specifications. In the context of the linear complementarity problem in equation (11) output supply and input demand schedules generated from the alternative models—symmetric E-V, nonsymmetric E-V, and linear programming—may be compared against observed behavior to determine which model performs best.

Illustrative Example

For illustrative purposes, the output supply functions from the fully constrained linear programming model and the partially constrained nonsymmetric E-V model in Musser *et al.*, are compared to examine the differences in comparative statics for two models which have similar primal optimal solutions.[5] Similar comparisons for derived input demand schedules and revenue functions are omitted for brevity. The linear programming step function (S_{LP}) and the kinked nonsymmetric E-V function for supply of soybeans (S_{E-V}) are illustrated in Figure 1. Notice that both supply functions nearly coincide on the optimal solution values for the selected primal variable (LP = 60.9 acres versus E-V = 59.8 acres) yet over a large range of prices the E-V output supply schedule lies to the left of the LP schedule.[6] The behavioral implication of the two schedules differs: inducing the risk averse farmer to produce a given acreage of soybeans usually requires a higher expected output price, ceteris paribus, than is required for inducing a risk neutral farmer to produce the same acreage of soybeans.[7] The importance of risk aversion in output prices can be assessed by comparing the supply response predictions of the two models to farmers' responses to actual changes in output prices in order to verify which prediction is more accurate. This type of comparison of the comparative statics of the models may be made using the "tracking" and "change" validation experiments proposed by McCarl and Apland (p. 160).

Additional information from the comparative statics validation procedure may be used to assess the importance of risk aversion. Recall that the confounding of risk aversion with activity and constraint specification may be a confounding in explaining enterprise diversification. Additional comparative static information on changes in crop mix resulting from an increase in a single output price may be useful for judging the appropriateness of risk aversion in explaining producer behavior. In the previous example, the output supply response for an increase in soybean price will affect acreage levels in other crops and thus the entire crop mix. Even if the soybean supply responses from both models were nearly identical over specific price ranges, the corresponding changes in crop mix among the remaining crops would not necessarily be similar. Thus changes in crop mix caused by parametric changes in a single output price provide additional information for judging the validity of the risk aversion specification.

Again for illustrative purposes, alternative specifications from Musser *et al.*, are compared to examine changes in crop mix as soybean prices are varied parametrically. The crop mixes are compared at the initial soybean price level ($141.96) and at the lower and upper bounds of soybean price in the optimal linear programming solution ($129.91 and $215.83). The relevant portions of the output supply schedules for the LP and E-V models with four alternative output risk aversion parameter values are represented in Figure 2 and the corresponding crop mixes are reported in Table 1. Although none of the crop mixes is compared to actual data, the comparative statics of the different specifications are clearly different. At the lower bound with a basis change, the linear programming solution includes cotton, peanuts and soybeans while two E-V specifications indicate more diversification by including wheat in the crop mix. At the upper bound with a basis change, the linear programming formulation tends towards specialization with only peanuts and soybean production while all the E-V specifications persist in predicting more diversified crop mixes: all four E-V solutions include cotton and the E-V solution with $\alpha = 0.0039$ includes significant acreage in wheat. These specific crop mix results for parametric changes in soybean price suggest that although optimal primal solution values for the LP and some E-V specifications were similar, the behavioral implications of changes in (expected) output prices are significantly different for the two models.

These limited comparative static results indicate that the confounding of risk aversion with constraint and activity specification in explaining enterprise diversification may occur for optimal solution values of the primal and dual variables but the behavioral implications for parametric changes in the two models may be appreciably different. The fact that the comparative static implications of the LP and E-V models differ is a positive result for specification search. The differing comparative static predictions provide additional information which the researcher can use to verify whether risk aversion is indeed an appropriate specification by performing the "tracking" and "change" experiments delineated by McCarl and Apland.

Summary and Conclusion

Musser *et al.*, demonstrate the confounding of risk aversion and constraint specification in explaining diversification of activities in firm or farm level mathematical programming models. In the more general setting of a symmetric quadratic programming problem specified with stochastic revenues and stochastic input supplies, an analogous confounding of risk aversion in input use and activity specification may also occur. Specification of extraneous activities may be confounded with the effects of risk aversion in input supply. When stochastic revenues and stochastic input supplies are appropriate assumptions for E-V models, researchers would be well advised to carefully specify constraints and activities for programming models.

The critical question in comparing a well specified linear programming model with an equally well specified symmetric E-V model is whether the risk aversion coefficient is different from zero. Classical statistical tests for testing whether the risk aversion parameter is significantly different from zero may not be tractable. Some of the validation experiments proposed by McCarl and Apland appear to be the second best solution to testing. Because the comparative statics of the linear programming and symmetric quadratic programming models may be quite different, the "change" and "tracking" experiments may be useful in comparing departures from the optimal solutions. For programming models of farm activity analysis, the characteristics of output supply, derived input demand, revenue schedules, and crop mix for each of the alternative models may provide additional information for judging the acceptability of specifying risk aversion in programming models.

Footnotes

[1] For an almost identical derivation of the symmetric QP problem see Bouzaher.

