AN EMPIRICAL ANALYSIS OF INTERTEMPORAL STABILITY OF RISK PREFERENCES AND THEIR RELATION TO FARM AND OPERATOR SOCIOECONOMIC CHARACTERISTICS

By

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A DISSERTATION

Submitted to
Michigan State University
in partial fulfillment of the requirements
for the degree of

DOCTOR OF PHILOSOPHY

Department of Agricultural Economics

1982

ABSTRACT

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Proper application of the expected utility theory requires explicit information about the decision maker's preferences. In the past, such information was not readily attainable. Although improved empirical estimating techniques have been developed, two interrelated problems still plague application of the estimated data. The first involves the possible intertemporal instability of risk preferences. The second occurs due to a desire to relate risk preferences to observable farm and operator socioeconomic characteristics. Previous studies supply no convincing evidence that this can be successfully done, nor is there any evidence that the relationships themselves will not change with time.

This study used the interval measurement approach, based on stochastic dominance with respect to a function, to obtain risk preference measures for 23 Michigan farmers in 1979 and 1981. The data were analyzed to examine how the risk preferences changed over the two year period. The relationships of the measured risk preference intervals to nineteen socioeconomic variables were also estimated for both time periods using discriminant analysis techniques. Finally, the intertemporal stability of the relationships was tested.

It was found that risk preferences demonstrated stability near typically experienced personal income levels. But preferences were less stable at other income levels. Farmers exhibited risk preferring as well as risk averse attitudes. Risk preferences varied at differing expected income levels. These results present implications as to the selection of functional form, the selection of range for incomes and the use of single valued estimates in estimating risk preferences.

Eighteen socioeconomic farm and farm operator characteristics were found able to accurately classify producers according to risk preferences for certain income levels. But a small number of easily attainable characteristics could not provide high accuracy. Analysis showed that on an individual basis, financial and social variables were more able to discriminate between risk preference groups than farm size and income variables. Finally, the relationships of socioeconomic characteristics to risk preferences were not stable over time, thus reducing the usefulness of such estimations.

ACKNOWLEDGEMENTS

I sincerely appreciate the time and effort Dr. Lindon Robison contributed as my dissertation advisor. The quality of this research is greatly improved because of his assistance.

A very special thanks is extended to Dr. John Brake, my major professor. His wise counsel and steadfast support greatly enhanced my graduate program. Possibly even more important is the contribution both he and Dr. Robison made to my professional and individual maturity.

I am also grateful to those faculty and graduate students who gave advice and direction to my research and program as well as offering well accepted friendship. Although the list is long, I would particularly note Mark Cochran, Dave Armstrong, Dr. Stanley Thompson and Dr. Stephen Harsh.

I would like to acknowledge the generous financial support of the Michigan State University Agricultural Experiment Station and Department of Agricultural Economics.

I lovingly thank my family for their support through it all. Special thanks goes to Barb Dickhaut for her assistance with this manuscript. And finally, to my wife, Kathy, for patience and love.

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Chapter 1

INTRODUCTION

1.1 Background

Decisions are choices among alternatives. Good decision making requires knowledge about what alternatives are available and the consequences of each alternative. Unfortunately, complete or perfect knowledge about alternatives and their consequences never exists. So decisions are made in a state of imperfect or incomplete knowledge known as uncertainty or risk. Farmers continually make production, marketing and financial decisions under uncertainty. Frequently decisions are made as if complete knowledge were available. Such an approach may be justifiable for several reasons. The decision maker faces forced action (Johnson, et al., 1958); he believes the imperfections in knowledge are trivial (Halter and Dean, 1971); he perceives that the costs of further learning about alternatives and their consequences exceed the benefits (Johnson, et al.); or he ignores uncertainty because of prior experience or predetermined decision rules. Despite these possible situations, an explicit consideration of uncertainty is justifiable in most decisions farmers face.

Changes in farm structure (Pope and Gardner, 1978; Tweeten,1980), government programs and policies (Gardner, 1978), foreign markets, and certain macro-economic occurrences (Melichar, 1979; Tweeten) have combined to increase the uncertainty of many farming decisions. A continued growth in farm size and degree of specialization marked the 1970's. These brought a greater dependency on off-farm inputs and external financing and made farmers more subject to fluctuations in farm prices, the general price level and interest rates determined in the financial markets. On the latter point, Melichar notes that over the past 25 years the nation's financial environment has become more unstable. This instability in the financial markets manifests itself in unanticipated adverse changes in the cost and availability of farm loans. For instance, in Michigan short and intermediate term interest rates for farm borrowers rose from about 8.5% in 1976 to 17.3% in 1981 while the debt-to-asset ratio for Michigan farmers rose about 15% over the same period.

The prices of the basic commodities, wheat and corn (Table 1-1), exemplify the increased price variation resulting from the changes in the farm sector. During the middle 1960's to early 1970's, the difference between season's high and low prices for corn never went above thirty-five cents or about 21% of the average price. Yet, in most of the seventies the difference was over three times the previous high while prices only doubled. The change is even more evident in wheat prices. Wheat prices for the later 1970's differed by from three to thirteen times the typical maximum difference experienced in the late 1960's-early 1970's.

The variability in prices paid for basic farm inputs also amplified during the decade. Price per ton of fertilizer (Table 1-2) exhibited a considerable increase in variability in the recent past. The coefficient of variation in price of fertilizer was about .07 for 1965 to 1972. This figure rose dramatically for 1972 to 1979 with a coefficient of variation for that period of .22. Variability in the typical dairy feed ration price displayed a similar change. The coefficient of variation for prices went from .04 for 1965-70 to .19 for 1972-79.

Table 1-1. Within Year Variation of Farm Prices Received: Two Examples*, Michigan, 1965-79

Market Year	Corn Prices Season High	Season Low	Difference	Wheat Prices Season High	Season Low	Difference
65-66	1.30	0.99	.31	1.63	1.27	.26
66-67	1.26	1.08	.18	1.74	1.46	.28
67-68	1.01	0.87	.14	1.36	1.19	.17
68-69	1.16	0.97	.19	1.15	0.97	.18
69-70	1.36	1.05	.31	1.38	1.08	.30
70-71	1.42	1.07	.35	1.55	1.24	.31
71-72	1.19	0.87	.32	1.48	1.25	.23
72-73	2.56	1.13	1.43	2.54	1.30	1.24
73-74	3.32	2.02	1.30	6.25	2.52	3.83
74-75	3.41	2.47	.94	4.42	2.70	1.72
75-76	2.75	2.14	.61	3.50	2.61	.81
76-77	2.24	1.52	.72	3.06	2.05	1.01
77-78	2.41	1.57	.84	2.81	1.82	.99
78-79	2.67	1.95	.72	3.59	1.11	2.48

*Michigan Farm Prices ($).

Source: Michigan Agricultural Statistics.

Table 1-2. Inter-year Variation of Farm Prices Paid: Two Examples, Michigan, 1965-79

	Dairy Feed[1]		Fertilizer[2]	
Year	Price	Change	Price	Change
65	75		85	
		+1		-1
66	76		84	
		+1		-2
67	77		82	
		-4		-5
68	73		77	
		0		-8
69	73		69	
		+2		+2
70	75		71	
		+7		+6
71	82		77	
		0		+5
72	82		82	
		+33		+8
73	115		90	
		+29		+58
74	144		148	
		0		+17
75	144		165	
		+12		-25
76	156		140	
		+8		0
77	164		140	
		-6		+4
78	158		144	
		+7		+24
79	165		168	

[1] 16% Protein Ration

[2] 6-24-24

Source: Michigan Agricultural Statistics.

Table 1-3 portrays several other relevant farm sector economic measures. While all of these measures depict a situation of increased uncertainty, the increase in variability of 217% (.06 to .19) for net cash income before taxes particularly emphasizes changes in the uncertain nature of farming from the 1960's to the late 1970's. These developments in the structure of agriculture along with the renewed emphasis by the federal government on "free trade" and reduced government involvement in farm programs intended to reduce uncertainty seem to underscore the need for improved decision-making techniques as farmers enter the decade of the 1980's.

Table 1-3. Variation in Farm Income and Expenditures, U.S.: 1960-69 and 1970-79

	Coefficient of Variation[a]	
	1960-1969	1970-1979
Gross Cash Income	.06	.12
Variable Costs	.06	.10
Fixed Costs	.11	.12
Net Cash Income Before Tax	.06	.19
Total Interest Payments	.20	.23
Non-Real Estate Interest Payments	.17	.27
Real Estate Interest Payments	.24	.20

[a] The coefficient of variation is the standard deviation of the data series by the mean.

Source: Burghardt and Watt, 1981.

Recent advancements in theory and analytical techniques have made it possible for scientists to more accurately account for attitudes toward risk in the decisions farmers face. The improved theoretical tools have created considerable possibilities for application to decisions made by farmers and others affecting the agricultural sector. Although major strides have been made, the successful application of decision analysis depends on an increased body of empirical knowledge to verify and improve the theory and techniques.

1.2 Problem Statement

The problem facing farmers is that they must make decisions in an increasingly uncertain environment. The decision makers thus may take actions which are not right. Taking non-right actions often leads to losses for the decision maker and society in general. Problems exist because a decision, situation or thing is not as good as, or is worse than, it could be. This is true of many decisions made under uncertainty. Theory and empirical techniques to improve the rightness of choices in an uncertain environment are available. This disciplinary knowledge makes it possible to understand what could be. Yet this disciplinary knowledge is not always adequately extended or applied to decisions faced by farmers, policy makers and others affecting the agricultural sector (Barry and Maberly, 1978; W-149 Project Statement, 1977). Walker and Nelson (1980) emphasized that "results . . . reveal a large gap between theory and practice in risky decision making."

Many reasons for the apparent gap exist. When the costs of acquiring new information exceeds the returns as perceived by producers, this gap is reinforced (Johnson, et al.; Conroth, 1973). Some of the decision theory tools have shown limited applicability (Gabriel and Baker, 1979; Baker and Sonka, 1978). The Cooperative Extension Service's understanding and acceptance of advancement in decision theory often lag research results in that area and these results are not always well coordinated with Extension needs (Walker and Nelson). The main reason, however, that decision theory tools are not applied in Extension programming is the measurement of individual risk preferences (Young, et al.; Officer, Halter and Dillon, 1967).

Despite the wide acceptance of expected utility theory, operational problems cause considerable difficulty in applying it to the analysis of actual decisions. Proper application of expected utility theory requires explicit information about the decision maker's preferences. King and Robison (1981) cite shortcoming in elicitation design and statistical estimation as serious inadequacies of most empirical estimations of preferences done to date. While fully appreciating the limitations imposed by previously employed methodologies, recent literature has stressed the need for an empirical data base of preferences (Binswanger, 1978; Lins, Gabriel and Sonka, 1981; Young, et al., 1979). Young, et al. state " . . . knowledge of risk preference of individual agricultural producers is necessary for many useful private managerial and public policy analyses of decision making under risk." Young, et al. expressed their primary reservations with eliciting risk preferences as twofold: (1) The errors inherent in previously used measurement techniques; and (2) The possible temporal instability of preferences. In reference to the former reservation, King and Robison presented a promising new methodology, based on stochastic dominance with respect to a function (Meyer, 1977), for measuring risk preferences. Their methodology over-comes many of the shortcomings attributed to previously employed measurement techniques. This study employs the King and Robison interval approach to examine the temporal stability of risk preferences. The need for examining risk preferences stability is well affirmed in the literature (Young, et al.; Halter and Mason, 1981; Whitaker and Winter, 1980). While the importance is understood, to date almost no empirical evidence is available to answer the question: are risk preferences stable? This study provides that evidence.

The second reservation implies a need to repeatedly elicit preferences. The costs and difficulties of direct elicitation have motivated research which studies the possibility of systematic relationships between risk preferences and producer attributes (Halter and Mason, Binswanger; Dillon and Scandizzo, 1978). The objective of this type of research is to find relationships which permit analysts to use obtainable data to determine risk preferences. In their recommendations, Young, et al. suggest that the relationship of producer attributes to risk preferences merits empirical research. With the stability of risk preferences in question, however, the usefulness of such indirect methods for measuring preferences is in doubt. Testing the temporal stability of the relationships between producer attributes and risk preferences is the second problem this thesis addresses.

1.3 Objectives of the Study

This study's goal is to increase the application of risk theory in agricultural research and extension. The following specific objectives contribute to this end:

1. Identify agricultural producers' risk preferences and analyze their intertemporal stability using paired samples of producers.

2. Examine the intertemporal stability of the relationships between observable socioeconomic characteristics in classifying farmers according to risk preferences.
3. Employ the interval measurement approach to enlarge the data base on producer risk preferences. And observe and describe the operational difficulties in application of the interval measurement approach in data collection, and suggest improvements.

1.4 Hypotheses

The fulfillment of these objectives will provide the data to test some hypotheses. The set of null hypotheses are:

1. Risk preferences of individual farmers are intertemporally stable.
2. Observable socioeconomic charactistics can be employed to classify decision makers according to risk preferences.
3. If socioeconomic farm and operator characteristics can be used as an indirect method for estimating risk preferences, the set of attributes and relative importance of individual characteristics are intertemporally stable.

1.5 Format of the Study

The remainder of this report is organized as follows. Chapter two reviews the literature on several experiments designed to measure farmers' risk preferences. It also discusses the problems associated with the measurement techniques and empirical results. Chapter three reviews previous efforts to identify relationships between farmers' socioeconomic attributes and risk preferences. Chapter four describes how risk attitudes were measured in this study. Chapter four also outlines the interval approach and its underlying theoretical foundation. Chapter five specifies the sample from which data was collected. Chapter six meets objective one by using the collected data to test hypothesis one. In chapter seven discriminant analysis results are used to test hypothesis two. Finally, chapter eight completes objective three. A summary of observations and conclusions is in chapter eight as well.

Chapter 2

REVIEW OF RISK PREFERENCE MEASUREMENT LITERATURE

2.1 Introduction

Most decision-making models require knowledge of the decision makers' risk preferences. Theory and techniques for measuring individual risk preferences have been available since the work of von Neumann and Morgenstern in the 1940's. Yet almost all research efforts to estimate farmers' risk preferences have occurred in the last fifteen years. Despite these efforts there is still little evidence on the nature of risk preferences. Furthermore questions about the validity of some previously employed preference measurement techniques diminish the credibility of the evidence which is available.

Measurement of risk preferences serves as an important condition to fulfilling the first objective of this study. Therefore review of previous research acts as an important learning tool as well as provides some measure of validation of results. This chapter discusses the basic concept of risk preference measurement and expected utility theory. It then outlines preference classification criteria and previously employed approaches to preference measurement. Sections also review the theoretical and operational shortcoming of the measurement approaches. Finally, this chapter discusses individual studies which estimated risk preferences of agricultural producers and the techniques employed.

2.2 Expected Utility

Utility is the relative preference among things or situations having the capacity to satisfy human wants and desires. Utility functions act as rules to order outcomes according to preferences. On occasion it is useful to use various levels of income (Y) as outcomes in the utility function. An individual's utility function can then be represented as

$$\text{Utility or } U = U(Y).$$

As a mathematical conceptualization of the way in which individuals rank alternative outcomes the utility function becomes the basis for preferences among action choices. Since decisions are made without complete knowledge, the outcomes from each action choice are described in probabilistic terms. The probabilistic description of the outcomes is always subjective although it is influenced from observed data. If a decision maker is consistent with his preferences, he seeks to maximize expected utility. This implies the use of Bernoulli's principle.

Daniel Bernoulli deduced his principle in recognition of the observation that an extra dollar is worth more to a poor man than a rich man. Although Bernoulli postulated his principle well over 200 years ago, not until a few decades ago did it become formalized into what is known as the expected utility hypothesis. Ramsey (1931) and von Neumann and Morgenstern (1944) showed that Bernoulli's Principle can be logically deduced from a set of reasonable postulates about human nature. Although the theorem has been proved in a variety of ways with somewhat differing sets of postulates, the postulates of ordering, transitivity, continuity, and independence provide a sufficient basis for deducing Bernoulli's Principle. If a decision maker's preferences are consistent with these postulates, his utility function associates a single utility value with each uncertain outcome for a certain level of wealth.

The expected utility hypothesis provides the means for ranking uncertain prospects in order of preference based on the expected utility of each prospect. It combines decision makers' preferences and probability expectations about outcomes into a simple decision rule.

2.2.1 Measurement of Expected Utility

Several measures have been used to represent individuals' willingness to bear risk. Table 2-1 depicts some of these measures and their relationship to risk attitude classification. All of the measures originate from the expected utility framework and can yield equivalent classifications. Most of the literature reviewed in this chapter employs one or another of these measures.

While utility functions serve to identify optimal risk actions so as to maximize expected utility, they unfortunately cannot be used directly for interpersonal comparison. This occurs because U(Y) is not a unique representation for a given set of preferences. In fact any positive linear transformation of U(Y) also yields the same preferences. In recognition of this property, Pratt (1964) developed an absolute risk aversion function r(Y) equal to $-[U''(Y)/U'(Y)]$ (see ii, Table 2-1) as a unique measure of risk preferences. The interval approach uses this measure developed by Pratt.

There are three approaches used to estimate risk preferences. These approaches are direct elicitation of utility, experimental, and observed economic behavior. It is useful to note that for all intents and purposes the experimental approach is a subset of direct elicitation; nevertheless, it will be treated separately in this review. These

Table 2-1. Risk Preference Classification Criteria Within Expected Utility Framework*

Measure	Range of measure for		
	Risk averse	Risk neutral	Risk preferring
(i) $U''(Y)$	<0	=0	>0
(ii) $-U''(Y)/U'(Y)$	>0	=0	<0
(iii) $\alpha EU/\alpha\sigma^2$	<0	=0	>0
(iv) $(d\mu/d\sigma^2)_{EU=constant}$	>0	=0	<0
(v) Risk premium	>0	=0	<0

*for utility function $U(Y)$ and associated expected utility function, $EU(\mu,\sigma^2)$, where μ is the expected value of the outcomes and σ^2 is the variance.

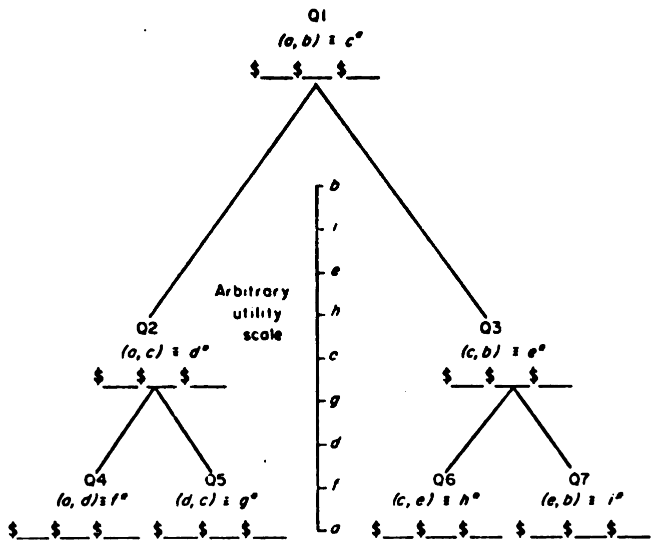
Source: Young, et al. (1979).

approaches and specific techniques are well documented in the literature (Young, et al. 1979; Robison, 1982). The next sections describe the approaches and explain some of their operational limitations. They also present a review of empirical experiments and the experimental results using these approaches.

2.3 Direct Elicitation of Utility

The most direct approach to the measurement of preferences is to estimate the decision maker's utility function. Direct elicitation typically determines a number of utility values by finding indifference points between hypothetical action choices. Several procedures have been developed for the estimation of indifference points. All of these procedures involve choices between lotteries of uncertain incomes and certain incomes until an indifference point between the lottery and the certainty equivalent income (CE) is found. Each set of choices may then be used to estimate a point on the utility function. Figure 2-1 serves as an example of a typical questioning procedure for estimating indifference points. This and other commonly used procedures are reviewed in Anderson, Dillon and Hardaker (1977).

The individual points are not very useful in themselves. Usually a function or curve is fitted to these estimated points to represent the relationship between utility and income for a range of incomes. The direct elicitation approach and the various techniques of point estimation and curve fitting have proven to have several serious shortcomings. Negative preferences toward gambling (Roumasset, 1977), noninteresting hypothetical choices (Binswanger, 1980), and the substitution of subjective for objective probabilities are typical criticisms of the design



Steps:
(1) Set the range *a* ($ worst) to *b* ($ best) for which preference is to be estimated.
(2) In Q1, find the CE c^* of the 50/50 lottery (a, b).
(3) In subsequent questions successively bifurcate the utility range into equal preference intervals.
(4) Graph points defining the curve as they are found.
(5) If checks reveal significant inconsistency, do again from the start.

Checks:
After Q3 is $(d, e) \equiv c$?
After Q6 is $(g, h) \equiv c$?
After Q7 is $(f, i) \equiv c$?

Figure 2-1: A Scheme for Directly Elicitating Points on a Decision Makers Utility Curve

Source: Halter and Dean

of elicitation interviews. Another more serious shortcoming of the direct elicitation approach results from using empirically estimated utility functions as exact representations. Yet for several reasons the utility functions are seldom exact. First errors may occur due to the interview technique biases. Errors also arise when respondents lack precise knowledge about their preferences (Robison). Knowles (1980) points out that if errors are made by the subject or as a result of the elicitation procedure, they compound or accumulate in subsequent utility estimates. Finally the fit of the function to the estimated utility points is not perfect, either due to lack of precision in identifying the points or use of a functional form not sufficiently flexible enough to accurately fit the data (Lin and Chang, 1978). This is especially true when the utility function's form is assumed a priori.

Despite the possible sources of imprecision in utility function estimation, once estimated it is treated as though it were an exact representation of preferences when ordering alternative action choices. And any absolute difference in the expected utilities associated with two choices is taken as indication of preference. Treating a utility function as an accurate description of a decision maker's preference when it is not can result in the recommendation of a choice other than that actually preferred by the decision maker. This is known as a Type I error. Therefore when utility functions estimated with the direct elicitation approach are used to order alternatives, considerable likelihood exists that Type I errors will be made.

Several studies have attempted to measure farmer risk preferences using the direct elicitation approach. All of these studies share the problems common to use of the approach. But each provide information useful to later stages of this report and the evolution of preference measurement in general.

2.3.1 Interstate Managerial Study

In 1954, Glenn Johnson and others surveyed 1,075 farmers in North Dakota, Iowa, Kansas, Kentucky, Indiana, Ohio and Michigan to obtain information relevant to a better understanding of the decision-making process. About half of the farmers included in the survey answered a set of questions involving hypothetical gains and losses from which utility functions were constructed. The hypothetical gain and loss situations were framed in a set of bets and insurance schemes. The individual had the opportunity of taking a certain loss (gain) or paying to get out (in) of each situation. The individual's responses were used to derive indifference points. The location of the indifference points provided the basis for estimating utility values. Out of the 529 respondents approximately 67 percent gave answers that could be used for the purposes of utility function estimation.

The equation $u = bx^2 + dx$, where u is the estimated utility and x is the amount of gain or loss, was fitted to each case in which at least one indifference point was derived. From the utility functions the authors estimated marginal utility at three income levels. They reported that for the $30,000 income level about 25% of the sample demonstrated marginal utility greater than one, 29% were estimated as having marginal utility near zero, and the remaining 46% had estimated marginal utility between one and zero. While marginal utility does represent relative comparison for this group, it cannot be used for interpersonal comparison outside of this experiment. Therefore the empirical results contribute limited information to this report.

2.3.2 Officer and Halter Study

Officer and Halter estimated disutility (elicitation questions framed in terms of costs) functions for five Australian wool producers in 1968. They used three different techniques for eliciting indifference points: von Neumann-Morgenstern, modified von Neumann-Morgenstern and the Ramsey techniques. The first two techniques require a series of choices by the individual between pairs of uncertain (gambles) and certain alternatives. The only difference between the two is the use of equal probabilities for the alternatives in the latter. The third technique, Ramsey, obtains indifference points from choices between two uncertain alternatives (gambles) with equal probability of each alternative (see Anderson, Hardaker and Dillon, 1977; or Officer and Halter, 1968).

They repeated this experiment one year later with the same sample using only the modified von Neumann-Morgenstern and Ramsey techniques. The von Neumann-Morgenstern technique was dropped because of its unreliability. Their evidence also showed disparity between measurements using the other two techniques. Based on the estimated utility points, they selected linear, quadratic or cubic functions to estimate the utility functions. They then used the slope of the indifference curve in mean-variance space (see Table 2-1) to estimate risk questions at one income (£800). For the first stage of the study, the modified von Neumann-Morgenstern technique showed three of the five farmers were risk averse while the Ramsey method showed three of the five risk preferring. Differences in outcome depending on which technique was used also occurred in the second stage, but were less dramatic. The disparity of outcomes suggests that caution is needed in using single valued utility function estimates obtained from the direct elicitation method.

Officer and Halter reported risk preference values ranging from -.0001 to .0006 based on the measure $(d\mu/d\sigma^2)_{EU = \text{constant}}$ (see measure iv, Table 2-1). Negative values represent risk preferring attitudes, while positive values represent risk averting attitudes. Some care should be taken in making comparison between these results and those of studies using Pratt risk aversion coefficients. The Officer and Halter measure is proportional to the Pratt coefficient. For quadratic functions the Pratt coefficient is twice the magnitude of the Officer-Halter measure. Thus interpretated as Pratt absolute risk aversion, the range on the coefficients is -.0002 to .0012.

2.3.3 Lin, Dean and Moore Study

Lin, Dean and Moore used a modified Ramsey technique to elicit points on the utility function of six large California producers. They compared the predictive ability of Bernoullian utility functions, lexicographic utility functions, and expected profit maximization models. They found that maximizing the expected value of Bernoullian utility functions predicted farmer behavior most accurately, while lexicographic utility functions being only slightly better than profit maximization. They also noted that all three predicted more risky behavior than actually occurred. According to the Bernoullian utility functions which they estimated, two farmers had constant marginal utility, three had diminishing marginal utility (risk averse) over the entire range, and one farmer had a function with a range of first diminishing marginal utility followed by a range of increasing marginal utility (risk preferring). As presented earlier, the risk aversion properties of decision makers is an empirical question and should not be predetermined by the functional form selected. By limiting the functional form both Officer and Halter, and Lin, Dean and Moore restricted the empirical outcomes.

2.3.4 Halter-Mason and Whitaker-Winter Studies

Halter and Mason (1978) elicited risk preferences from 44 grass seed farmers in the Willamette Valley in Oregon. They used the modified Ramsey technique for data elicitation. This technique differs from the Ramsey technique used by Officer and Halter in that it does not presume values for three of the four gamble outcomes. Rather it allows the procedure to establish the outcomes (see Lin, Dean and Moore). They fitted third degree polynomial equations to the indifference points. Pratt risk aversions coefficients were calculated at each individual farmer's gross income level. The authors did not report these coefficients. Rather, they stated that the proportions able to be classified as risk averse ($r(Y)>0$), and risk preferring ($r(Y)<0$) were about equal. In 1980, Whitaker and Winter repeated the Halter-Mason study using 37 of the original sample members. They applied the same techniques as Halter and Mason except they estimated utility functions from five indifference points rather than three. Once again individual data were not reported. They did report that the mean of the risk aversion coefficient evaluated at each farmer's gross income level was estimated to be -.29 in 1976 and .44 in 1974. Conflicting results between their study and Halter and Mason's so disturbed Whitaker and Winter that their report focused on identifying possible reasons for the differences.

2.3.5 Knowles Study

Knowles elicited utility data from four Minnesota farmers using the von Neumann-Morgenstern and Ramsey techniques. Several functional forms including constant absolute risk aversion, logarithmic and polynomial were applied to fit the data. Knowles estimated Pratt risk aversion ($r(Y)>0$) at these levels. Knowles also demonstrated how the techniques used in the direct elicitation approach may seriously compound errors in statistical estimation.

2.3.6 Other Studies

A few other studies using the direct elicitation approach have been completed. Most of these experiments were conducted in developing economies (e.g. Dillon and Scandizzo, 1978). Based on these studies, Young, et al, tentatively conclude that farmers in less developed countries appear to be more uniformly risk averse than those in developed countries. Because of the apparent differences in risk preferences and the fact that the same problems plague results from direct elicitation no matter what the state of the economy, these studies will not be reviewed.

2.4 Experimental Approach

The direct elicitation method is technically difficult to administer in a manner which does not bias results. This concern and the criticism that the direct elicitation approach relies on hypothetical gains and losses led to the experimental approach. Binswanger (1980) developed this approach to measure risk preferences of more than 350 peasants in rural India. Contending that games with actual financial compensation would result in different outcomes than those with hypothetical outcomes, Binswanger attempted both at several levels of gains.

The experimental approach required the individuals to choose among eight gambles whose outcomes were determined by a coin toss. The study was conducted during several visits with the respondent. The repeated visits and length of time was an effort to better simulate the typical length of time available in the decision process. This effort aimed at reducing the problem of immediate choice which Binswanger noticed during a pilot study using direct elicitation techniques. He also took considerable effort to avoid interviewer bias and attempted several within study experiments to test reliability.

Binswanger compared individuals' preferences through a summary statistic measure. This measure comes from assuming over the interval of the gamble that the utility function is of the form

$$U(Y) = (1-s)Y^{1-s}.$$

The corresponding absolute risk aversion function, $r(Y)$, is s/Y. Since $r(Y)$ decreases when Y increases it cannot be used as an average risk aversion measure. The summary statistic was used to characterize individuals' choices into various subjectively defined risk preference groups. For games with compensation near the peasant farmers' monthly incomes, Binswanger found more than 50% of the individuals as "extremely" or "severely" risk averse with only about 15% classified as neutral or risk preferring.

Grisley and Kellogg (1980) conducted a similar study (although smaller in scale) employing the experimental approach in Northern Thailand. Their techniques and results were quite similar to those of Binswanger. While both studies implied that measurements of risk preference are substantially affected by whether the decision maker is evaluating actual or hypothetical gains and losses, Binswanger reported several tests demonstrating little difference between hypothetical and actual game results. Binswanger also noted that in the experiment care must be taken to insure the compensation level is a significant amount for the subjects interviewed.

The latter conclusion makes the experimental approach infeasible in a developed nation because insuring an adequate compensation level would likely be too expensive. Even if funds were available, the game setting would probably not replicate the actual decision framework for agricultural producers (Lins, Gabriel and Sonka, 1981). And no definite advantage of using actual gains has been verified. The use of the summary statistic also makes comparison between Binswanger's results and others difficult. Knowles cites several other shortcomings of the experimental approach.

2.5 Observed Behavior Approach

In an effort to overcome some of the problems of the direct elicitation approach, researchers sought ways to indirectly measure risk preferences. The approach may take several forms, all of which attempt to infer preferences of individuals by observing their actual economic behavior. Studies of this nature have either focused on input utilization (Moscardi and de Janvry, 1977) or output supply of the individual (Brink and McCarl, 1978). The difference between actual behavior and the behavoir predicted by a theoretical model is considered the measure of risk preference.

Robison notes that the observed economic behavior approach has two advantages over direct elicitation. It bases preference measurement on real world choices not hypothetical gambles. And it allows for the handling of more data at lower costs, since private interviews are not required. Unfortunately the approach has several serious limitations. First the observed economic behavior approach assumes that risk preference is the only factor which inhibits attainment of the theoretical model used as the standard (profit maximization or safety-first, etc.). Young, et al. note that many other elements such as lack of complete knowledge or information, different resource endowments, non-preference constraints, and different objective functions may explain apparent behavior other than that of the selected model. But these elements are not part of the individual's attitude toward uncertainty. For further difficulties in the general approach, see Robison (1982).

2.5.1 Moscardi-de Janvry and Brink-McCarl Studies

Moscardi and de Janvry assumed a safety first model and used it to estimate risk preferences based on fertilizer application data. They applied this technique with a sample of 45 Mexican peasant farmers. As typical of other studies in developing economies, they found all respondents to have varying degrees of risk averse attitudes.

Brink and McCarl also indirectly derived estimates of risk aversion. They compared cropping plans elicited from 38 large corn belt farmers to those predicted by a Motad programming model. Their measure of risk aversion in the objective function was varied parametrically from zero (risk neutrality) upward until the difference between the elicited plan and the model's predicted plan was minimized. A rather wide range of coefficient values was reported. They tentatively concluded that risk aversion was not an important factor for explaining the difference in corn acreages for the group studied. The specific technique used by

Brink and McCarl had two serious problems. First, it precluded the chance that producers would be risk preferring. Second, the programming model did not include in its efficient set the decision maker's actual choices (Robison, 1982).

A shortcoming common of both the Moscardi-deJanvry, and Brink-McCarl studies involves the assumption of a constant risk aversion coefficient. They have assumed that a single parameter describes the whole utility function. Based on the data from this study such an assumption deserves careful re-examination. Robison (1982) in discussing this matter suggests that "An analogy to using single parameter values to infer preferences would be trying to infer from a profit maximization output the shape of a production function. To assume to know the form of the utility function without testing it, merely because it can be described with a single parameter, is to assume to already know what the researcher is supposed to measure."

