...NTIFYING LONG RUN AGRICULTURAL RISKS AND EVALUATING FARMER RESPONSES TO RISK

Proceedings of a Seminar sponsored by
Southern Regional Project S-232
"Quantifying Long Run Agricultural Risks and Evaluating Farmer Reponses to Risk"
Orlando, Florida
March 22-25, 1992

Department of Agricultural and Resource Economics
The University of Arizona
Tucson, AZ 85721

September 1992

SIMILARITY OF CHOICES AND THE PERFORMANCE OF THE EXPECTED UTILITY APPROACH: EMPIRICAL RESULTS

David E. Buschena and David Zilberman
Department of Agricultural and Resource Economics
University of California, Berkeley

April 22, 1992.

ABSTRACT

In light of normative and practical concerns regarding the use of the GEU models that alter the preference structure to allow for empirical violations of EU, this paper explores the dependence of choice on the characteristics of the risky alternatives used to show EU violations. The empirical results of our analysis show: 1) there is a strong effect on choice from the question characteristics, and 2) that the EU model holds for a particular and significant class of alternatives, with this classification having a representation through measurable characteristics of the alternatives.

We are grateful to Brian Wright, Barbara Mellers, James Chalfant, Michael Hanemann, Eddie Dekel, John Quiggin, Daniel Kahneman and George Judge for useful discussions of this work.
This paper is part of the senior author's dissertation. Comments welcome, please contact the authors before quoting.

INTRODUCTION

The Expected Utility (EU) model, first given an axiomatic representation by von Neumann and Morgenstern, is the dominant economic model for analysis of behavior under risk. This model has broadly recognized normative and practical appeal throughout economics. The EU model's flexibility and relative simplicity make it a very powerful tool of analysis of behavior under risk; for specific applications see Newbery and Stiglitz; Antle; Holthausen; Innes and Rausser; and Just and Zilberman.

Many controlled experiments, however, have shown that individuals exhibit direct violations of the EU model. Choices over well-defined risky alternatives show that the EU model is not robust to the alternatives' probability levels. See MacCrimmon and Larsson; Kahneman and Tversky; Lichtenstein and Slovic; Grether and Plott; Conlisk (89); Camerer; Battalio et. al. for examples of these experimental violations. In particular, violations of the critical Independence axiom of the EU model occur significantly for hypothetical payoffs in these settings.

A recently developed body of work models risky choices by weakening the basic structure of an individual's underlying preferences to allow for the empirical violations of EU. These models take as given the experimental independence violations of EU and strive to find axiomatic models of choice that allow for these paradoxes. Useful summaries of these efforts are given in Camerer; Fishburn (88); Machina(83,87). Some drawbacks to these Generalized Expected Utility (GEU) models are that they are difficult to put to use and that the normative motivation for their resulting preference structure is not strongly presented.

This paper shows the significant power of an alternative model of choice that allows for effects of the similarity of questions on choice; initial models of this similarity effect were explored by Leland; Luce (56); D. Friedman; Encarnacion; Ng; and Rubenstein. This similarity effect approach to explaining the violations of the EU model can be seen as a special case of the models of costly or bounded rationality for evaluation effort by Conery; Conlisk (88); Heiner; Lipman; March; and Simon.

The underlying motivation for this similarity effect stems from agents' costly or bounded evaluation of alternatives, where this evaluation cost depends on the similarity of the alternatives. Individual's choices between alternatives are taken as if they are made in the second stage of a two-stage decision process, after the relative benefits[1] of each alternative have been evaluated and weighed. That is, agents expend effort to recognize and evaluate the trade-offs between the alternatives' probabilities and the outcome levels. Therefore, risky choice patterns will reflect the factors that influence the selection of the evaluation effort level. Specifically, the similarity of the questions will affect the choices through the anticipated costs and benefits of the evaluation effort.

Statistical analysis of choice using discrete regression analysis makes operational a model of this similarity effect and shows the significance of the alternatives' similarity on choice.

This analysis is conducted with a more diverse population and over a more extensive set of risky choice alternatives than previous studies have been, giving a usable framework for a-priori determination of the validity of the EU model for particular populations and classes of risky choice questions. Further, the effect of question similarity on choice has support from both an objectively defined econometric model and from the individual's subjective perceptions of question similarity.

I. THE PROBLEM.

A. The Expected Utility Model.

The Expected Utility (EU) model is a pervasive model of behavior under risk in economics. It is relatively simple to use and is based on axioms with broadly recognized normative appeal. The model states that preferences ($\succ$) over probability distributions $\{p,q\} \epsilon P$ over a common n-dimensional outcome vector x have a cardinal representation u(), i.e.:

There exists a continuous function u() on P such that:

$$p \succ q \leftrightarrow \sum_{i=1}^{n} u(x_i)p(x_i) \geq \sum_{i=1}^{n} u(x_i)q(x_i). \tag{1}$$

A critical EU axiom, necessary for the EU representation, is Independence; this axiom states that the binary preference relation over distributions p and q must be consistent for arbitrary linear combinations of p and q with any other distribution r:

[p preferred to q] $\leftrightarrow$ [αp+(1-α)r is preferred to αq+(1-α)r for any $\alpha \epsilon (0,1)$]. (2)

The implications for choice of the EU model for the case of three outcomes are shown in Figure 1. This figure uses a probability triangle diagram that was introduced by Marschak, with its use being resumed by Machina (82). Points in this two-dimensional simplex represent each of the probabilities of receiving one of the three outcomes. The probability of receiving the lowest outcome (PL) is the value on the horizontal axis in this figure. The probability of receiving the highest outcome (PH) is the value on the vertical axis. Finally, the probability of receiving the medium outcome is given implicitly in the diagram since, by the rules of probability, PM = 1-PL-PH. For example, the alternative represented by point 1 in the figure has a lower probability of receiving both the lower and the higher outcome than does the choice represented by point 2; the alternative represented by point 1 thus has a higher probability for receiving the middle outcome. One can say that the gamble given by point 2 is a riskier alternative than that given by point 1.

Increases in preferences for risky alternatives by individuals who have monotonically increasing preferences are represented by movements to the "Northwest" in the triangle. The indifference curves (Ia through Ig) in the interior of the figure must be both linear and parallel under the EU model. The slopes of these indifference curves represent the degree of risk aversion for the particular outcomes. For the indifference curves in this figure, the riskier alternative represented by point 2 is preferred to the less risky alternative represented by point 1.

B. Violations of the Expected Utility Model

For all its normative appeal and ease of use, the EU model has been shown to lack complete descriptive validity for a large number of experimental studies. Of particular interest here, violations of independence over hypothetical payoffs have been shown to be quite robust for various populations. The majority of this empirical evidence against the EU model is from controlled experiments, with few examples of clear-cut "real-world" violations; see Machina (87) and Kahneman and Tversky for some proposed real-world examples. Findings from a limited number of studies using real payoffs (Conlisk (89)); Battalio et. al.; Harrison) have shown further evidence of EU violations with some support for a reduction in the degree (proportion) of violations under real payoffs.

The gain to conducting experimental tests of choice models like EU is that almost all other factors can be fixed, offering tight tests of a few particular issues. However, there remain important questions concerning the correspondence of these results to the non-experimental behavior of economic interest; see in particular the review paper by Smith for a view on the power of market feedback on the occurrence of behavioral violations of EU. We take the view that much can be learned about behavior through such experiments, that additional understanding of the basic factors affecting such results is needed, and that the degree of correspondence of these findings with behavior in non-controlled settings must be further explored.

Two well-known independence violations of the EU model are shown in Figures 2 and 3. In an experiment reported by Kahneman and Tversky, the choices made over the alternatives[2] in Figure 2 show a pattern of violation of the EU model known as the Certainty Effect (CE). The majority of their respondents (80%) selected alternative A over B, while, for another choice pair, 65% of the respondents selected the riskier alternative O over N. The individuals who selected A in the first pair and O in the second showed an independence violation of EU, since:

$$N = .25^{*}A + .75^{*}(\$0), \text{ and } O = .25^{*}B + .75^{*}(\$0),$$
$$A = 1.0^{*}A + .0^{*}(\$0), \text{ and } B = 1.0^{*}B + .0^{*}(\$0).$$

where ($0) indicates a degenerate lottery with a 100% chance of receiving $0. The Independence Axiom states that the choice between O and N, which are linear combinations of A and B with the distribution giving $0 with certainty, ($0), should not depend on this common probability distribution, nor on the factor (.25 or 1.0) defining the shares of the probabilities on AB.

Figure 2 shows the direction that the linear preference representations, "Indifference #1,#2", would need to take to be consistent with these choices; these curves cannot be parallel as called for by EU. A similar form of EU violation reported by Kahneman and Tversky for another risky choice pair is known as the Common Ratio Effect (CRE), shown in Figure 3. Most (86%) of their respondents selected alternative R over S, but 73% selected Y over X, even though both choice pairs were over alternatives with equal expected values. The linear "indifference curves" corresponding with the most common choices also cannot be parallel.

C. Alternative Models of Risky Behavior.

The empirical violations of EU were seen to be quite damaging to its validity in modelling behavior under risk. As a result, a considerable amount of effort has been devoted to finding alternative models of behavior that have greater positive accuracy for risky choices. In general, these models allow for the empirical violations of EU by weakening the Independence Axiom in various ways. We offer a brief review of some of the primary models set forth as alternatives to EU; for a more complete analysis, see Camerer, Machina (87), or Fishburn (88).

One model allowing for the empirical violations of EU is Kahneman and Tversky's purely descriptive Prospect Theory (PT). This model is primarily predictive with few requirements on the individual's treatment of the probabilities; the most striking part of this model is the general sub-additivity of the probabilities ($\sum_{i=1}^{n} p(x_i) < 1$). PT is quite successful in predicting agents' behavior, but it is often too general to allow for clear or testable predictions of behavior. In addition, PT is rather unwieldy[3] and is not well suited to addressing some questions of economic behavior for even partially rational agents; indeed, some of the behavior it allows directly violates critical notions of economic rationality such as the treatment of opportunity costs.

There is also a large group of axiomatic (GEU) models, more descriptively valid than EU, that weaken the independence axiom of EU, yet retain a great deal of the basic normative format of the EU model. These models generally seek to weaken the EU model's axioms just enough to allow for some of the initial examples of choice showing violations of the EU model, while keeping as close to EU as possible. However, the normative basis for such weakening is not presented strongly in these models. In addition, new examples (Camerer; Conlisk (89); Battalio et. al.) of systematic independence violations have been shown that are not explained by most of these models; among these models, Quiggin's (82) Rand Dependent Expected Utility model does rather well in predicting behavior (Camerer), but has the weakest assumptions and is thus the least operational of these models.

The new experimental findings for EU violations (Camerer; Conlisk (89); Battalio et. al.) raises questions regarding the dependence of the EU violations on the characteristics of the alternative pairs. These questions of the robustness of EU violations to the alternatives' characteristics are of no interest if the agents' actual (true) underlying preferences are as defined in PT or GEU models. These models take the preferences required to allow for the violations of EU as basic to the individual, precluding analysis of behavioral effects from perceptual limits or costs. Further, recent evidence from studies of the violations involving actual (real) monetary payoffs (Conlisk (89); Battailio et. al; Harrison) and the effects of alternative representations of the questions (Conlisk (89)) also casts doubt on the GEU approach of redefining underlying preferences to fit empirical behavior in an axiomatic framework for choice.