[2] The usual caveats regarding the underlying utility function are made. Either the utility function is quadratic (Markowitz) or the utility function is assumed to be a negative exponential function and returns are normally distributed (Freund).

[3] Dubman, Gunter, and Miller have noted that the risk-adjusted right-hand side could be larger than the expected value of input supply, b_i. Such a risk adjustment does not invalidate the economic interpretation of the constraints, however, because the sign of the risk adjustment is indeterminate (Paris, 1989).

[4] The parameters to be "tested" are customarily treated as being known with certainty so that the parameters only have a degenerate probability distribution. Strictly speaking, no classical hypothesis test is possible with such a probability distribution.

[5] The symmetric quadratic programming problem is not analyzed due to the lack of data on input supply variability.

[6] The results of Musser *et al.*, could not be reproduced identically from the data reported on pages 150 and 152 of their article. The difference in the results in Table 1 and those of Musser *et al.*, appears to be inconsequential.

[7] Note that for some price ranges the risk-averse farmer would produce more than the risk-neutral farmer.

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Table 1. Crop Mixes for Alternative Specifications of Nonsymmetric E-V Model, Musser *et al.*

Crops	Alternative E-V Models				
	LP	0.0005	0.0013	0.0017	0.0039
	Soybean Price = $129.91				
Cotton	60.9	90.3	81.9	77.8	27.2
Peanuts	60.9	60.9	60.9	49.5	23.7
Wheat	0	0	0	6.0	112.0
Soybeans	56.4	31.4	39.8	49.3	19.7
MAD[a]	0	13.6	9.4	10.4	54.9
Land Shadow Price	0	111.0	55.1	26.8	12.1
	Soybean Price = $141.96				
Cotton	63.1	86.0	80.2	79.3	27.0
Peanuts	58.7	60.9	59.8	48.0	23.9
Wheat	0	0	0	0	111.0
Soybeans	60.8	35.7	42.6	55.3	20.7
MAD	0	12.5	9.1	8.1	55.5
Land Shadow Price	12.0	118.0	61.8	28.9	25.3
	Soybean Price = $215.83				
Cotton	0	67.8	70.0	71.4	35.5
Peanuts	44.9	59.8	47.0	38.3	20.3
Wheat	0	0	0	0	84.6
Soybeans	137.7	55.0	65.7	72.9	42.2
MAD	0	41.3	36.0	35.7	60.1
Land Shadow Price	85.9	107.8	100.9	68.0	22.4

[a] Mean absolute deviations of E-V crop acreages from linear programming acreages.