2.6 Summary of Empirical Estimation of Risk Preferences

Considerable effort has been made to measure risk attitudes. This effort comes from modern decision making theory's requirement of risk preference information. This literature summarizes the major efforts to date. Each measurement approach used in these experiments has serious limitations. The direct elicitation approach is faulted for possible gambling and interviewer bias, difficulties in accurately fitting functions to data, the extreme sensitivity of outcomes, and the assumption of single value functions being exact representations. The observed economic behavior approach, while avoiding interviewer and gambling bias,has proven very difficult to implement. The possible misspecification of programming models as to action choices and the measure of risk preference reflecting non-risk preference parameters have yet to be overcome.

These experiments produced some general indications. They showed at least some proportion of farmers are risk preferring over some range of income. Farmers in developed countries have more risk preferring tendencies than those in developing countries. Several studies demonstrated expected utility as most accurately predicting producer behavior. Those studies which estimated and reported average absolute risk aversion (or a comparable measure) indicated a range of values from -.0002 to .0012. Finally, these results confirm the need for further progress in developing and testing techniques for measuring risk preferences.

Chapter 3

REVIEW OF RISK PREFERENCE-PRODUCER CHARACTERISTIC LITERATURE

3.1 Introduction

Objective 2 of this study requires the estimation of relationships between farmer risk attitudes and observable socioeconomic characteristics of the farm and operator. These results serve as preconditions to testing for intertemporal stability of the relationships. This chapter reviews empirical attempts to explain or correlate preferences with producer attributes. Much of the previous research designed to estimate risk preferences also concerned itself with relating preferences to socioeconomic phenomena. Consequently, several of the studies discussed in the previous chapter receive attention here. But for those cases, this chapter focuses on the preference-characteristics empirical results, not the measurement technique.

Several valid reasons have been proposed for doing the preference-characteristics relationship studies. The main reason is, however, that if a correlation can be established between risk attitudes and socioeconomic variables then scientists can avoid the costly process of directly eliciting utility functions. To find such a correlation has typically involved estimating risk preferences, or some measure of preferences, then regression, correlation or other statistical techniques are used to infer causal or non-causal relationships. The remainder of this chapter reviews some of the important studies in which risk preferences were tested for relationship to socioeconomic attributes.

Where necessary methods of preference estimation are described. And finally the conclusions and implications of each study are noted.

3.2 Interstate Managerial Survey

Probably the first empirical attempt to correlate agricultural producer characteristics with risk preferences was completed by Halter (1956) as part of the Interstate Managerial Survey (Johnson, et al., 1956). The survey offered individuals the possibility of taking a certain loss (gain) or paying to get out (in) of the situation (simulated, not actual gains and losses were proposed). The individuals could either respond yes or no with respect to leaving (entering) the group. The sample members were then classified according to their responses and the consistency of responses with the hypothesized utility function. Halter compared attributes and types of behavior to ascertain reasons for the differences in marginal utility of gains and the marginal disutility of losses. He found the amount of debt and type of farm as the two most meaningful variables related to marginal utility for gains. His findings also suggested that for Michigan the shape of the utility function for losses correlated with gross farm income and number of respondent's children. Moreover the Halter data indicate that many individuals could be both risk averse and risk preferring for different choice levels. Although the experiment was extensive, the contemporary techniques did not allow for utility estimation which could easily be related to attributes. While none of the relationships were statistically significant at normal levels, Halter still concludes that measures of net worth, income and debt show promise from the standpoint of future research.

3.3 Dillon and Scandizzo Study

Techniques for measuring preferences have changed since Halter's efforts. Dillon and Scandizzo (1978) utilized the direct elicitation approach to estimate indifference points between a certainty equivalent and various gambles. A series of four single valued risk attitude parameters for a sample of share croppers and landowners in Northeastern Brazil were derived from the individual's risk premium. The risk premium here is the risky prospect's expected value minus its certainty equivalent. These risk attitude parameters basically were mean-standard deviation measures similar to measure iii of Table 2-1. Dillon and Scandizzo regressed each of the four parameters on the farmer's age, income, household size and ethical attitude toward betting. They also considered as an explanatory variable the "risk" implicit in the final risky choice considered by each respondent. They used the standard deviation and the second moment minus the squared certainty equivalent as measures of "risk."

They found when subsistence was in jeopardy, an increase in riskiness tended to increase the required risk premium for both tenure groups. Ethical beliefs against gambling and age had a similar effect for both groups. Increases in income caused the risk premium to fall, and household size had mixed effects. Income proved to be the only variable with consistently statistically significant coefficients for small owners. No variables were consistently statistically significant for sharecroppers. Dillon and Scandizzo concluded that most, but not all, peasants were risk averse and that past income and possibly some other socioeconomic variables influence attitudes toward risk.

3.4 Binswanger Study

Binswanger (1980) attempted to utilize an interview procedure similar to that used by Dillon and Scandizzo, but found it unreliable in India. To overcome this problem, he developed an experimental method which involved the use of financial compensation at realistic levels. Binswanger then attempted to explain differences among individuals in their attitudes toward risk in terms of age, schooling, assets, land rented, salaried employment, working age adults per family, progressiveness, net transfers, luck in previous games and whether an individual liked to gamble. These variables were used in a number of cross-sectional regressions utilizing the summary statistics of risk classification (see 2.4) as the dependent variables. Binswanger computed separate equations at several levels of gains and for different subsets of the farmer sample.

Binswanger concluded that wealth had little effect on magnitude of risk aversion. Years of schooling and prior luck in the games tended to reduce risk aversion. The other personal characteristics used as independent variables had no clear impact on risk preferences. He attributed this lack of quantative impact in part to the similarity of risk attitudes. Even these conclusions must be tempered in light of the small proportion of variation, ranging between 5 and 20%, in the risk classification summary statistics explained by the independent variables.

3.5 Moscardi and de Janvry Study

In 1977 Moscardi and de Janvry conducted a study in Mexico focusing on the relationship between producer attributes and risk preferences. They developed an indirect measure of risk preferences based on observed economic behavior (see Section 2.5.1). The residual marginal factor cost between observed behavior and predicted behavior from a safety-first model served as their risk classification measure. Nitrogen fertilizer use was the dependent variable in a regression analysis for a sample of 45 peasant households. Several variables explained 30 percent of the variation. Off-farm income, extent of land under control and membership in a solidarity group were found to have statistically significant negative correlation with the Moscardi-de Janvry measure of risk aversion. The first two are consistent with the hypothesis of decreasing absolute risk aversion with respect to wealth. Family size and schooling had negative relationships with risk aversion, but were not statistically significant (t-values < .5). Finally, age had a positive coefficient indicating increasingly greater risk aversion with age. But again the coefficient had low statistical significance with a t-value of 1.07.

The studies by Dillon and Scandizzo, Binswanger, and Moscardi and de Janvry have helped to better understand preferences in developing economies. But as Young, et al. notes, "the vast differences between the peasant settings of these studies and modern commercial agriculture probably preclude generalizing the results to farmers in developing countries."

3.6 Halter and Mason Study

Although a long time in coming, there have been a few studies conducted in the United States since the Interstate Managerial Survey. Halter and Mason applied the modified-Ramsey technique to elicit points on individual utility functions for 44 Oregon grass seed farmers in 1974 (see Section 2.3.4). They completed a stepwise add and delete regression analysis with eleven farm and operator characteristics as independent variables and Pratt average risk aversion coefficients, evaluated at each respondent's 1973 gross income, as the dependent variable. Percentage of land owned, education and age were statistically significant in linear form. A negative relationship between education and risk aversion is consistent with Moscardi and de Janvry's and Binswanger's results. A postive relationship between greater percentages of ownership and risk aversion and the negative relationship of age with risk aversion depart from the results of the studies in developing economies. Variables representing the square of years of education, education-percent ownership product and education-age product also significantly related to the dependent variable. The signs of the coefficients on these non-linear variables were positive, negative and positive, respectively. Yet the effect of these interactive variables is very difficult to interpret. The amount of variation in the dependent variable explained by the independent variables was only 50% ($\bar{R}^2 = .50$). Halter and Mason also made comparisons with some of the variables held at selected levels. These comparisons included highly variable age and education effects. Regressed at various levels of percent ownership with education constant, individuals became more risk preferring with increasing age at all levels of ownership. When risk preferences were regressed on percent ownership for five levels of education, no pattern of relation became evident. In summarizing their results, the authors suggested that "one cannot account for observed trends between any one variable and risk attitude without considering effects of the other variables jointly or conditionally." They went on to conclude that "strictly speaking, one needs data gathered in more than one time period to draw conclusions about time effects and trends" with respect to relationships between characteristics and risk preferences.

It is interesting that no income variables were included in the list of eleven linear variables originally tested. This is especially strange considering in 1956 Halter suggested that one of the major deficiencies of his study probably involved not having individual income data to correlate with sample response. The authors noted that gross farm income was not included in the variable list because the observed correlation between the Pratt coefficient evaluated at the gross income level and gross income was -0.03. Of course, such a result might have been anticipated considering the method of selecting the point estimate. Whitaker and Winter critique the use of gross income of each respondent as the level to estimate the Pratt coefficient. Information presented in Chapters 6 and 7 of this study will further question this method.

3.7 Whitaker and Winter Study

Two years later, in 1976, Whitaker and Winter reestimated utility functions for 37 of the 44 grass seed producers in the Halter-Mason sample. Using the same methodology and variables as Halter and Mason, they also evaluated the risk preference-attribute relationships. Their results were most disturbing. The signs of each of the seven estimated regression coefficients changed between the 1974 and 1976 models. Neither of the two variables including age as a factor (age and age-education product) had coefficients statistically significant in the 1976 regression equation.

The authors suggested possible causes of the discrepancies between the '74 and '76 outcomes. Unfortunately, they were unable to provide useful conclusions. Moreover, some of their suggestions tended to be contradictory. They, like Halter and Mason, treated gross income as an unimportant independent variable when compared to risk coefficients estimated at those levels. Yet, they also stated that "Halter and Mason evaluated the Pratt coefficients using gross income, which could cause misleading results." The result of risk aversion coefficients evaluated at a standard level or levels of income might be an important contribution.

3.8 Other Studies

A few other attempts to correlate farm and operator characteristics with measures of risk preferences have been reported (Krause and Williams, 1971; Patrick, Whitaker and Blake, 1980; and Carman, 1979). Krause and Williams investigated correlation between various personality characteristics and an arbitrary risk aversion index for South Dakota farmers and their wives. They argued that knowledge of relationships between personality and business attributes of farmers could be useful to agricultural lenders. Because of the nature of the risk index and the problem of measuring personality traits these relationships were not all that clear. Although such knowledge might be useful in a very individualized situation, the personality data are not observable and require the same amount of effort to measure as risk preferences. Moreover, most economic policy analysis requires knowledge of the relationships between risk preferences and economic variables.

Patrick, Whitaker and Blake represented risk preferences of 91 Indiana farmers using two rather vague indices based on magnitude estimation rankings of certain goals. The ratio of magnitude estimation scores assigned to the goal "avoid being unable to meet loan payments and/or avoid foreclosure on my mortgage" with the goal "attain a desirable level of family living" served as one index. The second index was the ratio of scores for "a farm business that produces a stable income" with those of "attain a desirable level of family living." These ratios were labeled "Bankruptcy-Income" and "Stability-Income" respectively. They then used regression analysis with these ratios as the dependent variables. The independent variables included: age, education, children under 18, percentage of debt, off-farm job, planned future income, planned future percent debt, and planned net worth growth. The variables explained only about 13% and 35% ($\bar{R}^2$) of the variation in the dependent variable for the respective equations.

The authors drew several conclusions based on the coefficients in each equation. Such conclusions seem questionable. Eight of the eighteen regression coefficients were not statistically significant (at usual levels). Only off-farm job and children under 18 (both treated as binary variables) were statistically significant for both equations. The authors suggested the negative signs on the coefficients of the variables for farmers with children under 18 and/or when the operator or his wife had an off-farm job indicated more willingness to take risk. But the two indices used to approximate preferences have never been shown theoretically or empirically valid. Therefore the ratios are at best arbitrary scaling of risk preferences which allow for neither risk neutral nor risk preferring behavior. Due to these shortcomings, any conclusions based on the Patrick, Whitaker and Blake results probably should be considered as only tentative and of limited application.

Carman, whose results are not yet published, also attempted an experiment to test the ability of farm and operator attributes to classify operators into average absolute risk aversion groups. Carman conducted a survey employing the interval approach to estimate preferences. Since some of the data obtained by Carman is used as part of the first stage of this study, discussion of his analysis is postponed until chapter 7.

3.9 Summary

Efforts to correlate risk preference with producer attributes have not produced conclusive results. Studies from developing countries (Dillon and Scandizzo,; Binswanger; Moscardi and de Janvry) tended not to be applicable to the United States' situation and generally had equations which exhibited poor explanatory power and coefficients with low significance.

Halter in the IMS report suggested debt, farm enterprise type, number of children and gross income as being linked to risk attitudes. Yet, the nature of his data caused him to be unable to make conclusions on statistically significant estimation. The Halter and Mason experiment produced some fruitful hypotheses. Yet Young, et al. question the representativeness of their sample and their results were contradicted by those of Whitaker and Winter. Finally, others estimated the relationship between farmer characteristics and single value parameters which they attributed to represent risk preferences. The literature is critical of single value parameters as a measure of utility or preferences

(Robison, 1982), also the lack of empirical verification or theoretical justification make the use of these parameters questionable.

The reviewed reports demonstrated the characteristics of age, debt, education, off-farm job, number of children, amount of acreage and percentage net worth as likely candidates for future research. Income variables were found to be missing from most efforts, yet almost every report suggested the possible fruitful employment of income-related variables. Perhaps the main consensus comes in the continual affirmation of the need to find observable factors to reduce the dependency on direct elicitation and the finding that effects of these factors are likely highly interrelated.

Chapter 4

THE INTERVAL APPROACH TO RISK PREFERENCE MEASUREMENT

4.1 Introduction

This chapter discusses the methodology used to collect risk preference data. Completion of the objectives of this study requires these data. Chapter 2 reviewed and critiqued previous methods used to collect risk preference data. All the approaches had considerable theoretical or practical weaknesses. A relatively new method, the interval approach, based on stochastic dominance with respect to a function, offers an opportunity to overcome many of these deficiencies. Essentially the interval approach supplies the operational capability to classify farmers according to their average absolute risk aversion.

This chapter is organized in the following manner. The next sections describe stochastic dominance with respect to a function and contrast it with other methods of representing risk preferences. Next, empirical implementation of stochastic dominance with respect to a function through the interval approach is outlined. The following sections review the results of two empirical trials designed to test the effectiveness of the interval approach. The final section summarizes the advantages and disadvantages of using the interval approach.

4.2 Theoretical Base for Stochastic Dominance with Respect to a Function

4.2.1 Measurement Criteria

The utility function U(Y) is the most usual representation of preferences. Unfortunately, this representation cannot be used for interpersonal comparison because U(Y) is not a unique representation of preferences. But Pratt's absolute risk aversion function, r(Y), is a measure which is unique and thus valid for interpersonal comparison. The Pratt measure is defined as

$$r(Y) = -U''(Y)/U'(Y)$$

where U'(Y) and U"(Y) are the first and second derivatives for U(Y). Pratt absolute risk aversion coefficient mentioned in chapter 2 (see Table 2-1) simply represents the value of the risk aversion function at a particular level or in the neighborhood of a particular level of Y. Moreover when those values for r(Y) are estimated at $\bar{Y}$ the coefficients are only approximations. The larger is the dispersion around $\bar{Y}$, the less precise the approximation becomes. All the methods of preference measurement described in chapter 2 which depended on lotteries or gambles to find indifference points or risk premiums really only approximated absolute risk aversion over the range of the gamble. Consequently if one individual's absolute risk aversion has a more positive coefficient than another's all that can be said is that the first individual is on "average" more risk averse. Thus those risk aversion coefficients measured from the direct elicitation and experimental approaches are measures of average absolute risk aversion. The interval approach also measures average absolute risk aversion but the approximation may be made as accurate as deemed necessary.

4.2.2 Stochastic Dominance With Respect to a Function

In general stochastic dominance criteria define necessary and sufficient conditions on cumulative distributions $F(Y)$ and $G(Y)$ for $F(Y)$ to be preferred or indifferent to $G(Y)$ by all agents in a particular group. Stochastic dominance with respect to a function essentially supplies rules for description of classes of decision makers. If decision makers are assumed to choose between cumulative distribution functions $F(Y)$ and $G(Y)$ for the normalized interval [0,1], then the expected utility hypothesis states that $F(Y)$ is preferred or indifferent to $G(Y)$ by a decision maker with utility function $U(Y)$ if and only if

$$\int_0^1 [G(Y) - F(Y)]\, u'(Y)dY \geq 0.$$

Stochastic dominance with respect to a function is therefore a criterion which establishes the necessary and sufficient conditions for the distribution of outcomes defined by cumulative distribution function $F(Y)$ preferred to or indifferent to $G(Y)$ by all decision makers in a risk aversion class such that:

$$r_1(Y) \leq - u''(Y) / u'(Y) \leq r_2(Y).$$

Meyer uses optimal control techniques as described by Arrow and Kurz (1970) to derive the necessary and sufficient conditions to this problem. The proof of this derivation is outlined in Meyer (1977) and in King and Robison (1981a).

The solution to the problem of finding necessary and sufficient conditions is in the form of a rule. Meyer stated the rule in the following theorem (Meyer, p. 33, Theorem 5).

Theorem: An optimal control $-u''_o(Y)/u'_o(Y)$ which maximizes

$$-\int_0^1 [G(Y) - F(Y)]\, u'(Y)dY \quad \text{subject to}$$

$$r_1(Y) \leq [-u''(Y) / u'(Y)] \leq r_2(Y)$$

and $u'_o(0) = 1$ is given by

$$-\frac{u''_o(Y)}{u'_o(Y)} = \begin{cases} r_1(Y) \text{ if } & \int_0^1 [G(X) - F(X)]\, x\, dx \leq 0 \\ r_2(Y) \text{ if } & \int_0^1 [G(X) - F(X)]\, x\, dx \geq 0 \end{cases}$$

This theorem says that the value of the absolute risk aversion function minimizes (or maximizes depending on the sign of the objective function) the difference in the expected utilities associated with F(Y) and G(Y) depending on the sign of the objective function from some point Y forward to 1 using the optimal control over the interval [Y,1]. Such a solution involving calculation from end to front is typical of dynamic programming. An example of how the rule works can be found in King and Robison.

4.3 Comparison of Stochastic Dominance with Respect to a Function to Other Representations of Risk Preferences

4.3.1 Comparison with Single Value Utility Functions

Stochastic dominance with respect to a function does not require exact representation of the decision makers' preferences as do single valued utility functions derived from direct elicitation techniques described in Chapter 2. The import of this becomes evident when the type of error possible in selecting action choice sets using single valued functions is understood. When a function is fitted to a set of elicited data points of utility, that function is then assumed exact for application to decision analysis. Rare indeed is the case in which the fit is perfect so that the parameter values of the utility function can be known with certainty. Even with an extremely good fit, the shortcomings of elicitation techniques listed in Chapter 2 make it likely that the data points are measured with some error. Yet, given an action choice set the single valued function is then applied to select the efficient set or order action choices based on the expected utility. Any differences between expected utilities of choices is assumed to exactly indicate preference of one over another.

If an empirically estimated utility function does not accurately describe the decision maker's actual preferences, the preferred action choice might be excluded. Such an error becomes an important problem in using single valued utility functions. Stochastic dominance with respect to a function criterion reduces the opportunity for such error. Since the criterion does not require that an exact representation of the decision maker's preferences be specified, the analyst has flexibility to make explicit trade-offs between the error of exclusion of actual preferred action choice and the error possible due to too large an efficient set of choices.

4.3.2 Comparison With Efficiency Criteria

As described, stochastic dominance with respect to a function establishes criteria for classes of decision makers defined by:

$$r_1(Y) \leq r(Y) \leq r_2(Y) \text{ for all } Y.$$

Therefore the risk preferences of each decision maker in a particular class are defined by $r_1(Y)$ and $r_2(Y)$. Action choices may then be ordered on the basis of these bounds. The flexibility of the approach becomes more evident when stochastic dominance with respect to a function is compared to other efficiency criteria.

Hadar and Russell (1969) and Hanoch and Levy (1969) formulated the criteria known today as first and second degree stochastic dominance. These criteria are most often employed to eliminate and partially order choices from the decision maker's feasible set. First degree stochastic dominance is appropriate for all decision makers who prefer more to less:

$$U'(Y) \geq 0.$$

Unfortunately first degree stochastic dominance is not a particularly discriminating criteria.

Second degree stochastic dominance does allow for some additional ordering of action choices found impossible with first degree stochastic dominance. Second degree stochastic dominance requires an additional assumption about the decision maker's utility function. It requires the decision maker's marginal utility function to be both positive and decreasing:

$$U'(Y) > 0 \text{ and}$$

$$U''(Y) < 0.$$

Even second degree stochastic dominance is not a particularly discriminating evaluative technique (see Anderson, 1975). And empirical evidence strongly indicates that often second degree stochastic dominance's assumption of decreasing marginal utility does not hold for decision makers at relevant income levels (Officer and Halter; Halter and Mason; King, 1979).

First degree stochastic dominance and second degree stochastic dominance can be shown to be special cases of stochastic dominance with respect to a function (Meyer, 1977; Meyer, 1977a). The requirement of $U' \geq 0$ under first degree stochastic dominance places no restrictions on decision makers risk aversion function. For first degree stochastic dominance the lower bound $r_1(Y)$ and upper bound $r_2(Y)$ equal negative and positive infinity respectively. Under second degree stochastic dominance, the conditions that $U' > 0$, $U'' < 0$ imply $r_1(Y)$ equals zero and $r_2(Y)$ equals positive infinity. Therefore first and second degree stochastic dominance have qualities which limit their application except for restricted groups of decision makers.

Unlike other efficiency criteria stochastic dominance with respect to a function imposes no restrictions on the width or shape of the risk aversion space which defines the class of decision maker. Also, in contrast to second degree stochastic dominance, negative as well as positive levels of average absolute risk aversion can lie within the risk aversion interval at some or all levels of the performance measure. Because the bounds on average absolute risk aversion can be as wide or narrow as deemed necessary for a particular decision analysis, the criterion affords considerable flexibility in degree of precision.

4.4 The Approach for Measuring of Interval Bounds

The ordering procedure given the class of decision makers defined by bounds on r(Y) was solved by Meyer. Before stochastic dominance with respect to a function could be used in an applied context, however, an operational procedure had to be developed for determining those lower and upper bounds. In answer to this need, King developed the components of the interval approach.

The solution involves the choices between carefully selected distributions. Information from these choices may then be used to establish the upper and lower bounds on a decision maker's absolute risk aversion function. King's procedure for constructing interval measurement of decision maker preferences is based on the fact that under certain conditions a choice between two distributions defined over a relatively narrow range of outcome levels divides absolute risk aversion space over that range into two regions: one consistent with the choice and one inconsistent with it.

The decision maker's preferences, as revealed by his ordering of the two distributions, however, determine into which of these two regions his level of absolute risk aversion falls. Through a hierarchy of choices, wider portions of the risk aversion space may be shown as inconsistent with the decision maker's preferences until a desired level of accuracy is attained. Upper and lower limits for the level of average absolute risk aversion can be determined at several income levels. These values are used to estimate upper and lower limits for average absolute risk aversion over the relevant range of income. A simple example for clarification of this point is found in King and Robison (1981a).

Figure 4-1 presents an example of a bounded risk aversion function for three selected income levels. The hypothetical decision maker in this example has had direct interval measurements leading to risk aversion intervals of (-.0001 to .0001) for -$2,000 to $2,000, (.0001 to .0004) for $10,000 to $14,000 and (0.0 to .0003) for $20,000 to $24,000 range. The interval boundaries are estimated over the whole range of incomes by connecting the directly measured upper and lower bounds with linear segments.

4.4.1 Implementation of the Interval Approach

The two principal requirements for operationalization of the interval approach are the selection of appropriate distributions and identification of the boundary interval for any pair of distributions. King developed computer program INTID as a tool to serve this purpose. Implementation of the interval approach involves three interrelated phases. These phases are: the specification and employment of program INTID, design of the questionnaire, and interpretation of respondents' choices.

With a set of user supplied parameters (see next chapter for description and specific values used for this study), program INTID generates a set of sample income distributions. INTID then identifies a boundary interval for each pair of distributions. The boundary interval for two distributions, (λ_1, λ_2) is an interval in risk aversion space such that decision makers whose average absolute risk aversion lies everywhere below λ_1 unanimously prefer one distribution, while those whose average absolute risk aversion lies everywhere above λ_2 unanimously prefer the other. [1]

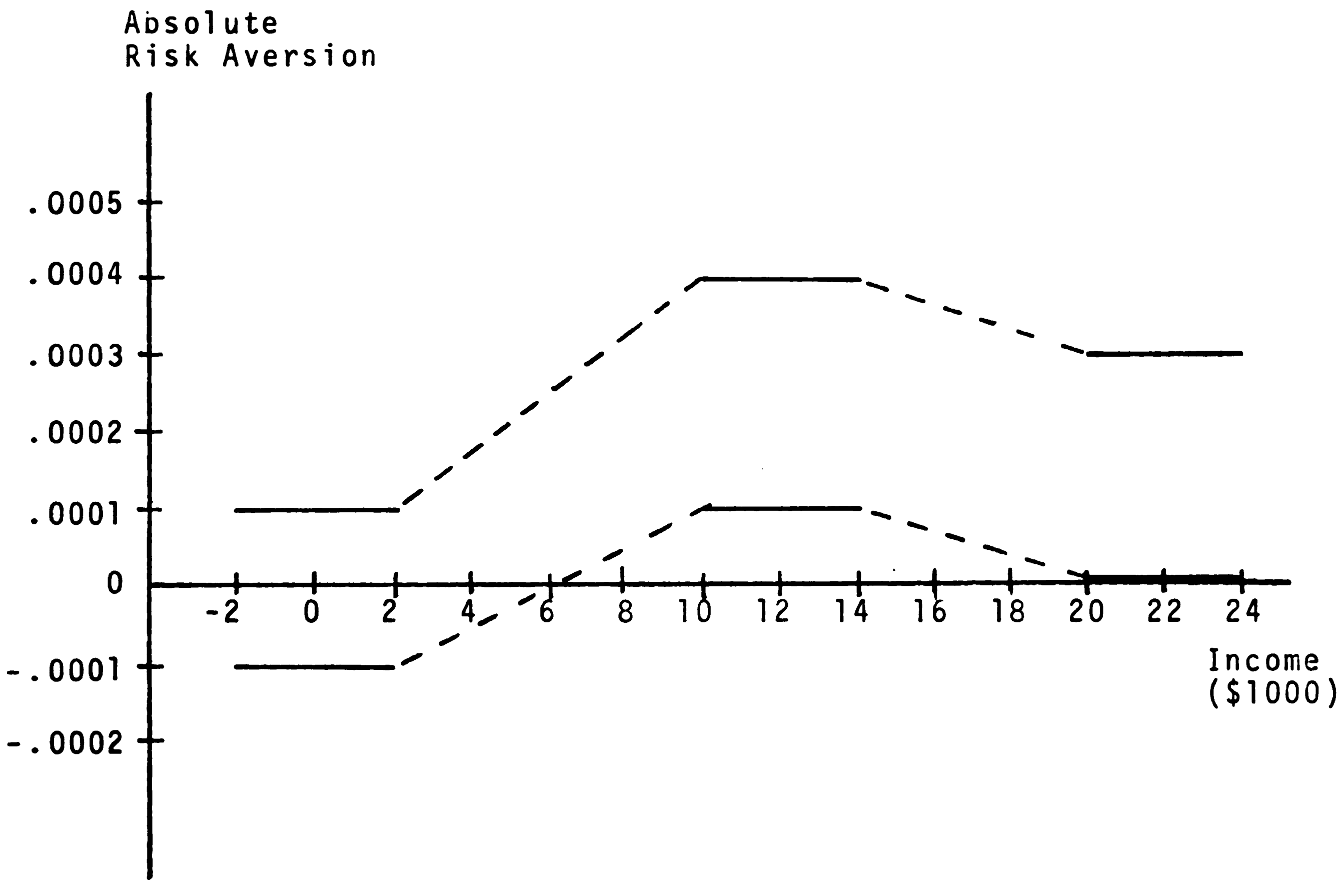


Figure 4-1. Estimated upper and lower bounds on average absolute risk aversion based on three interval measurements: an example.

Once sample distributions have been generated and boundary intervals have been identified, the series of choices between distributions that provide the information needed to construct an interval preference measurement in the neighborhood of a given income level can be formulated. This series of choices takes a form similar to a programmed learning test, since it directs the decision maker through a hierarchy of comparisons designed to continually increase the precision of the interval measurement (see Figure 5-2). A discussion of this process occurs in the next chapter. But basically the selected hierarchy serves as the questionnaire for measuring risk preference bounds (see Appendix A). This process can be repeated at several income levels within the relevant range of income.

4.4.2 A Test of the Interval Approach

King conducted a simple experiment to test the efficiency of the interval approach in the measurement of decision maker preferences. Three questionnaires were administered to a group of graduate research assistants from the Department of Agricultural Economics at Michigan State

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[1]Following is an example of an INTID output for boundary intervals.

	.001500	TO	.002500	DIST 14	PREFERRED BELOW	.001500	DIST 3	PREFERRED ABOVE	.002500
	.000400	TO	.000600	DIST 16	PREFERRED BELOW	.000400	DIST 3	PREFERRED ABOVE	.000600
A.	.000100	TO	.000200	DIST 17	PREFERRED BELOW	.000L00	DIST 3	PREFERRED ABOVE	.000200
	.001500	TO	.002500	DIST 19	PREFERRED BELOW	.001500	DIST 3	PREFERRED ABOVE	.002500
	.000600	TO	.000800	DIST 20	PREFERRED BELOW	.000600	DIST 3	PREFERRED ABOVE	.000800

Here boundary interval A is (.0001, .0002). The average absolute risk aversion space consistent with the choice of distribution 17 is everywhere below .0002 and that consistent with the choice of distribution 3 is everywhere above .0001.

University. The first questionnaire employed the interval approach to obtain an interval measurement of each subject's average absolute risk aversion. The second questionnaire used the direct elicitation approach to acquire information required for the construction of a single-valued utility function for each subject. Finally, the third questionnaire asked the respondent to make a series of six choices between pairs of distributions, each distribution being comprised of six elements and each being defined on the interval over which preferences had been measured. Information from the first two questionnaires was used to predict the choices made by each respondent in the third questionnaire, and these predictions were compared to the actual responses. In this way the accuracy of each of the two approaches to the measurement of preferences was tested.

Table 4-1 presents the results of the experiment. It shows a clear trade-off between discriminatory power and accuracy. The single-valued utility function and first-degree stochastic dominance represent extremes of the trade-off. But the interval approach makes the trade-off explicit. The discriminatory power of the interval measurement increases with an increase in the number of questions asked. On the other hand, the accuracy from interval measurements falls as the number of questions increases, but it falls much more slowly than discriminatory power increases. And even at its lowest level of accuracy the interval approach shows greater precision than directly elicited utility functions. One other point indicated by the test is the relatively greater ability of the interval measurements to order choices versus the capabilities of first- and second- degree stochastic dominance criteria.

Table 4-1. Performance indicators for alternative preference measures: A test of the interval approach

Performance Indicator	Interval Measurement: Number of Questions 1	2	3	4	Single Valued Utility Function	First Degree Stochastic Dominance	Second Degree Stochastic Dominance
1. Percent of choices predicted correctly	98	88	78	72	65	100	98
2. Percent of choices ordered	9	50	83	91	100	0	7

Source: King (1979).

4.4.3 An Empirical Test With Agricultural Producers

King also tested the interval approach's ability to perform in a more practical setting. He administered questionnaires using the interval approach to seventeen Michigan farmers as part of an extension marketing workshop. Intervals on average absolute risk aversion were measured in the neighborhood of four income levels: -$3,000, $7,000, $17,000, and $27,000. King noted that "the farmers had little difficulty in completing the questionnaires, and they seemed to find the choices interesting." A wide variation in responses characterized the outcomes of the questionnaires. Individuals ranged from extremely risk averse to extremely risk preferring over some range of incomes. Only four of the seventeen farmers had lower level average absolute risk aversion bounds which were everywhere non-negative. Such a result casts doubt upon the applicability of a criterion like second-degree stochastic dominance or a priori selecting functional forms valid only for decision makers who are risk averse at all income levels.

Finally King had each respondent make a series of choices between distributions, as done in the previously discussed test, to test the ability of the interval measurement to predict choices. Ninety-one out of 102 possible choices were predicted correctly for a success rate of .892.