II. AN ALTERNATIVE EXPLANATION OF THE PARADOXES.

A. The Effects of Question Similarity

Another notion has been proposed (Leland; Luce (56); Viscusi; D. Friedman; Encarnacion; Ng; Rubenstein) as a motivation for the observed independence violations of EU. This explanation relies on limited sensitivity of evaluation due to costs or bounds on evaluation efforts, dependant on the nature of the alternatives in the choice pairs. In light of behavioral violations, this explanation holds that agents are in general rational (here their choices are taken to be consistent with the EU model), subject to costs or bounds on evaluation ability as in a limited or bounded rationality model (March and Simon). For example, the evaluation of alternatives in a manner completely consistent with the rules of probability may be too costly or difficult for some distributions over outcomes, leading to other less demanding methods of evaluation. Under the resulting simplification for difficult choices, agents' true preferences (which are taken here to have an EU representation) are not the only factor considered for choice between the alternatives. As a consequence, maximization of the EU representation may not be followed for some difficult choices, giving rise to violations of EU when these choices are paired with those over simpler pairs as if evaluated through an EU representation.

In a number of the similarity models suggested by other authors, the similarity of the alternatives affecting their evaluation are defined by the differences between the outcomes and the probabilities for the choices between simple alternatives. The evaluation method, hence the pattern of choice, is taken to differ among similar and dissimilar pairs of risky alternatives. For example, the choice between AB and RS in Figures 2 and 3, respectively, are made over dissimilar alternatives; the choices between NO and XY in these figures are made over similar alternatives. A parallel view of decision making that has received recent emphasis is found in models of Change of Process theories in Psychology that are reviewed by Payne; in these models, choice procedures differ due to the characteristics of the alternatives. Empirical support for this evaluation method, switching over similar and dissimilar risky alternatives, is given in a study of preference reversals Mellers et al. and by Johnson et al.).

B. A Statistical Model of Choice Evaluation Under Similarity

Although the similarity models are intuitively appealing and can be formulated to allow for many of the independence violations of EU, questions still remain concerning their empirical validity. Descriptive analysis of some new experiments in Leland lends further support for the significance of similarity effects, but more complete statistical analysis over a wider range of risky choice alternatives is needed to test for the effects of similarity on choice. This paper reports the results of in-depth statistical analysis of choice over an extensive set of risky choice questions.

The significance of the effects of question similarity on choice is tested through discrete regression analysis. This analysis extends the definition of similarity proposed by other authors to address behavior over a larger set of risky alternatives. In this statistical model, choices are observed between pairs of risky alternatives, where one of the alternatives is objectively less risky than the other. The dependent choice variable has a value of 1 if the more risky choice (B) is selected over the less risky one (A).

For each alternative pair (indexed by $j=\{1,...m\}$), every decision maker (indexed by $i=\{1,...n\}$) has a probability[4] of selecting the more risky alternative B over A (likewise for selecting the less risky alternative A over B) that depends on characteristics of the alternatives and characteristics specific to the individual. These probabilities are defined as:

$$\begin{aligned} P(B_{ij}/\{A_j,B_j\}) &= \phi(p_j,q_j,x_j,\alpha_i,\lambda_i,\varepsilon_{ij}) \\ P(A_{ij}/\{A_j,B_j\}) &= [1-\phi(p_j,q_j,x_j,\alpha_i,\lambda_i,\varepsilon_{ij})] \end{aligned} \qquad (3)$$

The probability and outcome vectors (p,q,x) are as previously defined. The term α represents a vector of personal characteristic variables and λ is a variable reflecting question attenuation or learning. The random term ε is taken to have a logistic cumulative distribution function that is identical for all agents and over all choice pairs.

Because the alternatives in this study are constructed as linear (in probabilities) combinations of a few specific risky choice pairs, the critical relationships between the probability vectors and the outcomes can be defined through the use of summary measures on these factors. In particular, a measure of the dissimilarity (δ) between the probability vectors of the alternatives is used for the effects of the probabilities on choice. Another vector of summary measures (υ) are functions over the expected values of the alternatives; these measures capture the relevant outcome effects on choice after the dissimilarity measure has accounted for the effects of the probability differences. Further, a base choice variable (β) is constructed for the agents' choice, $\beta \epsilon \{0,1\}$, between a pair of relatively "dissimilar" risky alternatives. These summary measures replace p,q and x for the riskier choice probability expression given above in (3):

$$\begin{aligned} P(B_{ij}/\{A_j,B_j\}) &= \phi(\delta_j, \upsilon_j, \beta_i, \alpha_i, \lambda_i, \mu_{ij}) \\ P(A_{ij}/\{A_j,B_j\}) &= [1 - \phi(\delta_j, \upsilon_j, \beta_i, \alpha_i, \lambda_i, \mu_{ij}] \end{aligned} \tag{4}$$

Under the logistic distributional assumption for the random term μ, and with a linear in the parameters (γ) model for the effect of the explanatory variables, $z_{ij} = (\delta_j, \upsilon_j, \beta_i, \alpha_i, \lambda_i)$, the probability of the riskier choice is:

$$P(B_{ij}/\{A_j,B_j\}) = \frac{1}{1 + \exp(-z_{ij}'\gamma)} \tag{5}$$

For the statistical model with n individuals and m choice pairs, the model becomes:

$$\left[P(B_{ij}/\{A_j,B_j\})\right]_{mn \text{ by } 1} = \left[\frac{1}{1 + \exp(-z_{ij}'\beta)}\right]_{mn \text{ by } 1} \tag{6}$$

The logit model for choice uses identical parameters (γ) over all individuals and alternative pairs; only the vector of explanatory variables (z_{ij}) differ between the observations.

The parameter estimates for this logit model of choice should offer valuable insights into individuals' choices over risky alternatives and over the factors influencing the propensity for EU violations. In particular, the parameter estimate on the base choice variable will indicate the level of support for the EU model, the parameter estimate on the similarity and question characteristic variables measure the effects of perceptions and evaluation costs or limits, and the parameter estimates on the personal characteristic variables will allow analysis of the effects of population differences on risky choices.

C. Objective Definitions of Similarity

Tests of the significance of similarity in a reduced form framework of choice depend crucially on its definition, this definition is particularly important for alternatives where more than one non-zero outcome is given positive probability of occurrence.

Most of the previous models of similarity over risky choices use simple lotteries where each of the alternatives have only one non-zero payoff, called prospects by Kahneman and Tversky. For this type of question, objective representation of the dissimilarity between the pair of alternatives is fairly straightforward. One of these pairs gives an outcome of x with probability p (otherwise zero), while the other gives an outcome of y with probability q (otherwise zero). Similarity can be viewed as a function, often linear, of the differences between the outcomes and the probabilities of each of the alternatives, i.e. similarity = $f[(x-y),(p-q)] = \alpha^*(x-y) + \gamma^*(p-q)$. The representation of similarity for a more general (larger dimensional) problem needs to be a bit more complex due to the richness of the differences between the alternatives. The differences in the alternatives can again be viewed, though to a more limited degree, by measures of the differences over functions of the relevant outcomes and probabilities.

One measure of the difference between the probabilities of the alternatives for the n-dimensional discrete case is the distance or metric measure, where the alternatives have been assigned the probability vectors $\{p_1,p_2,...p_n\}$ and $\{q_1,q_2,...q_n\}$ over the common outcome vector $\{x_1,x_2,...x_n\}$. This measure allows for a general treatment of the differences between the probabilities of discrete alternatives and is given by:

$$metric(p,q) = [\sum_{i=1}^{n} (p_i - q_i)^2]^{\frac{1}{2}} \quad (7).$$

In addition to this measurement of the probability difference, a measure of the relevant outcome differences is needed for the definition of similarity. Such a measure is more difficult to construct, since the outcome vector is common to both alternatives. Functions based on the expected values (EVs) of the alternatives should capture many of the relevant outcome differences since the probability differences have already been accounted for. Another approach to summarizing the outcome effects for similarity would be to select a particular functional representation for EU, such as an exponential utility function, and define a function of the differences in the alternatives' EU values under this representation. We will use functions of the EVs in this analysis.

The metric measure of distance in the probability space can be generalized to the case of continuous outcomes by a measure based on the cumulative distribution functions of the alternatives. This CDF measure is defined for any $x \in X$ in the range of the outcome space where f(x) is the probability density function for the alternative and is defined as:

$$Distance(CDF) = \frac{\int_{-\infty}^{x_n} |CDF(z)_b - CDF(z)_q| dz}{Range\ x}, \qquad (8)$$

$$where\ \ CDF(x) = \int_0^y f(z)dz$$

Note that this measure would include effects of the relative differences between the outcomes. Normalizing (8) by the range of outcomes is equivalent to normalizing the outcomes by dividing them by the largest outcome. Without such a factor, the scale of the outcomes would affect this area measure of similarity for the probability distributions; we wish to separate the effects of probabilities and payoffs in the similarity measure.

These CDF functions have the interpretation of giving the probability of reaching at most a level of outcome x and take values between zero and one. The CDF's for two continuous distributions p and q are shown in Figure 4. The CDF for distribution p compared with that for q shows a lower probability of occurrence for outcomes below x_1, equal probability of occurrence for outcomes below x_2 and equal probability of occurrence for outcomes below x_3. Note that, by using the absolute value of the difference between the CDF's in this term, one distribution could dominate the other (in the first degree sense), but still be judged as similar to the other. Although this measure has no direct relationship with the metric measure of distance in (1), its use in defining similarity will correspond with that from the metric measure for many choice problems.

III. EMPIRICAL STUDY FOR RISKY CHOICE

A. Survey Design

We elicited choices for risky alternatives through an extensive set of questions over hypothetical outcomes. These questions were variants of the well-known Certainty Effect (CE) and Common Ratio Effect (CRE) examples of Kahneman and Tversky discussed earlier, developed to cover a larger range of probability and outcomes than in the original examples. This design gave a wider range of explanatory variables of distance and dimensional effects for choice between the alternatives.

The specific questions in the study are given in Tables 1A, 1B, 1C, and 1D. These alternatives use variants of the probabilities, and to some degree the outcomes, used by Kahneman and Tversky to show CE and CRE, respectively. We based our design on the examples used by Kahneman and Tversky because of the familiarity of most researchers with these examples and because the outcomes are close enough to those of risky choices regularly faced by individuals in real-life. The first two alterative pairs in Tables 1A and 1D give choices {AB,NO,RS,XY} with identical probabilities as used in Kahneman and Tversky; the remaining questions use linear combinations of these two questions with other points in the triangle. Specific attention was given to include a wider range of questions throughout the probability triangle (the two-dimensional simplex) than has been done previously. The experimental design for Tables 1A and 1D is also shown by Figures 5 and 6; the capital letters indicate one of the alternatives within the pairs offered in Tables 1A and 1D. Many of the alternatives faced by the individuals were combinations of the gambles represented by the points in Figures 5 and 6; choices were elicited over pairs of points on the point loci in these figures. The original questions showing the CE are those for pair AB and NO in Figure 5; the original questions showing the CRE are those for pair RS and XY in Figure 6.