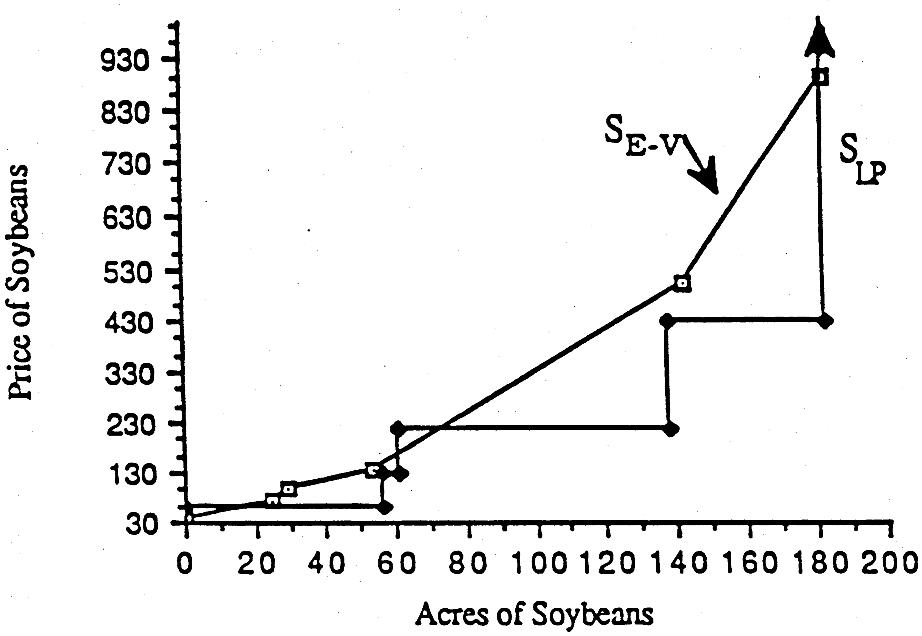

Figure 1. Soybean Supply for LP and E-V Models

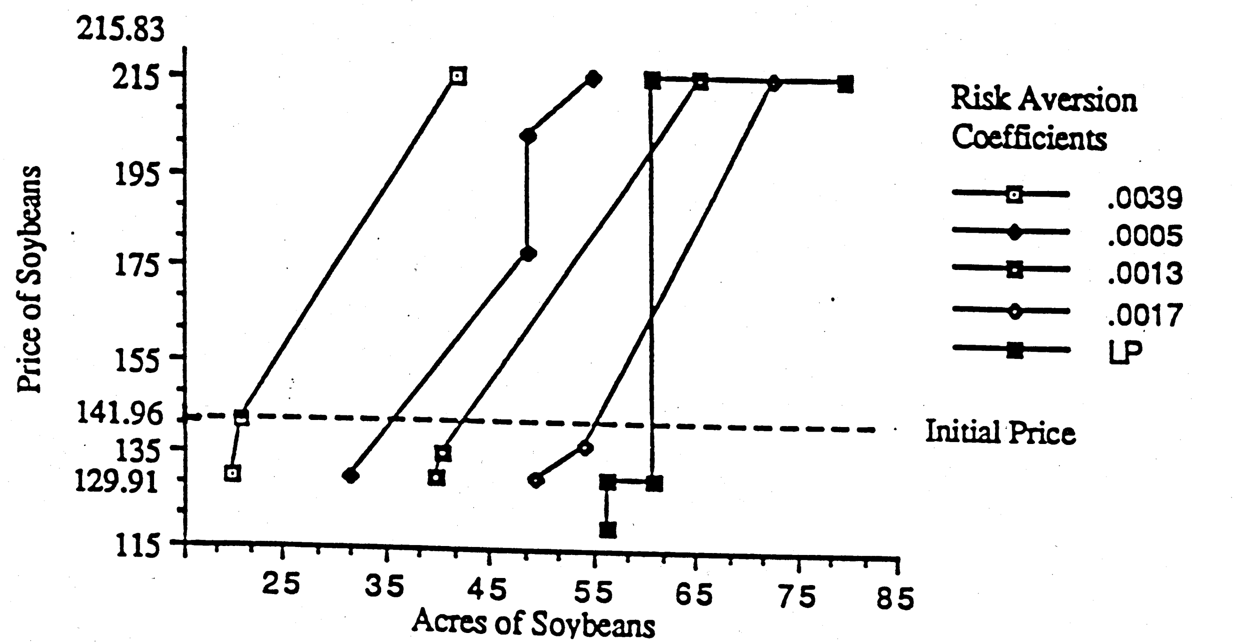

Figure 2. Soybean Supply for LP and E-V Models with Alternative Risk Aversion Coefficient Values

DESIGNING EXPERT SYSTEMS FOR EFFECTIVE DELIVERY OF EXTENSION PROGRAMMING

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ABSTRACT

Expert Systems offer potential to be important additions to the current methods used to deliver extension programming to clients. This paper discusses the design of such systems from the viewpoint of learning theory and cost effectiveness.

INTRODUCTION

The delivery of extension education programs to clients in commercial agriculture is a cornerstone of the extension service charter. Unfortunately, effective delivery of relevant extension programs has become more difficult as: 1) agriculture has become more technologically advanced; 2) relatively homogeneous family farms have been replaced by a mixture of large scale commercial enterprises and smaller part-time farms resulting in a very hetrogeneous mix of clientele, problems, and clientele resources available to solve problems; 3) institutional intervention in the form of regulations and government participation in agricultural markets has increased; and 4) extension budgets for commercial agriculture programs have decreased in real terms. To counteract the increased difficulty of delivering extension programing to commercial agriculture clientele, computer based expert systems, computer driven multi-media programs, and use of electronic media to replace or supplement the traditional one-on-one extension approach are often mentioned as means of improving the effectiveness of extension educational programs.

This study was developed to contribute to the discussion of this issue, focusing on the design of techniques to effectively deliver extension educational and problem solving services via computer based expert systems. Presentation of the findings is organized into five major sections. First, the objectives and methodology are discussed. Next, a brief definition of expert systems is presented. Third, an example is presented to illustrate the potential for use of expert systems in extension programming. This is followed by an analysis of expert systems compared to other teaching methods used in extension. Finally, conclusions and implications of the study are outlined and an estimate of the cost effectiveness of the example is presented.

Objectives and Methodology

The purpose of this paper is to critically evaluate the design of expert systems as a means of improving the delivery of extension program to agricultural clients. The educational impact model developed by Joyce and Showers will be used first as a model to guide the design of an expert system and then as a basis for a qualitative evaluation of the contents and expected effectiveness of expert systems compared to other extension teaching aids. In addition, preliminary results, including measures of cost effectiveness, of ongoing field tests designed to quantify the technique's actual educational impact will be presented.

Educational Impact Model

Joyce and Showers state that when students use what has been learned to solve problems they are demonstrating that their training has had the highest level of impact possible. Their research into teaching methods led to the following general rules to judge the level of impact a teaching program will have. They concluded that the level of impact is affected by the following training components:

1. **presentation of theory or description of skill or strategy,**
2. **model or demonstration of skills or models of teaching,**
3. **practice in simulated and classroom settings,**
4. **structured and open-ended feedback, and**
5. **coaching for application.**

Further, Joyce and Showers indicate that components one through five have increasingly greater levels of impact on students' abilities to solve problems. When all five components are included in a teaching program, up to 75 percent of students are able to apply what has been learned. The research by Joyce and Showers supports the notion that teaching techniques which incorporate more of the five components will have greater impact than techniques involving fewer training components. This conclusion and the conceptual