4.4.4 A Summary of the Advantages and Disadvantages of the Interval Approach

Previous discussion brought attention to several of the advantages of the interval approach. Those and others are outlined here. (1) The interval approach does not require the identification of indifference between action choices. Instead, it only requires that a few carefully selected action choices be ordered by the respondent. (2) The approach allows for application of realistic levels of income. Measurement can occur over several ranges in a relatively short interview. (3) The approach bounds an interval of risk aversion space, thus reducing the errors often accompanying point estimates. (4) The approach imposes no predetermined functional form on the respondents' risk function. (5) The approach is flexible and can be adjusted to the problem under consideration or for the desired level of precision. (6) Finally, the approach is based on the expected utility hypothesis.

The interval approach still does not overcome two disadvantages of most preference estimation techniques. It still uses gaming techniques (i.e. not actual gains and losses) in locating an individual's interval. And it measures average absolute risk aversion over a range of incomes, not actual absolute risk aversion for every level of income. Yet the flexibility mentioned above makes this less of a problem than for other approaches, because the level of accuracy can be as good as the analyst desires. Other improvements still need to be made in the actual questionnaire design and explicit decisions on certain trade-offs. But these are not shortcomings of the approach only a function of the limited application to date. Chapter 8 discusses some of the adjustments needed to improve the application of the interval approach.

4.5 Summary

This chapter outlined the procedure used for collection of risk preference data. It presented the theoretical background based on stochastic dominance with respect to a function and showed that in many ways the interval approach is more desirable than previously employed preference estimation methods. Two successful empirical trials of the approach were also discussed. The next chapter defines some of the parameters of program INTID not here defined and gives examples of question design and interpretation specific to this study.

Chapter 5

DATA COLLECTION PROCEDURES

5.1 Introduction

This chapter concerns itself with collection of the data used in analysis. Completion of the objectives requires two types of data. The first type of data is risk preferences measured at two points in time. These data were acquired using the interval approach outlined in the previous chapter. The second type of data involves social and economic characteristics of the farm and operators who participated in risk preference measurement. Some of these data come from primary sources as part of the questionnaire containing interval measurement choices. But most come from a secondary source, computerized farm records. All the data were collected or calculated for both the 1979[1] and 1981 stages of the study.

This chapter is organized according to the following format. The next sections describe specification of the components and parameters from program INTID. Those sections also discuss the design and interpretation of the risk preference measurement part of the questionnaire. Subsequent sections describe the socioeconomic data requirements and sample selection criteria. The final sections supply descriptive information about the sample.

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[1]Risk interval data for 1979 was collected by Garth Carman.

5.2 Risk Preference Data Collection

Implementation of the interval approach involves three interrelated phases. These phases are: the specification and employment of program INTID, design of the questionnaire, and interpretation of respondents' choices. While the phases were briefly outlined in the previous chapter, the following sections specify the interval approach as applied in this report.

5.2.1 Specification of INTID

Implementing program INTID involves several steps. These steps relate to the requirement of different kinds of user (designer of questionnaire) supplied information necessary for output generation. The first step for user supplied information to INTID is the selection of the relevant income range over which preferences are estimated. The selection of the income range depends on the performance measure. The performance measure selected is after-tax farm income. The measure seems most relevant to the decision maker. The specified income range should include all reasonable incomes experienced by sample members. A range which assures inclusion of most respondents also serves the purpose of measuring preferences at levels above and below those typically experienced. From review of Telfarm records (the sample is taken from a subset of the population of farmers participating in Telfarm record keeping system, see Section 5-4 for explanation) a range of -$1,000 to $50,000 included a large percentage of the incomes experienced by the subset of the population.

The second step involves selection of the number and magnitude of the points along the income range where risk preference is to be measured. The choice of the number is a tradeoff between accuracy and respondent bias. King suggests measuring preferences in the neighborhood of three or four income levels. Considering the fairly wide range of relevant incomes, four levels of income were selected. The neighborhood of one would include the highest income and that of another the lowest income in the range. The intermediary levels were also specified. The income levels are: I. \$0; II. \$10,000; III. \$25,000; IV. \$45,000.

The width of the neighborhood about each income level is the third specification step. The preference intervals are measured over four ranges of income. Each range includes one of the income levels as the mean. Ranges do not overlap. The user supplies a standard deviation (STD) of distribution for each income level. The mean income level (\$0, \$10,000, \$25,000 and \$45,000) plus and minus two standard deviations defines the range. The standard deviations selected are \$500, \$500, \$1,500 and \$2,500 for income levels I through IV respectively. The following ranges result for each level:

Level I	-\$1,000 to \$1,000
Level II	\$9,000 to \$11,000
Level III	\$22,000 to \$28,000
Level IV	\$40,000 to \$50,000

Within these income ranges INTID generates the magnitudes of the paired distributions.

The upper and lower boundaries on average absolute risk aversion are considered to be constant over each income range. King and Robison note that "This is a result of the assumption that the decision maker's absolute risk aversion function can be approximated by a constant in the neighborhood of any particular outcome level." Some questions as to specifying differing size standard deviations for different income levels has merit. Implicit in such design is the assumption of a wider range of constant risk aversion for higher incomes than lower incomes. It does seem reasonable that narrow distributions at higher income levels might prove difficult for the respondent to differentiate. Yet the more narrow the interval the more accurate average absolute risk aversion is as an estimation of the risk aversion function. All the standard deviations used fell within the suggested values (King and Robison), yet these values are based on limited empirical work. To this point the trade-off between ease of response and accuracy of estimation has not been studied. The question unfortunately arose after the first stage data was collected. Since no change occurred from the first stage of data collection to the second, due to a desire to hold the measurement process as constant as possible, the problem ought to be considered in future applications of interval approach.

Several other parameter specifications are related to the selection of the standard deviation of distribution. These include: the number of elements in each distribution (NE), the number of sample distributions generated (ND) and the number of reference levels on the measurement scale (NG). NE was set equal to six. King notes that preliminary tests indicate six elements of a distribution appears optimal. The number allows for interesting distributions without too great a complexity. King and Robison recommend the number of sample distributions generated to be set at 40. This number almost guarantees that at least one pair of distributions will have its boundary interval at any specified level. Finally, a set of 16 reference levels was selected. A minimum of 2^n is required, where n is the number of questions at each income level. For this study n is three, thus NG had to be at least eight. A set of 16 was decided upon for its ability to reduce the prospective incremental interval size.

The final step in specifying INTID entails the selection of the measurement scale, i.e. the 16 reference levels mentioned above. Sixteen reference levels define 15 intervals. The 16 reference levels are listed in Figure 5-1.

Given the specified set of input parameters, INTID computes the two sets of desired output. The 40 sample distributions are constructed in a random manner with each of the six elements of a distribution said to have an equal probability of occurrence. The program also identifies the boundary intervals, (λ_1, λ_2) for as many interval pairs as possible (see Section 4.4.1 for example). The process is repeated four times, once at each income level.

5.2.2 Design of Questionnaire

The next phase necessary to implement the interval approach involves design of the questionnaire. From the set of generated boundary intervals a series of distributions must be selected to construct an interval preference measurement in the neighborhood of each of the four income levels. This series of choices takes a form similar to a programmed learning text, since it directs the decision maker through a hierarchy of comparisons designed to continually decrease the width of the interval measurement.

.01000

.00500

.00250

.00150

.00100

.00080

.00060

.00040

.00030

.00020

.00010

.00000

-.00010

-.00025

-.00050

-.01000

Figure 5-1. Absolute Risk Aversion Measurement Scale

The first question of the hierarchy should focus on the boundary interval near the center of the measurement scale. Figure 5-2 represents the hierarchy for income level II. From the specified boundary intervals, interval (.0003, .0004) was selected. A choice of Dist 17 vs. Dist 3 will almost halve the risk aversion space. With later questions an attempt is made to again divide the subregion of absolute risk aversion consistent with prior choices. In other words, if Dist 3 is preferred, the next question would compare Dist 13 and Dist 2 which focuses on the new boundary interval (.001, .0015). The complete questionnaire used for each stage of the study is found in Appendix A.

5.2.3 Interpretation of Questionnaire Results

The final phase of preference elicitation with the interval approach becomes the interpretation of the decision maker's responses. This is a rather simple procedure. An example from Figure 5-2 will serve to illustrate the procedure. Assume that the individual selected Dist 17 over Dist 3, then Dist 4 over Dist 8; then Dist 6 over Dist 40. The preference interval consistent with the first choide is $(-\infty, .0004)$. That consistent with the first and second choice is (-.0001, .0004). And that consistent with all three choices is (.0001, .0004). The latter interval represents one of the eight possible depending on the choices within the hierarchy. This procedure is repeated for the respondent's choices at each of the four income levels.

5.2.4 Application of Risk Preference Measurement Portion of Questionnaire

Although the questionnaire and accompanying instructions are

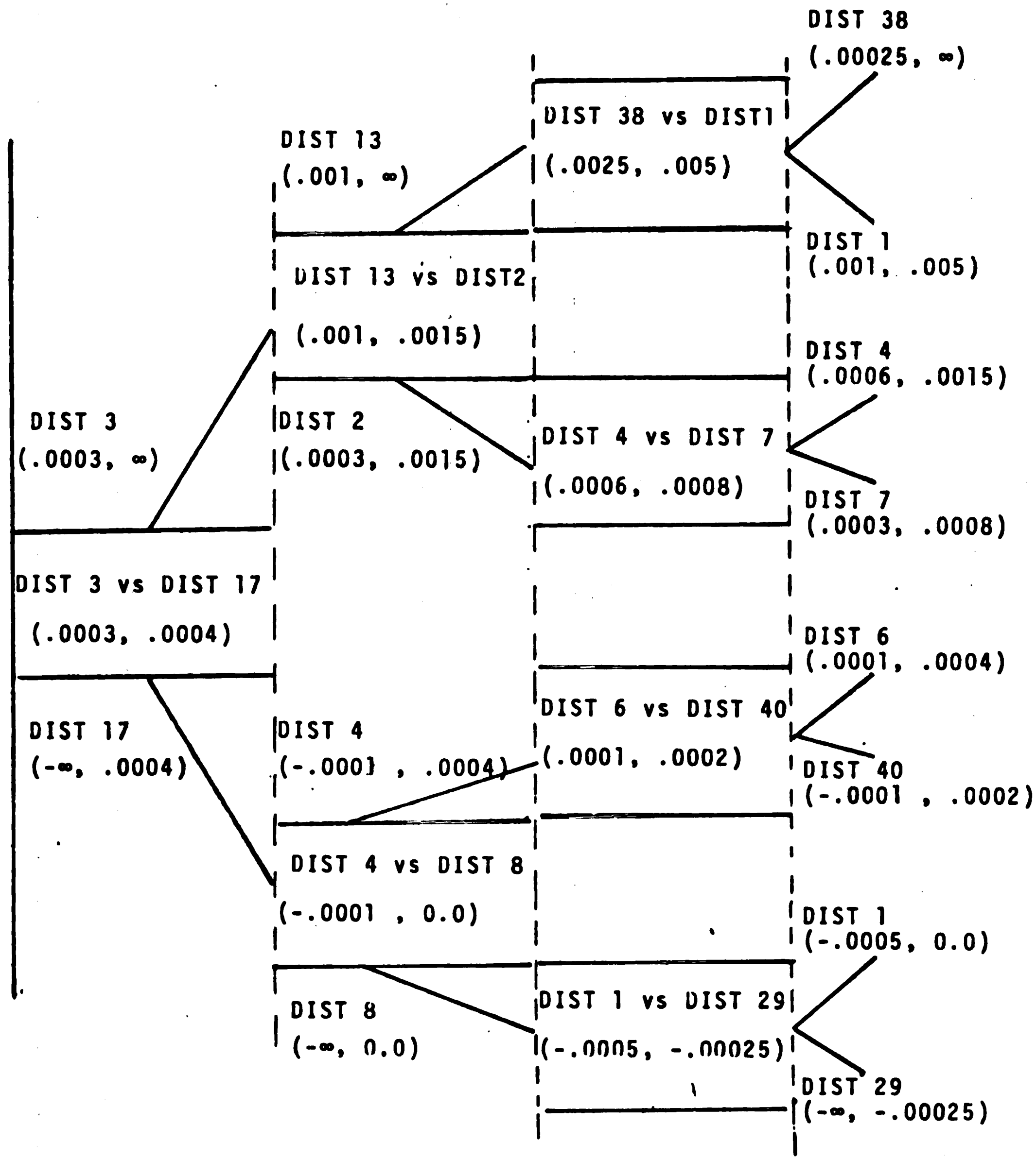


Figure 5-2. Hierarchy of comparison for income level II.

listed in Appendix A, several significant procedural points with respect to interval measurement deserve notation. First, for best results the questions ought to be put in the context of actual decision analysis. Second, some attempt to encourage the respondent to relate the process to his own situation is useful. A change was made in the instructions to the interval measurement section from 1979 to 1981. The change relates to the aversion to gambling problem encountered in some previous studies (Officer and Halter, 1968) and discussed in Chapter 2. The instructions for the first stage (1979) related the equal probabilities of the six possible outcomes in a distribution to the six sides of a die. Several individuals in the first stage sample were not particularly comfortable with this analogy. Although none of those individuals became part of the second stage (1981) sample (thus not part of intertemporal testing), a slight modification in the instructions seemed wise. The instructions were revised to simply state that each outcome has an equal change of occurring.

5.3 Other Data Collected by Questionnaire

The interval elicitation questions made up the beginning section of the questionnaire. The second part of the questionnaire asked for respondent data about the operator social characteristics. While the preference measurement portion remained unchanged from 1979 to 1981, the latter portion of the questionnaire did change. Carman collected respondent data on: marital status, age, number of children, education level, years living on the farm, years managing the farm, percentage of family income from farm, respondent's share of farm income, acreage, and selected personality traits. The 1981 survey did not attempt to include questions pertaining to all these data. Particularly questions were eliminated when their answers would either not change or could be calculated from 1979 survey answers. Such questions would include those on age, education, years living on farm, years managing the farm, etc. The answers to other questions such as those referring to acreage were available through other sources (see Section 5.4). Finally, the questions involving personality types were not carried into the 1981 survey. Carman (1979) found these data did not contribute to discrimination between groups. Neither are such nonobservable characteristics particularly useful in practical settings (Young and Findeis, 1979).

Questions added to the questionnaire (in 1981) included: the farmer's definition or risk, machinery-use acquisition and repair strategies, land tenure strategies and borrowing risk considerations. The data from these additional questions could not be applied to the intertemporal testing since it was available for only 1981. This will however be incorporated in a future report.

Prior to each stage of elicitation the questionnaire was pretested to improve instructions and design. Ten farmers participated in one or more stages of the pretesting. The main components of the interval approach and the questionnaire have been outlined. Work by King (1979) and Carman (1979) and experience of this study proved the interval approach was one the farmers could easily complete. The following sections include a discussion of sample selection. Descriptive characteristics of the sample members are presented, as is the secondary data source (Telfarm records).

5.4 The Sample Used for Data Collection

Sample selection is an important aspect of empirical research. The sample for this study is primarily purposive in nature. For the 1981 data collection stage the obvious purpose originates in the need to have a paired response. Several factors dominated the 1979 stage sample selection. These factors included: (1) the need for data to analyze the relationship between risk preferences and socioeconomic characteristics; (2) a need for stability in the sample so that participants would be available for intertemporal analysis; (3) cooperation of the sample members; and (4) a desire to represent several farm enterprise types (due to criticism of previous studies (Young, et al., 1979).

The sample was selected from the population of farmers participating in the Telfarm system. Telfarm represents a voluntary computerized record-keeping system coordinated by the Agricultural Economics Department of Michigan State University. Telfarm participants were selected as the sub-population because the system fits the factors for selection well. It provides complete and up-to-date records of farm income and financial data. Many of the members have been in the system for a considerable period and were not likely to withdraw. The Telfarm farmers also have a good track record of willingness to participate.

Within the Telfarm population the potential participants were chosen based on three criteria. The first criterion required that the sample come from one of three farm enterprise types: dairy, cash crop or cash crop-beef. These three groups represent the primary farm enterprises in Michigan. The use of several enterprises serves two important purposes. It reduces the nonrepresentativeness problem of previous studies critiqued by Young, et al., and Young and Findeis (1979). It also allows for the possible test of hypothesis that risk preferences are highly individualized and are not particularly correlated to farm enterprise type (Halter and Mason, 1980).

The second criterion of selection among the Telfarm population was their inclusion in the annual Business Analysis (1979 and 1981). All Telfarm members do not supply the proper information in a timely manner. Due to this problem, the yearly income and financial data would not be available and complete. Since it is the availability of these data that makes the Telfarm population so valuable to the analysis in Chapter 7, farmers not contributing data could not be used. The final criterion concerns the location of the sample. For cost purposes, and to a somewhat lesser degree, geographical homogeneity, the sample comes from six lower Michigan counties. It was within these criteria that the sample was selected.

Using a sample of this sort does involve certain disadvantages, particularly representativeness of the sample. While this sample is very representative of the Telfarm population, that population may not represent all farms in Michigan or in the U.S. In 1965 Rhoade tested the ability of Michigan Mail-in farm account data (prior to Telfarm) to represent the general population of Michigan farmers. He found dairy, cash grain and livestock (other than dairy and poultry) farms to be the most representative of census data. The farm account data was particularly representative for tillable acres, total receipts, total expenses and value of farm assets. Because of the nature of census data Rhoade could not make direct comparison for net income type data. Given the farm enterprise types selected (in this study), Rhoade's results indicate Telfarm records as fairly representative of Michigan for categories of larger farms within those enterprise types. A review of the most recent census data (1979 Census of Agriculture) reveals the Telfarm population as a reasonable proxy for commercial farms with sales greater than $20,000. The proportions of sample in each of the standard sales categories over $20,000 is similar to census figures. Other characteristics such as age and acreage generally reflect the U.S. averages. Thus the sample probably does not represent very large farms, small and part-time farms, or specialty farms. Yet for those commercial farms producing the bulk of the food and feed stuffs, the sample works well. Finally, representative or not, since the objectives are to test paired individuals, the use of a purposive sample in no way invalidates the testing.

In stage one (1979) mail questionnaires were sent to 80 Telfarm operators meeting the proposed criteria. Thirty-nine of the questionnaires were returned. Of the 39 returned 31 respondents completed the survey accurately enough to prove acceptable for analysis. In the second stage it was desired to have accurately completed questionnaires for 20 to 25 of these individuals. Thus, about a 70% return rate was required. The desired high return rate gave impetus to the use of personal interview technique for the second stage. It is well documented that personal interview surveys usually have a considerably better response rate than direct mailing (Mendenhall, Ott and Schaefer, 1971). Lower costs typically cause the latter to be used.

In this case having a maximum of 31 individuals to contact and all within a reasonable geographic area, cost was not a major consideration. The personal interview also facilitated the second part of the stage two (1981) questionnaire. All the questions in this section could not easily be assigned an objective marking system. The personal interview allowed more detailed answers for these questions.

The use of direct mailing for stage one and personal interviews for stage two constitutes a definite change in technique. Considerable effort was taken to eliminate any occurrence of interviewer bias during stage two. The interviews were conducted by only one person, the author. The instructions for completing the risk interval part of the questionnaire (the same for both stages) were read by the respondent and the interviewer answered questions only for clarification of instructions. And the interval measurement section was administered first so that none of the subjective questioning would influence answers. Due to these measures the change in survey technique most likely did not bias test results.

5.5 Sample Description

Twenty-five of the usable stage one respondents were contacted. One of these no longer enrolled in Telfarm and another refused the interview. The sample for intertemporal testing thus consists of 23 farm operators. Therefore the response rate equalled the desired 70% level. The sample consists of 12 dairy farmers, 7 cash crop farmers and 4 beef-cash crop farmers. These proportions are almost exactly the same as the percentage for each enterprise type making up the original 80 contacted in stage one. Figure 5-3 designates the six

Figure 5-3. Number of Sample Farms in Each of Six Michigan Counties.

counties included in the survey and the number of sample farms in each.

Socioeconomic characteristics of the respondents play an important role in objective two. Various measures are also useful in understanding just what size farms and type of farm families the sample represents. Some of the more descriptive characteristics are found in Table 5-1. As seen from the table most of the individuals in the sample operate medium to large commercial farms. Only two or three of the farms would be considered part time. Even on the part-time farms the farm income comprises 50% of the individual's income. Seventy-four percent of the respondents were solely dependent on farm income (95% or more of their income from the farm). Established farmers comprised most of the sample, with no farmer having less than five years managing experience in 1979. While eleven of the twenty-three farmers were in their fifties, eight of the eleven were in a partner or corporate arrangement with a younger family member.

The typical sample member had three children. The majority (52%) were educated through the high school level. Seventeen percent did not complete high school. Twenty-two percent completed some college (usually ag-tech) and nine percent had a bachelor degree. All but one has resided on a farm since early childhood.

Twenty-one of the 23 operators were married in 1979. The same was true in 1981. Little change occurred in acreage owned between 1979 and 1981. The income measures mostly increased in dollar amount, but care should be taken with generalization as not all farmers had increased incomes. Interesting to note is that while income measures went up and little land was purchased the percentage equity remained about the same. This result is probably indicative of the

Table 5-1. Selected Measures for Descriptions of the 23 Sample Farms

Measure	1978-79	1980-81
Gross Income: $		
Median	170,668	245,662
Range	36,739 to 635,907	52,663 to 766,177
Total sales: $		
Median	169,600	231,900
Range	22,017 to 470,000	52,900 to 680,300
Net farm income: $		
Median	45,500	52,500
Range	-15,161 to 155,340	-62,200 to 230,500
Net cash income: $		
Median	46,617	67,542
Range	-12,565 to 132,832	16,500 to 149,705
Tillable acres owned: A		
Median	217	220
Range	0 to 608	34 to 698
Total acres tilled: A		
Median	405	408
Range	134 to 998	137 to 1019
Age: years		
Median	45	47
Range	20 to 58	22 to 60
Years managing farm:		
Median	24	26
Range	5 to 38	7 to 40
Net worth/total assets: $		
Median	.70	.73
Range	.25 to 1.03	.27 to 1.02

Source: Michigan Telfarm Records and unpublished data collected by Garth Carman.

farm sector in general over that period.

5.6 Summary

This chapter outlined the specification of the interval measurement approach as used in risk preference data collection. It also discussed other data needs for testing preference-characteristic relationships. A sample of commercial Michigan farmers was selected for its ability to fulfill the selection criteria. The chapter described the sample as to geographic location, enterprises, farm size, farm income and operator characteristics. The next chapter reports the risk interval data measured using this sample and analyzes it for intertemporal stability.

Chapter 6

INTERTEMPORAL COMPARISON OF RISK PREFERENCES

6.1 Introduction

What do agricultural economists know about the intertemporal stability of risk preferences? First, just what does "know" mean in this situation? Scientific inquiry is a general process for the search of knowledge. Cohen and Nagal (1953) write that "scientific method aims to discover what the facts truly are." Knowledge is the evidence and the understanding of that evidence as to the truth or falseness of a fact. Carnap (1953) notes that we can have knowledge as to truth of fact in two forms: analytic and synthetic. Analytic knowledge is that which does not refer to the real world. This type of knowledge is expressible in purely logical statements. Such statements are either true or contradictory. The validation of the truth of these statements is strictly based on syntax.

Most empirically tested hypotheses are synthetic statements about fact. Cohen and Nagal state that "The 'facts' for which every inquiry searches out are propositions for whose truth there is considerable evidence. Consequently what the 'facts' are must be determined by inquiry, and cannot be determined antecedently of inquiry." Moreover, what is believed to be the facts depends on the stage of inquiry. There is therefore no sharp line dividing facts from hypotheses. "Risk preferences are intertemporally stable" is a hypothesis about fact. The accuracy of the hypothesis with respect to fact must be tested. The truth or falseness of a synthetic statement is tested through the process of verification. The evidence of a hypothesis' correspondence with actual real world occurrences forms the basis for its verification. And the evidence necessary to verify the hypothetical proposition as true or false fact usually comes from experiments designed for the collection and analysis of empirical data.

With knowledge being defined as this evidence and the understanding of the evidence it is now possible to approach the question proposed at the commencement of this section. The next sections of this chapter review the evidence available from previous empirical studies. Later sections report and analyze additional evidence supported by the data from this study.

6.2 Previous Research on Preferences at Two Points in Time

It would appear that agricultural economists working in the area of decision theory often hold the hypothesis that individual's risk preferences change over time (Officer and Halter). At the same time most research excludes the effects and implications of time varying risk preferences (Halter and Mason; Young, et. al.). In investigating the possibility of large scale estimation of U.S. agricultural producers' risk preferences, Young, et al. said "Changing objectives, information and attitudes could make an individual's risk aversion coefficient an elusive moving target." One of the primary reservations with respect to eliciting risk preferences in the Young, et al. paper was the possibility that risk preferences are not intertemporally stable. Young, et al. goes on to note the lack of verification of this proposition in stating, "The issue of the stability of risk preferences is ultimately an empirical question whose resolution would require longitudinal studies." This concern is not new. Over fifteen years ago Officer and Halter realized that if risk preference estimation was to be useful in applied decision making, the question of the effect of time on preferences would need to be resolved. Some of the most recent literature (Robison, 1982; Whitaker and Winter) still notes the importance and lack of resolution of this question.

Although the literature is not completely void of reports on empirical research in intertemporal risk preferences, the numbers are few. There are two studies of note. Officer and Halter in their pioneering work on risk attitude measurement of agricultural producers did estimate risk attitudes for two points in time. One of their hypotheses was that "if utility functions are to serve as a guide to the decision maker, they must be derived at each point in time." Their hypothesis in effect implies lack of intertemporal stability. The sample consisted of four wool producers in Australia. Two direct elicitation techniques were employed to derive utility: a modified von Neumann-Morgenstern technique and the Ramsey technique. The first technique requires a series of choices by the individual between pairs of uncertain and certain alternatives. The latter has individuals choose between pairs of uncertain outcomes. Officer and Halter surveyed the producers two times, one year apart, using both methods to elicit points on the utility functions. Functions of first, second or third powers were then fitted to each set of points. Officer and Halter used the slope of the indifference curves in mean-variance space as the measure of risk aversion (see measure iv, Table 2-1). This measure is directly proportional to the Pratt risk aversion coefficient defined in Chapter 2 (i.e. Pratt coefficient equals two times the Officer-Halter index for a quadratic utility function). The risk aversion indices were estimated for one income level only, Ł800. The indices reported in the first stage of their paper were based on utility functions from the modified von Neumann-Morgenstern technique. Those for the second stage came from the estimated functions based on the Ramsey technique. Halter and Officer's analysis showed the following: One farmer changed from risk neutral to slightly risk averse; one changed from slightly risk averse to slightly risk preferring, and two became only slightly less risk averse. The only conclusion they reached as to their hypothesis of intertemporal instability or risk preferences was that "over a period of a year . . . their (the farmers') utility functions did not change radically."

Time has proven that there are significant shortcomings in the reliability of their results. Officer and Halter themselves questioned the appropriateness of the modified von Neumann-Morgenstern approach. They also noted the small sample size. Lin, Dean and Moore called attention to another problem of the study. They noted that Officer and Halter arbitrarily affected the shape and origin scale of the utility functions when using the Ramsey approach. So, too, should one question the direct elicitation approach in general (see Chapter 2). Finally, the use of different techniques of utility function estimation for comparison is not fully understood. Officer and Halter never explained why they did not compare indices derived from utility functions estimated by the same technique. Using the Ramsey technique alone, two individuals changed from risk preferring to risk averse, one became slightly less risk preferring and the fourth changed from slightly risk averse to more risk averse. This comparison seems to indicate less intertemporal stability than the authors concluded using two different techniques.

Whitaker and Winter also completed a longitudinal study of risk preferences. They used estimated utility function data from a 1974 study by Halter and Mason on 44 Willimette Valley (Oregon) grass seed producers. Whitaker and Winter reestimated utility functions for 37 of these producers in 1974. The modified Ramsey approach (see Chapter 2) was used to estimate points on the producer utility functions at each stage. Whitaker and Winter did not specifically address the question of intertemporal stability of risk preferences. Rather they used regression techniques to explain the individual's risk attitudes as a function of certain socioeconomic characteristics.

Analysis for the 1974 and 1976 stages was completed in the same manner. Pratt risk aversion coefficients were estimated at the producers' individual gross income levels. The risk aversion coefficients were then regressed on a set of socioeconomic independent variables. The 1976 regression coefficients were then compared to the 1974 Halter-Mason results. While the regression coefficients were compared, no effort was made to document the change or lack of change between time periods in the risk aversion coefficients. Whitaker and Winter only report that the mean value for the Pratt coefficient went from .4 in 1974 to -.29 in 1976. They report nothing as to the distribution of risk aversion coefficients or individual pairings.

It would be interesting and helpful to have the Whitaker and Winter data reported and analyzed in a published form. On the surface, based on the regression results and the comparison of risk aversion coefficient means, their data might imply instability of risk preferences. One ought to be very careful in making such an inference. First, regression coefficients sign change does not imply a change in individual risk preferences. Especially when the income level used to estimate risk aversion varies both between time periods and within each cross-section resulting in a stochastic point of reference for income, making accurate comparison difficult. Also in comparing cross-section data, the possibility exists that changes in independent variables may cause sign changes just as readily as changes in the dependent variable. Moreover, comparison of the sample means between time periods may indicate instability, but mean comparison can be very misleading without further information. Finally, their technique for elicitating utility shares the same problems as all direct elicitation methods.

6.3 Data Format

The interval measurement approach described in Chapter 4 was used to estimate risk aversion intervals for twenty-three central lower Michigan commercial farmers. Risk aversion measures in the neighborhood of four income levels were estimated in 1979 and 1981. The income ranges (bounds on the neighborhood) and the mean income levels (in parentheses) corresponding to each range are: I. -$1,000 to $1,000, ($0); II. $9,000 to $11,000 ($10,000); III. $22,000 to $28,000, ($25,000); and IV. $40,000 to $50,000, ($45,000).

Each individual in the sample was required to make three choices between pairs of distributions of possible after-tax incomes (see Appendix A for questionnaire). This procedure was repeated for each of the four income ranges. Based on these choices, the individual's average absolute risk aversion could be bounded by one of eight intervals. Each interval may be defined by its bounds for example:

$$x = [r_A(y^*)_L, r_A(y^*)_U]$$

where:

$r_A(y)_L$ is the average absolute risk aversion coefficient at income y^* for the lower bound of interval x

$r_A(y)_U$ is the average absolute risk aversion coefficient at income y^* for the upper bound of the interval x.

Figure 6-1 depicts interval x graphically. Table 6-1 displays the possible intervals for each of the four income ranges used in this research. The intervals are derived based on the procedure outlined in Chapter 4.

The elicited risk preference data thus consists of two sets of four intervals each per sample member. One set represents the 1979 results and the other the 1981 results. An example of a bounded risk aversion interval is found in Figure 6-2. The example is specific to the actual income ranges and intervals used in the survey. The individual represented in the figure has an average risk aversion bounded by interval #2 for the neighborhood of \$0, interval #5 for \$10,000, interval #4 for \$25,000 and interval #3 for \$45,000. Similar bounded intervals could be constructed for each individual in each measurement period.

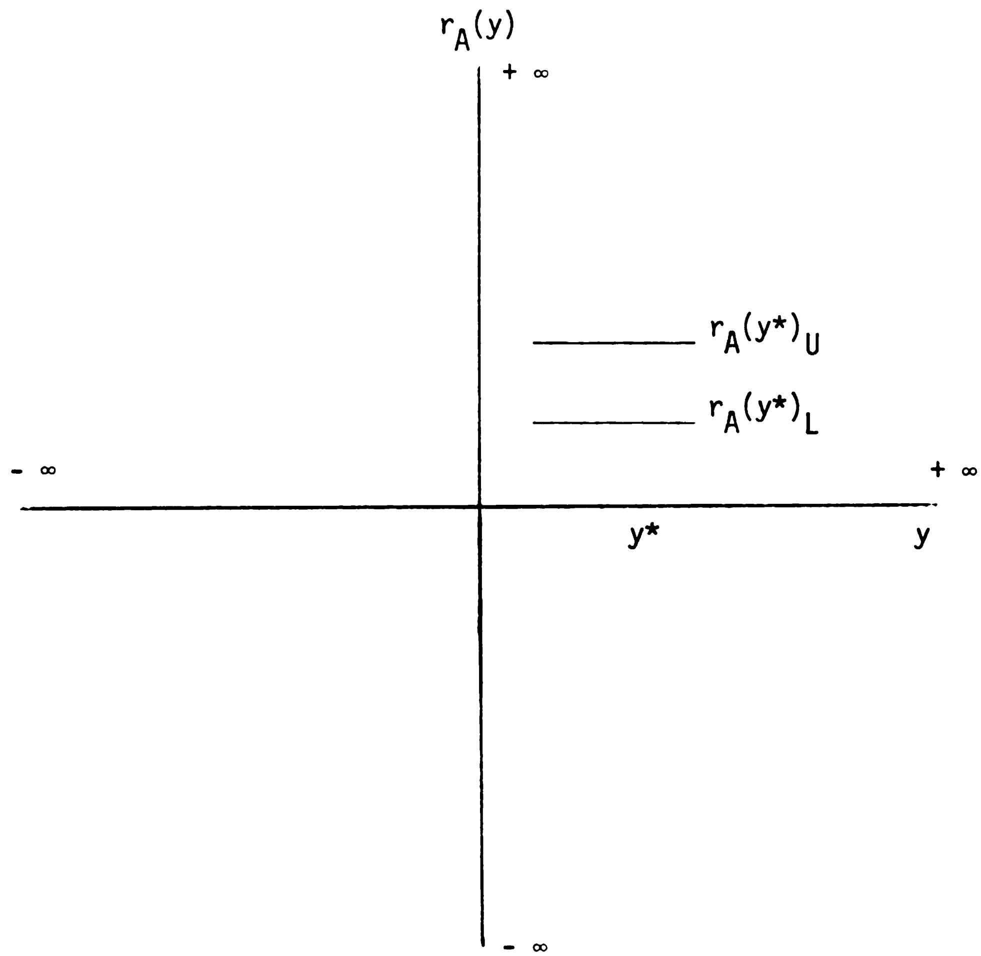


Figure 6-1. Example of an Average Absolute Risk Aversion Interval Measured Over Income Range Represented by Mean Income y*.