The alternative pairs given in 1B and 1C offer a wider range over the makeup of the alternative pairs. Pairs in Table 1B include choices over alternative pairs with four dimensions for two outcome patterns ($0,$3000,$3800,$4000) and ($0,$200,$3000,$4000) with the two sets of probabilities over these outcomes. These pairs are linear combinations of the pair CD (#4) in Table 1A and the new outcomes of ($200 and $3800). This framework allows for an additional test of the validity of the EU model for the case of four outcomes. Pairs in Table 1C use the identical probabilities (as do questions 1 and 2 in Table 1A) as those used by Kahneman and Tversky to show the certainty effect, but with different outcome levels. Adjustments for inflation and for the exchange rate[5] would show Kahneman and Tversky's payoff levels being bracketed by the {$0,$750,$800} payoff set in the first two pairs (#29 and #31 in Table 1C) and the {$0,$3000,$4000) payoff set used in the alternative pairs (#1 and #2 in Table 1A and repeated in Table 1C).

The survey included two forms of question, with the practice questions of each type given to the participants shown in Table 2. The first question type (Practice Question 1) asks respondents to select their preferred alternative from the pair of risky choices; this type of question corresponds with those previously used to show EU violations. Twenty-four questions of this first type were given to each participant. Eight questions of the second type (Practice Question 2) asked respondents to first give their preferences among the two alternatives, then to indicate their perceptions of the dissimilarity between the alternatives and their strength of preference between the choices. These dissimilarity and strength of preference judgements were given on a continuous and bounded scale from 1 to 9, with qualitative terms {Similar, Somewhat Dissimilar, Dissimilar, Very Dissimilar} and {Indifferent, Somewhat Strong, Strong, Very Strong} given to the respondents to aid in their point selection. Subjects were urged to consider points other than integers for the dissimilarity and strength of preference judgements in written and verbal instructions.

These dissimilarity perceptions will later aid in the selection of objective factors characterizing dissimilarity and in the determination of the correspondence between the previous theoretical (and somewhat narrowly defined) models of "dissimilarity" with the actual perceptions of individuals faced with risky choices. We will show that this subjective measure does rather well in capturing the objective question characteristics that influence choice and offers an unbiased guide for model selection using objective measures. This framework is particularly valuable since so little prior information is known about the objective factors determining similarity effects.

The pairs of alternatives given in Tables 1A-1D were broken into two groups (priority and secondary) in the elicitation for 125 of the respondents[6] to give a large number of observations for those alternative pairs of particular interest. These pairs of special interest were members of a set defined to allow tests of particular patterns of choice. The question number in the Tables for these pairs of special interest were:

Table 1A: {1,4,5,6,7,14,16,17,18,19,20,21,23,}
Table 1C: {29,30,31,32}

The specially selected group in Table 1A included pairs that allowed for tests of a specific pattern of violations of EU. The specially selected pairs from Table 1C were included to evaluate the occurrence of the basic paradoxes for varied outcomes. These 17 priority questions were given in random order in each respondent's survey. A random ordering of 17 of the 22 remaining secondary questions was used to complete the survey: thus, not all of the alterative pairs were faced by each respondent, but all questions were faced by some of the population[7].

The survey population was further differentiated by altering the ordering of the questions faced by respondents. This ordering was based on the magnitudes of the metric measures over the probability vectors, a variable expected to be important for modeling the dissimilarity. For the surveys given to Test Group 1, the 21 questions with low metric measures, e.g. pair EF in Figure 5 and VW in Figure 6, were randomly given (interspersed with the priority questions) to the respondents first, followed by a random ordering of a subset from the high metric ("dissimilar") secondary questions. Test Group 2 received a random ordering from among the high metric secondary and the priority questions first, followed by a random ordering from among a subset of the low metric measure secondary questions. Finally, a control group received a random ordering first over the 17 priority questions and then over a subset of the secondary questions, with no distinction based on the metric measures of the questions. These three groups were developed to allow tests of a theory of survey effects; it was thought that respondents might become accustomed to making choices among the alternatives to a degree dependent on the type of questions faced previously.

B. Initial Results

To date, 162 responses to the risk survey were obtained from undergraduate[8] students (44%), graduate students and faculty at the University of California at Berkeley's Department of Agricultural and Resource economics (35%), and members of the general population. Survey administration took place over a four month period from November, 1991 to February, 1992. The undergraduates were given the surveys near the beginning of spring semester courses for immediate completion; these students took from 25 to 40 minutes to complete the survey. The graduate students, faculty and general population subjects were given the survey with verbal instructions and allowed to complete them at their leisure; turnaround time for this group was on average about one week.

The mean dissimilarity judgments and the mean proportion selecting the riskier choice for each of the 38 questions are listed in Table 1A-1D and presented graphically in Figure 7. This figure reflects the primary relationship (correlation -.67) between the two factors. The metric measure's correlation with this mean proportion of the riskier choice is -.77. Therefore, this subjective measure captures a primary relationship of the question characteristics that affects individuals' choices over risky alternatives and also corresponds quite well with the objective metric measure of distance. Thus, there is an empirical connection between the ideas of dissimilarity set forth in theoretical models and the unstructured reported perceptions of dissimilarity.

Of particular interest in Table 1A are the pairs showing the influence of the distance between the alternatives' probabilities on the mean proportional choice and dissimilarity perception. These effects are quite evident for the mean proportional risky choice and the dissimilarity judgements for the large distance measure pairs for pairs AB (# 1), CB (# 14) and RS (# 33) versus those for the lower distance pairs NO (# 2), EF (# 5) and VW (# 36). The results shown in these tables also reflects some qualitative measures of dimension on the similarity judgements. The primary dimensional effects are evident for pairs where one alternative has a zero probability of the lowest outcome, henceforth referred to as pseudo-certainty, for the choices between AC (3), KL (12) and Zα (37).

The relationship between low dissimilarity and high proportion of risky choice is also strong for those questions with probabilities used to show violations of EU by Kahneman and Tversky (AB and NO in Table 1A, RS and XY in Table 1D); the questions with low metric measures and low mean dissimilarity judgements are more prone to have a high proportion of individuals selecting the riskier alternative.

The results in Table 1B show the effects of changing the relative outcomes on both the mean dissimilarity judgements and on the mean percentage selecting the riskier alternative. The addition of the relatively large common payoff ($3800) altered these levels significantly from those for the pair CD (#4) in Table 1A., while the addition of the relatively small outcome ($200) in a linear combination to the alternatives did little to change either the proportion selecting the riskier alternative or the mean dissimilarity perceptions. Notably, the proportion selecting the riskier alternative was affected very little by the probability (.25 or .75) of the new outcome in the alternatives for either case. However, there was an effect on the mean dissimilarity judgements of this probability for questions 25 and 26. This dissimilarity effect of the probabilities would be captured by either the metric or the CDF based probability distance measures for these questions, while the CDF based measure alone would capture the effects of the differences in outcomes on the dissimilarity judgements.

Table 1C gives the population proportion selecting the riskier alternative for the pairs with the same probabilities but different outcomes than the original questions used to show the CE. The proportion of respondents selecting the riskier pairs under the {$0,$750,$800} outcome framework compares in magnitude to the proportions from the questions given by Kahneman and Tversky to Israeli students and faculty (unspecified proportions) in the late 1970's. Kahneman and Tversky used payoff levels so that the median net monthly family income (3000 Israeli pounds) was used as the second term in the three outcome framework. The difference between the relative proportions here and those of Kahneman and Tversky may be explained by the more diverse population (undergraduates, graduate students and faculty, and non-academics) used in this study, or by differences between the population of late 1970's Israeli students and faculty and the population of respondents from early 1990's Californians.

The results in Table 1A-1D indicate a large degree of violations of not only the EU model, but also for many of the alternative GEU models. A forthcoming paper will analyze the individual patterns of choice that show significant violation of the models put forth by Segal (87), by Chew and by Dekel and for the fanning out property suggested by Machina (82,87). As in Camerer, Quiggin's Rank Dependent Expected Utility model and Prospect Theory showed no significant direct violations for choice between two pairs of questions. We will give evidence showing that both of these models also are significantly violated when choices between a wider set of question pairs is considered.

The initial population proportion results point to the need for a more in-depth analysis of the effects on choice of the dissimilarity between alternatives. This paper seeks to make operational, estimate and test the effects of objective and observable characteristics of the alternatives on dissimilarity judgments, and to test for the influence of these dissimilarity judgments on choices between risky alternatives. These elicitation process effects may be measured by objective characteristics of the questions, the personal characteristics of the respondents, and perhaps researcher and venue bias. Our survey design allows for rigorous tests of the effects of some of these factors for choices over risky alternatives and to assess their influence on the degree of violations of the EU model.

IV. ESTIMATING DISSIMILARITY JUDGEMENTS

We develop an operational model for dissimilarity where the reported dissimilarity perceptions are taken to be a function of objective and observable characteristics of the alternatives. There are two models of interest; one using the metric measures in the probability space for the distance between the alternatives in equation 1, while the other used the CDF-based measure discussed earlier in equation (8). The objectively measurable question characteristics for both regression models are given in Table 3. Both quantitative measures such as the distance measures, and discrete terms such as the indicators for dimensional effects are used to model dissimilarity. These regression models were linear in the parameters for the explanatory variables.

Personal differences of dissimilarity perceptions were allowed for in the regressions by creating an indicator variable for each person. This approach was used because of the absence of strong prior guidelines for the correct personal variables affecting dissimilarity judgements. Thus, these models evaluate the effects of measurable question characteristics on dissimilarity judgements, allowing for very general individual location differences.

The results of the linear OLS regressions on these parameters are given in Tables 4a and 4b for the metric and the CDF based distance measures, respectively. The large number of observations allows favorable degrees of freedom (877) for significance tests. There was only limited evidence of heteroskedasticity between individuals in the regression errors. In Table 4a, the cubic relationship on the metric shows dissimilarity judgements increasing at a decreasing rate, with the combination effect from the three terms and their coefficient estimates being positive throughout since the metric measures are near enough to 1. As the distance increases, the dissimilarity judgments increase. Also, pairs where one alternative gives a zero probability of the lowest outcome (here referred to as pseudo-certainty), are judged to be significantly more dissimilar. Alternatives with equi-dimensional support were judged to be significantly less dissimilar. The terms that are functions of the expected values of the alternatives were offsetting; pairs with larger values for the minimum of the expected values of the alternatives were given larger dissimilarity judgments, while increases in the absolute difference between the expected values, and the ratio of this difference to the minimum expected value gave decreases in the dissimilarity judgements. Additional variability over the outcomes of the alternatives may be needed to give more interpretable signs for these EV variables.

The fit and coefficient estimates for the OLS regression of dissimilarity using the CDF based distance measure (Table 4b) were quite like those for the model using the metric measures of distance, with some difference in coefficient significance for the EV based terms and the equi-dimensional indicator; the contribution of these EV based variables to the regression is reduced, most likely because the CDF based measure includes effects of the relative outcomes. The metric model has some advantages in simplicity, while the CDF based distance measure is more general as it applies to continuous distributions over outcomes.