Table 6-1. Enumeration of Interval Boundaries on Average Absolute Risk Aversion

Level	I	II	III	IV
Income Range:	$-1000 to 1000	9000 to 11000	22000 to 28000	40000 to 50000
Interval No.	Bounds on Average Risk Aversion			
1	(-∞, -.00025)	(-∞, -.00025)	(-∞, -.00025)	(-∞, -00025)
2	(-.0005, 0.0)	(-.0005, 0.0)	(-.0005, 0.0)	(-.0005, 0.0)
3	(-.0001, .0002)	(-.0001, .0002)	(-.0001, .0002)	(-.0001, .0002)
4	(.0001, .0004)	(.0001, .0004)	(.0001, .0004)	(.0001, .0004)
5	(.0003, .0008)	(.0003, .0008)	(.0003, .0008)	(.0003, .0008)
6	(.0006, .0025)	(.0006, .0015)	(.0006, .0015)	(.0006, .0015)
7	(.0015, .005)	(.001, .005)	(.001, .005)	(.001, .005)
8	(.0025, ∞)	(.0025, ∞)	(.0025, ∞)	(.0025, ∞)

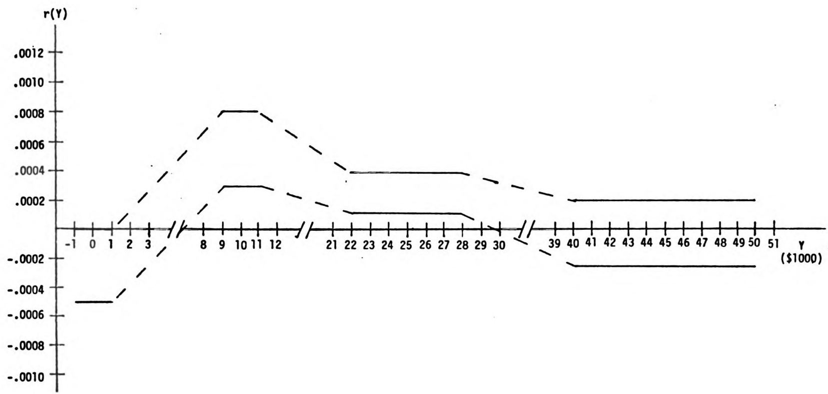


Figure 6-2. Example of an Average Absolute Risk Aversion Interval Using the Interval Specification and Income Ranges of the Survey

6.4 Data Analysis

6.4.1 Introduction

Data analysis in this chapter is keyed to hypothesis number one. Hypothesis number one states that risk preferences of individual farmers are intertemporally stable. While the verification of the hypothesis depends on analysis of individual data, analysis of cumulative data provides some insight as well. This is especially true considering the capabilities of the interval approach as an instrument for grouping farmers into risk preference classes for decision making. Such information is especially important to the possibility of including risk theory in policy making and group prescription (Lins, Gabriel and Sonka, 1982; Officer, Halter and Dillon, 1967).

The data are analyzed from two frames of reference. First risk preferences of the sample as a whole are described and the group data are compared between time periods. The latter compares individual risk preferences between time periods. This analysis supplies the evidence necessary to test the intertemporal stability hypothesis.

6.4.2 Analysis of Aggregate Data

Table 6-2 records the percentage of sample members whose average risk aversion is estimated to lie within each interval, for both 1979 and 1981. Table 6-3 presents the same data as cumulative percentages. The percentages cumulate from the interval bounding the most risk preferring regions (1) to that interval bounding the most risk averse regions (8). Several preliminary deductions could be based on the group results. The data demonstrate, at all levels of income tested, that the average risk aversion of at least some individuals could be located within wholly risk preferring intervals, wholly risk

Table 6-2. Percentage of risk aversion functions bounded by each interval. 1979 and 1981

Panel A.

Income Level	1979			
	I	II	III	IV
Interval #				
1	26.1	17.4	21.7	26.1
2	17.4	8.7	21.7	13.0
3	47.8	21.7	21.7	30.4
4	0	21.7	21.7	8.7
5	8.7	17.4	0	8.7
6	0	8.7	4.3	0
7	0	0	4.3	8.7
8	0	4.3	4.3	4.3

Panel B.

Income Level	1981			
	I	II	III	IV
Interval #				
1	34.8	21.7	34.8	21.7
2	8.7	13.0	21.7	26.1
3	30.4	17.4	8.7	13.0
4	8.7	21.7	30.4	13.0
5	0	17.4	0	8.7
6	4.3	0	0	0
7	4.3	0	0	4.3
8	8.7	8.7	4.3	13.0

Table6-3. Cumulative percentage of risk aversion functions bounded through each interval, 1 to 8. 1979 and 1981

Panel A.	1979			
Income Level	I	II	III	IV
Interval #				
1	26.1	17.4	21.7	26.1
2	43.5	26.1	43.4	39.1
3	91.3	47.8	65.1	69.5
4	91.3	69.5	86.9	78.2
5	100.0	86.9	86.9	86.9
6	100.0	95.6	91.1	86.9
7	100.0	95.6	95.6	95.6
8	100.0	100.0	100.0	100.0
Panel B.	**1981**			
Income Level	I	II	III	IV
Interval #				
1	34.8	21.7	34.8	21.7
2	43.5	34.8	56.5	47.8
3	73.9	52.1	65.2	60.8
4	82.6	73.8	95.6	73.8
5	82.6	91.1	95.6	82.6
6	86.9	91.1	95.6	82.5
7	91.1	91.1	95.6	86.9
8	100.0	100.0	100.0	100.0

averse intervals and intervals allowing for mixed as well as risk neutral functions. This result is not unexpected based on previous studies measuring risk preferences in developed economies. Halter and Mason reported their estimations showed approximately an equal division between risk averse, risk neutral and risk preferring. Young, et al. reviewed previous empirical experiments designed to measure farmers' risk preferences. And based on those studies taking samples from developed countries and applying measurement techniques which allow for risk preferring, mixed or neutral, and risk averse outcomes, the percentages of the samples falling in each reference classification were 28%, 33% and 39% respectively. Some care should be taken using these results. Special difficulties occur in aggregating these data. The differing measurement techniques and nonuniformity of income level used for risk preference estimation cause the difficulty. It does seem evident that the data in Table 6-2, while not conclusive, definitely reinforce the likelihood of there being risk averse, risk preferring and risk neutral decision makers at each income level examined.

The respondents tended to be least risk averse for incomes in the neighborhood of $0. For both 1979 and 1981 the cumulative percentages of the three most risk preferring intervals were highest for income level I. This point is most easily recognized when Figures 6-3A, B are compared with Figures 6-4A, B; 6-5A, B; 6-6A, B. The percentage of individuals' average risk aversion estimated to lie within any given interval varies least (least evenly distributed) at income level I and is most dense over the first three intervals. This outcome might have been expected for several reasons.

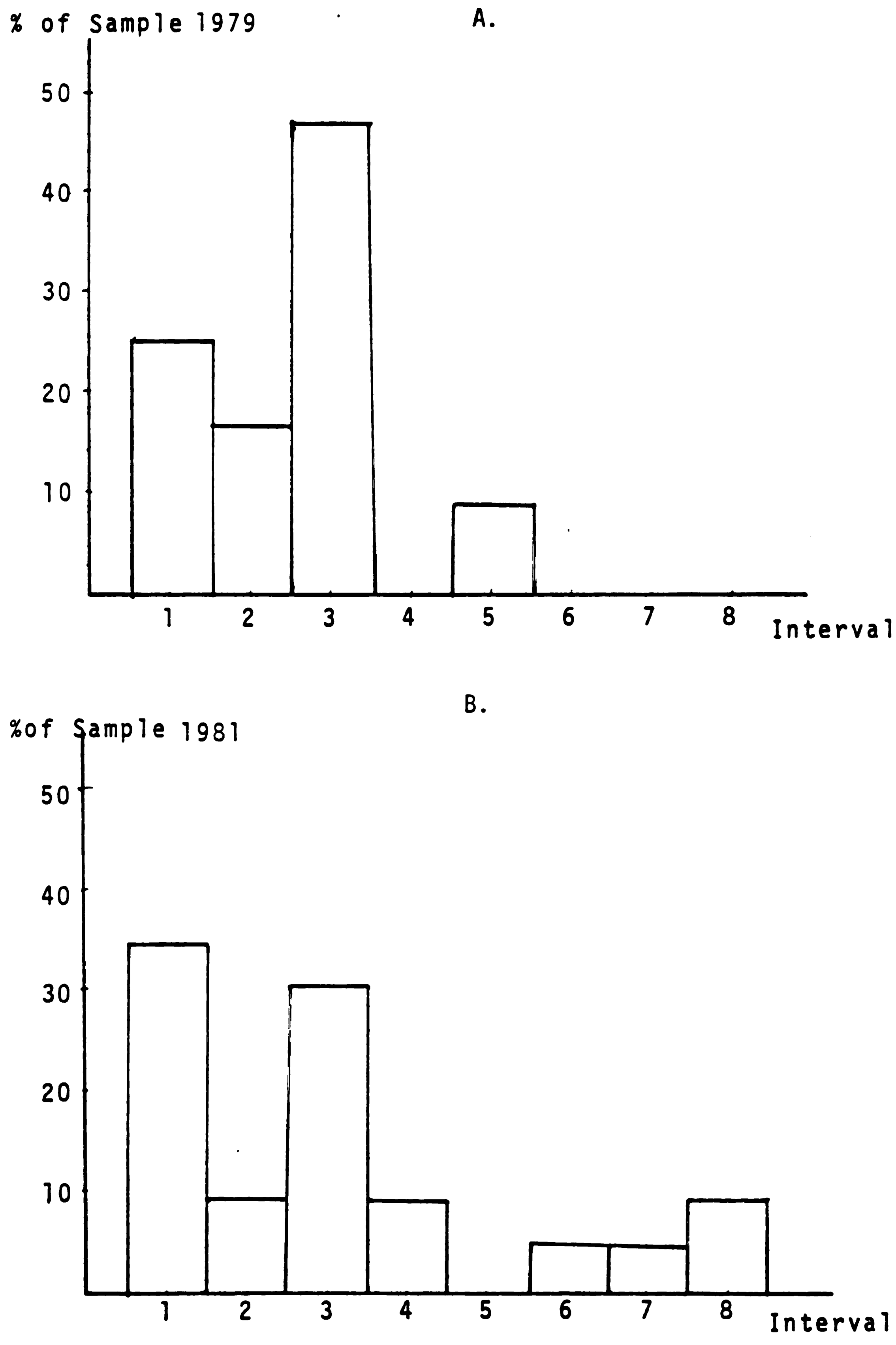
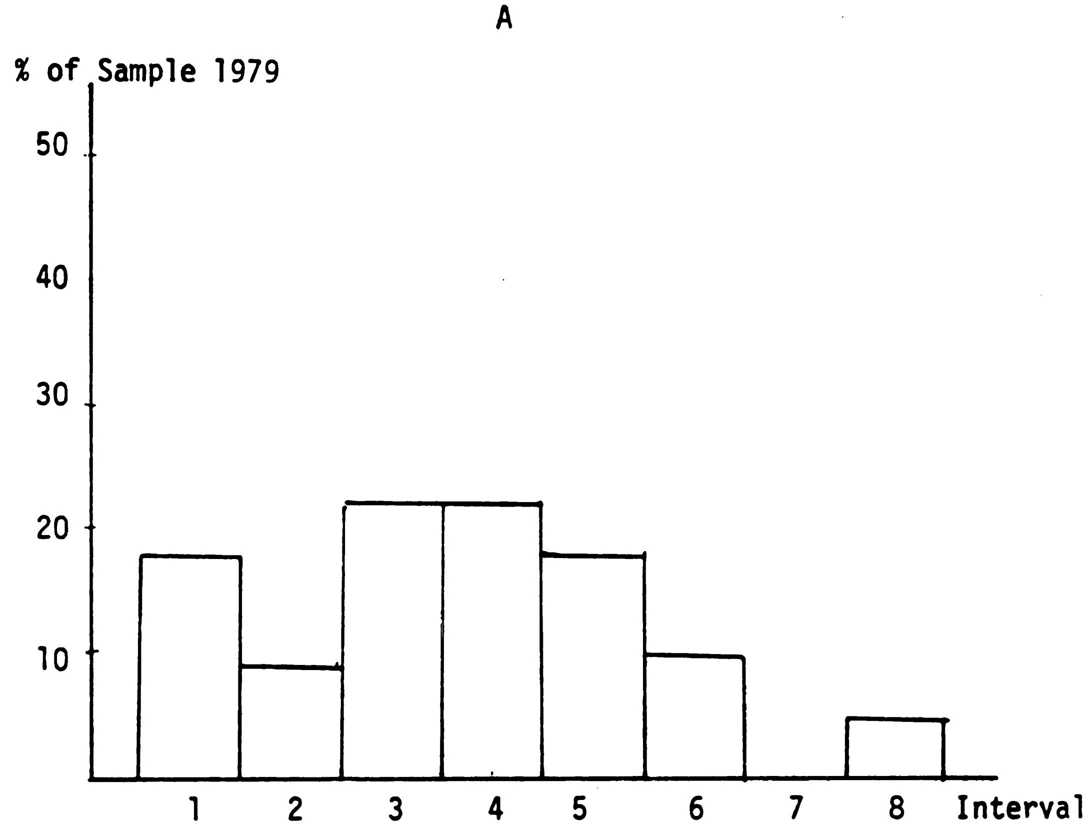


Figure 6-3. Percentage of sample in each interval for income level I: 1979 and 1981.



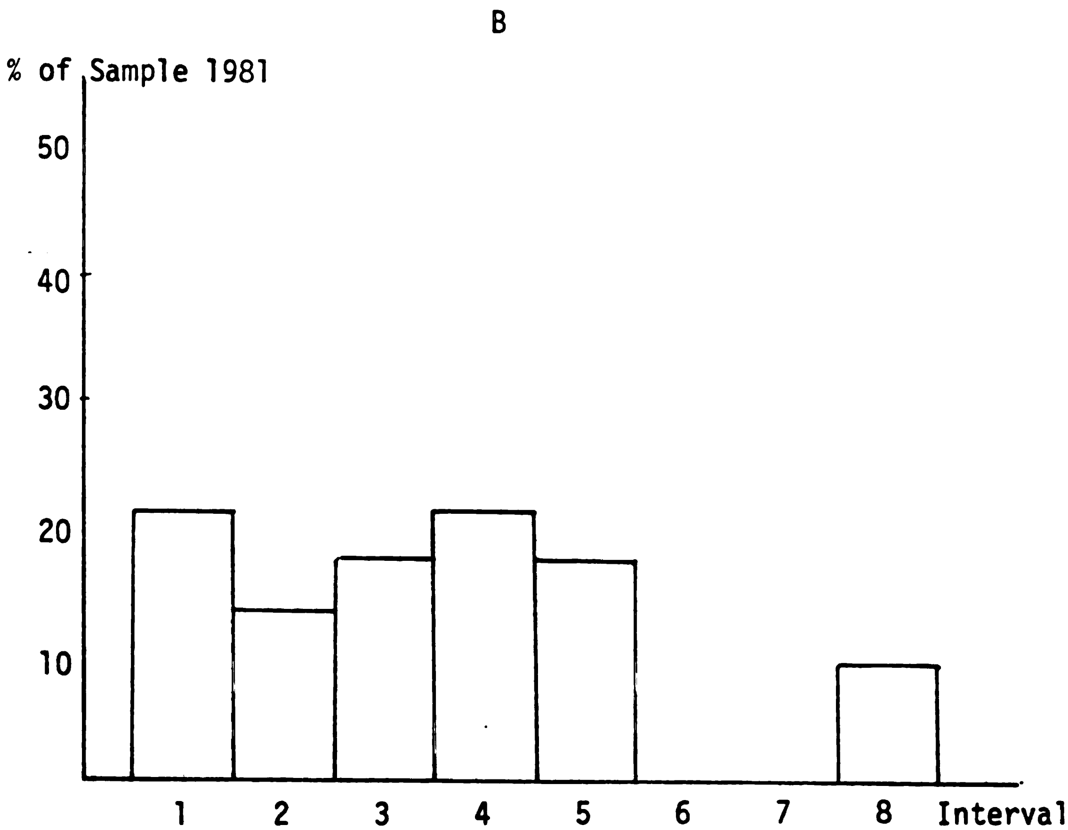


Figure 6-4. Percentage of Sample in Each Interval for Income Level II: 1979 and 1981

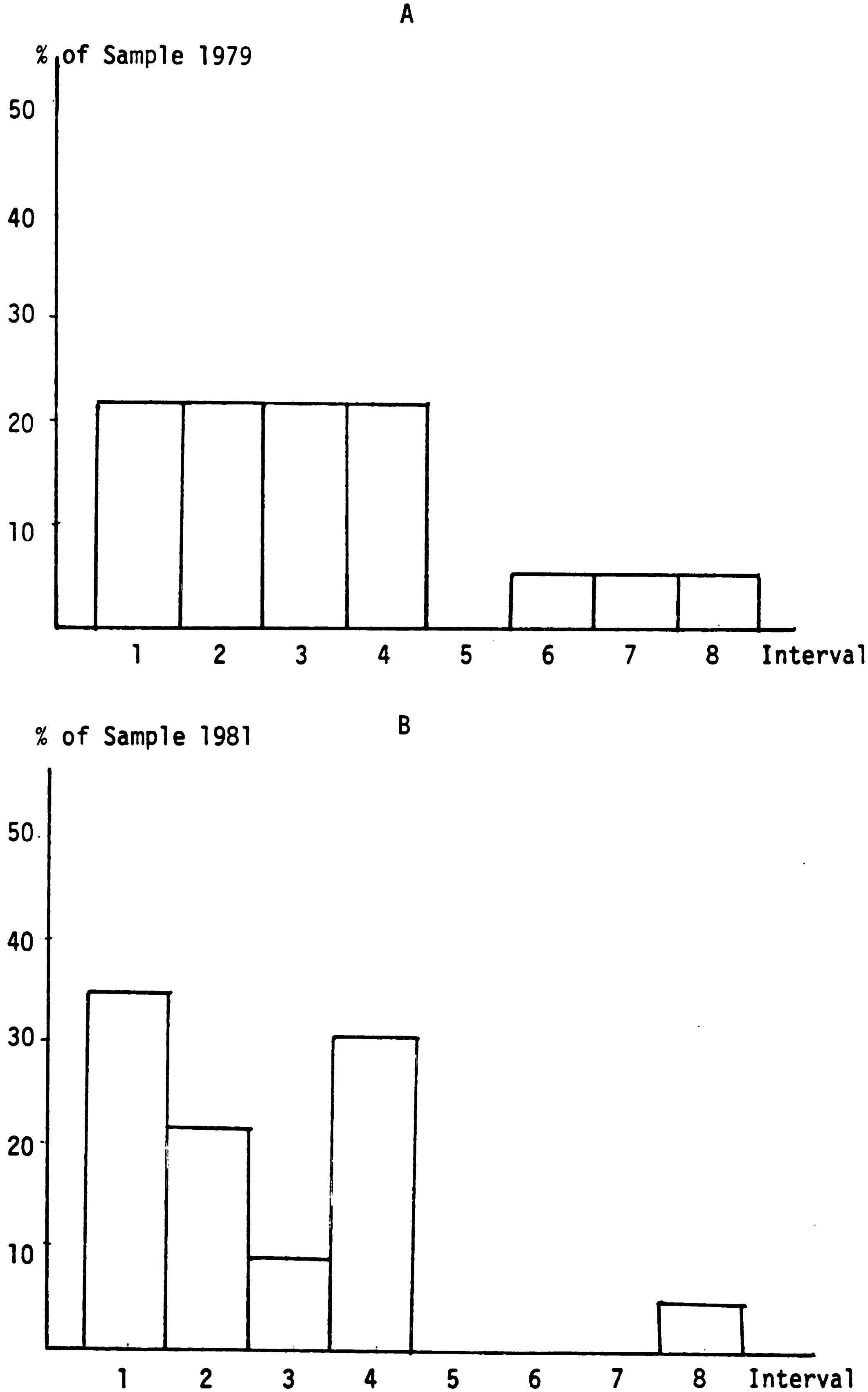


Figure 6-5. Percentage of Sample in Each Interval for Income Level III: 1979 and 1981

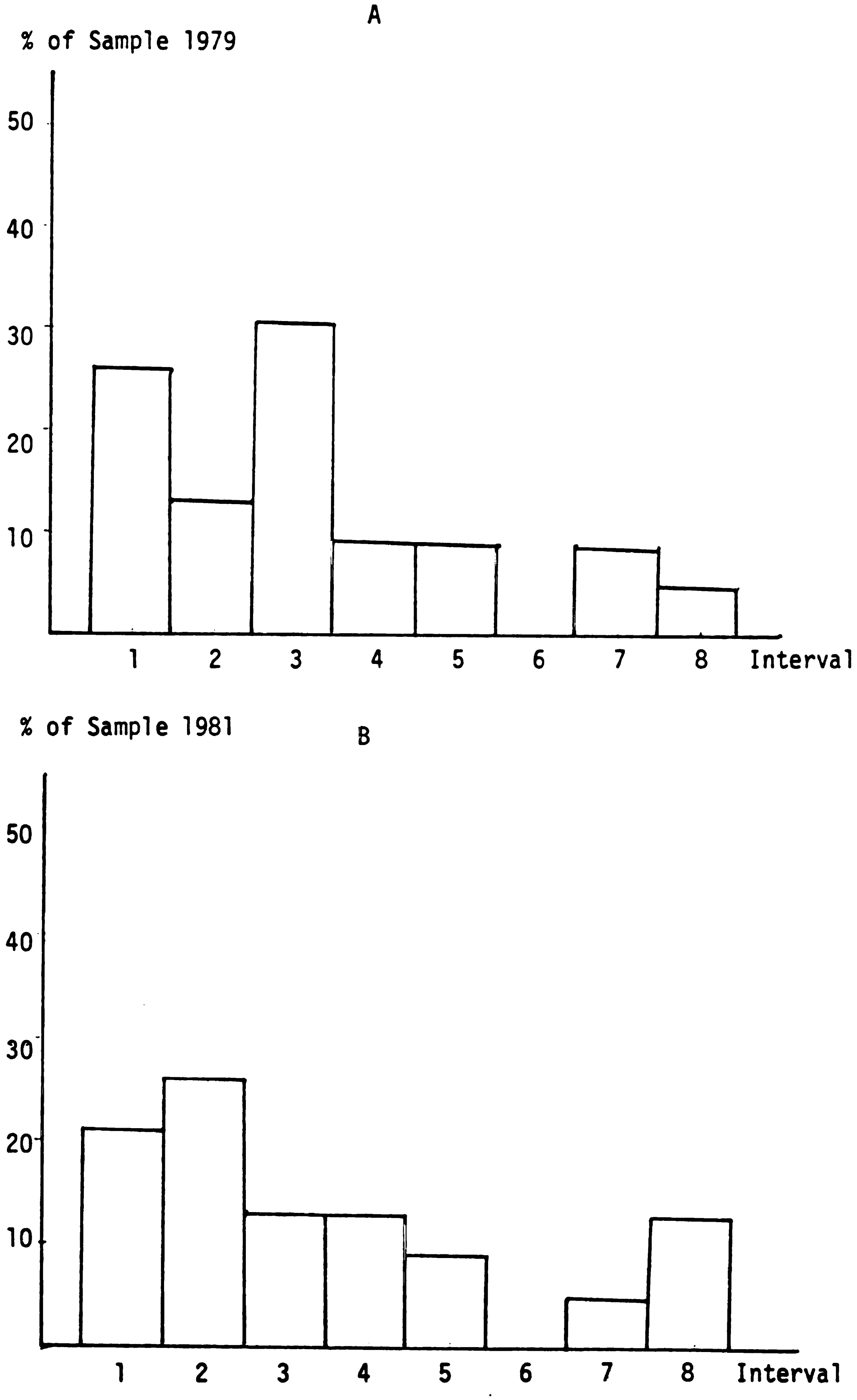


Figure 6-6. Percentage of Sample in Each Interval for Income Level IV: 1979 and 1981

Farmers may have been willing to take added risk at the $0 income level due to the relatively small magnitude of absolute dollar amounts and variability of the paired distributions. It was noted from farmer comments that while they make decisions involving a wide range of dollar values, many put little time and effort into decisions involving dollar amounts in the $0 - $500 range. If this be the case, perhaps there exists a critical dollar amount below which the intermediate steps in a typical decision process are not exercised. Therefore a somewhat altered decision process might be used for small monetary values, resulting in some of the difference between distributions.

It also became apparent that the sample members almost never experienced the $-1,000 to $1,000 income range. Therefore comparison at that level becomes difficult and unrealistic. Robison (1982a) deduced a theoretical model from observed behavior similar to that here observed. In combining properties of the safety-first and expected loss criteria with those of stochastic dominance he refers to a "disaster" income. Outcomes below the "disaster" income are viewed no worse than the disaster income itself. It does not appear that one year's income at or near Level I constitutes a disaster outcome for most farmers in the sample. Yet, since most have not experienced such incomes in the recent past nor likely expect to in the near future, outcomes at this level may take on some of the properties of "disaster" incomes.

Risk averse tendencies were greatest for the $9,000 to $11,000 income range. Figures 6-4A and 6-4B show the respondents most evenly distributed among the intervals at income level II. So too does Level II have the lowest percentage of respondents in either the three or four least risk averse intervals (1 thru 3 and 1 thru 4). This is true of the 1979 and 1981 data. Such a response seems rather reasonable. Income level II represents "poor year" scenario incomes typically experienced by the sample members. In other words, incomes around $10,000 probably represent the lowest most individuals in the sample have experienced in the recent past or expect to experience in the near future. At or near the level II range of incomes the loss of an extra $1000 or so might mean considerable hardship on the farm family or critically reduce the ability to meet fixed responsibilities. Thus, farmers as a group might tend to be more averse over this range.

Although such inference may come from the aggregate data, it should be understood that the same may not be true based on individual risk preference intervals. In reviewing the bounds on each respondent's average risk aversion it is possible to derive at least one measure from the individual results. That measure is the percentage of sample members whose average risk aversion was bounded by no interval more risk averse at the other income levels than at level II (i.e. percentage whose interval number for level II $\geq$ highest interval number for levels I, III and IV). The measure is 56% for the 46 data points for 1979 and 1981. A broader base of individual data is also available. These data include the 46 sample points aforementioned and 24 additional points of nonpaired respondents from 1979 to 1981. For this group of seventy, the proportion most risk averse at level II is 59%.

Unfortunately no previous studies had an experimental design which could supply evidence to this observation. All either limited their risk measure to one income point or range, or assumed a particular functional form. The observation may give some cause to reconsider two functional representations of preferences previously developed. Both the Friedman-Savage function and safety-first criterion in part represent this outcome. Yet neither demonstrates enough flexibility to explain the extent of variability experienced.

The proportions of the sample in risk preferring, risk neutral and mixed, and risk averse regions were similar for the upper two income levels. This similarity holds for both 1979 and 1981. It is interesting to note that the proportions in these regions for the highest income level (IV) most resemble the proportions reported by Halter and Mason. Halter and Mason estimated risk aversion coefficients at a single income point, the farmers' gross incomes. Income level IV represents incomes less than the gross incomes of all the respondents in this study. One would thus expect if the Halter and Mason results are at all valid or generalizable the data presented here would most approximate their results at the highest level (IV). Which indeed did occur. Despite this, the variability of individual functions presented in this study (see Table 6-4) make such a comparison questionable. Therefore any conclusions from extending the risk aversion intervals past the high point of level IV would truly be heroic.

Interval three allows for the average risk aversion to be slightly averse, neutral or slightly preferring. For income levels II, III and IV, approximately 20% of the sample was located in this interval. Given this result, the assumption of risk neutrality may be valid for many decisions farmers make. Conversely at least 70% of the sample's estimated risk aversion functions lie in intervals not including risk neutrality.

The high percentage not at or near risk neutrality supports the conclusions of Lin, Dean and Moore, "that Bernoullian utility maximization explains actual farmer behavior more accurately than profit maximization." The results also reinforce the call for improved application of utility theory to decision making.

The group data should also be reviewed with respect to comparisons between 1979 and 1981. Several observations may be garnered. First, the 1981 estimations show more sample members falling into the extreme intervals (1 and 8) than the 1979 results (note Figures 6-3A, B through 6-6A,B). In all but one of the income levels the percentage of the individuals whose average risk aversion is bounded by intervals 1 and 8 is greater than or equal to the 1979 percentage. No reason for this change is apparent. However two prospects do come to mind. These include a possible change due to increased uncertainty experienced from 1979 to 1981 and the chance of a learning process due to past experience with the questionnaire.

The proportion of the sample responses in risk preferring intervals #1 and #2 increased from 1979 to 1981 for each of the three higher income ranges (see Figures 6-7 and 6-10). For income levels II, III and IV the increase was 28%. Although the validity of their results is questionable, this tendency is at least similar to the direction of change implied in the Whitaker-Winter study.

6.4.3 Analysis of Individual Data

Due to the assumption of the interval approach and the primary intent of testing individual risk preferences, further analysis on cumulative data could be misleading. More appropriately the data of the individual sample members requires consideration. Table 6-4 lists the

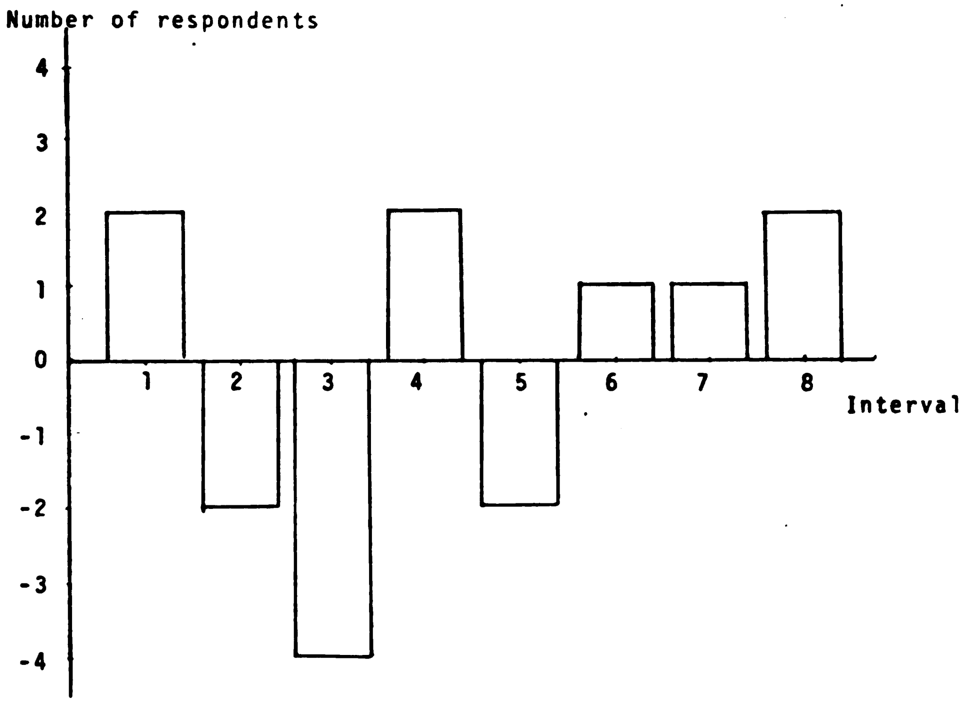


Figure 6-7. Change in number of sample members in each interval from 1979 to 1981 for income level I.

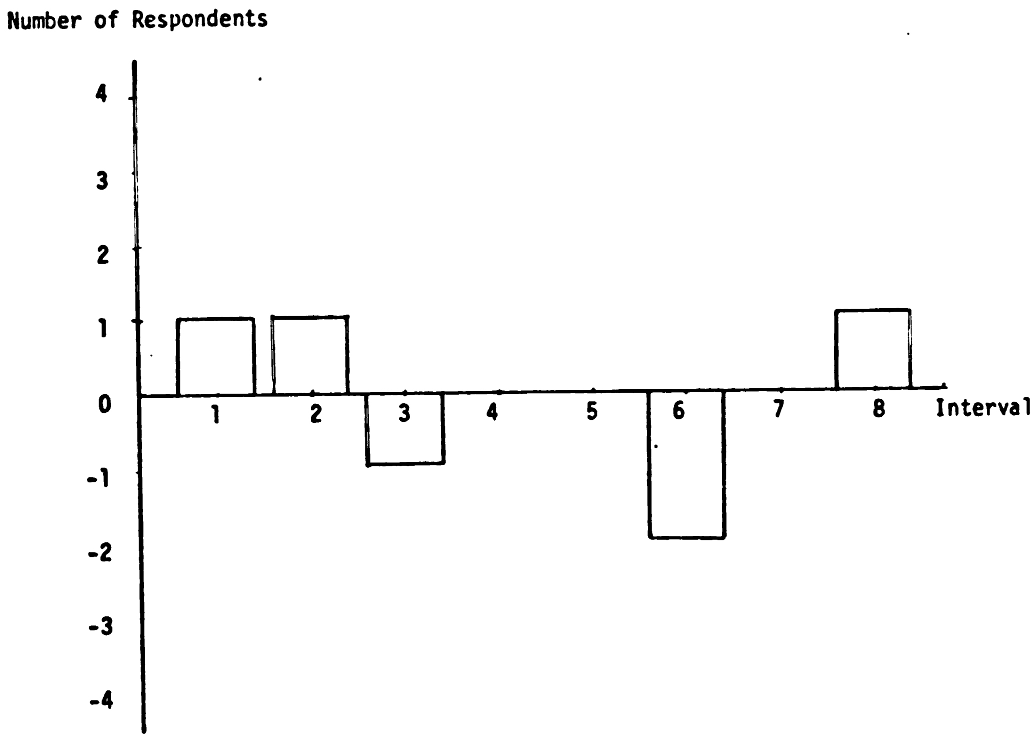


Figure 6-8. Change in Number of Sample Members in Each Interval from 1979 to 1981 for Income Level II.

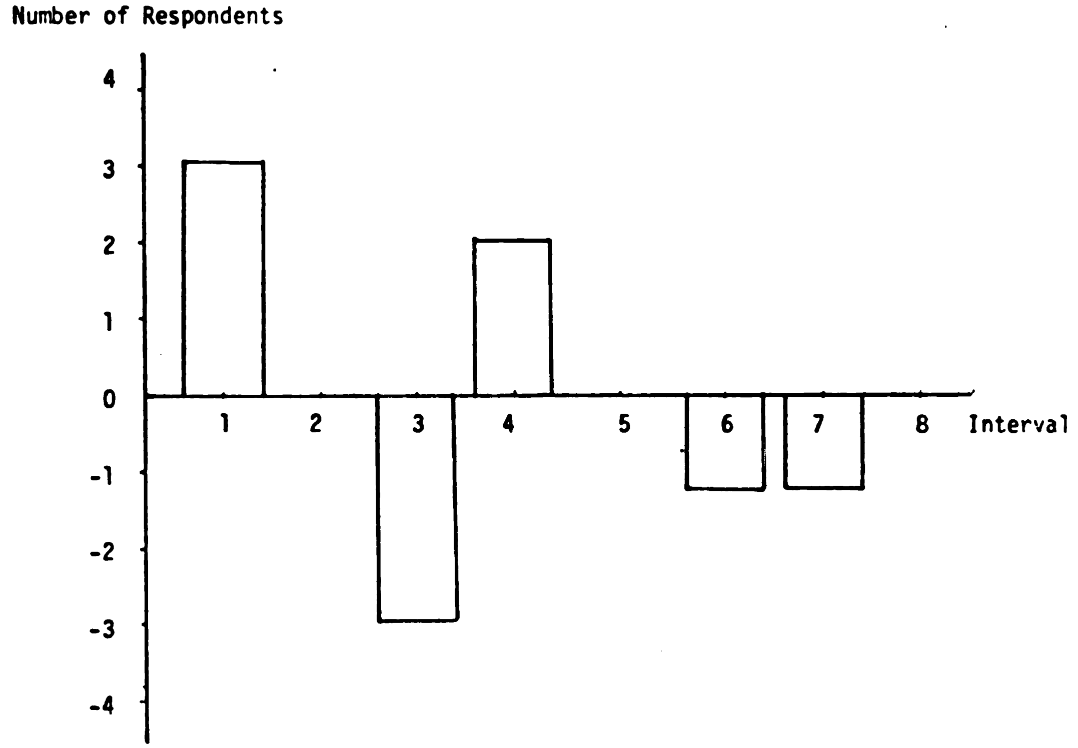


Figure 6-9. Change in Number of Sample Members in Each Interval from 1979 to 1981 for Income Level III

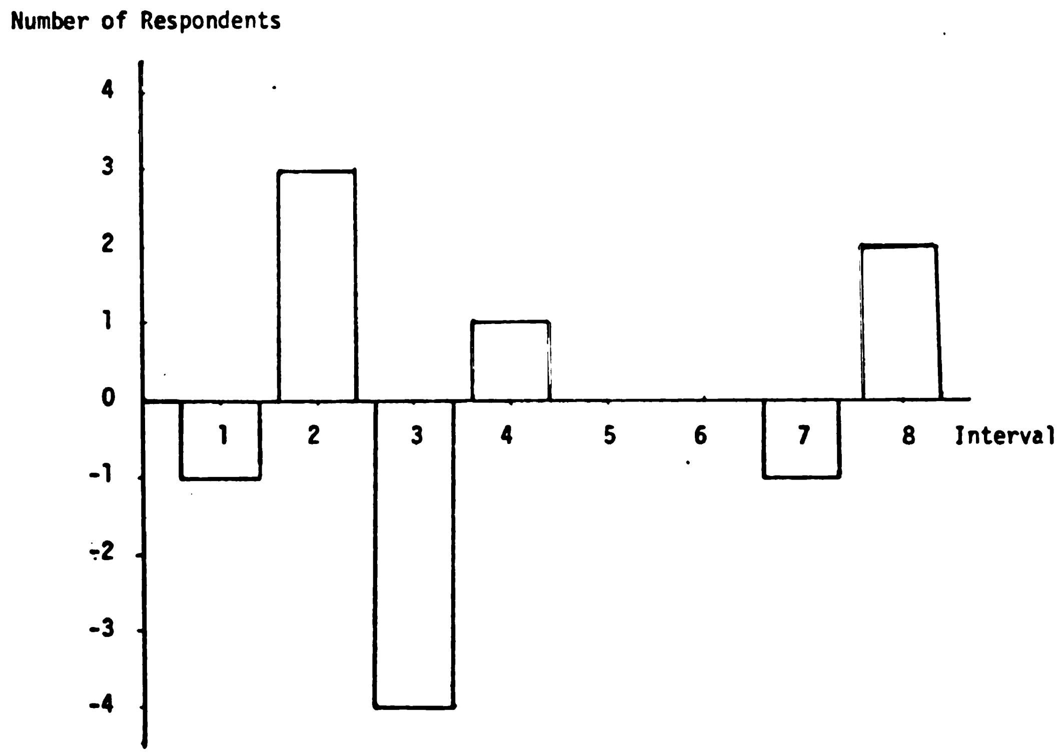


Figure 6-10. Change in Number of Sample Members in Each Interval from 1979 to 1981 for Income Level IV

Table 6-4 Individual Interval Measurements: 1979 and 1981

Year	1979				1981			
Level	I	II	III	IV	I	II	III	IV
Mean Income: $	0	10000	25000	45000	0	10000	25000	45000
Farmer #	Interval				Interval			
1	3	1	1	1	3	4	1	1
2	3	6	6	4	2	5	4	4
3	2	2	3	3	3	4	4	2
4	3	4	1	1	7	1	1	2
5	1	1	1	7	8	1	2	8
6	3	3	1	1	4	3	1	5
7	3	4	2	1	1	2	4	4
8	3	3	2	3	1	3	2	3
9	3	2	1	1	3	4	1	1
10	1	3	2	5	3	3	2	3
11	1	4	3	4	1	5	1	1
12	2	4	2	2	4	2	3	4
13	1	8	7	1	8	3	2	8
14	3	1	4	2	1	1	4	2
15	5	5	3	3	1	5	4	2
16	3	5	4	3	3	1	4	5
17	2	5	4	3	6	8	8	8
18	5	6	2	2	1	5	1	1
19	2	3	3	3	1	2	2	7
20	1	1	4	7	1	8	4	2
21	3	4	4	5	3	4	1	2
22	3	3	3	3	2	1	3	3
23	1	5	8	8	3	4	1	1

Table 6-5. Measures of Interval Change and Related Test Statistics

Panel 1				
Income level	I	II	III	IV
Measure	Percentage			
A. No interval change	26	30	43	26
B. No change or change to adjacent interval	48	52	70	48
C. No change more than two adjacent intervals	74	74	82	61
D. Change from risk preferring to averse (from 1 or 2 to 4-8)	9	17	4	17
E. Change from risk averse to preferring (from 4-8 to 1 or 2)	9	17	13	17
Panel 2				
Chi-square for measure A	3.45	6.17	18.78	3.45
(alpha)	(.1)	(.025)	(<.005)	(.1)
Chi-square for measure B (alpha)	1.72	3.07	12.27	1.72
	(>.1)	(.1)	(<.005)	(.1)

risk intervals corresponding to each individual measured at four income levels. The data are arranged so that each individual's preferences for the two time periods are on the same line. Farmer #1's risk preference intervals in 1979 over income levels I, II, III and IV were 3, 1, 1 and 1 respectively. In 1981 these risk preference intervals over the same income levels were 3, 4, 1 and 1.

Each set of four intervals represents an average risk aversion upper bound and an average risk aversion lower bound as a function of income (see Chapter 4 or Figure 6-2). The data evidence no clear pattern of functional form on these bounds. Quite the contrary, almost every functional form possible is represented. This result is important for two reasons. First, those studies assuming a priori the shape of utility or risk aversion functions limit their ability to include all relevant decision makers. Second, studies representing the decision maker's risk aversion as a single point or in the neighborhood of one income must carefully consider the choice of the income level. And researchers must be prepared to limit any conclusions or prescriptions to the particular income level investigated.

The estimated intervals bounding the risk aversion function over specified income ranges did change from 1979 to 1981. All twenty-three sample members changed intervals for at least one income level. Twenty-six percent changed intervals for two income levels, 22% for three income levels and 35% changed at all four levels. These statistics might be somewhat misleading in that many of the estimated risk aversion bounds remained quite stable. Only five of the twenty three sample members' estimated intervals demonstrated relatively extreme changes. There is even evidence that two of those five are peculiar cases. One was a very young farmer who in 1979 owned no land, had less than $50,000 gross income and had almost no net worth. By 1981 he owned land, had gross income over $100,000 and had six times his 1979 net worth. The other farmer depended on a real estate business for over 50% of his family income. And between 1979 and 1981 the Michigan real estate market experienced a fairly noticeable downturn. Consequently neither of these situations approximated the typical farm in the survey and might be expected to be more volatile.

The changes in intervals evidence no clear pattern between 1979 and 1981. In other words, statements as to general tendencies toward greater or lesser risk aversion cannot be verified. Neither is it possible to verify any distinct change in general functional form from 1979 to 1981. This evidence indicates that a change in risk preferences may not generally be affected by structural changes in agriculture or the general economy. Such an indication assumes that any changes in risk preferences caused by a structural change would follow a similar pattern among all producers. Of course the assumption itself might be faulty. Yet Halter and Mason suggested a hypothesis based on their analysis which implies that individuals' risk preferences are not affected by general economic changes. Further study of this proposition might prove interesting. Especially to those who believe farmer risk attitudes might be estimated or at least classified based on personal and business characteristics.

Although mentioned in Chapter 4, it seems important to elaborate on one of the properties of the interval approach. In using the interval approach the closest one can come to actually estimating preferences is to bound the average risk aversion. Rather than a shortcoming of the approach, the flexibility of setting the interval widths is a strength (King). What is important to note is that estimates of exact preferences are not resultant. This is true because nothing is known about the location of average risk aversion within an interval. Therefore in this study the risk aversion interval becomes the basic measure for testing intertemporal stability. While not exactly the same as comparing risk preferences, the relative narrowness of the bounded intervals makes for a good approximation.

What can be inferred from the data about the null hypothesis that risk preferences are intertemporally stable? Table 6-5 lists several measures of risk interval stability. Line A of panel 1 summarizes the percentages of individuals who did not change intervals between 1979 and 1981. This measure is obviously relevant with respect to interval stability. The percentage of the sample remaining at the same risk aversion interval for income levels I, II, III and IV is 26%, 30%, 43% and 26% respectively. Income level III, the $22,000 to $28,000 range, demonstrated the most stability.

Pertinent, too, is the measure represented by line B. Measure B cumulates the percentage of the sample not changing interval (measure A) and the percentage changing to an adjacent interval. The following factors make measure B almost as relevant for testing as Measure A.

1. Due to the nature of the interval approach, it is not specifically known where within an interval the average risk aversion lies.

2. Adjacent intervals partially overlap.

3. The bounded intervals are constructed so as to be relatively narrow.

Because of these three factors, the average risk aversion estimated to be in an adjacent interval may actually lie in both at once or at least be very close to the bounds of both. Based on measure B, risk preferences once again proved most stable for income level III. In the neighborhood of $25,000 income, 70% of the respondents either did not change intervals or changed to an adjacent interval between 1979 and 1981.

It is possible to statistically test the hypothesis of stability at each income level using these measures. Chi-square statistics are used to test the hypothesis that the frequency of interval change experienced is less than or equal the frequency of random occurrence. If this proxy hypothesis cannot be rejected, then the stability of the risk preferences is no better than a random event. The implication of this result is the rejection of the intertemporal stability hypothesis. Table 6-5, panel B reports the Chi-square test statistics. The maximum significance attainable at each income for measures A and B is also listed. The proxy hypothesis could not be rejected at the .01 significance level for either measure over income ranges I, II and IV. However, the proxy hypothesis could be rejected at the .01 significance level (and much higher) for both measure A and measure B over income range III. These results imply rejection of the hypothesis of intertemporal stability for incomes in the neighborhood of $0, $10,000 and $45,000; but not for those in the neighborhood of $25,000.

The test outcome is of special consequence in that most of the sample members' personal after-tax incomes are estimated to be in the $16,500 to $34,000 range. Unfortunately tax data for the sample are not available. But average farm income over a four year period, percentage of farm income the respondent received and the proportion of his total income from farm sources serve as the basis for a reasonable approximation. From this information it is estimated that the incomes of approximately 74% of the sample members fall in the aforementioned range. The $16,500 income figure represents the mean between income range II's upper income and income range III's lower income. Likewise $34,000 represents the mean between income range IV's lower income and income range III highest income. Incomes of 74% of the sample are thus best represented by level III. A more detailed investigation of the individual data indicates a similar outcome. Of the 43% of the sample which didn't change interval (measure A, level III), approximately 70% had incomes best represented by income range III. The percentage rises to about 81% of the respondents falling into the measure B category at level III. It therefore seems likely that risk preferences are not intertemporally stable over all incomes. The outcome does suggest that for incomes close to those typically experienced by farmers, risk preferences are reasonably stables.

Lines D and E of Table 6-5 list two other, albeit less specific, measures of stability. These measures bring particular consequence for application of decision theory to group prescription. So too, this information may make contribution to consideration of some policy analysis issues where more general knowledge as to changes in risk preference is desirable. Measure D represents the proportion of the sample whose measured average risk aversion changed from being within the risk preferring region (intervals 1 and 2) to a risk averse region (intervals 4 through 8). Measure E represents the proportion changing from risk averse to risk preferring regions (from 4 through 8 to 1 or 2).

What is evidenced by these measures (Lines D and E) of stability? In general if an individual was risk averse (preferring) in 1979 for a given range of incomes, while he might become slightly more or less risk averse (preferring), he likely remained risk averse (preferring) in 1981. These measures again showed the preferences were most stable for incomes in the neighborhood of $25,000.

Founded on much less information and less conclusive results, Officer and Halter maintained that a similar effect in their experiment suggested fairly stable preferences over time. What seems important is the degree of accuracy necessary for a given decision situation.

Knowledge of stability based on measures D and E may suffice for some general marketing strategies or government policy decisions. For such cases, this study supports the Officer and Halter conclusion. Yet decisions such as crop rotation and the particular plant varieties to use within those rotations may require information about intertemporal stability more refined than measures D and E provide. How large or small an interval ought to be is an empirical question, specific to particular types of decisions. Measure A might be too broad in some instances, whereas measure B might be more than sufficiently accurate for other decisions. King and Carman each discuss the need to make explicit the trade-offs between errors due to setting interval size (see chapter 4 for discussion). While these issues deserve study, a third type of error, here proposed, may be even more important. That error occurs when Extension prescription and teaching are framed in theories which assume, a priori, risk neutrality (or for that matter theories that assume only risk preferring or only risk averse behavior). One type of error described by King and Carman relates to an interval being too narrow, such that the best action would be excluded and hence a less than best action might be recommended. The other is the possibility of too wide an interval making selection of action choice difficult. While these errors refer to missing the best action they may not be worse than the error of assuming risk neutrality and excluding a whole set of better actions. Of course, Officer and Halter and Lin, Dean and Moore addressed this type of error in their studies and concluded that indeed it had considerable practical importance. Considering this third type of error, one is struck with the possibility of coming full circle and wondering if inference about intertemporal stability based on D and E aren't most significant.

6-5 Chapter Summary

An analysis of the data demonstrated several important results. Producer interviews found risk preferring, risk averting and risk neutral attitudes all existed among the sample members. Many farmers exhibited all three types of intervals over the range of incomes. The bounds on average risk aversion demonstrated no consistent pattern between individuals or time periods. As a group, farmers tended to be most risk averse in the neighborhood of $10,000 income and least risk averse for incomes near $0. Farmers' risk aversion functions differed from risk neutrality a large proportion of the time. This finding reaffirms the need to not depend solely on expected profit maximization theory in economic analysis and prescription.

Intertemporal stability of individual preferences was a primary concern of the chapter. None of the sample members' measured intervals remained the same at all four income levels between 1979 and 1981. Nor were any general tendencies or patterns of intertemporal change observed.

Risk aversion functions proved to be most stable for incomes around those most typically experienced by farmers. Stability for income levels I, II and IV was not any better than would be expected of random happening. This outcome implies rejection of intertemporal stability of measured intervals for these incomes. Intertemporal stability for level III could not be rejected. While all individuals changed measured intervals to some extent, remarkably few went from risk averse regions to risk preferring or vice versa. Finally, risk preference intervals measured at one point in time may very well be stable enough to be applied to future decision analyses. But accurate representation will likely depend on size of intervals (width and height), type of decision and be limited to incomes typically experienced by the individuals in question.

Chapter 7

RESULTS OF DISCRIMINANT ANALYSIS AND TESTING FOR INTERTEMPORAL STABILITY OF SOCIOECONOMIC CHARACTERISTIC-RISK PREFERENCE RELATIONSHIP

7.1 Introduction

This chapter addresses the study's second objective. It examines the importance of observable socioeconomic characteristics in classifying farmers according to risk preference. Little information exists which relates farmers' risk attitudes to their socioeconomic characteristics. Yet the literature attests to the need to better understand and estimate possible relationships. Barry and Baker (1977) state that "the need to test hypotheses on risk behavior is one area needing further study. For example, how do risk premiums required by primary producers vary with selected personal, business and economic attributes." Lins, Gabriel and Sonka (1981) recognized the same need: "The important point is that in modeling the behavior of farm operators, . . . researchers must be cognizant of the impact of age, type of farm, form of business structure, and other characteristics which affect risky decisions."

This chapter reports additional information for the evaluation of relationships between attributes and risk preferences. Examination of the cross-sectional results for 1979 and 1981 provides this information. Although the cross-sectional analysis is necessary it is not sufficient to fulfill objective two of this study.

As discussed, scientists estimate these relationships (at least in part) to reduce the need to repeat preference measurement due to changes over time. If these relationships do change with time, then the usefulness of estimating them is diminished. Young, et al. expressed a similar concern:

> Even if researchers were to hand an extension worker an elaborate set of equations relating risk aversion at all relevant loss and gain levels to personal and business attributes for farmers in his district, the personal and evolutionary nature of attitudes toward risk would probably prevent their confident application to specific individuals.

They imply that even if a set of socioeconomic variables could be used to classify producers according to risk attitude, the unsureness as to stability of the relationships would reduce applicability. The implication may very well be true. Yet the stability of these relationships has not been tested. Analysis in this chapter specifically examines the stability (over time) problem. And in so doing it supplies the sufficient conditions to fulfill objective two.

The Young, et al. quote highlights a second concern. They suggest that making individual recommendations on these estimated relationships would be difficult. Such a suggestion, while true in some cases, overlooks the major emphasis of research in this area. The Extension service generally supplies information usable by wide categories of farmers and makes group recommendations subject to alteration by the individual. Officer, Halter and Dillon (1967) make it quite clear that group recommendation and not individualized service ought to be the goal of practical risk preference-attribute research. This point makes using the group oriented interval approach and discriminant analysis so appropriate in measuring and testing the relationships.

Discriminant analysis is a statistical technique which relates a nominally measured or group variable to interval measured variables. The sections immediately following discuss how to use this technique. Later sections describe how the two principal components of discriminant analysis, the variables and groups, are used in this research. Later sections also report the estimated standardized coefficients of the discriminant functions as well as the structure coefficients. Finally this chapter presents the classification results based on the discriminant functions. The main concern will be the ability of the socioeconomic variables to accurately classify the sample members according to their risk preferences at different time periods.

7.2 Review of Discriminant Analysis

Discriminant analysis is a statistical technique which allows the study of differences between two or more groups with respect to several variables simultaneously. It supplies the evidence necessary for the determination of: (1) which, if any, of those variables are useful in prediction of classification; (2) how these variables might be combined into a mathematical equation to predict membership in a group; and (3) the accuracy of the derived equation.

Discriminant analysis is particularly well adapted to the problem. The interval approach serves as a measurement technique through which a series of choices reduces the risk aversion region bounding an individual's average risk aversion function for a range of incomes. While setting interval width entails great flexibility, each individual's average risk aversion lies in one of the intervals. Each interval or combination of intervals defines a class or group of decision makers. Discriminant analysis treats these classes of decision makers as the dependent variable and the socioeconomic attributes as the discriminating variables.

A comparison with regression analysis might prove useful. Regression techniques usually relate an interval level measured dependent variable to interval level measured independent variables. Discriminant analysis, on the other hand, relates a nominal level measured variable to several interval level measured discriminant variables. Regression analysis attempts to combine the independent variables to minimize the distance between the function and values of the dependent variables. But discriminant analysis combines the discriminating variables so as to maximize the distance between the groups.

7.2.1 Definition of Terms

Several terms applied to discriminant analysis require explanation. Data cases are the basic units of analysis. These are the elemental things being studied, such as people, animals, economic factors, etc. The individual farmer's measured risk preference interval at an income level constitutes a data case for this study. The data cases should be members of two or more mutually exclusive groups. Section 7.5.4 specifies the grouping used in this study. Finally, the characteristics used to distinguish among the groups are called discriminating variables. Here discriminating variables refer to those income, financial and personal charactersitics of farm and operator.

7.2.2 Assumptions of Discriminant Analysis

Certain assumptions underlie the mathematical model on which the most common approaches to discriminant analysis rest. A summary of the assumtions follows:

g = number of groups

p = number of discriminating variables

n_i = number of cases in group i

n = total number of cases over all the groups

the assumptions

(1) $g \geq 2$

(2) $n_i \geq 2$

(3) $0 < p < (n-2)$

(4) discriminating variables are measured at the interval level

(5) no discriminating variable may be a linear combination of other discriminating variables

(6) the covariance matrices of each group must be (approximately) equal

(7) each group is drawn from a population with a multivariate normal distribution on the discriminating variables.

If the data for a particular problem do not satisfy the assumptions, the statistical results will not be the most precise reflection of reality. This problem has varying degrees of severity depending on what is being inferred, how well the data approximate the assumed properties, and the degree of accuracy required. The problems of violating assumptions are discussed as they arise in analysis.

7.2.3 Form of Discriminant Function

A canonical discriminant function is a linear combination of the discriminating variables formed to satisfy certain conditions. It has the following mathematical form:

$$s_{km} = u_0 + u_1X_{1km} + u_2X_{2km} + \dots + u_pX_{pkm} \qquad \text{Equation 7-1}$$

where S_{km} = the score on the canonical discriminant function for case m and group k;

X_{ikm} = the value on discriminating variable X_i for case m in group k;

U_i = coefficients which produce the desired characteristics in the function.

The coefficients (the u's) for the function are derived so that the group means on the function differ as much as possible. Positionally a group may be described by its centroid. A group centroid consists of an imaginary point which has coordinates that the group's mean on each of the variables. In other words, the centroid represents the typical position for the group.

Discriminant analysis is actually a broad term which refers to several closely related statistical activities. For description purposes these activities are divided into those used for interpreting the group differences and those employed to classify cases into groups.

7.3 Interpretation of Group Differences

Engaging in interpretation activities relates to studying the ways groups differ, that is, the discrimination between groups on the basis of some set of characteristics, how well do they discriminate and which are the most powerful discriminators. Much can be learned about interpretation from description of two types of coefficients: standardized discriminant coefficients and structure coefficients. The former involve the examination of the relative positions of the data cases and group centroids. The latter refer to studying relationships between the individual variables and the function.

7.3.1 Standardized Coefficients

The u's in equation 7-1 represent the unstandardized coefficients. While the unstandardized coefficients do tell the absolute contribution of a variable in determining the discriminant score, this information may be misleading when the units of the variables are not all the same. To know the relative importance of the variable, it is necessary to examine the standardized coefficients. The following formula transforms u's to c's (standardized coefficients).

$$c_i = u_i \sqrt{\frac{w_{ii}}{n-g}} \qquad \text{Equation 7-2}$$

where w_{ii} is the sum of squares for variable i, n is the total number of cases and g is the number of groups. The standardized coefficients will prove important in analysis. The magnitude of these coefficients directly determines which variables contribute most to determining the discriminant scores. And the discriminant score supplies the information necessary for assignment of a data case to a group.

7.3.2 Structure Coefficients

The second type of coefficient contributing to interpretation is the structure coefficient. Two specific kinds of coefficients take the designation of structure coefficients. One, based on total correlations, is referred to as a total structure coefficient. These coefficients help identify the kind of information carried by individual variables for discrimating between groups. The other concerns itself with how the functions relate to the variables within the groups. These coefficients are called within-groups structure coefficients. Here within-group correlation, not total correlation, serves to weight coefficients. Structure coefficients give some idea as to those variables best demonstrating the same as the functions themselves either between groups or among data cases within groups.

Structure coefficients tell something quite different from that communicated by the standardized coefficients. The standardized coefficients give the variable's contribution to calculating the discriminant score. Using the standardized coefficients has some limitations. The contributions of a discriminating variable as measured by a standardized coefficient might prove greater or lesser depending on correlation between variables. While later sections report the values for both types of coefficients, analysis of intertemporal stability focuses on the total structure coefficients.

7.3.3 Number of Functions

One other factor has a place of importance in interpreting data: the number of functions employed to discriminate a given set of groups. The maximum number of nontrivial functions equals the number of groups minus one. While this is the maximum number of nontrivial functions, all these functions may not be significant. How many functions are significant is not a clear-cut decision. At times using eigenvalues, canonical correlation coefficients and contribution to classification in deciding on the number of functions becomes more of an art than a science. Section 7.6.1 prescribes the number of functions used in interpretation and classification.

7.4 Classification

The other major activity under the heading of discriminant analysis is classification. Classification is the process leading to a decision of a specific case belonging to, or more closely resembling, one particular group than another. The discriminating variables and canonical functions carry the information necessary for making this decision. Basically this entails using the discriminant scores of the data cases to compare a case's position to each group's centroid in order to locate the "closest" one. Consequently the information allows for the prediction of the group to which a case most likely belongs.

This distance concept provides two measures of classification. The first, $Pr(X|G_k)$, is the probability of a case in that group having a location as far from the centroid as the case in question. The second measure, $Pr(G_k|X)$ is more revealing. $Pr(G_k|X)$ represents the probability of the case in question belonging to group k. Assignment of cases to groups depends on the group with the highest value for $Pr(G_k|X)$. Since the latter are posterior probabilities they sum to one across all groups. Thus the closer to a magnitude of one, the more likely that the case belongs to that group. This interpretation is important in considering how well the canonical functions serve in classification. Higher probabilities reflect increased likelihood of correct classification and less need for concern over violation of the assumptions.

The predicted group classification is often portrayed in the form of a classification matrix. When group classification is known in advance, as with measured risk preference intervals, the percentage of those cases correctly classified gives a measure of discrimination accuracy. Yet the error statistic tau serves more accurately for testing classification capability. This statistic allows for the comparison of the percentage correct in relation to random assignment. For example, if there were three groups one would expect to get 33% of the predictions right purely by chance. The following mathematical equation defines tau:

$$\text{tau} = \frac{n_c - \sum_{i=1}^{q} p_i n_i}{n - \sum_{i=1}^{q} p_i n_i}$$

where n_c is the number of cases correctly classified and p_i is the prior probability of group membership. Thus, tau gives a standardized measure of improvement over random occurrence regardless of the number of groups.

In summary, the two primary activities of discriminant analysis are interpretation and classification. Classification serves as a test of the socioeconomic variables' ability to correctly classify individuals into risk aversion intervals. The temporal stability of the variables' contribution to discrimination is evaluated using both interpretation results and tests of classification ability.

7.5 Specification of Discriminant Analysis

7.5.1 Discriminating Variables

Sample selection and questionnaire design facilitated the accumulation of data on a broad spectrum of socioeconomic farm and operator characteristics. These data make up the set of discriminating variables available for statistical analysis. For organizational purposes the discriminating variables are divided into three categories: operator-social, farm size and financial, and income related. Those variables in the operator-social category include: marital status, age, number of children, education, years living on the farm, and years managing the farm. This list embraces most of the social variables discussed in the literature as candidates relating to risk attitude. Age, number of children and education have all been evidenced as variables with possible significance (Halter and Mason; Binswanger, 1980; Moscardi and de Janvry, 1977). Johnson, et al. (1956) and Officer and Halter (1968) hypothesized correlation between managerial experience and risk attitudes. Years living on the farm and years managing the farm serve as proxy variables for managerial experience. The farm size and financial variable category contains gross income, total sales, dairy sales as a percentage of total sales, acres owned, acres rented, net worth and net worth as a percentage of total assets. The Halter-Mason and Moscardi-de Janvry results suggested gross income, total sales, acres owned and acres rented as variables warranting investigation. Although the variables' net worth and net worth as a percentage of assets were not previously tested with much success, Young, et al. stress the need to examine these and other factors related to the financial ability to bear risk to preferences. Some researchers hypothesize that type of farm enterprise makes a difference in risk attitude (Johnson et al.; Lins, Gabriel and Sonka). Hence, dairy sales as a percentage of total sales perform the function of differentiating the dairy enterprise from other farm enterprises in the sample.

The variables net farm income, management income, net cash income and nonfarm income belong to the income category. Most previous analyses neglected these variables or similar income variables (except for nonfarm income). While Dillon and Scandizzo (1978) did have some success in correlating measures of income to risk preferences, limited easy access to income data most probably explains their absence from other studies. Halter and Mason, and Whitaker and Winter did not have income variables among those in their regression analysis. Yet the concluding remarks of each study suggested income variables ought to be considered.

The questionnaires were administered in the springs and summers of 1979 and 1981. So the most recent income data available came from 1978 and 1980 respectively. This is not a problem since using the most recent past year's income is a usual procedure in similar analyses. It constitutes the only complete annualized data available to either the scientist for research or the farmer for formulating expectations. The variable list also includes 1977 and 1979 figures for some income variables. Expectations are that these data also relate to risk attitude. The data are expected to be of relevance for several reasons. First, many farmers use tax management techniques to move income from one year to the next; thus, a set of two years' incomes may better represent their situations. An examination of the data showed the cattle feeders registering good incomes and poor incomes in two-year cycles. So, due to lags between stocking and slaughter of feeder cattle, market cycles and some tax management, the inclusion of two years' income appears appropriate. Finally it seems likely that the basis for attitudes is comprised of more than just the most recent experience, and some weight ought to be given less recent experiences, not unlike expectations models (see Nerlove, 1958).