Interpersonal heteroskedasticity was suspected for the individual's reported perceptions of dissimilarity. This heteroskedasticity would have straightforward interpretation since the "spread" of the dissimilarity judgements may well differ among each individual; this spread would also not be corrected for by the individual indicator variables in the OLS models. Although the coefficient estimates from the OLS models under such heteroskedasticity would be asymptotically unbiased, the covariance matrix for these estimates would be biased, casting doubt on the validity of significance tests for the entire model and for individual coefficients. The bias in the covariance matrix would further not be improved by increasing the number of respondents.

Table 4C reports the results of a GLS model using the same explanatory variables as in Table 4A. The estimated covariance matrix has on the diagonals the average squared error for each individual, a estimator for σ_i^2 where each individual's variance is allowed to differ (heteroskedasticity). This GLS model can also be viewed as a weighted regression model, where both the explanatory variables and the dissimilarity judgements are weighted (divided by) the square root of the individual's average squared error (σ_i).

Overall model fit for the GLS model in Table 4C is significantly improved from that in Table 4A, with the adjusted R^2 measure increasing from .45 to .71. As anticipated for such a large sample, there is little difference between the coefficient estimates in Table 4A (OLS) and in Table 4C (GLS). Qualitatively, the t-values indicating the significance of the coefficients are generally the same; notably, all of the terms as functions of the expected values are significantly estimated at the .05 level.

The coefficient estimators for the factors affecting dissimilarity perceptions are reasonably robust to the specification as an OLS or a GLS model. In order to keep the dissimilarity model relatively operational, we will use the coefficient estimates from the OLS model in Table 4A to model dissimilarity judgments in the forthcoming analysis.

V. MODELING THE EFFECTS OF DISSIMILARITY ON CHOICE

A. Logistic Model 1: Fitted Dissimilarity

We address the hypothesis that the dissimilarity between the alternatives affects the choices under risk. A logistic regression was run on the probability for a particular individual to choose the riskier alternative (observation = 1) over the less risky in the choice pair. These variables are given in Table 5. This regression used the fitted dissimilarity from the OLS coefficient estimates using the coefficient estimates from the OLS regression as an explanatory variable. The individual location differences in the OLS regression of the dissimilarity judgments were abstracted from by using only the variables and coefficient estimates for the observable question characteristics, i.e. the personal indicator variables and coefficient estimates were ignored.

Functions of the expected values of the alternatives were also included as explanatory variables to capture the effects of the relevant outcome differences of the alternatives. Variables reflecting personal characteristics (age, education, and etc.) and interaction terms using combinations of the personal characteristics variables and the question characteristic variables were also included. Some variables, e.g. those based on the expected values, are allowed to affect both the dissimilarity judgments and to have a separate effect on choice over and above their effects through the fitted dissimilarity.

A variable of particular interest was an indicator of the choice for one of two relatively dissimilar pairs of alternatives; we call this variable the base rate. This base rate uses the choice from among one of the pairs {(CB), (CD)} in Table 1A and Figure 5. If the individual was given the choice between the pair (CB), that response was used for the base rate value; if the choice between the pair (CB) were not elicited but that between the pair (CD) was faced, the alternative selected for the pair (CD) was used as the base. The individual's choice from among one of these two pairs was taken to be indicative of the risk attitudes of the individual when facing dissimilar outcomes. The coefficient on this variable, when multiplied by the value of the density function at the mean [$f(x\beta)=.083$], indicates of the propensity of the individual to choose the riskier alternative relative to these base questions, when other factors such as the degree of fitted dissimilarity and population characteristics have been accounted for. We discuss the results from additional logistic regressions that allow for direct tests of the EU model relative to these base questions.

The coefficient estimators, standard errors and asymptotic t-values for the logistic regression model of the propensity to choose the riskier alternative is given in Table 6. The log-likelihood ratio for this regression and its test statistics were favorable for the significance of the model. The percentage of correct predictions was 68%, with an 88% success rate for estimating the less risky choice and 45% success rate for estimation of the more risky choice.

1. Estimation of the Question Specific Variables:

The coefficient estimate for the fitted similarity of -.589 is significant and of the expected sign; as this measure of dissimilarity among the pairs increases, the probability of an individual choosing the riskier alternative decreases under the logit model. The order with which the pair is chosen has a significant negative sign but is small (.006) in magnitude, indicating a somewhat lower likelihood of a risky choice as the individual moves through the questions. Of the three terms giving additional effects from the

Expected Values of the alternatives (in addition to their dissimilarity effects), the difference between the expected values and the minimum expected value were significantly estimated, with the expected negative signs; fewer respondents selected the riskier alternative as the stakes increased.

2. Coefficient Estimation of the Effects of the Personal Characteristics:

The significant coefficient on the base rate term of 1.130 indicates support for of the EU hypotheses when other factors are accounted for. Males showed a significant increase (.31*.083) in probability to select the riskier choice at the mean values. Older individuals showed a significantly lower (but small at .031) potential to select the riskier alternative. Of the education variables, only one, the indicator for a college (but not a graduate or professional) degree was significantly estimated at -.948, with these individuals being much less likely to select the riskier alternative. Individuals in Survey Population Group 2, who received the questions with larger metric measures (more "dissimilar") at the start of the survey, were significantly more likely to select the riskier alternative than the base population. The income indicator variables reveal a significant income effect on the willingness to bear (hypothetical) risk for the two most affluent ($50,000 to $100,000) individuals at .73, with some support (non-significant) for the very affluent (over $100,000) to take additional risks. The remainder of the coefficients on the personal characteristics were not significant; of particular note is the lack of significance for the undergraduate and non-academic indicators.

3. Coefficients on the Population Interaction Terms:

Of the interaction variable terms, only the coefficient on the base choice for the non-academic population showed a significant difference from the population as a whole. A test for the significance (difference from zero) for the combination of the overall population base term plus this non-academic interaction term showed that this population still had significant non-zero effects from the base question on choice. The absence of significant coefficient estimates for the population interaction terms with estimated dissimilarity is notable. The fitted dissimilarity between the alternatives did not differ significantly among the populations of undergraduates, academics and the general population.

B: Logistic Models 2 and 3: Direct Violations of the EU Model.

The previous logistic regression on choice showed the influence of the alternatives' fitted dissimilarity on the propensity of individuals to select the riskier alternative. This finding supported, but did not directly test for, the effects of dissimilarity on the probability of violations of the EU model.

We developed another logistic regression framework to test for these effects. The question sample was split into two groups based on the question type. One group was defined for variants of the CE and in Table 1A (save for the question used to construct the base choice variable), Table 1B, and Table 1C. Choices over these questions were directly comparable through the EU model. The base choice variable for this group was defined using the same dissimilar alternative pairs {CD,CB} used in Logistic Model 1. The other explanatory variables used in this regression were identical to those used in the previous regression and included measures of question characteristics, personal characteristics and interactive terms for the population.

The group of questions for Logistic Model 3 included the variants of those pairs RS and XY (questions 33 and 34 in Table 1D); this group used the questions in Table 1D. The base choice variable for this logistic choice equation was the choice over the pair RS. The responses tested in these equations were from Table 1D, except for the base response of the choice between R and S.

The results of this Logistic Model 2 regression on the CE Pattern are given in Table 7. The overall fit of this model, as indicated by the log-likelihood test terms and the proportion of correct predictions, is comparable to that of the previous logistic regression over the general set of risky choice questions. As in Logistic Model 1 regression for risky choice, the estimates of these coefficients for the perceived dissimilarity between the alternatives shows a significant negative effect on the probability (at the means) to select the riskier alternative. The estimated coefficient for the base choice variable directly shows the power of the EU model with its positive, large and significant sign. The remaining coefficient estimates are much like those (in magnitude and sign for the significant variables) as those for the more inclusive regression in Table 5. In this model, the Test Group 2 variable was not significant while the coefficient for Test Group

1 was; more initial choice questions over low distance measure questions led to lower violations of the CE pattern.

The estimation results for the Logistic Model 3 regression on the CRE pattern are given in Table 8. Again, the coefficient on the estimated dissimilarity of the alternatives and the base choice variable were significant factors in the regression in the hypothesized direction. The remaining variables are similar in sign and magnitude (for those that differed significantly from zero) to those given in the previous logistic choice models reported in Tables 6 and 7. The log-likelihood statistics and the proportion of correct predictions was more favorable for this choice population than for the previous models; 76% of the predictions were correct versus 68% for the Logistic Model 2 for the CE pattern question group. The prediction proportions given in the prediction success table were superior for this question group relative to the two previous groups. One reason for this superior fit may be the more distinct similarity/dissimilarity dichotomy for this question group relative to those in the CE group. The dissimilarity judgements were more extreme for this CRE group; inspection of the probability vectors representing each alternative in Table 1D reveals the extreme difference in the probabilities between the pairs.

C. Logistic Model 4: A Reduced Form Model.

The results from the previous logistic analysis showed the strength of the fitted dissimilarity judgements for modeling risky choice behavior. These fitted dissimilarity measures capture important factors affecting choice and the propensity of violations of EU. The coefficients on this variable also have an appealing interpretation as a variable that is thought to affect the costs and benefits of evaluation effort as set forth for general problems by Conlisk (88); Lipman; Heiner; March; and Simon.

We constructed another choice model using the question characteristic terms which had explanatory power in the original OLS regression were used as independent variables in a logistic regression model for risky choice. The terms in this reduced form model are given below in Table 9. This model uses direct incorporation of the question characteristics that are thought to influence choice through the dissimilarity judgments and allows definition of characteristics of the questions for which EU performs favorably.

The results of this model are given in Table 10. The model fit is comparable to that using the fitted dissimilarity judgements; the exclusion of some reduced form variables that had little predictive power (non-significant coefficient estimates) for dissimilarity judgments did not significantly harm general model fit.

Risky decisions are significantly less likely to be selected for alternatives with larger metric terms. The pseudo-certainty indicator is also significant with a negative sign; if one of the alternatives has a zero probability of the lowest (zero) outcome, respondents are quite likely to select it. The positive and significant sign on the absolute expected value difference ratio (adjusted by the minimum of the expected values) shows some willingness to take risks if there is a large enough gain in expected value.

The variable giving the alternative selected in the base questions is still quite strong, supporting the strength of the Expected Utility model. Males and Non-Academics were significantly more willing to take risks. The group (Test Group 2) that received relatively more high metric measure pairs initially were more likely to take risk, while those (Test Group 1) receiving a relatively larger number of the low metric measure questions were less likely to take risks.

Non-Academics were affected less by the base choice, but still had a significant difference from zero for the sum of the population base and the non-academic/base interaction coefficient. None of the coefficients on the population interaction with the metric measure were significant.

V. EVIDENCE SUPPORTING DISSIMILARITY OVER ALTERNATIVE MODELS

In addition to shedding light on the occurrence of EU independence violations, violations of a complete and transitive ordering of the alternatives would be possible under a model where dissimilarity affects choice. To see the motivation for this claim, consider again Figure 5. If individuals are more prone to select the risky alternative when the choices are similar, a pattern of choice with $E \succ C$, $F \succ E$, $D \succ F$, $B \succ D$ could arise, since dissimilarity depends primarily on the distance between these alternatives. However, when faced with a choice between C and B, the relative dissimilarity between the alternatives could lead the individuals to select C over B, giving a violation of a transitive and complete ordering when coupled with the choice pattern over the less dissimilar alternatives. Such intransitivities would be predicted under effects of dissimilarity on the evaluation and subsequent choice between alternatives.