7.5.2 Some Variables Not Included

The list of discriminating variables includes almost all those types of variables generally viewed as likely related to risk preferences. One other category of variables has been suggested by previous research efforts. Sets of variables having to do with personality traits comprise this category (see Krause and Williams, 1971; Carman, 1979). Personal experience and study uphold the hypothesis that indeed personality makes a difference in willingness to take chances. Unfortunately, while these variables are possibly correlated to risk preferences, two serious shortcomings preclude their application. First, they, like risk preferences, must be directly elicited from each individual farmer. Second, the techniques to accurately measure personality variables are even more suspect than those used in preference estimation. The discriminating variables here employed therefore represent those variables easily observable or calculatable from typical farm records.

7.5.3 Variable List and Definitions

The following list presents the discriminating variable names, definitions and units. The variable names will be used throughout the remainder of this chapter.

MARITAL - the operator's marital status, where one equals married and zero equals not married.

AGE - the age of the respondent, in years.

NUMCHILD - the number of children.

EDUCAT - the education level completed by respondent, in years.

YLOF - the length of time the respondent has lived on a farm, in years.

YMF - the length of time the respondent has managed a farm, in years.

GROSINC - the gross income of the farm unit; includes farm income from all sources adjusted for items purchased for resale and changes in inventory, in dollars.

TOTSALES - the total value from the sales of farm products, in dollars.

DSALETOT - the percentage of total sales made up of sales from the dairy enterprise, ratio level measurement.

TACROWN - the tillable land owned by the farm unit, in acres.

TACRRENT - the tillable land rented by the farm unit, in acres.

NW - the net worth or equity of the farm unit, in dollars.

NWOFASST - the net worth as a percentage of total assets of the farm unit, ratio level measurement.

NFI - the net farm income for the farm unit; equals gross income minus depreciation, plus or minus the change in farm inventory, in dollars.

MGTI - the management income for the farm unit; equals net farm income minus a value for operator's labor and a charge to owned capital, in dollars.

NCI - the net cash income or the difference between cash income and cash expenses, in dollars.

NONFI - the nonfarm income; this constitutes income from nonfarm sources, one equals nonfarm income over 5% of total income and zero for 5% or less.

The three income variables (NFI, MGTI and NCI) are differentiated according to year they represent (i.e. NFI78 is net farm income for 1978).

7.5.4 Selection of Groups

The mathematical objective of discriminant analysis is to weight and linearly combine the discriminating variables so that the groups of cases are forced to be as statistically distinct as possible. Defining the groups is an important step toward interpretation and classification. As discussed, the interval approach to risk preference measurement does not specify exact risk aversion functions. Rather the approach sets bounds on the functions, thus allowing for classification of decision makers according to risk aversion for each range of incomes. The approach, as implemented in this study, defined risk aversion space with eight intervals. The individual's responses to the choices on the questionnaire cause him to be classified into one of these eight intervals at a given income level. So the maximum number of classifications or groups is eight. This large a number of groups would be extremely difficult to work with. Also many intervals contained zero or one responses (see Table 6-2), thus violating the second assumption of discriminant analysis. Three or four groups based on some combination of the intervals seems most practical.

The basic units of analysis, data cases, are here specified as an individual's bounded average risk aversion function measured at a given income level. Assignment of data cases to a particular group depends on which of the eight intervals represents the risk preferences. It is extremely important that the group definition remain the same both between income levels and time periods if analysis is to be realistic and understandable (Klecka, 1980). This brings up one of the shortcomings of the cross-sectional discriminant analysis completed by Carman on the 1979 portion of the data. Carman redefined the groups (according to which intervals were contained in each group) from one income level to the next. He then attempted to make interincome comparisons from the discriminant analysis results. In effect he compared outcomes from inconsistently specified groups as if they were consistent. In this study,testing for intertemporal stability requires group definitions be consistent over income levels and between temporal stages.

Group specification depends on four criteria. The first criterion centers on selecting groups so as to divide the risk aversion space in a most theoretically logical manner. This pertains particularly to assigning only adjacent intervals to groups and dividing risk aversion space with the different meanings of various regions of risk aversion in mind. The second involves a desire to divide risk aversion space giving ease of practical application priority. The calculating procedures of discriminant analysis provide the basis for the third criterion. The mathematical processes require some minimum group size for reasonably accurate estimates. Finally the bounds on the previously defined eight measurement intervals constrain the grouping decision (i.e. the groups must be some combination of the intervals).

Two patterns of grouping generally meet the criteria. The first divides the risk aversion space into areas of: 1) wholly risk preferring ($r(Y) < 0$), 2) slightly risk preferring to slightly risk averse (including risk neutrality), 3) and wholly risk averse ($r(Y) > 0$). Given the interval bounds, the groups would be:

Group 1	Interval 1
Group 2	Intervals 2, 3
Group 3	Intervals 4, 5, 6, 7, 8

This grouping scheme satisfies the four criteria. Only adjacent intervals are grouped together. The three groups are especially well suited for application to policy analysis or group recommendations. The specification of decision makers into the three primary risk preference classes makes interpretation by extension personnel, policy makers and farmers easier. Officer and Halter recommend this division as the obvious first step beyond assuming all decision makers to be risk neutral. The grouping scheme allows for a reasonable number of data cases per group at each income level. Finally, the three-way division improves on efficiency criteria which allow less flexibility of risk attitude.

The second grouping scheme divides risk aversion space into four groups. The first two groups remain the same as the three group scheme, but the third group is divided into two. Data cases whose average risk aversion lies in slightly to moderately risk averse areas (intervals 4,5) and those in moderately to very risk averse areas (intervals 6, 7, 8) comprise groups three and four respectively. This latter grouping scheme is desirable because it separates individuals characterized by the maximin criterion (see Halter and Dean, 1971) from those less drastically risk averting. Unfortunately, this grouping scheme is not as intuitively appealing from a practical use standpoint. Neither does it as effectively fulfill the criterion of minimum group size given the available sample data. Several groups would have no data cases at all and several others would have only one or two. These shortcomings make statistical analysis of intertemporal and interincome differences more difficult and any conclusions less reliable.

Because the three-group scheme bests fits the criteria, the narrative analysis in the next sections is based on the discriminant analysis results of this grouping. However, since the four-group scheme does contain some desirable properties, Appendix B reports the discriminant analysis results using the four groups.

7.6 Analysis Results

7.6.1 Selection of Number of Functions

The discriminant functions contain most of the information necessary for interpretation and classification. The maximum number of nontrivial functions is the number of groups minus one (i.e. G-1). Yet all of these functions may not contribute to the analytical process. Making a decision as to the number of functions to use in analysis at each income level turns out to be rather complex. Four interacting and partially related factors serve as the criterion contributing to decisions about the number of functions. These factors are: relative percentage of discrimination, canonical correlation, significance level of Wilkes lambda, and the classification ability. Relative percentage of discrimination refers to the percentage of the whole discriminatory power each function determines based on the eigenvalues. The canonical correlation, a measure of association, summarizes the degree of relatedness between the groups and the discriminant function. A value of zero denotes no relationship and increasing values up to one show increasing degrees of association. The significance level of Wilkes lambda is a Chi-square test of the likelihood that the sampling process showed group discrimination when in fact no group differences occur in the population. Finally, classification ability refers to the percentage of the sample which the discriminant function(s) classify correctly into preassigned groups. Only one of these criteria depends on the sample being random, the significance level of Wilkes lambda. Since the sample is understood not to be random from the population of all farms, Klecka (1980) advises conservative interpretation of this statistic and placement of greater emphasis on the other criteria.

One other criterion in selection of the number of functions deserves consideration. The complexity of interpretation increases markedly from one function to two and two to three. Basically the change goes from interpreting along one axis to two axes to three. While no simple coefficient depicts the degree of intuitiveness of the outcomes, the understandability of the analysis diminishes as the number of functions increase. Thus for borderline decisions fewer functions are better.

Tables 7-1 and 7-2 list the values of four factors for the three group scheme in 1979 and 1981. Several of the decisions between using one or two functions seem straightforward. Groups 2, 3 and 4 in 1981 and Groups 2 and 3 for 1979 each have first functions whose properties make them considerably better discriminators than the second functions. Each also carries sufficient information to produce good classification results. For Group 1 of 1981 the first function holds only

Table 7-1. Estimation Statistics For the Discriminant Functions: 1979

	Income Level			
	I	II	III	IV
Percentage of Discrimination				
Function 1	81%	73%	89%	59%
Function 2	19%	27%	11%	41%
Canonical Correlation				
Function 1	.94	.97	.96	.90
Function 2	.82	.92	.80	.87
Significance of Wilkes Lambda				
before 1 Function	.46	.05	.30	.46
before 2 Functions	.81	.26	.86	.49
Cases Correctly Classified				
one Function	65%	100%	91%	78%
two Functions	100%	100%	100%	100%

Table 7-2. Estimation Statistics For the Discriminant Functions: 1981

	Income Level			
	I	II	III	IV
Percentage of Discrimination				
Function 1	70%	88%	83%	90%
Function 2	30%	12%	17%	10%
Canonical Correlation				
Function 1	.94	.96	.98	.97
Function 2	.88	.80	.91	.86
Significance of Wilkes Lambda				
before 1 Function	.08	.10	.00	.03
before 2 Functions	.28	.69	.20	.55
Cases Correctly Classified				
one Function	95%	100%	100%	100%
two Functions	100%	100%	100%	100%

70% of the discriminatory power, but its classification ability is good and the other factors do not supply an obvious direction to the decision. Thus for Groups 1, 2, 3 and 4 of 1981 and Groups 2 and 3 of 1979 only one function is used in interpretation. Groups 1 and 4 of 1979 provide the two most difficult choices as to number of functions. While the significance of one function for Group 1 might be questionable at .46, the second function almost surely attempts to discriminate differences which may not exist (significance only .81). The first function also carries 81% of the discriminatory power compared to 19% for function two. Unfortunately classification on one function only is rather poor at 65%, although this might be expected since significance level and classification ability are somewhat interrelated. Based on these points, one function serves for interpretation of Group 1, 1979. Group 4 of 1979 has about the same properties as Group 1 with the major difference marked by the similarity between the factors for the first and second functions in Group 4. Finally if one function is used (even though it is not particularly good) then why not two functions, after all they are very similar? The final criterion of intuitive understanding tips the balance here in favor of one function as opposed to two.

7.6.2 Interpretation of Discriminant Analysis

Discriminant analysis computer programs (SPSS, 1979) were executed on all the income levels for each year. After considerable testing 19 of the 20 variables described in section 7.5.3 improved the functions for at least one group. NONFI was the only variable consistently not contributing to discrimination (actually detracting from the results in some groups). Given the sample properties one would expect

NONFI to contribute little to discrimination. During the 1981 stage of the survey only one operator expressed the belief that nonfarm income affected the decisions made on the farm. Only three operators had nonfarm income greater than 10% of their farm income. The contribution of NONFI may have been greater for a sample with greater weight on less-established farmers or part-time operators.

The coefficients of some variables do not show up in the functions in every group (i.e. MGTI79 and MGTI80 for income level 1, 1981). These variables failed the minimum tolerance test for entry. An extremely low tolerance level is a sign that the computer program would have difficulty inverting a covariance matrix which included this variable. If a variable with very low tolerance is used, large rounding errors may occur while computing the coefficients. This could lead to faulty estimates and inaccurate classifications.

7.6.3 Standardized Coefficient and Centroid Results: 1979

This section reports the standardized coefficients of all the variables passing the tolerance test for each discriminant analysis. The section presents both nontrivial discriminant functions for each income level. But as previously discussed, interpretation is limited to only the coefficients of the first functions at each level.

Table 7-3 lists the standardized coefficients of the discriminant functions for income level I ($0) in 1979 for the three group scheme. The standardized coefficients determine which variables contribute most to the estimation of the discriminant scores. The larger the magnitude (ignoring the sign), the greater is that variable's contribution to the score. Table 7-3 also reports the calculated group centroids or the

Table 7-3. Canonical Discrimination Functions for Income Level I: 1979.

Variable Name	Standardized Discriminant Function Coefficients: Function 1	Function 2
MARITAL	-.84	.49
AGE	2.74	-.42
NUMCHILD	-.85	-2.87
EDUCAT	1.39	1.73
YLOF	-2.88	3.58
YMF	1.85	-.93
GROSINK	6.99	17.10
TOTSALES	-5.71	-6.94
DSALETOT	-.83	1.69
TACROWN	-1.02	-2.74
TACRRENT	-.36	-1.64
NW	1.58	-.40
NWOFASST	-1.94	-1.49
NFI78	3.27	-1.07
NFI77	-.99	-2.90
MGTI78	-8.43	-6.12
MGTI77	-.03	1.13
NCI78	2.31	2.12
NCI77	-1.61	.56
<u>Location of Group Centroids</u>		
Group 1	5.36	-.08
Group 2	-1.44	.71
Group 3	-1.73	-3.42

"most typical" position for each group. The plot in Figure 7-1 graphically portrays the relative positions of each individual's score and the three group centroids. The likelihood of correct classification improves as the centroids become more distinct from each other (further apart).

As seen in Table 7-3 MGTI78, GROSINC, and TOTSALES contribute the most to the discriminant scores. Comparatively, MGTI77, TACRRENT, DSALETOT, NUMCHILD, NFI77 contribute little. Little difference exists between the centroids in Groups 2 and 3. Consequently, as can be seen, difficulty arose in assigning data cases between Groups 2 and 3. The low significance level and percentage classification reflect this difficulty (see Table 7-1). The four variables contributing most to the discriminant scores are all 1978 income related variables. These variables all correlate positively to each other. For instance the correlation of GROSINC with TOTSALES is .93 and that of MGTI78 and NFI78 is .98. So given the signs of the coefficients and relative magnitudes these variables tend to cancel each other out. This outcome exemplifies the reason for not relying on the standardized coefficients for interpretation. The structure coefficients for each function supply more reliable information for analysis. And these are reviewed immediately following the sections on standardized coefficients.

Table 7-4 gives the standardized coefficients for income level II ($10,000). MGTI78 and NFI78 are the major contributors to the discriminant scores. The land tenure variables of TACROWN and TACRRENT carry the next most weight, but of considerable less magnitude than the income variables. While the income variables again tend to cancel each other, both land tenure variables demonstrate a negative effect on the score. Noting

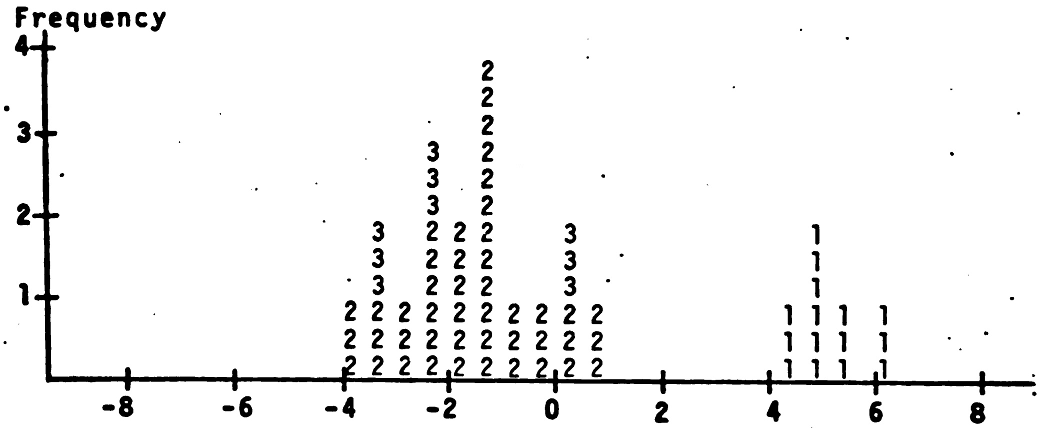


Figure 7- 1. Plot of data case and group centroid estimated locations: income level I, 1979.

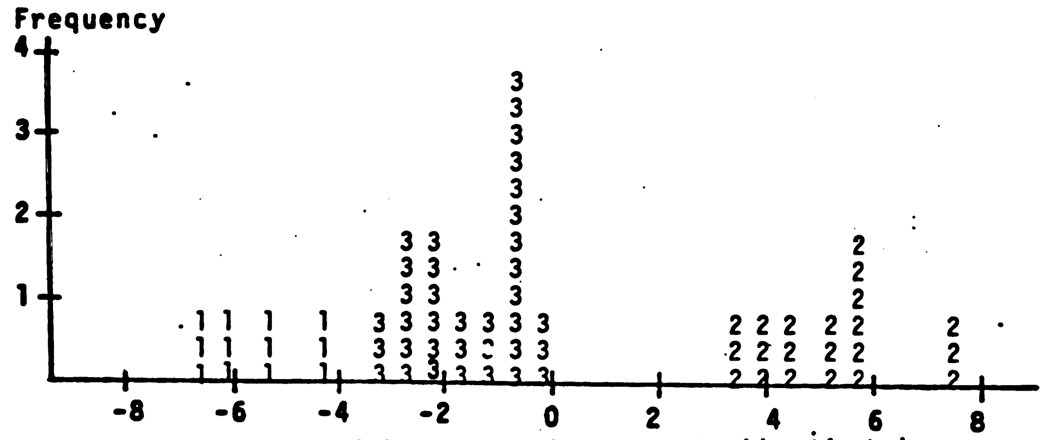


Figure 7- 2. Plot of data case and group centroid estimated locations: income level II, 1979.

Table 7-4. Canonical Discriminant Functions for Income Level II: 1979

Variable Name	Standardized Discriminant Function Coefficients	
	Function 1	Function 2
MARITAL	.48	2.65
AGE	-4.57	2.74
NUMCHILD	2.60	-2.21
EDUCAT	1.65	1.47
YLOF	5.36	.29
YMF	-3.01	-1.13
GROSINK	3.99	-3.59
TOTSALES	5.27	3.21
DSALETOT	-2.29	.05
TACROWN	-6.15	-4.50
TACRRENT	-8.53	.57
NW	5.47	.92
NWOFASST	-3.36	-1.65
NF178	14.13	1.48
NF177	-3.91	.83
MGTI78	-19.90	1.30
MGTI77	-.88	1.08
NCI78	1.64	-.77
NCI77	2.22	-.55
<u>Location of Group Centroids</u>		
Group 1	-5.55	3.65
Group 2	5.14	1.46
Group 3	-1.15	-2.06

the group centroids (Table 7-4) and the group plot in Figure 7-2, it appears that owning and renting greater acreage tend to increase the chances of an individual being in Groups 1 or 3.

The plot and the centroid locations also depict a situation where the groups were discriminated well on the variables. This result contrasts with that of income level I. The information in Table 7-1 shows that the observation for level II also holds true for income level III (i.e. one function more accurately assigns the individuals to groups for income levels II and III than levels I and IV). In Chapter 6 individuals were shown to have preferences most stable near typically experienced income levels. Here differences in individual's preferences are best related to socioeconomic variables at those same income levels. Therefore these results reinforce the conclusion (in Chapter 6) that measurement of preferences may be most accurate and reproducible for income ranges most often experienced by the individuals in question. Their use of risk aversion coefficients estimated at gross income levels may explain the considerable inconsistencies between the Halter-Mason results and those of Whitaker and Winter.

The standardized coefficients of the discriminant functions for income level III ($25,000) are found in Table 7-5. GROSINC, NFI78, TOTSALES and MGTI78 take the highest absolute magnitudes. The opposing signs on these income variables again cause them to cancel each other's effect. The financial, land tenure and social variables differ between individuals considerably less than the income variables. The sample members are especially homogeneous for the MARITAL and NONFI variables. Such variables discriminate poorly simply due to the fact that the objective function attempts to maximize the differences

Table 7-5. Canonical Discriminant Functions for Income Level III: 1979

Variable Name	Standardized Discriminant Function Coefficients	
	Function 1	Function 2
MARITAL	-1.29	-.65
AGE	.13	2.57
NUMCHILD	7.17	-.56
EDUCAT	-2.52	-.15
YLOF	-3.99	-2.19
YMF	-1.10	.38
GROSINK	-21.61	-1.01
TOTSALES	14.32	-1.99
DSALETOT	-4.29	1.43
TACROWN	-.98	.55
TACRRENT	-1.19	2.59
NW	.12	-.68
NWOFASST	1.43	-.04
NF178	17.95	6.02
NF177	1.94	1.19
MGTI78	-9.88	-3.11
MGTI77	-2.75	.78
NCI78	.04	-2.34
NC177	1.36	-.57
<u>Location of Group Centroids</u>		
Group 1	4.52	1.80
Group 2	1.42	-1.36
Group 3	-4.60	.57

between groups and these variables are the same for all data cases.

Table 7-6 displays the coefficients for the functions representing the highest income level ($45,000). As expected, from previous discussion, income variables have the highest magnitudes. MGTI78 and NFI78 contribute far more than the other coefficients with GROSINC and TOTSALES the next highest. Unlike income levels II and III one function discriminates poorly between the groups. Figure 7-4 shows the first function as unable to distinguish between groups 1 and 3. The low significance level for one function, shown in Table 7-1, predicted this outcome.

7.6.4 Standardized Coefficients and Centroid Results: 1981

The size (TOTSALES, GROSINC) and most recent year's income (MGTI78, NFI78) variables established a pattern of relative importance for 1979. With only a few exceptions that pattern continues in the 1981 stage. The first function's coefficients listed in Table 7-7 show NCI80, GROSINC, NCI79 and AGE as having the greatest effect on discriminant scores for income level I. The positive coefficient on the age variable tends to classify older operators into more risk averse groups. Figure 7-5 shows that the variables discriminate the groups fairly well. The same is reflected in Table 7-2. Where the high significance of Wilkes lambda prior to one function indicates strong differences between groups at all income levels.

For income level II, TOTSALES, AGE and GROSINC have the coefficients with the greatest absolute magnitudes. While AGE contributes relatively strongly to the discriminant score its effect becomes offset by the negative coefficients on the highly correlated YLOF and YMF

Table 7-6. Canonical Discriminant Functions for Income Level IV: 1979

Variable Name	Standardized Discriminant Function Coefficients	
	Function 1	Function 2
MARITAL	1.07	-.75
AGE	-1.59	4.92
NUMCHILD	-.29	.29
EDUCAT	-.30	.92
YLOF	1.15	.11
YMF	-.40	.11
GROSINK	-3.98	8.68
TOTSALES	3.98	-6.24
DSALETOT	.46	.55
TACROWN	-.07	2.53
TACRRENT	-.59	.72
NW	.54	-2.89
NWOFASST	1.35	1.12
NF178	-10.61	1.83
NF177	-1.22	-.52
MGTI78	11.55	-3.73
MGTI77	-.09	.48
NCI78	.44	-1.78
NC177	N.E.	N.E.
<u>Location of Group Centroids</u>		
Group 1	-1.77	-2.36
Group 2	2.27	-.01
Group 3	-1.73	2.04

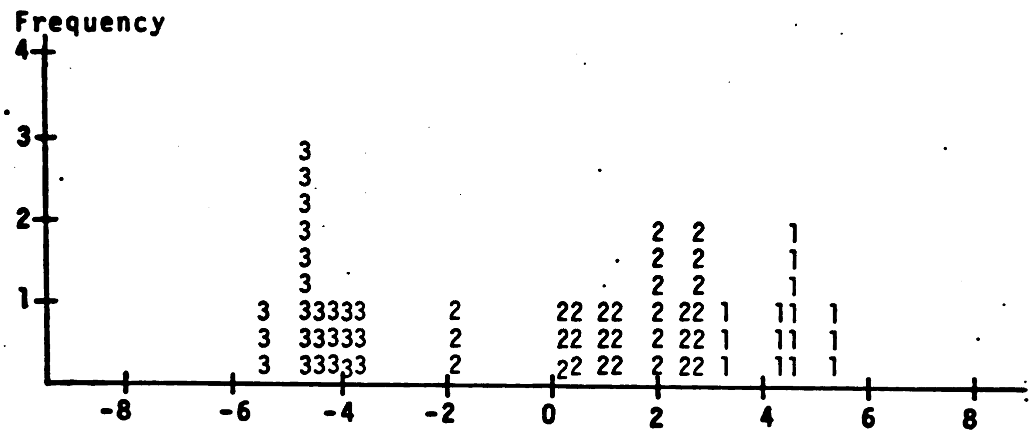


Figure 7- 3. Plot of data case and group centroid estimated locations: income level III, 1979.

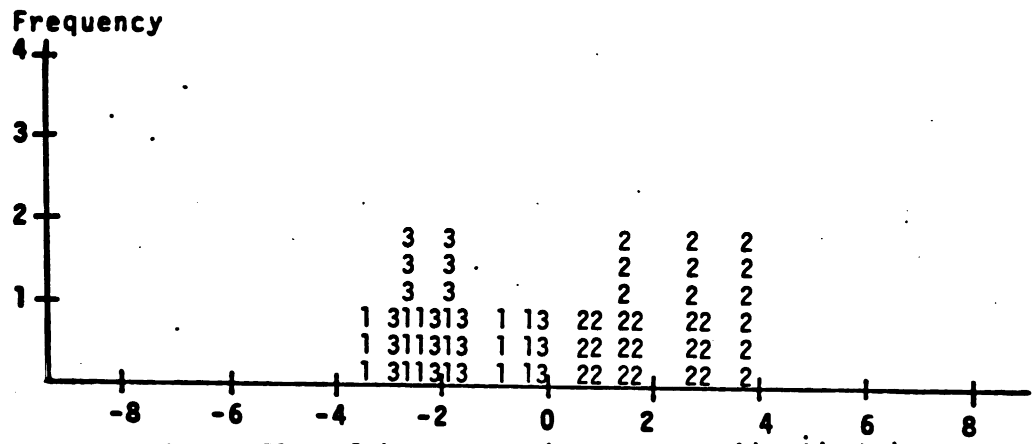


Figure 7-4. Plot of data case and group centroid estimated locations: income level IV, 1979.

Table 7-7. Canonical Discriminant Functions for Income Level I: 1981

Variable Name	Standardized Discriminant Function Coefficients	
	Function 1	Function 2
MARITAL	-1.57	.21
AGE	4.66	1.92
NUMCHILD	-1.73	-2.70
EDUCAT	1.66	-.05
YLOF	-2.30	-1.04
YMF	.15	.79
GROSINK	6.96	11.05
TOTSALES	.15	-8.27
DSALETOT	.26	1.82
TACROWN	-3.40	-1.28
TACRRENT	-2.38	-.24
NW	-.72	.59
NWOFASST	-.29	-.26
NFI80	-2.04	-1.68
NFI79	3.75	-1.75
MGTI80	N.E.	N.E.
MGTI79	N.E.	N.E.
NCI80	-8.60	-.26
NCI79	4.95	1.85
Location of Group Centroids		
Group 1	-3.59	-.69
Group 2	2.69	-1.37
Group 3	.75	2.98

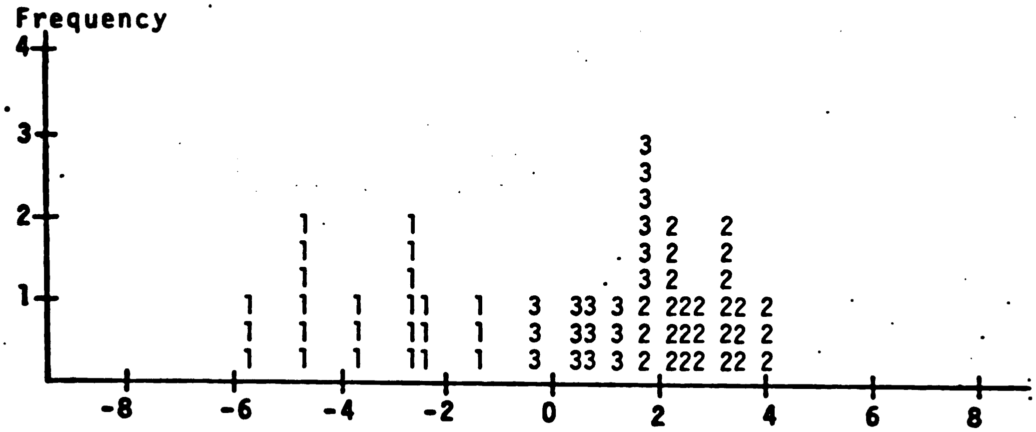


Figure 7-5. Plot of data case and group centroid estimated locations: income level I, 1981.

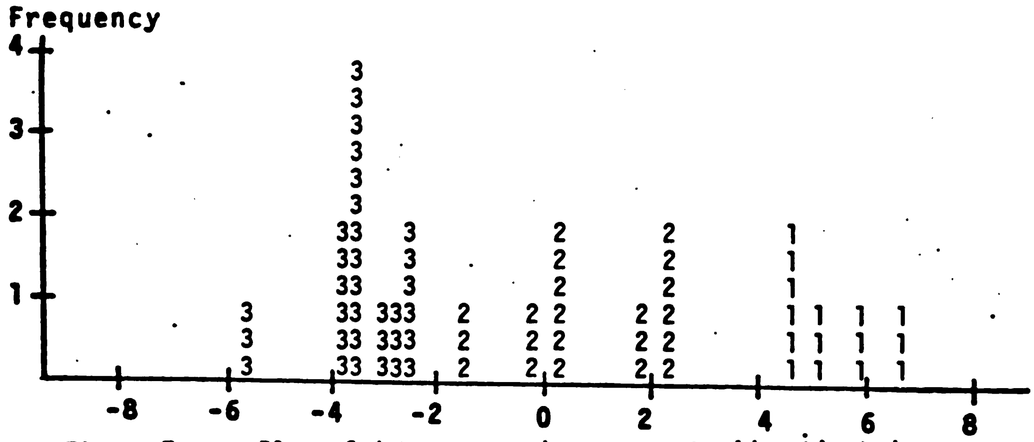


Figure 7-6. Plot of data case and group centroid estimated locations: income level II,1981.

variables (correlation of AGE with YLOF and YMF is .92 and .88 respectively). The groups are extremely well discriminated on the 17 variables. MGTI78 consistently ranked high for the 1979 stage standardized coefficients. Yet MGTI80 is conspicuously absent from income levels I and II in 1981. This occurred primarily because MGTI80 did not pass the tolerance test at either income level.

Table 7-9 gives the standardized coefficients with GROSINC, MGTI80, TOTSALES and NW as the variables with the highest coefficients (ignoring sign). NW's high rank suggests some interesting implications especially since the other financial variable, NWOFASST, ranked in the top five variables at the income level II. At income level II the combined effect of the financial variables was to classify those with more secure financial positions into more risk preferring groups and those with lower NW and NWOFASST into less risk preferring groups. Yet these same variables cause individuals with better financial situations to be classified in the middle group (2) at income level III. Chapter 6 showed individuals least willing to take risk at level II incomes. Here the analysis demonstrates that lower values on the financial variables likely mean even more risk averse tendencies at level II. But for higher incomes designated by level III, the farm's financial situation has a less clear-cut effect. Level II may be an extremely important level for those with a high debt to equity ratio. These individuals likely have fixed responsibilities they must meet at these incomes. As the income level goes up, discretionary income increases and the lower equity (and percentage equity) individual appears less likely to remain so risk averse. Discussion of the structure coefficients in the next

Table 7-8. Canonical Discriminant Functions for Income Level II:1981

Variable Name	Standardized Discriminant Function Coefficients	
	Function 1	Function 2
MARITAL	.70	-1.50
AGE	5.14	3.71
NUMCHILD	-2.05	1.12
EDUCAT	1.22	-.41
YLOF	-2.00	-1.45
YMF	-3.03	-2.16
GROSINK	3.92	-.38
TOTSALES	5.11	2.25
DSALETOT	-.64	-1.41
TACROWN	-3.22	.40
TACRRENT	-1.15	.52
NW	-.23	-2.35
NWOFASST	3.06	1.59
NFI80	-.07	.16
NFI79	-.14	.73
MGT79	N.E.	N.E.
MGTI79	.01	-.36
NCI80	-3.09	-.95
NCI79	N.E.	N.E.
<u>Location of Group Centroids</u>		
Group 1	5.53	1.27
Group 2	.99	-1.89
Group 3	-3.15	.63

Table 7-9. Canonical Discriminant Functions for Income Level III:1981

Variable Name	Standardized Discriminant Function Coefficients	
	Function 1	Function 2
MARITAL	1.74	-.42
AGE	.30	2.17
NUMCHILD	-.27	.25
EDUCAT	4.43	-.70
YLOF	-1.03	-3.76
YMF	1.56	.19
GROSINK	11.68	2.31
TOTSALES	-7.31	-.34
DSALETOT	-1.46	1.83
TACROWN	-4.18	-2.68
TACRRENT	-5.10	-.39
NW	6.66	2.66
NWOFASST	-.45	.58
NFI80	N.E.	N.E.
NFI79	-3.13	-2.55
MGTI80	-7.39	1.70
MGTI79	-.27	-1.36
NCI80	4.48	-3.90
NCI79	-1.80	5.24
<u>Location of Group Centroids</u>		
Group 1	-5.78	1.39
Group 2	6.04	1.80
Group 3	.49	-2.97

section supports the relative importance of the financial variables.