Previous findings of intransitivities (Tversky) seem to rely on the similarity/dissimilarity dichotomy for choice when the outcomes are defined over only one non-zero outcome. The tests for intransitive behavior carried out here are over more general outcome vectors.

We constructed a test of two particular patterns of intransitivity that were called for by the dissimilarity model. The individuals were asked to select between the particular an array of relatively similar choices and one dissimilar choice as randomly presented in the survey. Pattern 1 used those pairs in the example above, choices were made over the low metric measure (similar) pairs {(CE),(EF),(FD),(DB)} and over the larger metric measure (dissimilar) pair (CB). Pattern 2 used some of the same pairs, with choices over the similar pairs {(EF),(FD),(DB)} and over the relatively dissimilar pair (EB).

The population statistics of the occurrence of these intransitivity patterns are given in Table 11, where the individuals select the more risky alternative for the similar choices and the less risky for the dissimilar choices. Eleven individuals of the 117 and 115 individuals (six individuals showed both patterns) (9%) showed Pattern 1 and Pattern 2 of intransitivity. These population proportions were significantly different from zero for both of the patterns, with the intransitivity proportion in Pattern 1 also being significantly different from that expected under pure chance.

These findings of intransitivities supporting the importance of evaluation method dependence on the dissimilarity between the alternatives and cast significant doubt on the validity of Prospect Theory and the GEU models as completely accurate positive models of choice under risk. There are some models that do allow for intransitivities, e.g. Loomes and Sudgen's and Bell's Regret Theory models and Fishburn's (88) Skew-Symmetric Bilinear model. The results found here, in pointing to the importance of the nature of the elicitation questions themselves on choice, raise new questions about the degree to which allowances for intransitivities should be built into normatively, positively and prescriptively based models of behavior.

CONCLUSION

This paper makes operational and tests the effects of dissimilarity between question pairs as it applies to risky choice for a wider class of problems for which models of similarity (Leland; Encarnacion; D. Friedman; Ng; and Rubinstein) have been defined over. The experimental design extends analysis of choice over risk from a base of two well-known question pairs used by Kahneman and Tversky to show Independence violations. The design then constructs a large number of choice pairs from this base with substantial variability between the observable factors affecting dissimilarity of the alternatives. The dissimilarity between alternatives is fitted in a regression framework using observable characteristics of the alternatives and personal variables of the individual respondents. A significant difference in the likelihood of EU violations in a logistic regression analysis is shown for between question pairs that are perceived to be similar and those that are perceived to be dissimilar.

We found empirical support for the effects of similarity on choice from both subjectively reported perceptions of the respondents and from subsequent models of dissimilarity defined over objective characteristics of the questions. For this notion of similarity, there is a strong connection between the hypothesized objective definition and the individual's relatively ungoverned perceptions.

This regression analysis offers a substantial contribution to the study of behavior under risk. It yields a descriptive and predictive model for applications of the dissimilarity of the alternatives based on observable characteristics of the alternatives. It defines a model giving the characteristics of the alternatives that lead to Independence violations of the EU model; this rigorous empirical modeling framework should also prove useful for addressing other violations of the EU such as preference reversals and intransitivities. The empirical findings support a forthcoming modified model of choice where individuals select from among dissimilar alternatives using a method that corresponds with an EU representation when the alternatives are dissimilar, while using heuristic or rules of thumb when the alternatives are rather similar.

Thus, while the empirical Independence violations of the EU model occur for a class of questions, the EU model is well supported for the class of decisions that are perceived as being dissimilar. This dissimilarity can be made operational through a functional relation with observable characteristics of the pairs of alternatives.

Finally, the dissimilarity model is the basis for an extended framework of tests of the EU and GEU models of choice, as well as of Kahneman and Tversky's Prospect Theory and subsequent Cumulative Prospect Theory models. This testing framework yields a pattern of behavior showing a significant violation of all of these models; there were significant intransitive choices for our population in the direction supported by a reduced form model of behavior where the evaluation effort or method depends on the dissimilarity of the alternatives.

This paper should offer both confidence and caution to researchers seeking to use the EU model for risky decisions. There is a wide class of problems for which the EU model holds, and another wide class for which violations of the EU model are prevalent.

Further, the probability of occurrence of these violations can be predicted by a model using objective characteristics of the questions. These objective characteristics further correspond with notions of dissimilarity discussed by Leland; Rubinstein; D. Friedman; Encarnacion, and relate to models of evaluation costs proposed by Conlisk, Heiner and March.

1.Although all of the outcomes are hypothetical here, individuals are thought to project these outcomes onto their utility space. This projection of mapping may well differ from that going from real payoffs to utilities; i.e. the benefits from these hypothetical outcomes may be "dampened". The significance of this dampening effect is testable through use of real payoffs.

2.The outcomes in Kahneman and Tversky's experiments were made using late 1970's Israeli pounds, rather than the 1991/92 U.S. dollar outcomes used in this paper.

3.Recent hybrid models using Prospect Theory plus assumptions from another choice model (Tversky and Kahneman, 1991; Luce and Fishburn, 1991) offer a more well defined model of behavior.

4.Forthcoming work will develop a more specific and testable model for risky choice behavior based on first principles with evaluation effort costs.

5.The period of the late 1970's was a particularly difficult one for finding accurate applicable exchange rate measures for Israeli pounds to dollars.

6.The remainder of the subjects received a random ordering of the 39 questions in an earlier version of the survey.

7.Due to a sampling oversight, only two of the individuals received pair #24. This pair will receive special focus in later survey work.

8.The undergraduates were taken from the Political Economy of Natural Resources (PENR) courses at UC-Berkeley. These students included freshmen (roughly 30%) through seniors (roughly 20%). The major has a focus on applied micro-economics; the students have received course work comparable with those of similar class year in the economics or business major.

REFERENCES

Antle, John. "Nonstructural Risk Attitude Estimation." *Amer. J. Agr. Econ.* 71 (1989):774-84.

Battalio, Raymond C., John H. Kagel, and Romain Jiranyakul. "Testing Between Alternative Models of Choice Under Uncertainty: Some Initial Results." *Journal of Risk and Uncertainty*. 3(1990):25-50.

Bell, David E. "Regret in Decision Making Under Uncertainty." *Operations Research*. 30 (1982):961-981.

Camerer, Colin. "An Experimental Test of Several Generalized Utility Theories." *Journal of Risk and Uncertainty*. 2(1989):61-104.

Conery, J. Mental Cost: A Function of Error and Effort. *Unpublished Manuscript, UC San Diego*. Reported in Russo, J Edward and Barbara Anne Dosher. "Strategies for Multiattribute Binary Choice." *Journal of Experimental Psychology: Learning, Memory and Cognition*. 9(1983):676-696.

Conlisk, John. "Three Variants on the Allais Example." *American Economic Review*. 79(1989):392-407.

Conlisk, John. "Otimization Costs." *Journal of Behavior and Organization*. 9 (1988):213-228.

Dekel, Eddie. "An Axiomatic Characterization of Preferences Under Uncertainty Weakening the Independence Axoim" *Journal of Economic Theory*., 40 (1986):304-318.

Encarnacion, J. "Preferences and Lexicographic Choice." *Journal of Economic Behavior and Organization*. 8(1987):231-248.

Fishburn, Peter C. *Nonlinear Preference and Utility Theory* (1988) Baltimore: John's Hopkins University.

Fishburn, Peter C. "Intransitive Indifference in Preference Theory: A Survey." *Operations Research*. 18(1970):207-228.

Friedman, Daniel. "The S-Shaped Value Function as a Constrained Optimum." *American Economic Review*. 79 (1989):1243-1248.

Grether, David M. and Charles R. Plott. "Economic Theory of Choice and the Preference Reversal Phenomenon." *Amer. Econ. Review*. 69(1979):623-638.

Gul, Faruk. "Why do Economists Resist Non-Expected Utility Theories?" *Working Paper Stanford University*. 1990.

Harrison, W. Glen. "Flat Payoff Functions and the Experimentalists: Reply to the Critics." *Unpublished Working Paper, University of South Carolina*, (Feb. 1992).

Heiner, Ronald A. "Imperfect Decisions in Organization: Toward a Theory of Internal Structure." *Journal of Economic Behavior and Organization.* 9(1988):25-44.

Holthausen, Duncan M. "A Risk-Return Model With Risk and Return Measured as Deviations From a Target Return." *American Economic Review*. 71(1981):182-188.

Innes, Robert D. and Gordon C. Rausser. "Incomplete Markets and Government Agricultural Policy." *American Journal of Agricultural Policy.* 71(1989):915-931.

Johnson, Eric J., John W. Payne and James R Bettman. "Information Displays and Preference Reversals." *Journal of Behavior and Human Decision Processes.* 42 (1988):1-21.

Just, Richard and David Zilberman. "Assyemtry of Taxes and Subsidies in Regulating Stochastic Misshap." *Quarterly Journal of Economics*. (1979):139-148.

Kahneman, Daniel and Amos Tversky. "Prospect Theory: An Analysis of Decision Under Risk." *Econometrica.* 47(1979):263-291.

Leland, Jonathan W. "A Theory of Approximate Expected Utility Maximization." *Working Paper, Department of Social and Decision Sciences, Carnegie Mellon University.* (1990).

Lichtenstein, Sarah and Paul Slovic. "Response-Induced Reversals of Preferences in Gambling: an Extended Replication in Las Vegas." *Journal of Experimental Psychology.* 101(1973):16-20.

Lipman, Barton L. "How to Decide How to Decide How to...: Modeling Limited Rationality." *Econometrica*, 59 (1991):1105-1125.

Loomes, Graham and Robert Sugden. "Regret Theory: an Alternative Theory of Rational Choice Under Uncertainty." *Economic Journal*. 92(1982):805-824.

Loomes, Graham and Robert Sugden. "Disappointment and Dynamic Consistency in Choice Under Uncertainty." *Review of Economic Studies.* 53(1986):271-282.

Luce, R. Duncan. "Semi-orders and a Theory of Utility Discrimination." *Econometrica*, 24 (1956):178-191.

MacCrimmon, Kenneth R. and Stig Larsson. *Utility Theory: Axioms Versus "Paradoxes".* Expected Utility Hypothesis and the Allais Paradox (ed. Maurice Allais and Ole Hagen), pp. 333-409. Dordrecht, Holland: Reidel.

McFadden, Daniel. "Conditional Logit Analysis of Qualitative Choice Behavior." in P. Zarembka, ed. *Frontiers in Econometrics*. pp.105-142. New York: Academic Press (1974).

Machina, Mark J. "Choice Under Uncertainty: Problems Solved and Unsolved." *Journal of Economic Perspectives*. 1(1987):121-154.

Machina, Mark J. "Expected Utility Without the Independence Axiom." Econometrica. 50 (1982):227-323.

Machina, Mark J. "Comparative Statics and Non-expected Utility." *Journal of Economic Theory*. 47 (1989a):393-405.

Machina, Mark J. "Dynamic Consistentcy and Non-Expected Utility Models of Choice Under Uncertainty." *Journal of Economic Literature*. 27 (1989b):1622-68.

Maddala, G.S. *Limited-Dependent and Qualitative Variables in Economics*. Cambridge: Cambridge University Press (1983).

March, James G. "Bounded Rationality, Ambiguity and the Engineering of Choice." *Bell Journal of Economics*. 9(1978):587-608.

Marshack, Jacob. "Rational Behavior, Uncertain Prospects, and Measureable Utility." *Eonometrica*. 18(1950):11-41. Errata, 1950, p.312.

Mellers, Barbara, Shi-jie Chang, Michael H. Birnbaum and Lisa D. Ordonez. *Preferences, Prices and Ratings in Risky Decision Making*. Draft, Department of Psychology Working Paper, U.C. Berkeley (1991).

Newbery, David M. G. and Joseph E. Stiglitz. *The Theory of Commodity Price Stabilization: A Study in the Economics of Risk*. Oxford: Oxford University Press, 2nd ed., 1985.

Ng, Yew-Kwang. "Bentham or Bergson? Finite Sensitivity, Utility Functions and Social Welfare Functions." *Review of Economic Studies*. 42 (1975):545-569.

Quiggin, John. "A Theory of Anticipated Utility." *Journal of Economic Behavior and Organization*. 3(1982):323-43.

Payne, John W. "Contingent Decision Behavior." *Psychological Bulletin*. 92 (1982):382-402.

Rubenstein, Ariel. "Similarity and Decision Making Under Risk: (Is There a Utility Theory Resolution to the Allais Paradox?" *Journal of Economic Theory*. 46(1988):145-153.

Russo, J Edward and Barbara Anne Dosher. "Strategies for Multiattribute Binary Choice." *Journal of Experimental Psychology: Learning, Memory and Cognition.* 9(1983):676-696.

Schkade, David A and Eric J. Johnson. "Cogntive Processes in Preference Reversals." *Organizational Behavior and Human Decision Processes.* 44(1989):203-231.

Segal, Uzi. "The Ellsberg Paradox and Risk Aversion: An Anticipated Utility Approach." *International Economic Review.* 28 (1987):175-202.

Simon, Herbert A. *The New Sciense of Management Decision.* New York: Harper and Brothers. (1960).

Smith, Vernon L. Review: "Rational Choice: The Contrast Between Economic and Psycholgy.", ed. by Hogarth and Reder. *Jour. of Pol. Econ.* 99(1991):877-897.

Tversky, Amos. "Intransitivity of Preferences." *Psychological Review.* 76(1969):281-299.

Tversky, Amos and J. Edward Russo. "Substitutability and Similarity in Binary Choice." *Journal of Mathematical Psychology.* 6 (1969):1-12.

Viscusi, W. Kip. "Prospective References Theory: Toward an Explaination of the Paradoxes." Journal of Risk and Uncertainty. 2(1989):235-264.

von-Neuman, John and Oscar Morganstern. *Theory of Games and Economic Behavior.* Princeton, NJ:Princeton University Press, 3rd ed., 1953.

FIGURE 1: Probability Triangle
for EU Preferences.

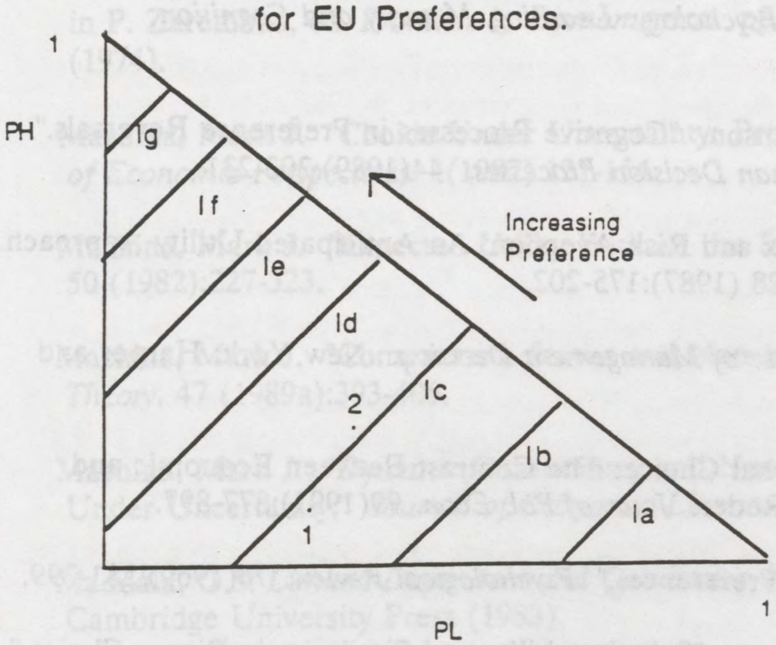
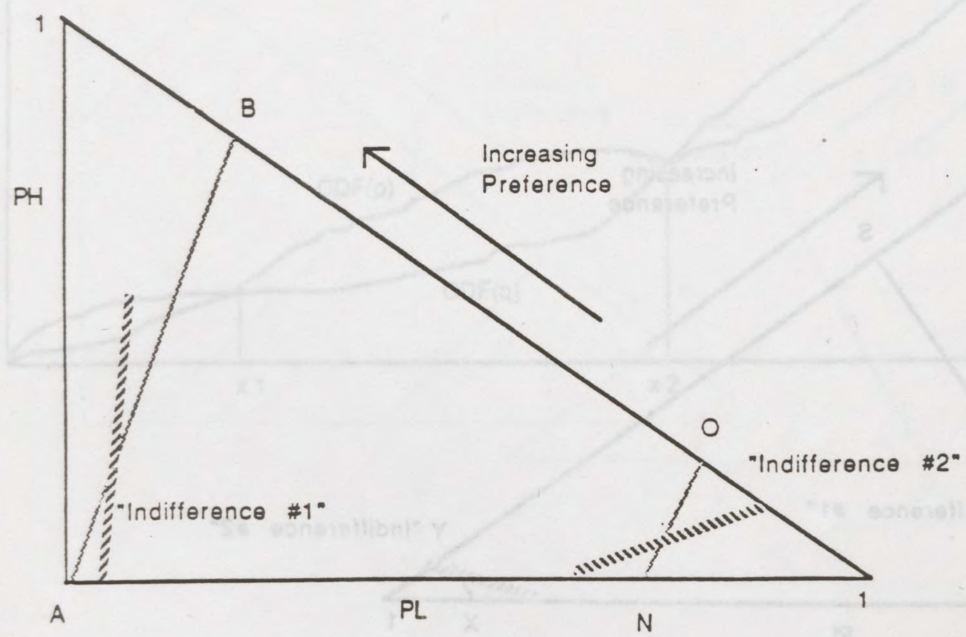


Figure 2: CERTAINTY EFFECT



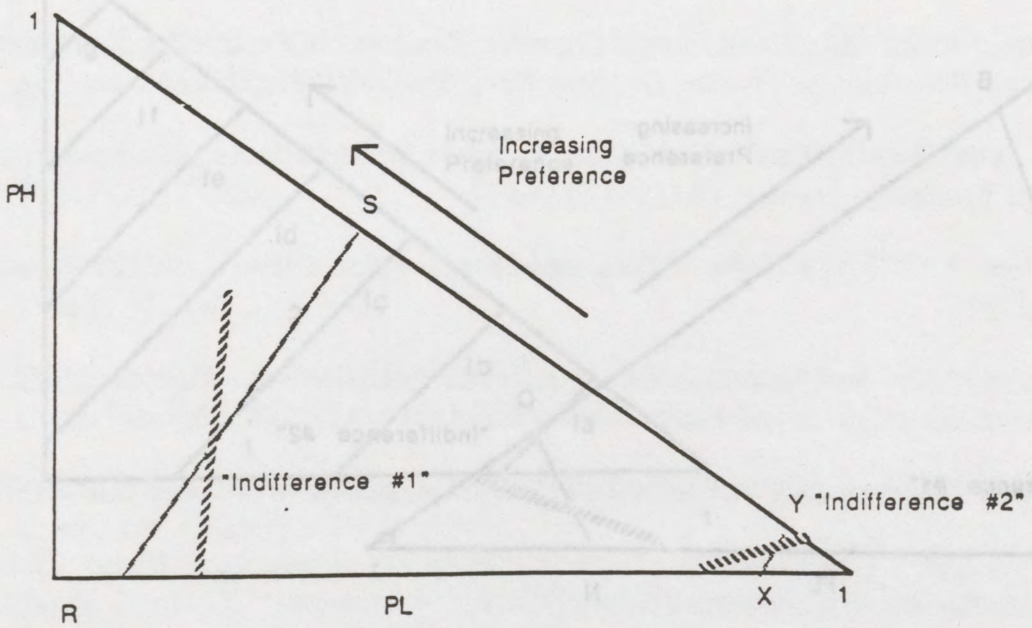
PAIR 1:

A:	vs.	B:
\$3000 prob. 1.0		\$4000 prob. .8
		\$ 0 prob. .2

PAIR 2:

N.	vs.	O:
\$3000 prob. .25		\$4000 prob. .20
\$ 0 prob. .75		\$ 0 prob. .80

Figure 3: COMMON RATIO EFFECT



PAIR 1:

R:		vs.	S:
$3000 prob. .9			$6000 prob. .45
$ 0 prob. .1			$ 0 prob. .55

PAIR 2:

X:		vs.	Y:
$3000 prob. .002			$6000 prob. .001
$ 0 prob. .998			$ 0 prob. .999

FIGURE 4:
CUMMULATIVE
DISTRIBUTION
FUNCTIONS.