The groups for income level III were those most easily discriminated by the variables of all eight levels tested (i.e. I-IV 79 and I-IV 81). The considerable differences in the centroid locations emphasize this result (see Figure 7-7). As in the 1979 stage, the variables best represented group differences at levels of income close to those typically experienced.

GROSINC and TOTSALES had by far the highest standardized coefficients at income level IV (see Table 7-10). Thus differences in these variables contributed most to classification of the data cases among groups. It would appear that the variables discriminate well between the groups at this income level (Figure 7-8).

7.7 Results for Structure Coefficients: 1979 and 1981

Standardized coefficients reflect the contribution of the variables to the discriminant scores and thus help classify individuals into different groups. Correlation among variables distorts the relative ability of the individual standardized coefficients to reflect the information carried by the function. This is a serious limitation on the use of standardized coefficients for interpretation of individual variables. Structure coefficients tell something quite different from that communicated by the standardized coefficients. This section presents the values for two types of structure coefficients: within-groups structure coefficients and total structure coefficients. The structure coefficients represent the relative ability of an individual variable to supply the same information as the discriminant function. The coefficients are on a zero to one scale (absolute value). When

Table 7-10. Canonical Discriminant Functions for Income Level IV:1981

Variable Name	Standardized Discriminant Function Coefficients	
	Function 1	Function 2
MARITAL	.41	.94
AGE	-3.60	1.01
NUMCHILD	-3.17	-1.69
EDUCAT	-.24	1.08
YLOF	1.51	1.08
YMF	3.59	-.82
GROSINK	18.66	4.91
TOTSALES	-15.50	-2.33
DSALETOT	2.51	-.45
TACROWN	1.63	-1.60
TACRRENT	-2.69	-.96
NW	1.37	.10
NWOFASST	-2.37	.61
NFI80	N.E.	N.E.
NFI79	-2.13	.12
MGTI80	-6.93	-2.35
MGTI79	.01	1.57
NCI80	3.95	.63
NCI79	-1.58	-.25
Location of Group Centroids		
Group 1	-1.87	-2.92
Group 2	-4.44	1.20
Group 3	5.48	.41

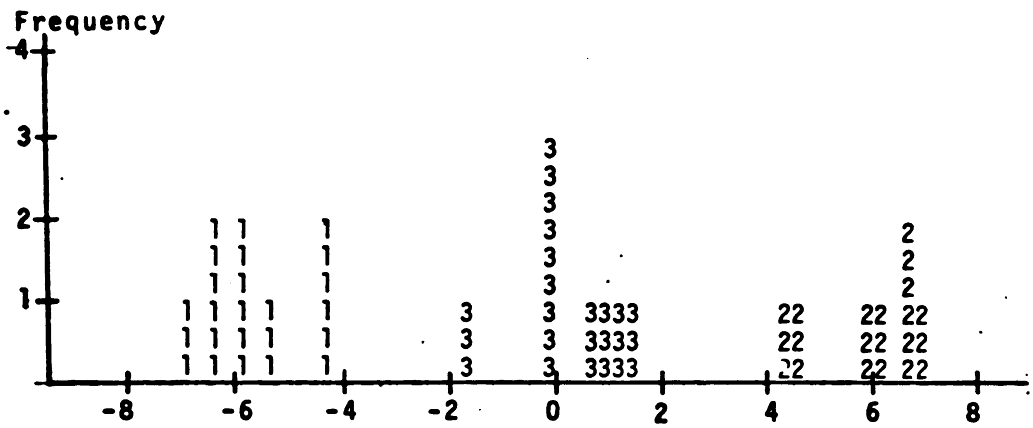


Figure 7- 7. Plot of data case and group centroid estimated locations: income level III, 1981.

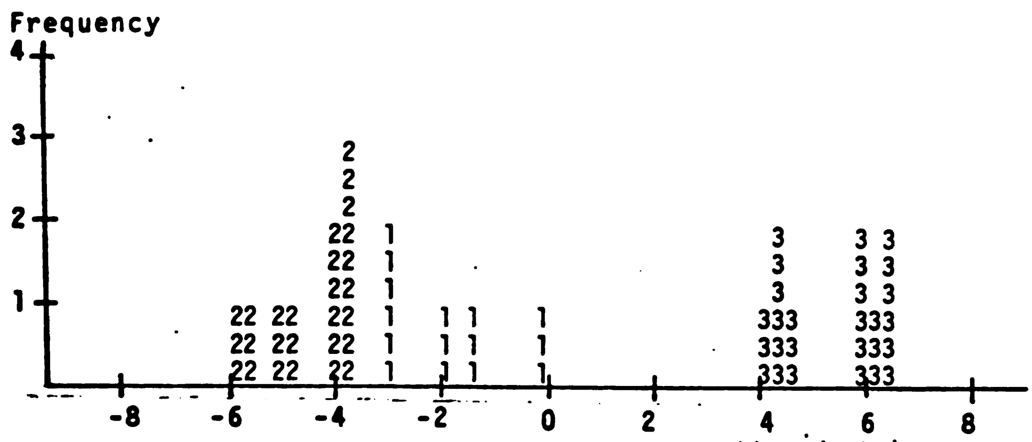


Figure 7- 8. Plot of data case and group centroid estimated locations: income level IV, 1981.

the absolute magnitude of the coefficient is very large (near +1.0 or -1.0) the variable carries much the same information as the function. When the coefficient is near zero the two have little in common.

7.7.1 Within-Group Structure Coefficients

Table 7-11 lists those four variables with within-group coefficients which have the highest absolute magnitudes for each income level in 1979 and 1981. These coefficients tell which variables best reflect the differences among data cases within the groups (i.e. the differences causing one person to be just barely in a group's bounds and another located right on the centroid). Several general observations are recognized from the coefficients. None of the variables correlate particularly well with the within-group differences. The greatest absolute magnitude of any coefficients is .37. Several income levels do not have any variables with coefficients above .30. What this means is that no one or two variables may be singled out as most important. Rather, it suggests that for within-group differences a set containing many of the 19 variables is required to carry information similar to the function.

The table also demonstrates that no single variable or pair of variables dominates across income levels. While a few income related variables do show up at most levels (TOTSALES and MGTI78 in 1979; NFI80 in 1981), the low absolute magnitudes and variation of relative position make it unlikely that these income related variables supply sufficient information by themselves for good within-group location. Thus, income and total sales are not directly related to risk preferences as often assumed.

Table 7-11. The Four Variables with the Highest Absolute Magnitudes for their Within-Group Structure Coefficients at each Income Level: 1979 and 1981

1979

Income Level							
I		II		III		IV	
NFI78	-.37	TOTSALES	.36	TOTSALES	.23	NFI77	-.34
MGTI78	-.32	TACRENT	-.29	NUMCHILD	.23	MGTI78	.27
YLOF	.28	NWOFASST	-.27	NCI78	.21	DSALETOT	-.21
TOTSALES	.20	NGTI78	-.23	TACRRENT	.17	TOTSALES	.17

1981

Income Level							
I		II		III		IV	
NCI80	-.30	MGTI80	.22	TACRRENT	.28	DSALETOT	.22
NWOFASST	-.20	NW	.20	NW	.25	GROSINC	.20
NFI80	-.22	TOTSALES	.20	MARITAL	.21	MARITAL	.20
MGTI79	.21	NFI80	.19	EDUCAT	.20	NFI80	-.19

Finally comparison of the relative order of the discriminating variables supplies evidence of instability of relative importance among variables for within-group discrimination between 1979 and 1981. The order of the variables differs considerably from one time period to the next. For instance, of the four highest ordered variables at income level I, 1979, only one variable repeats in the highest four in 1981. Even that variable (NFI78 and NFI80) does not hold the same relative position. A similar result occurs at income levels II and IV. For income level III no variables included in highest four for 1979 were also in the top four in 1981.

The within-group coefficients make a strong case against intertemporal stability of the relative impact of socioeconomic attributes for within-group discrimination of individuals according to risk preferences. This evidence implies rejection of hypothesis three. But the hypothesis specifically pertains to the stability of the socioeconomic variables' relative ability to explain differences between groups. While the within-group coefficients may sometimes indicate between group differences they do not most directly apply to the hypothesis.

7.7.2 Total Structure Coefficients: 1979

The total structure coefficients identify the information carried by the individual variables for discriminating between groups. These coefficients directly apply to testing hypothesis three. Also, they are probably most easily interpreted and understood. Each coefficient represents the bivariate correlation between the data case scores and the variable values. A variable with a coefficient near +1.0 or -1.0 supplies almost the same information for differentiation between groups as the function.

Table 7-12 lists the variables whose total structure coefficients have the highest absolute magnitudes. For 1979 the income related variables are again among the most important. Yet the income variables do not dominate quite the way they did with the standardized and within-group coefficient rankings. The table also shows that social and financial variables probably correlate better to group differences than implied by the standardized coefficients.

Although none of the variables carry nearly so much information as the function, DSALETOT and MGTI77 for income level III and NFI77 for income level IV carry close to 50% of the information. The 1979 total structure coefficients tell a different story than the standardized coefficients. For example, income variables remain important, but unlike the standardized coefficients, income related variables for 1977 rank higher than those for 1978 (most recent) for income levels II, III, IV. This implies that in some instances income data lagged one period could differentiate between the groups more accurately than the most recent data. The result supports the hypothesis for including lagged variables in the set of discriminating variables.

Another feature of the 1979 total structure coefficients is the relative importance of DSALETOT at the first three income levels. The percentage of sales coming from the dairy enterprise turned out to be the best single parameter to differentiate among the groups over these incomes. A higher degree of sales from the dairy enterprise causes the assignment of an individual to groups 2 or 3 at income level I. This same characteristic brings assignment to group 2 at income level II and group 1 at income level III (i.e. the more dairy oriented the farm the

Table 7-12. The Five Variables with the Highest Absolute Magnitudes for their Total Structure Coefficients at each Income Level: 1979 and 1981

1979

Income Level							
I		II		III		IV	
DSALETOT	-.33	NFI77	-.34	DSALETOT	.53	NFI77	-.47
MGII78	-.30	DSALETOT	.25	MGTI77	-.48	NWOFASST	.34
NWOFASST	-.29	AGE	-.20	NCI77	.40	MARITAL	.29
NUMCHILD	-.29	YMF	-.18	TACROWN	-.35	MGTI78	.26
NFI78	-.28	NUMCHILD	.16	NCI78	.35	GROSINC	.17

1981

Income Level							
I		II		III		IV	
NWOFASST	-.33	NWOFASST	.46	NWOFAAST	.40	EDUCAT	-.58
NGTI79	.28	NFI80	.39	MARITAL	.38	YMF	.45
MGT80	-.28	MGTI80	.36	NW	.32	AGE	.39
TACRRENT	.26	NW	.33	AGE	.32	TACROWN	.39
NFI80	.26	GROSINC	.29	YLOF	.23	NW	.37

more likely the operator is risk averse at very low incomes and more risk preferring at higher levels). Although this result is by no means conclusive due to the low coefficients, it does support the hypothesis of difference between farm type suggested by Lins, Gabriel and Sonka.

7.7.3 Total Structure Coefficients: 1981

Individual income related variables have considerably less discriminatory power in 1981 than in 1979. As a matter of fact at the two highest income levels, income variables correlate very poorly to group differences. Unlike 1979 when DSALETOT performed relatively high for the first three income levels, in 1981 NWOFASST demonstrated a pattern of relative importance for the same income ranges. For levels I and II higher ratios of equity to debt cause an operator to be classified into more risk preferring groups. But higher ratios move a person closer to group 2 at level III. Thus farmers with higher equity to debt ratios tend to be those most willing to take risk at low income levels. Probably fixed commitments for mortgage payments and family living reduced the willingness of more leveraged individuals to take risk at low income levels. That result begins to change at the third income level so that by the $45,000 income level NWOFASST shows very little correlation to the discriminant scores.

At first inspection it might be possible to construe the change in relative importance from DSALETOT in 1979 to NWOFASST in 1981 as indicative of a structural change in agriculture. Two major events did occur between the two surveys. First, the base price for dairy supports was reduced (not increased as expected) the first quarter of 1981 or just before the second survey. Second, the interest rate Michigan farmers paid rose dramatically between 1979 and 1981 causing many farmers to incur increased repayment commitments. Either of these events could precipitate a shift from DSALETOT to NWOFASST. Yet, care should be taken with such reasoning. Even though these variables rank high compared to the others, they really carry only a small portion of the information. Only once does either of them carry half as much information as the function.

As far as the other 1981 variable rankings EDUCAT has the coefficient with the greatest absolute magnitude of any at -.58. Education, years managing the farm, and operator's age relate best to the between group differences at income level IV. Here more education causes one to be assigned to groups 1 or 2. But the older the operator is or the longer he has been managing the more likely he will be assigned to group 3. Thus level of education and age have opposing effects at this income level in 1981.

7.7.4 Intertemporal Comparisons Based on Total Structure Coefficients

What do the total structure coefficients indicate concerning acceptance or rejection of the third hypothesis? A comparison of the five variables with the highest coefficients demonstrates considerable differences from 1979 to 1981. Except for level 1, none of the variables ranked highest in 1979 remained the same in 1981. Even at income level I there is considerable difference between the two years. Comparison between the variables for 1979 and 1981 at level III makes a particularly strong case for rejection of the stability of the characteristic-preference relationships. Analysis in Chapter 6 demonstrated risk preferences most intertemporally stable over this income range. And the statistics in Table 7-1 and 7-2 showed that the same set of discriminating variables discriminated the groups well for both 1979 and 1981. Therefore one would expect that if the results from any income range would support hypothesis three, it would be those for income level III. Despite the expectations none of the variables with the best relationships to the group differences were the same between 1979 and 1981. As a matter of fact, whereas financial and social variables dominate in 1981, income and farm size variables were most important in 1979. The differing outcomes supply strong evidence for rejection of intertemporal stability of farmer attribute and risk preference relationships. The next section uses classification ability to further emphasize this point.

7.7.5 Classification Results

Classification is an activity in which either the discriminating variables or the canonical discriminant functions are used to predict the group to which a case most likely belongs. This section discusses the ability of the 19 discriminating variables to accurately predict risk preference group membership. This accuracy acts as evidence with respect to hypothesis two. Recall that hypothesis two stated that observable socioeconomic characteristics can be employed to classify decision makers according to risk preferences.

Tables 7-1 and 7-2 enumerated the percentage of cases correctly classified for each income level in 1979 and 1981. For 1979, one function predicted 65%, 100%, 91% and 78% correctly for income levels I, II, III and IV respectively. For the same income levels in 1981 the correct classification was 95%, 100%, 100% and 100%. The values for tau, a standardized measure of improvement regardless of the number of groups (see Section 7.4) are found in Table 7-13.

Table 7-13. Tau* Statistics for Each Income Level for 1979 and 1981

	Income Level			
	I	II	III	IV
Tau Statistic: 1979	.54	1.00	.88	.71
Tau Statistic: 1981	.94	1.00	1.00	1.00

*Tau is a standardized measure of classification improvement over random occurrence regardless of the number of groups.

These statistics show that for six of the eight discriminant functions the variables do an excellent job predicting group membership. Only for income levels I and IV in 1979 is the classification only moderately successful. While these statistics do support the second hypothesis, one ought to question how much weight should be given the classification ability. In other words, are there a lot of borderline cases which are just barely classified correctly or are most cases strongly assigned to groups? Here an inspection of the posterior probabilities of group membership $Pr(G_k | X)$ serve as good indicators. Values at or near one indicate a strong probability the case is correctly classified. However values close to .50 indicate marginal accuracy. The percentage of correctly classified cases with a $Pr(G_k|X)$ greater than .85 for each income level are as follows: 1979 Level I - 13%, Level II - 100%, Level III - 100%, Level IV - 50%; 1981 Level I - 72%, Level II - 100%, Level III - 100% and Level IV - 83%. These results reinforce the group classification outcomes. All levels, save levels I and IV 1979, show a high percentage of the correctly classified cases have a high probability of membership.

These accuracy of prediction statistics also serve to measure the difficulties caused by not meeting the assumption of a multivariate normal distribution for the population (the most difficult assumption to meet). If a particular case has a .90 probability of belonging to group 1 and only a .10 probability of belonging to group 2, it is reasonably assured that small inaccuracies due to violation of assumptions will not cause a problem.

Overall the socioeconomic variables carried sufficient information to accurately distinguish the data cases into the correct risk preference groups. Both 1979 and 1981 results depicted the best classification ability at incomes around $10,000 and $25,000. These support the second hypothesis. But the results for the $0 and $45,000 income levels are not as clear cut and at best do not indicate a certain rejection. It therefore appears that certain observable socioeconomic characteristics may be used to classify individuals into risk preference groups with some success. Although this result has some possible applications in decision research and extension, if the relationships between variables and preferences do not remain reasonably stable over time, the extent of application is diminished.

7.7.6 Classification and Intertemporal Stability

This section applies classification to testing the intertemporal stability of the variable-preference relationships. In previous sections, interpretation produced evidence indicating rejection of stability of the relationships. Test results in this section will provide information toward a similar conclusion.

If the variable-preference relationships remain stable over a period of time, one would expect the estimated discriminant functions in one time period to classify data cases from another time period almost as well as the original. Thus the discriminant functions for 1979 are used to predict classification of the 1981 data cases and vice versa. For instance, substituting 1981 values into the 1979 functions could be represented mathematically as follows:

$$f_{km} = u_{0,79} + u_{1,79}\, X_{1km,81} + u_{2,81}\, X_{2km,81} + \ldots$$

where f_{km} = the score on the canonical discriminant function for case M in group K;

$X_{i\,km,81}$ = the value on discriminating variable X_i in 1981 for case M in group K;

$u_{i,79}$ = coefficients which produce the desired characteristics in the function for 1979.

Based on these scores data cases are assigned to groups and the results compared to actual group membership.

Table 7-14 gives the percentage of 1981 cases correctly classified using the 1979 estimated discriminant functions for each income level. It also provides the percentage of 1979 cases correctly classified by the 1981 functions. The income level I functions showed extremely poor accuracy. Yet, due to the lower relative classification ability at this level documented in the previous section, less is expected at this income level. However, expectations for the other income levels should be considerably greater, especially for II and III where in the original classification a 100% accuracy was achieved for both 1979 and 1981. Despite expectations, the functions for levels III and IV performed poorly. At these income levels the 1979 discriminant functions could only correctly classify 43% of the cases using the 1981 values for the variables.

7-14. The Percentage of 1981 (1979) Data Cases Correctly Classified When 1981 Variable Values Are Substituted Into the 1979 (1981) Discriminant Functions*

Income Level	1979 Discriminant Functions 1981 Variable Values	1981 Discriminant Functions 1979 Variable Values
I	17	22
II	60	60
III	43	30
IV	43	30

*Based on one function at each income level.

The discriminant functions for income level II proved the best. Even these functions could only classify 60% of the data cases correctly. If the risk preference groups had been very narrowly defined on risk aversion space the 60% figure would not be too bad. But risk aversion space was only divided into three categories of decision makers, which causes even 60% accuracy to be unacceptable.

Information from the test indicates rejection of intertemporal stability of the relationships between the socioeconomic variables and risk preferences (hypothesis three). This supports conclusions as to stability of the relationships interpreted from the structure coefficients.

7.8 Chapter Summary

In this chapter discriminant analysis was used to test hypotheses two and three. The standardized coefficients for the discriminant functions showed farm size and farm income variables as those most important to determination of the discriminant scores. The structure coefficients indicated several conclusions. First, no single variable or small subset of the variables carries a major part of the information of the whole set. Thus the idea of finding a small, easily manageable set of variables to accurately classify producers according to risk preference seems remote. Second, the total structure coefficients show individual financial and social variables as at least equally able to discriminate between risk preference groups as do size and income variables. Finally, those variables with the greatest relative ability to differentiate among risk preference groups did not remain the same between 1979 and 1981. This result was true even for those income levels shown most intertemporally stable in Chapter 6.

The socioeconomic variables successfully discriminated the data cases into appropriate groups for the sample. The ability of the varaables to differentiate the data cases accurately was especially good for income levels II and III. Thus, for income levels typically experienced by producers, hypothesis two could not be rejected.

Finally, the 1979 (1981) discriminant functions were tested for their ability to accurately classify farmers into risk preference groups based on the 1981 (1979) data. The results from this test demonstrated considerable change from one time period to the other in the estimated variable-preference relationships. This information combined with that from interpretation of the structure coefficients implies rejection of hypothesis three.

Chapter 8

8.1 Introduction

Farmers make decisions in an uncertain environment. In many areas the uncertainty increased during the 1970's and the uncertainties will likely continue into the 1980's and beyond. As a result of the increased uncertainty, there is a need to improve the theory and methods of risky decision making. Important operational problems cause considerable difficulty in applying contemporary decision theory based on expected utility theory to the analysis of actual decisions. Proper application of expected utility theory requires explicit information about the decision maker's preferences. Despite several studies designed to estimate farmers' risk preferences, little reliable information is available. And much of that information was collected using empirical estimating techniques with serious inadequacies.

Even if risk preferences could be measured accurately two interrelated problems will plague application of the collected data. The first involves the possible intertemporal instability of risk preferences. Almost no empirical evidence is available with respect to this question. The second problem occurs due to a desire by many scientists to relate risk preferences to observable farm and operator socioeconomic characteristics. If such variables could be used to estimate risk preferences, then the cost of direct elicitation and the need to repeatedly measure preferences due to intertemporal instability could be reduced. Yet the literature supplies no convincing evidence that this can be successfully done, nor is there any evidence that the relationships themselves will not change over time. These problems led to the following objectives of this report:

1. Identify agricultural producers' risk preferences and analyze their intertemporal stability using paired samples of producers.
2. Examine the intertemporal stability of the relationships between observable socioeconomic characteristics in classifying farmers according to risk preferences.
3. Employ the interval measurement approach to enlarge the data base on producer risk preferences. And observe and describe the operational difficulties in application of the interval measurement approach in data collection, and suggest improvements.

The next section summarizes the research effort in fulfilling and completing the first two objectives. While the third objective is in part a result of completion of objective one, section 8-3 discusses the latter portion of the objective. Finally, conclusions and requirements for future research are presented.

8.2 Summary of Data Collection and Analysis

8.2.1 Risk Preference Measurement and Intertemporal Comparison

Risk preferences were measured using a new method, the interval approach, based on stochastic dominance with respect to a function. This approach reduces many of the problems attributed to methods previously used to measure preferences. Average absolute risk aversion intervals were measured in the neighborhood of four incomes: $0,

$10,000, $25,000, and $45,000. A sample of twenty-three central, lower Michigan farmers was surveyed in both 1979 and 1981.

The sample demonstrated risk preferring, risk averting and risk neutral attitudes. Many farmers exhibited all three types of attitudes over the range of income. No pattern occurred on the bounds of average absolute risk aversion over the income range, either between individuals or time periods. The sample tended to be most risk averse in the neighborhood of $10,000 income and least risk averse for incomes near $0. A large portion of farmers' measured risk aversion intervals differed from risk neutrality, thus reaffirming the need for economic analysis and prescription done in an expected utility framework.

Analysis used paired individual data to test intertemporal stability of risk preferences. Every sample member's measured intervals changed to some extent for at least one income level between 1979 and 1981. Yet many changed only a small amount and no patterns of change were observed. Farmers who were risk averse (preferring) at each income level tended to remain risk averse (preferring) in 1981. Risk preference intervals were quite stable for income levels typically experienced by farmers. But at incomes in the neighborhood of $0, $10,000 and $45,000 stability was no better than expected of random happening. Therefore the hypothesis that risk preferences are stable over time was rejected for all but incomes near $25,000.

8.2.2 Estimation of Attribute-Preference Relationships and Testing their Intertemporal Stability

Chapter VII concerned itself with estimating the relationships of 19 socioeconomic variables to risk preferences and testing the intertemporal stability of those relationships. Discriminant analysis techniques were applied to group individuals into three risk preference classes at each of the income levels used for preference measurement for 1979 and 1981.

The variables classified the individuals into risk preference groups most accurately for the middle two income levels ($10,000 and $25,000). Farm size and farm income variables proved most important to determination of the discriminant scores and group assignment. But analysis of structure coefficients showed that on an individual variable basis financial and social variables are equally or even more able to discriminate between risk preference groups. Moreover no single variable or small subset of the 19 variables is capable of the accuracy of classification exhibited by the whole set.

Comparison of the discriminating variables' standardized and structure coefficients indicated considerable differences between 1979 and 1981. Finally, the 1979 (1981) discriminant functions were tested for their ability to accurately classify farmers into risk preference groups based on the 1981 (1979) variable data. The results from this test also demonstrated considerable change in the estimated variable-preference relationships from one time period to another. This information combined with that from interpretation of the coefficients implies a lack of intertemporal stability for the relationships.

8.3 Suggestions for Improvement of Risk Preference Measurement with the Interval Approach

Overall the interval approach served quite well as a practical method of measuring risk preferences. Yet after observing about forty individuals answer risk interval questionnaires and interpreting those results it appears evident that in several areas improvements can be made. First it is difficult to create a set of instructions which are meaningful for several different farm types. Ideally the instructions should help the farmer understand the questioning process, as well as put the choices in a framework applicable to his farm. If an example is used, it often will not be relevant for some farm situations in a mixed sample of enterprise types. Thus the sample should be limited to one farm type. The nature of the questionnaire and the necessity to put the choices in a practical setting causes some doubt as to the ability of a mail survey to adequately acquire the information. Some of the suggestions in this section and in Cochran (1982) may reduce this problem, but at present, experience suggests personal interview techniques are the most appropriate method for selecting risk preference data. If the interviews took place in a group situation, this would reduce the cost.

After observing the difficulty some respondents had with the concept of equal probabilities for each outcome in the income distributions (i.e. each outcome had a one sixth chance of occurring). Chapter IV noted that a few individuals did not appreciate the analogy to the six sides of a die, because of the possible gambling interpretation. On the other hand, simply stating that the probabilities were each one sixth or equal did not appear to be the best possible procedure. Putting the choices in terms of a cumulative probability next to the set of distributions at each question might prove most operational. This may also reduce the respondent's placing subjective probabilities on the outcomes in each distribution (i.e. some individuals appeared not to believe the worse outcomes could happen to them).

Results found in Chapter VI indicate that the division of risk aversion space needs reexamination. While early tests showed the measurement scale as appropriate, more extensive data show few individuals in intervals 5, 6 and 7 and considerably greater numbers than expected in interval 1. Thus more divisions within risk preferring regions and fewer in risk averse regions would allow better differentiation.

Finally more research must be directed at understanding the trade-off between accuracy of estimating absolute risk aversion and the practical nature of the distribution choices. The larger the standard deviation which is specified for the distributions generated by INTID, the broader the income range will be over which absolute risk aversion is estimated. Since average absolute risk aversion is the estimate, its accuracy may decrease as the income range increases. But small standard deviations ($500 or less) result in distributions which appear very similar (this is especially true at higher income levels). Respondents find such distributions difficult to choose between and not particularly interesting. Therefore the intervals cannot be estimated over too narrow an income range if good responses are expected from the individuals completing the questionnaire.

8.4 Some General Conclusions

The analysis was completed in order to test several hypotheses. The general set of null hypotheses were:

1. Risk preferences of individual farmers are intertemporally stable.

2. Observable socioeconomic characteristics can be employed to classify decision makers according to risk preferences.
3. If socioeconomic farm and operator characteristics can be used as an indirect method for estimating risk preferences, the set of attributes and relative importance of individual characteristics are intertemporally stable.

The data and analysis outlined in this report support several conclusions in relation to the hypotheses.

1. Risk preferences at incomes typically experienced by the individuals demonstrate stability over time. But preferences are less stable at other income levels.
2. Farmers exhibit risk preferring as well as risk averse attitudes. They are not risk neutral for most of their choices.
3. Analyses using risk preferences must carefully select the income levels and interval size dependent on the farmers in question and type of decision.
4. A priori selection of functional forms for utility functions to estimate risk preferences over a range of incomes will not be accurate in most cases. Neither are safety-first, first degree and second degree stochastic dominance flexible enough to represent the variety of risk attitudes exhibited.
5. Risk preferences appear to vary at differing income levels so that point estimates or single values cannot adequately represent preferences.

6. Socioeconomic farm and operator characteristics are able to accurately classify producers according to risk preferences for certain income levels. But a small number of easily attainable characteristics are not likely to provide high accuracy.
7. The relationships of socioeconomic characteristics to risk preferences change over time and it is unlikely that an "every man's" utility function based on a limited number of socioeconomic characteristics is estimable.

8.5 Future Research

More risk preference data measured with the interval approach would provide a better understanding of risk preferences as well as improve the operationalization of the approach. This is especially true of data acquired from other types of farms and other geographical areas. More longitudinal data is extremely important to testing the results described in this report.

Research designed to better understand the two types of trade-offs involved in application of the interval approach would also be helpful. The first trade-off is the Type I-Type II errors (error of omission of action choice and error of difficulty in ordering) related to height (risk aversion axis) of the risk aversion interval. The second trade-off is that of accuracy in estimation of absolute risk aversion and practicality of the questionnaire choices. This trade-off is related to the width (income axis) of the interval.

Since individuals were found to be other than risk neutral much of the time, scientists must continue to examine farmer behavior and discover those areas with the most potential for application of risky decision making theory. Agricultural economists also need to develop methods, strategies, and computer software based on contemporary decision theory to assist farmers in the decision process.

Finally, analysis in this report suggests a need to study the impact of major structural changes in the agricultural sector on farmers' risk preferences. Such research could have considerable implications to policy makers, consumers and those industries related to agriculture.

BIBLIOGRAPHY

BIBLIOGRAPHY

Anderson, J.R. "Programming for Efficient Planning Against Non-Normal Risk," Australian Journal of Agricultural Economics, Vol. 19, 1975.

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

Arrow, K. J. and M. Kurz. Public Investment, the Rate of Return, and Optimal Fiscal Policy, Johns Hopkins Press, Baltimore, 1970.

Baker, C.B. and S. T. Sonka. "Effects of Lending Practices and Marketing Options on Risk Management," in Market Risks in Agriculture: Concepts, Methods and Policy Issues, TR-78-1, Dept. of Agricultural Economics, Texas A & M University, 1978.

Barry, Peter J. and C. B. Baker. "Management of Firm Level Financial Structure," Agricultural Finance Review, E.R.S. USDA, Vol. 37, 1977.

Barry, Peter J. and Edwin D. Maberly. "Price Expectations and Producer Marketing Strategies," in Market Risks in Agriculture: Concepts, Methods and Policy Issues, TR-78-1, Dept. of Agricultural Economics, Texas A & M University, 1978.

Binswanger, H. "Attitudes Toward Risk: Experimental Measurement in Rural India," American Journal of Agricultural Economics, Vol. 62, 1980.

Brink, L. and B. McCarl. "The Tradeoff Between Expected Return and Risk Among Cornbelt Farmers," American Journal of Agricultural Economics, Vol. 60, 1978.

Burghardt, William G. and David L. Watt. "Agriculture's Changing Financial Structure, Repayment Ability, and Borrowed Capital Requirements Through 1985," Michigan State University, Agricultural Economics Staff Paper No. 81-48, 1981.

Carman, Garth A. "The Relationship of Producer Attributes to Risk Preference and Management," Unpublished Dissertation draft, 1979.

Carnap, Rudolf. "Formal and Factual Science," in Readings in Philosophy of Science, edited by H. Feigl and M. Brodbeck, Prentice Hall, 1954.

Cochran, Mark. "Selection of Optimal Pest Management Strategies Under Uncertainty: A Case Study in Michigan Apple Production." Unpublished Ph.D. dissertation, Michigan State University, 1982.

Cohen, M.R. and E. Nagel. An Introduction to Logic and Scientific Method, Harcourt and Brace, 1956.

Conklin, Frank and Kenneth O. Hanson. "Information for Decision Making Under Uncertainty: Its Value and Values," in Market Risks in Agriculture: Concepts, Methods and Policy Issues, TR-78-1, Dept. of Agricultural Economics, Texas A & M University, 1978.

Conroth, D.W. "From Statistical Decision Theory to Practice, Some Problems with the Transition," Management Science, 19, 1973.

Dillon, J.L. and P. L. Scandizzo. "Risk Attitudes of Subsistence Farmers in Northeast Brazil: A Sampling Approach," American Journal of Agricultural Economics, Vol. 60, 1978.

Gabriel, Stephen C. and C. B. Baker. "Concepts of Business and Financial Risk," American Journal of Agricultural Economics, Aug. 1980.

Gardner, Bruce L. "Farm Policy and Research on Risk Management," in Market Risks in Agriculture: Concepts, Methods and Policy Issues, TR-78-1, Dept. of Agricultural Economics, Texas A & M Univ., 1978.

Grisley, William and Earl D. Kellogg. "Risk Taking Preferences of Farmers in Northern Thailand-Measurement and Implications," Paper presented at American Agricultural Economics Association Meetings, Urbana, Ill., 1980.