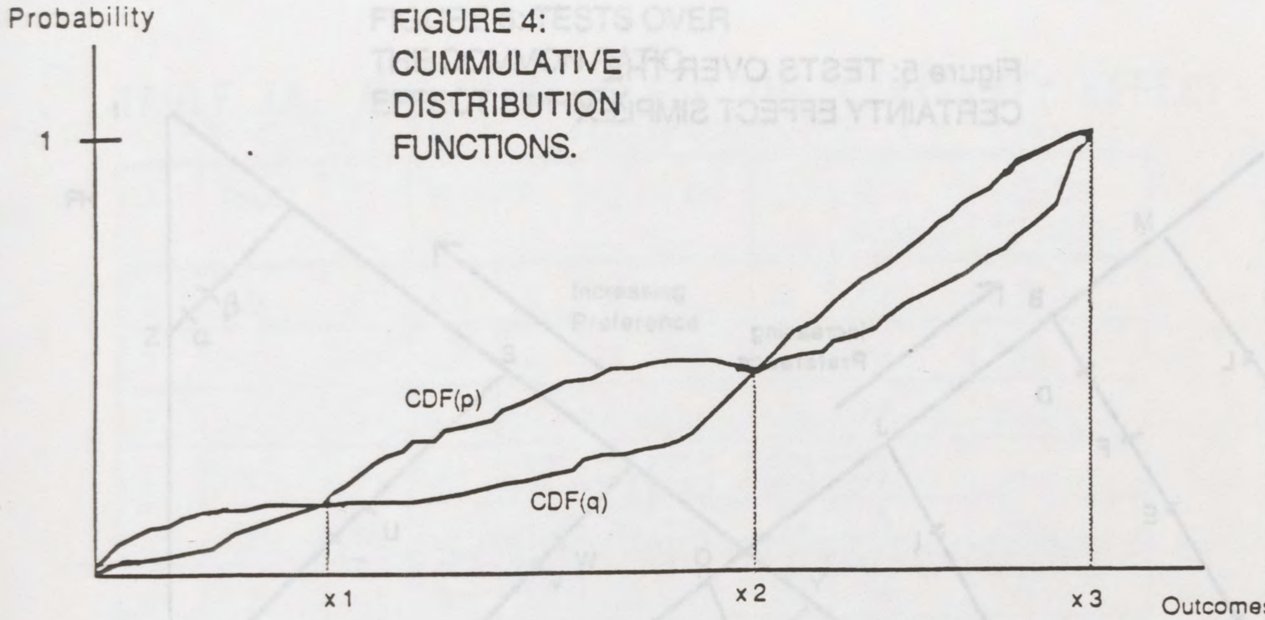
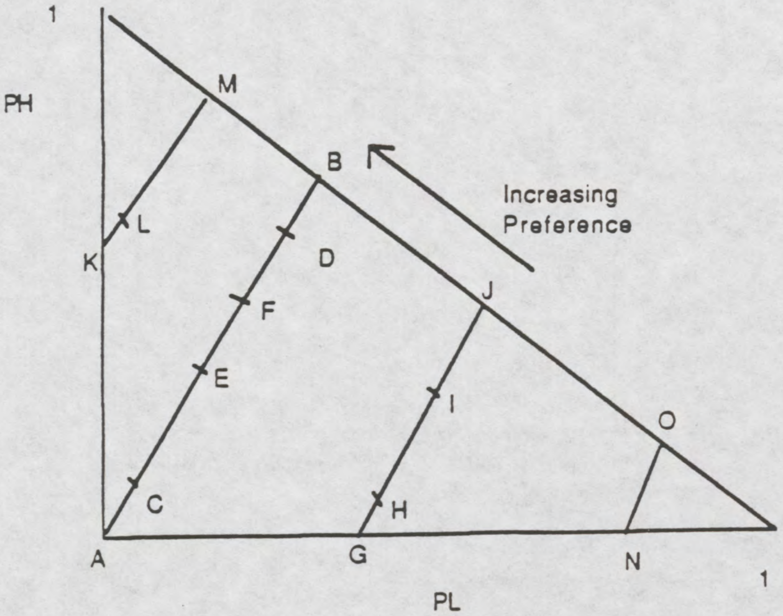


Figure 5: TESTS OVER THE CERTAINTY EFFECT SIMPLEX

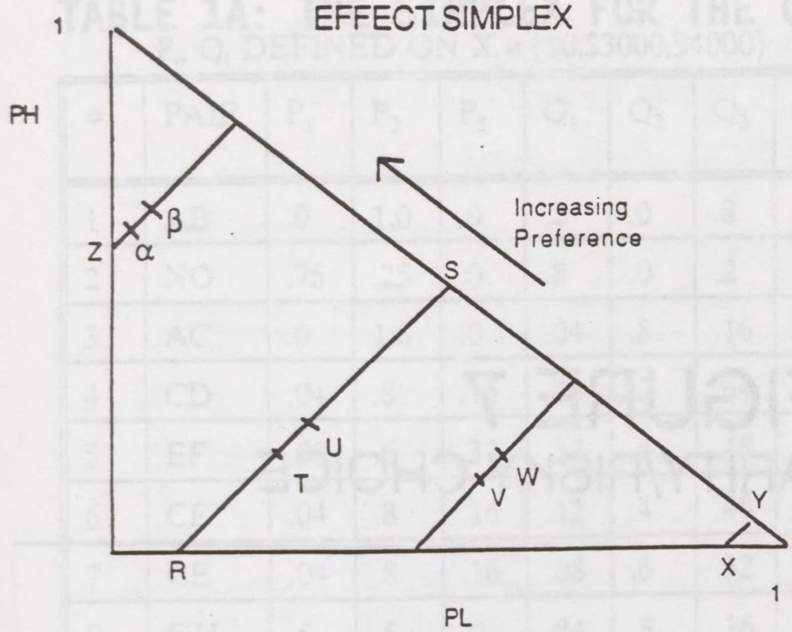


EXAMPLES:

E:	VS.	F:
$4000 PROB. .32		$4000 PROB. .48
$3000 PROB. .60		$3000 PROB. .40
$ 0 PROB. .08		$ 0 PROB. .12

K:	VS.	L:
$4000 PROB. .20		$4000 PROB. .28
$3000 PROB. .80		$3000 PROB. .70
		$ 0 PROB. .02

FIGURE 6: TESTS OVER
THE COMMON RATIO
EFFECT SIMPLEX



EXAMPLES:

T:	VS.	U:
\$ 6000 PROB. .3		\$6000 PROB. .301
\$ 3000 PROB. .3		\$3000 PROB. .298
\$ 0 PROB. .4		\$ 0 PROB. .401

FIGURE 7
DISSIMILARITY/RISKY CHOICE

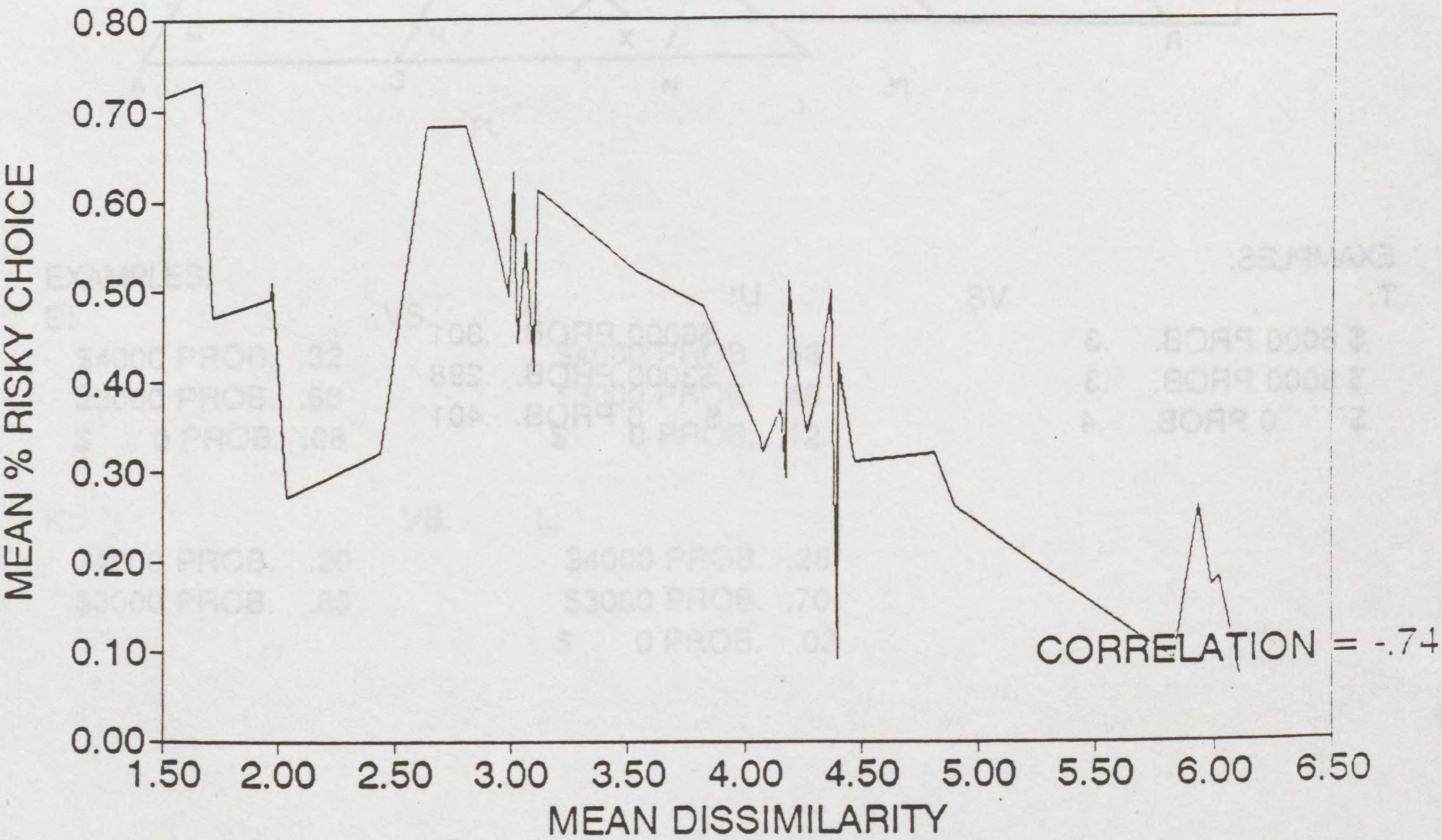


TABLE 1A: THE SIMPLEX FOR THE CERTAINTY EFFECT: P_i, Q_i DEFINED ON $X_i = \{\$0,\$3000,\$4000\}$

#	PAIR	P_1	P_2	P_3	Q_1	Q_2	Q_3	% RISKY	MEAN DISSIM.
1	AB	.0	1.0	.0	.2	.0	.8	.09	5.82
2	NO	.75	.25	.0	.8	.0	.2	.49	2.98
3	AC	.0	1.0	.0	.04	.8	.16	.18	6.02
4	CD	.04	.8	.16	.16	.2	.64	.31	4.47
5	EF	.08	.6	.32	.12	.4	.48	.47	1.71
6	CF	.04	.8	.16	.12	.4	.48	.34	4.06
7	CE	.04	.8	.16	.08	.6	.32	.60	1.85
8	GH	.5	.5	.0	.54	.3	.16	.55	1.87
9	GJ	.5	.5	.0	.6	.0	.4	.41	3.09
10	HI	.54	.3	.16	.56	.2	.24	.68	2.80
11	HJ	.54	.3	.16	.6	.0	.4	.52	3.52
12	KL	.0	.8	.2	.02	.7	.28	.37	2.15
13	KM	.0	.8	.2	.16	.0	.84	.26	5.94
14	CB	.04	.8	.16	.2	.0	.8	.26	3.97
15	LM	.02	.7	.28	.16	.0	.84	.32	4.81
16	BD	.2	.0	.8	.16	.2	.64	.50	4.36
17	FB	.12	.4	.48	.2	.0	.8	.41	4.21
18	AD	.0	1.0	0	.16	.2	.64	.09	5.83
19	AF	.0	1.0	.0	.12	.4	.48	.17	5.98
20	ED	.08	.6	.32	.16	.2	.64	.42	4.39
21	EB	.08	.6	.32	.2	.0	.8	.34	4.26
22	GI	.5	.5	.0	.56	.2	.24	.39	4.31
23	FD	.12	.4	.48	.16	.2	.64	.63	3.00
24	IJ	.56	.2	.24	.6	.0	.4	1.0 *	2.35

* Only two respondants; pair not used in regression analysis.