Hadar, J. and W. R. Russell. "Rules for Ordering Uncertain Prospects," American Economic Review, Vol. 59, 1969.

Halter, Albert N. "Measuring Utility of Wealth Among Farm Managers," Unpublished Ph.D. thesis, Michigan State University, 1956.

Halter, A. N. and G. W. Dean. Decisions Under Uncertainty with Research Applications, Southwestern Publishing, Cincinnati, 1971.

Halter, A. N. and R. Mason. "Utility Measurement for Those Who Need to Know," Western Journal of Agricultural Economics 3:99-109,1978.

Hanoch, G. and H. Levy. "The Efficiency Analysis of Choices Involving Risk," Review of Economic Studies, Vol 36, 1969.

Harris, Richard. A Primer of Multivariate Statistics, Academic Press, N.Y. 1975.

Johnson, G.L.,et al. A Study of Managerial Processes of Midwestern Farmers, Iowa State University Press, Ames, 1961.

King, Robert P. "Operational Techniques for Applied Decision Analysis Under Uncertainty," Unpublished Ph.D. thesis, Michigan State University, 1979.

King, R. P. and L. J. Robison. "An Interval Approach to Measuring Decision Maker Preferences," American Journal of Agricultural Economics 63:510-520, 1981.

__________. "Implementation of the Interval Approach to the Measurement of Decision Maker Preferences," Research Report 418, Agricultural Experiment Station, Michigan State University, East Lansing, 1981a.

Klecka, William. Discriminant Analysis, Sage University Paper, Beverly Hills, 1980.

Knowles, G. J. "Estimating Utility of Gain Functions for Southwest Minnesota Farmers," Unpublished Ph.D. thesis, University of Minnesota, St. Paul, 1980.

__________. "Estimating Utility Functions," in An Economic Evaluation of Managing Market Risks in Agriculture, a Proceedings, AE-4492, University of Illinois, Urbana-Champaign, 1980.

Krause, K. and P. Williams. "Personality Characteristics and Successful Use of Credit by Farm Families," American Journal of Agricultural Economics, Vol. 53:619-624, 1971.

Lin, W., G. W. Dean and C. V. Moore. "An Empirical Test of Utility vs. Profit Maximization in Agricultural Production," American Journal of Agricultural Economics 56:497-508, 1974.

Lins, David A., Stephen C. Gabriel and Steven T. Sonka. "An Analysis of the Risk Aversion of Farm Operators: An Asset Portfolio Approach," Western Journal of Agricultural Economics, July, 1981.

Melichar, Emanuel. "Farm Risks from Instability in Financial Markets," Proceeding, Western Regional Research Project W-149, Agricultural Economics Report-4478, University of Illinois at Urbana-Champaign, 1979.

Mendenhall, W., L.Ott and R. L. Schaeffer. Elementary Survey Sampling, Duxbury Press, California, 1971.

Meyer, J. "Choice Among Distributions," Journal of Economic Theory 14: 326-336, 1977.

Meyer, Jack. "Second Degree Stochastic Dominance with Respect to a Function," International Economic Review, Vol. 18, 1977a.

Moscardi, E. and A. de Janvry. "Attitudes Toward Risk Among Peasants: An Econometric Approach," American Journal of Agricultural Economics 59:710-716, 1977.

Nerlove, Marc. The Dynamics of Supply: Estimation of Farmers' Response to Price, Johns Hopkins Press, Baltimore, 1958.

Nie, Norman H., Editor. Statistical Package for the Social Sciences, McGraw-Hill, New York, 1975.

Officer, R. R. and A. N. Halter. "Utility Analysis in a Practical Setting," American Journal of Agricultural Economics 50: 257-277, 1968.

Officer, R. R., A. N. Halter and J. L. Dillion. "Risk, Utility, and the Palatability of Extension Advice to Farmer Groups," Australian J. Agr. Econ., 11, 1967.

Patrick, G. F., S. H. Whitaker and B. F. Blake. "Farmers' Goals and Risk Aversion: Some Preliminary Analysis," in Risk Analysis in Agriculture: Research and Educational Developments, AE-4492, Dept. of Agricultural Economics, Univ. of Illinois, 1980.

Pope, Rulon and B. Delworth Gardner. "The Structure of Agriculture and Risk," in Market Risks in Agriculture: Concepts, Methods and Policy Issues, TR-78-1, Dept. of Agricultural Economics, Texas A & M Univ., College Station, 1978.

Pratt, J. W. "Risk Aversion in the Small and in the Large," Econometrica 32:122-136, 1967.

Rhoade, R.R. "Adjusting Farm Account Data for Representative Research Use," Unpublished Ph.D. thesis, Michigan State University, 1965.

Robison, Lindon J. "An Appraisal of Expected Utility Hypothesis Tests Constructed from Responses to Hypothetical Questions and Experimental Choices," American Journal of Agricultural Economics, Vol 64, No. 2, 1982.

__________. "An Explanation of Apparently Risk Preferring Behavior by Risk Averse Decision Makers," Unpublished manuscript, Michigan State University, 1982a.

Roumasset, James A. Risk and Uncertainty in Agricultural Development, ADC Seminar Report No. 13, Oct. 1977.

Tweeten, Luther G. "Macroeconomics in Crisis: Agriculture in an Under-achieving Economy," American Journal of Agricultural Economics, December, 1980.

U.S.D.A., Michigan Agricultural Statistics, Michigan Department of Agriculture, Lansing. Various issues.

Walker, Odell L. and A. Gene Nelson. "Dealing with Risks in the Management of Agricultural Firms: An Extension/Teaching Viewpoint," in Risk Analysis in Agriculture: Research and Educational Developments, AE-4492, Dept. of Agricultural Economics, Univ. of Illinois, 1980.

Whittaker, J. K. and J. R. Winter. "Risk Preferences of Farmers: An Empirical Example, Some Questions, and Suggestions for Future Research," Risk Analysis in Agriculture: Research and Educational Developments, Proceedings. W-149, Univ. of Illinois Bulletin AE-4492, 1980.

Young, Douglas and Jill Findeis. "Characteristics of Producers: Their Willingness and Ability to Bear Risk," Paper presented at WAEA Meetings, Bozeman, Montana, 1978.

Young, D., W. Lin, R. Pope, L. Robison and R. Selley. Risk Preferences of Agricultural Producers: Their Measurement and Use, A Report of the Subcommittee on Risk Preference Measurement of Western Research Project, W-149, 1979.

APPENDIX A

INSTRUCTIONS FOR COMPLETING SECTIONS I - IV

This part of the questionnaire is designed to measure your attitude towards risk. Each question asks you to make a comparison between two plans. Below each plan are listed six numbers, which represent levels of after-tax farm profit. One of the six income levels will be realized but assume you don't know which one at the time you select a farm plan. Each level has an equal chance of happening, yet only one outcome will occur.

This is similar to choosing between two crops knowing that six different prices and weather situations would occur. Suppose you could plant Crop A and Crop B and your after-tax farm profit is that listed under each state of nature.

STATE OF NATURE	CROP A	CROP B
(1) Poor prices, poor weather	-5,000	5,000
(2) Poor prices, average weather	5,000	10,000
(3) Average prices, poor weather	6,000	12,000
(4) Average prices, good weather	15,000	13,000
(5) Good prices, average weather	20,000	14,000
(6) Good prices, good weather	25,000	15,000

You don't know what the weather will be like nor do you know what prices will be, but you still must decide which crop you are going to produce. Again, you must decide if you are willing to plant Crop A with lower levels of income for bad outcomes so that you could realize higher income levels if good outcomes occurred or whether you would produce Crop B giving up a chance of high income levels so you won't have to take a chance with low income levels. More importantly this decision is based on the difference in income levels between the two crops for each state of nature. In other words how much are you willing to give up for a chance of being better off to avoid a chance of being worse off? This is the analysis you should make.

There are several factors to keep in mind as you complete this questionnaire.

(1) There are no right or wrong answers. Everyone has different attitudes towards taking chances as opposed to playing it safe.

(2) Try to relate this experiment to your own situation. Assume that at the beginning of the year there were the two farm plans available to you and that you had to choose one for that year.

(3) Assume each income level represents your after-tax farm profit for the entire year. With this in mind think about what you would do if a good outcome occurred (good prices and weather) and you took the plan with the higher income level. On the other hand think about what you would do if a bad outcome occurred (poor prices and weather) and you took the plan with the lower income level.

(4) The "-" sign preceding the income level means income losses.

In each section you are asked to make a comparison and based on which plan you select, you are asked to go to another question. As a result, you are only asked to respond to three of the seven questions in each section.

Each section examines different income levels. In the first section there are negative income levels (or losses). Assume that if you didn't take one of these plans, your losses would be even greater. In each of the following sections the income levels increase.

With these instructions in mind, please complete Sections I, II, III, and IV.

SECTION I

1. If you were required to choose between PLAN 17 and PLAN 3, put a check in the box to the right of the one you would select.

PLAN 17 ☐	PLAN 3 ☐
\$-1,000	\$- 650
\$- 950	\$- 550
\$- 850	\$- 450
\$ 0	\$- 300
\$ 700	\$ 150
\$ 1,100	\$ 300

If you prefer PLAN 17, go to Question 3.
If you prefer PLAN 3, go to Question 2.

2. If you were required to choose between PLAN 7 and PLAN 3, put a check in the box to the right of the one you would select.

PLAN 7 ☐	PLAN 3 ☐
\$-1,000	\$- 650
\$- 450	\$- 550
\$- 150	\$- 450
\$ 400	\$- 300
\$ 450	\$ 150
\$ 1,100	\$ 300

If you prefer PLAN 7, go to Question 5.
If you prefer PLAN 3, go to Question 4.

3. If you were required to choose between PLAN 8 and PLAN 4, put a check in the box to the right of the one you would select.

PLAN 8 ☐	PLAN 4 ☐
\$- 950	\$- 450
\$- 50	\$- 300
\$ 0	\$- 200
\$ 50	\$ 50
\$ 150	\$ 100
\$ 200	\$ 200

If you prefer PLAN 8, go to Question 7.
If you prefer PLAN 4, go to Question 6.

4. If you were required to choose between PLAN 2 and PLAN 12, put a check in the box to the right of the one you would select.

PLAN 2 ☐	PLAN 12 ☐
$- 550	$- 350
$ 0	$- 150
$ 0	$- 150
$ 400	$ 100
$ 650	$ 250
$ 1,100	$ 500

Stop and go to Section II.

5. If you were required to choose between PLAN 7 and PLAN 4, put a check in the box to the right of the one you would select.

PLAN 7 ☐	PLAN 4 ☐
$-1,000	$- 450
$- 450	$- 300
$- 150	$- 200
$ 400	$ 50
$ 450	$ 100
$ 1,100	$ 200

Stop and go to Section II.

6. If you were required to choose between PLAN 26 and PLAN 5, put a check in the box to the right of the one you would select.

PLAN 26 ☐	PLAN 5 ☐
$- 950	$- 600
$- 500	$- 150
$- 150	$- 100
$ 250	$- 100
$ 250	$ 50
$ 450	$ 150

Stop and go to Section II.

7. If you were required to choose between PLAN 29 and PLAN 1, put a check in the box to the right of the one you would select.

PLAN 29 ☐	PLAN 1 ☐
$-1,000	$- 300
$- 200	$- 250
$ 0	$- 100
$ 100	$ 450
$ 600	$ 450
$ 1,050	$ 600

Stop and go to Section II.

SECTION II

1. If you were required to choose between PLAN 3 and PLAN 17, put a check in the box to the right of the one you would select.

PLAN 17 ☐	PLAN 3 ☐
$ 9,000	$ 9,350
$ 9,050	$ 9,450
$ 9,150	$ 9,550
$10,000	$ 9,700
$10,700	$10,150
$11,100	$10,300

If you prefer PLAN 17, go to Question 2.
If you prefer PLAN 3, go to Question 3.

2. If you were required to choose between PLAN 8 and PLAN 4, put a check in the box to the right of the one you would select.

PLAN 8 ☐	PLAN 4 ☐
$ 9,050	$ 9,550
$ 9,950	$ 9,700
$10,000	$ 9,800
$10,050	$10,050
$10,150	$10,100
$10,200	$10,200

If you prefer PLAN 8, go to Question 4.
If you prefer PLAN 4, go to Question 5.

3. If you were required to choose between PLAN 2 and PLAN 13, put a check in the box to the right of the one you would select.

PLAN 2 ☐	PLAN 13 ☐
$ 9,450	$ 9,700
$10,000	$ 9,850
$10,000	$ 9,950
$10,400	$10,350
$10,650	$10,400
$11,100	$10,800

If you prefer PLAN 2, go to Question 6.
If you prefer PLAN 13, go to Question 7.

4. If you were required to choose between PLAN 29 and PLAN 1, put a check in the box to the right of the one you would select.

PLAN 29 ☐	PLAN 1 ☐
$ 9,000	$ 9,700
$ 9,800	$ 9,750
$10,000	$ 9,900
$10,100	$10,450
$10,600	$10,450
$11,050	$10,600

Stop and go to Section III.

5. If you were required to choose between PLAN 6 and PLAN 40, put a check in the box to the right of the one you would select.

PLAN 40 ☐	PLAN 6 ☐
$ 9,150	$ 9,350
$ 9,400	$ 9,550
$ 9,750	$ 9,650
$10,200	$ 9,950
$10,600	$10,550
$10,600	$10,600

Stop and go to Section III.

6. If you were required to choose between PLAN 7 and PLAN 4, put a check in the box to the right of the one you would select.

PLAN 7 ☐	PLAN 4 ☐
$ 9,000	$ 9,550
$ 9,550	$ 9,700
$ 9,850	$ 9,800
$10,400	$10,050
$10,450	$10,100
$11,100	$10,200

Stop and go to Section III.

7. If you were required to choose between PLAN 1 and PLAN 38, put a check in the box to the right of the one you would select.

PLAN 1 ☐	PLAN 38 ☐
$ 9,700	$ 9,700
$ 9,750	$ 9,900
$ 9,900	$10,000
$10,450	$10,050
$10,450	$10,250
$10,600	$10,450

Stop and go to Section III.

SECTION III

1. If you were required to choose between PLAN 29 and PLAN 4, put a check in the box to the right of the one you would select.

PLAN 29 ☐	PLAN 4 ☐
$21,900	$23,650
$24,350	$24,100
$24,900	$24,300
$25,350	$25,150
$26,850	$25,350
$28,250	$25,700

If you prefer PLAN 29, go to Question 3.
If you prefer PLAN 4, go to Question 2.

2. If you were required to choose between PLAN 2 and PLAN 11, put a check in the box to the right of the one you would select.

PLAN 2 ☐	PLAN 11 ☐
$23,300	$23,600
$24,900	$24,250
$25,100	$24,500
$26,250	$25,800
$26,950	$25,950
$28,300	$27,700

If you prefer PLAN 2, go to Question 5.
If you prefer PLAN 11, go to Question 4.

3. If you were required to choose between PLAN 17 and PLAN 4, put a check in the box to the right of the one you would select.

PLAN 17 ☐	PLAN 4 ☐
$21,900	$23,650
$22,150	$24,100
$22,450	$24,300
$25,000	$25,150
$27,200	$25,350
$28,400	$25,700

If you prefer PLAN 17, go to Question 7.
If you prefer PLAN 4, go to Question 6.

4. If you were required to choose between PLAN 6 and PLAN 3, put a check in the box to the right of the one you would select.

PLAN 6 ☐	PLAN 3 ☐
$22,950	$23,000
$23,650	$23,350
$23,850	$23,600
$24,800	$24,100
$26,700	$25,500
$26,850	$26,000

Stop and go to Section IV.

5. If you were required to choose between PLAN 2 and PLAN 1, put a check in the box to the right of the one you would select.

PLAN 2 ☐	PLAN 1 ☐
$23,300	$24,050
$24,900	$24,200
$25,100	$24,700
$26,250	$26,450
$26,950	$26,450
$28,300	$26,850

Stop and go to Section IV.

6. If you were required to choose between PLAN 6 and PLAN 4, put a check in the box to the right of the one you would select.

PLAN 6 ☐	PLAN 4 ☐
$22,950	$23,650
$23,650	$24,100
$23,850	$24,300
$24,800	$25,150
$26,700	$25,350
$26,850	$25,700

Stop and go to Section IV.

7. If you were required to choose between PLAN 17 and PLAN 1, put a check in the box to the right of the one you would select.

PLAN 17 ☐	PLAN 1 ☐
$21,900	$24,050
$22,150	$24,200
$22,450	$24,700
$25,000	$26,450
$27,200	$26,450
$28,400	$26,850

Stop and go to Section IV.

S E C T I O N I V

1. If you were required to choose between PLAN 2 and PLAN 1, put a check in the box to the right of the one you would select.

PLAN 2	PLAN 1
$42,100	$43,450
$44,850	$43,650
$45,200	$44,500
$47,100	$47,450
$48,250	$47,450
$50,550	$48,100

If you prefer PLAN 2, go to Question 2.
If you prefer PLAN 1, go to Question 3.

2. If you were required to choose between PLAN 19 and PLAN 1, put a check in the box to the right of the one you would select.

PLAN 19	PLAN 1
$41,250	$43,450
$44,500	$43,650
$45,500	$44,500
$45,800	$47,450
$46,350	$47,450
$50,450	$48,100

If you prefer PLAN 19, go to Question 5.
If you prefer PLAN 1, go to Question 4.

3. If you were required to choose between PLAN 14 and PLAN 3, put a check in the box to the right of the one you would select.

PLAN 14	PLAN 3
$41,350	$41,650
$42,200	$42,250
$44,400	$42,650
$44,700	$43,500
$47,250	$45,850
$47,500	$46,700

If you prefer PLAN 14, go to Question 6.
If you prefer PLAN 3, go to Question 7.

4. If you were required to choose between PLAN 28 and PLAN 1, put a check in the box to the right of the one you would select.

PLAN 28 ☐	PLAN 1 ☐
$41,250	$43,450
$44,500	$43,650
$44,550	$44,500
$48,700	$47,450
$49,150	$47,450
$49,400	$48,100

Stop and go to Section V.

5. If you were required to choose between PLAN 9 and PLAN 1, put a check in the box to the right of the one you would select.

PLAN 9 ☐	PLAN 1 ☐
$41,200	$43,450
$42,900	$43,650
$43,250	$44,500
$45,400	$47,450
$45,850	$47,450
$50,000	$48,100

Stop and go to Section V.

6. If you were required to choose between PLAN 2 and PLAN 11, put a check in the box to the right of the one you would select.

PLAN 2 ☐	PLAN 11 ☐
$42,100	$42,700
$44,850	$43,750
$45,200	$44,100
$47,100	$46,300
$48,250	$46,550
$50,550	$49,500

Stop and go to Section V.

7. If you were required to choose between PLAN 2 and PLAN 35, put a check in the box to the right of the one you would select.

PLAN 2 ☐	PLAN 35 ☐
$42,100	$42,150
$44,850	$42,600
$45,200	$44,800
$47,100	$45,000
$48,250	$47,500
$50,550	$47,750

Stop and go to Section V.

SECTION V

In this section you are asked to make the same type of comparisons you just made in Sections I-IV only over a wider range of possible income levels. Listed below are five plans:

PLAN 1	PLAN 2	PLAN 3	PLAN 4	PLAN 5
$-1,100	$ 5,000	$10,000	$- 800	$ -200
$ 3,000	$11,000	$15,000	$ 2,000	$10,000
$18,000	$19,000	$20,000	$11,000	$22,000
$35,000	$26,000	$25,000	$25,000	$25,000
$45,000	$32,000	$28,000	$40,000	$35,000
$50,000	$37,000	$30,000	$48,000	$40,000

Compare each set of plans listed below and put a check in the box to the right of the one you prefer:

PLAN 1	☐	OR	PLAN 2	☐
PLAN 1	☐	OR	PLAN 3	☐
PLAN 1	☐	OR	PLAN 4	☐
PLAN 1	☐	OR	PLAN 5	☐
PLAN 2	☐	OR	PLAN 3	☐
PLAN 2	☐	OR	PLAN 4	☐
PLAN 2	☐	OR	PLAN 5	☐
PLAN 3	☐	OR	PLAN 4	☐
PLAN 3	☐	OR	PLAN 5	☐
PLAN 4	☐	OR	PLAN 5	☐

Go to Section VI.

RISK MANAGEMENT STRATEGY QUESTIONNAIRE

1. When you are deciding on whether or not to buy a piece of machinery or equipment, what are the most important considerations?

____

____

____

   a. Does the ability of the machine or equipment to reduce production risks play a role in the decision? (Examples: timeliness of planting and harvest, quality of crops and storage, flexibility, etc.). ____________________

   b. How do you approach this problem when deciding to buy machinery or equipment?

   ____

   ____

   c. Does the risk of repairs (both on present machinery and that considered for purchase) enter into the decision process? ______________________________

   d. What methods do you use to reduce the problems of repair risk?

   ____

   ____

   e. Is the source (dealer, farmer or other) from which you make the purchase important? ____________________

   f. What do you look for in a source as being important (other than price)?

   ____

   ____

   g. How does uncertainty related to inflation effect your decision?

   ____

   ____

h. Does the possibility of technological obsolescence (out of date before worn out) effect your decision process?

____

i. If so, how do you handle this uncertain situation?

____

____

2. Do you ever lease or rent machinery? ______________

a. Do you see this as a method for reducing or transferring risk? If so, what strategies do you use for leasing or renting? ________

____

____

3. Do you custom hire machine services? ______________

a. Do you see this as a method for reducing or transferring risk? If so, what strategies do you use for hiring machine services? ________

____

____

4. Do you ever purchase machinery with other farmers (co-ownership)? ______________________________

Do you see this as a method for reducing or transferring risk? If so, what strategies do you use for co-ownership?

____

____

____

5. Do you rent land? ______ Cash rent? ______; Share rent ______

a. What methods do you use to help reduce risks involved in renting? (these risks include: the land remaining available, rental rate increases, etc.)

____

____

b. Given the going price for land and rental rates, do you believe it is less costly for you to purchase land or rent it? ______________________________

c. Would you purchase the land you rent if it became available for sale? ______________________________

d. If so, is this in part a strategy to reduce the risks involved in renting? ______________________

6. What do you see as the important considerations when deciding where to borrow money?

____

____

a. What methods do you use to insure your borrowing ability or to improve the terms of the loan?

____

____

b. How important is the loan officer's or institution's agricultural lending experience?

____

____

c. Does using an experienced ag lender, who understands the various enterprises, production uncertainties and agricultural cycles serve as a risk reduction strategy?

____

7. Do you ever use dealer or manufacturer financing? _______

a. Why or why not? ______________________________

b. Do you ever use this method of financing to reduce the uncertainty or difficulty of getting other financing?

____

c. Do you ever use this method of financing to keep from reducing the amount your lender is willing to loan you in the future? ______________________

8. What are the most important considerations when you are setting up repayment schedules with your lender?

____

____

a. Do you work with your lender to tailor repayment to your income patterns? ____________________

b. Do you do this to help reduce the risk of cashflow - repayment problems? ____________________

c. Have you made machinery or equipment purchases on delayed payment plans? ____________________

d. Do you do this to help reduce the risk of cash flow - repayment problems? ____________________

e. Do you have nonfarm income? ____________________

f. What role does this nonfarm income play in your repayment strategy?

____

____

9. When you consider using management strategies, certain characteristics of the strategies probably are more important than others.

Rank the following characteristics from 1 to 9, according to their importance when deciding on management strategies. (1 = most important; 9 = least important).

______ Manager's time required to make strategy work.

______ How easy it is to understand the strategy.

______ Out of pocket start up costs.

______ Length of time before initial results.

______ Where you learned about the strategy.

______ Information available to you to make the strategy work.

______ How well the strategy fits your farm set-up.

______ Previous experience you and others have had with this strategy.

______ Other.

APPENDIX B

Appendix B presents the results from discriminant analysis based on the four group scheme described in Chapter 7.

Group	Interval
1	1
2	2,3
3	4,5
4	6,7,8

Table B-1. . Goodness of estimation statistics for the discriminant functions for the four group scheme: 1979.

	Income Level			
	I	II	III	IV
Percentage of Discrimination				
Function 1	81%	66%	57%	82%
Function 2	19%	26%	39%	10%
Canonical Correlation				
Function 1	.94	.98	.96	.98
Function 2	.82	.95	.95	.89
Significance of Wilkes Lambda				
before 1 Function	.46	.04	.13	.04
before 2 Functions	.81	.25	.40	.47
Cases Correctly Classified				
one Function	65%	70%	81%	96%
two Functions	100%	100%	100%	100%

Table B-2. Goodness of estimation statistics for the discriminant functions for the four group scheme: 1981.

	Income Level			
	I	II	III	IV
Percentage of Discrimination				
Function 1	66%	72%	85%	74%
Function 2	22%	21%	15%	21%
Canonical Correlation				
Function 1	.98	.96	.98	.98
Function 2	.94	.89	.94	.94
Significance of Wilkes Lambda				
before 1 Function	.00	.20	.00	.00
before 2 Functions	.04	.64	.14	.19
Cases Correctly Classified				
one Function	83%	100%	100%	100%
two Functions	87%	100%	100%	100%

Table B-3. Canonical discriminant functions for income level I :1979, four group scheme.

	Standardized Discriminant Function Coefficients	
Variable Name	Function 1	Function 2
MARITAL	-.84	.49
AGE	2.74	-.42
NUMCHILD	-.85	-2.87
EDUCAT	1.39	1.73
YLOF	-2.88	3.58
YMF	1.85	-.93
GROSINC	6.99	17.10
TOTSALES	-5.71	-6.94
DSALETOT	-.83	1.69
TACROWN	-1.02	-2.74
TACRRENT	-.36	-1.64
NW	1.58	-.40
NWOFASST	-1.94	-1.49
NFI78	3.27	-1.07
NFI77	-.99	-2.90
MGTI78	-8.43	-6.12
MGTI77	-.03	1.13
NCI78	2.31	2.12
NCI77	-1.61	.56
Location of Group Centroids		
Group 1	5.36	-.08
Group 2	-1.44	.71
Group 3	-1.73	-3.42
Group 4		

Table B-4. Canonical discriminant functions for income level II :1979, four group scheme.

	Standardized Discriminant Function Coefficients	
Variable Name	Function 1	Function 2
MARITAL	-1.92	2.78
AGE	-6.83	.38
NUMCHILD	4.25	-.68
EDUCAT	1.61	1.39
YLOF	7.21	1.41
YMF	-2.84	-2.00
GROSINC	19.86	-9.81
TOTSALES	1.93	5.95
DSALETOT	-5.12	.81
TACROWN	-6.86	-4.06
TACRRENT	-14.00	-.26
NW	3.24	4.27
NWOFASST	-3.05	-2.39
NFI78	8.86	10.48
NFI77	-5.64	-.30
MGTI78	-22.58	-6.45
MGTI77	-3.02	1.38
NCI78	5.06	-1.73
NCI77	4.11	-.40
Location of Group Centroids		
Group 1	-8.18	.58
Group 2	4.05	3.58
Group 3	2.17	-3.40
Group 4	-5.08	1.06

Table B-5. Canonical discriminant functions for income levelIII :1979, four group scheme.

	Standardized Discriminant Function Coefficients	
Variable Name	Function 1	Function 2
MARITAL	.02	-.91
AGE	-5.04	.90
NUMCHILD	6.45	2.99
EDUCAT	.53	-2.40
YLOF	-1.25	-2.71
YMF	1.96	-.34
GROSINC	-6.10	-19.94
TOTSALES	14.03	9.88
DSALETOT	-5.03	-1.18
TACROWN	-2.18	-1.20
TACRRENT	-5.62	1.77
NW	-1.39	2.74
NWOFASST	3.48	-.40
NFI78	-2.03	7.25
NFI77	1.92	1.63
MGTI78	N.E.	N.E.
MGTI77	-3.55	-.88
NCI78	-.07	.48
NCI77	1.04	.21
Location of Group Centroids		
Group 1	-.10	4.16
Group 2	2.37	.30
Group 3	.54	-4.59
Group 4	-8.65	-.28

Table B-6. Canonical discriminant functions for income level IV :1979, four group scheme.

	Standardized Discriminant Function Coefficients	
Variable Name	Function 1	Function 2
MARITAL	-.98	1.07
AGE	-11.18	.11
NUMCHILD	6.51	-.99
EDUCAT	.20	-.25
YLOF	2.47	.45
YMF	3.07	-.75
GROSINC	2.84	-3.57
TOTSALES	2.66	3.14
DSALETOT	-2.20	.76
TACROWN	3.81	-.30
TACRRENT	-.72	-.43
NW	-2.49	.59
NWOFASST	6.58	.70
NFI78	14.62	-12.25
NFI77	-.86	-1.16
MGTI78	-20.70	13.75
MGTI77	.51	-.10
NCI78	-1.58	.48
NCI77	N.E.	N.E.
Location of Group Centroids		
Group 1	-.57	-1.86
Group 2	1.61	2.04
Group 3	6.07	-2.08
Group 4	-12.31	-.30

Table B-7. Canonical discriminant functions for income level I :1981, four group scheme.

	Standardized Discriminant Function Coefficients	
Variable Name	Function 1	Function 2
MARITAL	.66	1.99
AGE	-3.64	.15
NUMCHILD	-1.99	-3.67
EDUCAT	.11	-.57
YLOF	3.71	-.49
YMF	2.14	1.73
GROSINC	-7.96	5.90
TOTSALES	11.48	-6.68
DSALETOT	1.66	2.94
TACROWN	-8.07	.32
TACRRENT	-1.27	1.54
NW	4.92	.12
NWOFASST	-3.61	-.09
NFI80	N.E.	N.E.
NFI79	1.77	-3.63
MGTI80	-.44	1.26
MGTI79	.14	1.76
NCI80	-2.71	2.08
NCI79	N.E.	N.E.
<u>Location of Group Centroids</u>		
Group 1	-2.92	1.22
Group 2	1.10	-3.21
Group 3	13.74	3.69
Group 4	-3.49	2.93

Table B-8. Canonical discriminant functions for income level II :1981, four group scheme.

	Standardized Discriminant Function Coefficients	
Variable Name	Function 1	Function 2
MARITAL	-.61	2.44
AGE	-5.11	-3.66
NUMCHILD	1.93	-3.11
EDUCAT	-1.14	1.83
YLOF	2.03	2.37
YMF	3.13	3.26
GROSINC	-3.29	-13.24
TOTSALES	-5.66	-13.60
DSALETOT	.73	2.26
TACROWN	3.18	-1.24
TACRRENT	.94	-1.97
NW	.27	1.68
NWOFASST	-3.13	-2.33
NFI80	-.10	-4.03
NFI79	.06	-1.77
MGTI80	N.E.	N.E.
MGTI79	.06	1.97
NCI80	3.23	3.73
NCI79	N.E.	N.E.
<u>Location of Group Centroids</u>		
Group 1	-5.42	-.96
Group 2	-.93	1.56
Group 3	3.00	-1.56
Group 4	3.29	3.97

Table B-9. Canonical discriminant functions for income level III:1981, four group scheme.

	Standardized Discriminant Function Coefficients	
Variable Name	Function 1	Function 2
MARITAL	-2.22	-.53
AGE	1.16	.46
NUMCHILD	.88	-.13
EDUCAT	-6.71	-.43
YLOF	2.67	-3.41
YMF	-5.71	2.35
GROSINC	-21.97	4.77
TOTSALES	17.29	-4.63
DSALETOT	-.68	3.04
TACROWN	6.73	-2.22
TACRRENT	6.76	.16
NW	-10.90	2.54
NWOFASST	1.88	-.39
NFI80	N.E.	N.E.
NFI79	6.31	-2.84
MGTI80	11.23	1.02
MGTI79	-1.03	-.01
NCI80	-6.62	-2.63
NCI79	1.53	4.31
Location of Group Centroids		
Group 1	6.05	2.35
Group 2	-8.76	1.07
Group 3	1.84	-3.76
Group 4		

Table B-10. Canonical discriminant functions for income level IV :1981, four group scheme.

	Standardized Discriminant Function Coefficients	
Variable Name	Function 1	Function 2
MARITAL	.75	-.31
AGE	-7.18	4.65
NUMCHILD	-2.64	-1.88
EDUCAT	-.04	-.30
YLOF	4.57	-4.21
YMF	4.79	-1.01
GROSINC	9.89	16.41
TOTSALES	-8.39	-11.77
DSALETOT	1.97	1.50
TACROWN	.25	2.33
TACRRENT	-2.63	-1.01
NW	2.75	-1.83
NWOFASST	-4.62	3.25
NFI80	N.E.	N.E.
NFI79	.50	-4.54
MGTI80	-6.27	-3.00
MGTI79	N.E.	N.E.
NCI80	5.39	-1.62
NCI79	-4.62	4.62
Location of Group Centroids		
Group 1	-1.05	-2.04
Group 2	-4.96	-.24
Group 3	7.93	-1.98
Group 4	2.56	5.58