TABLE 1B: EXPERIMENTAL DESIGN #2: DIMENSIONAL VARIANTS ON THE CERTAINTY EFFECT SIMPLEX.

P_i, Q_i DEFINED ON X_i = {$0,$3000,$3800,$4000}

#	P_1	P_2	P_3	P_4	Q_1	Q_2	Q_3	Q_4	% RISKY	MEAN DISSIM.
25	.01	.2	.75	.04	.04	.05	.75	.16	.51	1.77
26	.03	.6	.25	.12	.12	.15	.25	.48	.48	3.82

25: 1/4 * C + 3/4 * [3800] vs. 1/4 * D + 3/4 * 3800

26: 3/4 * C + 1/4 * [3800] vs. 3/4 * D + 1/4 * 3800

P_i, Q_i DEFINED ON X_i = {$0,$200,$3000,$4000}

#	P_1	P_2	P_3	P_4	Q_1	Q_2	Q_3	Q_4	% RISKY	MEAN DISSIM.
27	.01	.75	.2	.04	.04	.75	.05	.16	.32	4.08
28	.03	.25	.6	.12	.12	.25	.15	.48	.29	4.18

27: 1/4 * C + 3/4 * [200] vs. 1/4 * D + 3/4 * 200

28: 3/4 * C + 1/4 * [200] vs. 3/4 * D + 1/4 * 200

TABLE 1C: EXPERIMENTAL DESIGN #3: CERTAINTY EFFECT PROBABILITIES, VARIED OUTCOMES.

PROBABILITIES AS IN QUESTION #1 (AB IN FIGURE 1)

$P^1 = (0,1.0,0)$ vs. $Q^1 = (.2,0,.8)$

#	OUTCOME VECTOR	POP. % RISKY	MEAN DISSIM.
1	X = ($0,$3000,$4000)	.09	5.82
29	X = ($0,$750,$1000)	.27	4.76
30	X = ($0,$12000,$16000)	.09	5.12

PROBABILITIES AS IN QUESTION #2 (NO IN FIGURE 1)

$P^2 = (.75,.25,0) = 1/4\ P^1 + 3/4 * (0)$ vs. $Q^2 = (.8,0,.2) = 1/4 * Q^1 + 3/4 * (0)$

#	OUTCOME VECTOR	POP. % RISKY	MEAN DISSIM.
2	X = ($0,$3000,$4000)	.49	2.98
31	X = ($0,$750,$1000)	.61	3.11
32	X = ($0,$12000,$16000)	.59	2.89

RESULTS REPORTED BY KAHNEMAN AND TVERSKY:

OUTCOMES (0,3000,4000) ISRAELI POUNDS.

PAIR	% CHOOSING RISKY
P^1,Q^1	.21
P^2,Q^2	.68

TABLE 1D: EXPERIMENTAL DESIGN #4: THE SIMPLEX FOR THE COMMON RATIO EFFECT:

P_i, Q_i DEFINED ON $X_i = \{\$0, \$3000, \$6000\}$

#	PAIR	P_1	P_2	P_3	Q_1	Q_2	Q_3	% RISKY	MEAN DISSIM.
33	RS	.1	.9	.0	.55	.0	.45	.07	6.11
34	XY	.998	.002	.0	.999	.0	.001	.73	1.66
35	TU	.4	.3	.3	.401	.298	.401	.49	1.96
36	VW	.72	.2	.08	.721	.198	.081	.51	1.68
37	Zα	.0	.5	.5	.001	.498	.501	.32	3.67
38	αβ	.001	.498	.501	.002	.496	.502	.44	3.02

P_i, Q_i DEFINED ON $X_i = \{\$0, \$3000, \$5800\}$

#	P_1	P_2	P_3	Q_1	Q_2	Q_3	% RISKY	MEAN DISSIM.
39	.998	.002	.0	.999	.0	.001	.68	2.25

TABLE 2: PRACTICE QUESTIONS IN THE RISK SURVEY

PRACTICE QUESTION 1.

I. Circle one of the following alternatives (A or B) that you would prefer to have:

A. Gives:	B. Gives:
$5000 with a 20% chance	$6000 with a 15% chance
$ 0 with an 80% chance.	$ 0 with a 85% chance.

****

****

PRACTICE QUESTION 2.

I. Circle one of the following alternatives (A or B) that you would prefer to have:

A. Gives:	B. Gives:
$5000 with a 5% chance	$5000 with a 10% chance
$4000 with a 15% chance	$4000 with a 5% chance
$ 0 with an 80% chance.	$ 0 with an 85% chance.

II. Mark a point on the scale from 0 (Similar) to 9 (Very Dissimilar) with a slash (/) mark to rate how DIFFERENT A and B seem to be:

DISSIMILARITY SCALE:

0	3	6	9
(Similar)	(Somewhat Diss.)	(Dissimilar)	(Very Dissimilar)

III. Mark a point on the scale from 0 (Indifferent) to 9 (Very Strong) with a slash (/) mark to rate how STRONGLY you would prefer to have the alternative (A or B) that you circled above.

STRENGTH OF CHOICE SCALE:

0	3	6	9
(Indifferent)	(Somewhat Strong)	(Strong)	(Very Strong)

****

****

TABLE 3: EXPLANATORY VARIABLES FOR DISSIMILARITY OLS

QUESTION CHARACTERISTICS:

PROBABILITY DISTANCE (METRIC OR CDF BASED MEASURE)
DISTANCE SQUARED, DISTANCE CUBED,
INDICATOR VARIABLE FOR PSEUDO-CERTAINTY ($P_1=0$ OR $Q_1=0$),
INDICATOR VARIABLE FOR EQUI-DIMENSIONAL SUPPORT,
THE ORDER OF THE ALTERNATIVE PAIR IN THE SURVEY,
THE DIFFERENCE IN THE EXPECTED VALUES OF THE ALTERNATIVES,
THE MINIMUM OF THE EXPECTED VALUES OF THE ALTERNATIVES,
THE RATIO OF THE EV DIFFERENCE OVER THE MINIMUM EV.

INDIVIDUAL CHARACTERISTICS:

AN INDICATOR VARIABLE FOR EACH INDIVIDUAL

TABLE 4A: DISSIMILARITY OLS: METRIC MEASURE

VARIABLE	ESTIMATED COEFFICIENT	STANDARD ERROR	T-RATIO 869 DF
QUESTION CHARACTERISTICS			
METRIC	9.5234	1.1105	8.5758
METRIC ^ 2	-9.9410	1.9955	-4.9817
METRIC ^ 3	4.1545	1.0408	3.9918
PSEUDO-CERT IND.	1.0359	0.14591	7.0994
EQUI-DIM. IND.	-0.38911	0.13066	-2.9781
ORDER	0.29E-03	0.01050	0.0276
EV DIFFERENCE	-0.16E-02	0.11E-01	0.0276
MINIMUM EV	0.17E-03	0.52E-04	3.3296
EV DIFF./MIN. EV	-31.596	13.799	-2.2897
CONSTANT	3.3028	0.68188	4.8436

R-SQUARE = 0.5186 R-SQUARE ADJUSTED = 0.4459

TABLE 4B: DISSIMILARITY OLS: CDF MEASURE

VARIABLE	ESTIMATED COEFFICIENT	STANDARD ERROR	T-RATIO 871 DF
QUESTION CHARACTERISTICS			
CDF MEASURE	25.570	3.7611	6.7986
CDF MEAS. ^ 2	-82.158	23.333	-3.5212
CDF MEAS. ^ 3	104.58	40.490	2.5829
PSEUDO-CERT IND.	1.1548	0.14999	7.6988
EQUI-DIM. IND.	-0.08609	0.13238	-0.65033
ORDER	-0.64E-02	0.010683	0.60252
EV DIFFERENCE	0.34E-04	0.10E-02	0.03409
MINIMUM EV	0.15E-03	0.53E-04	2.9284
EV DIFF./MIN. EV	-14.621	4.6143	-3.1685

R-SQUARE = 0.4994 R-SQUARE ADJUSTED = 0.4248

TABLE 4C: DISSIMILARITY GLS: METRIC MEASURE MODEL WEIGHTED BY AVERAGE INTRAPERSONAL VARIANCES

VARIABLE	ESTIMATED COEFFICIENT	STANDARD ERROR	ASYMPTOTIC T-RATIO
QUESTION CHARACTERISTICS			
METRIC	9.8604	0.8738	11.284
METRIC ^ 2	-10.392	1.5264	-6.8078
METRIC ^ 3	4.3122	0.7823	5.5121
PSEUDO-CERT IND.	0.9137	0.1090	8.3792
EQUI-DIM. IND.	-0.2086	0.0949	-2.1970
ORDER	0.32E-02	0.87E-02	0.3722
EV DIFFERENCE	-0.14E-02	0.76E-03	-1.8506
MINIMUM EV	0.14E-03	0.41E-04	3.3384
EV DIFF./MIN. EV	-22.310	3.6077	-6.1839
CONSTANT	1.0237	0.26591	3.8498

R-SQUARE = 0.7498 R-SQUARE ADJUSTED = 0.7130

TABLE 5: EXPLANATORY VARIABLES FOR THE LOGISTIC CHOICE REGRESSIONS FITTED DISSIMILARITY.

<u>QUESTION CHARACTERISTICS</u>:

THE ESTIMATED DISSIMILARITY OF THE ALTERNATIVES
THE DIFFERENCE IN THE TWO EXPECTED VALUES,
THE LOWER OF THE TWO EXPECTED VALUES, A MEASURE OF THE (HYPOTHETICAL) STAKES INVOLVED,
THE RATIO OF THE DIFFERENCE IN THE EXPECTED VALUES OF THE ALTERNATIVES OVER THE LOWER OF THE TWO EXPECTED VALUES,
THE ORDER OF THE QUESTION.

<u>PERSONAL CHARACTERISTICS</u>:

BASIC CHOICE BETWEEN A DISSIMILAR PAIR
AGE,
PERSONAL INDICATOR VARIABLES:
- GENDER (1=MALE),
- INDICATOR FOR MARRIED INDIVIDUALS,
- INDICATOR FOR INDIVIDUALS WITH CHILDREN,
- INDICATOR FOR UNDERGRADUATES,
- INDICATOR FOR NON-ACADEMICS AND NON-UNDERGRADUATES,
- EDUCATION INDICATORS: (HIGH SCHOOL GRADUATE BASE):
  - SOME COLLEGE
  - COLLEGE GRADUATE
  - GRADUATE OR PROFESSIONAL STUDIES,
- INDICATOR FOR LOTTERY TICKET PURCHASE,
- INCOME (1991) LEVEL INDICATOR ($0-$10000 AS BASE):
  - $10,000 TO $30,000 INDICATOR,
  - $30,000 TO $50,000 INDICATOR,
  - $50,000 TO $100,000 INDICATOR,
  - OVER $100,000 INDICATOR.

SURVEY TEST GROUP INDICATOR:
- GROUP 1 (INITIALLY MORE LOW-DISTANCE PAIRS)
- GROUP 2 (INITIALLY MORE HIGH-DISTANCE PAIRS).

TABLE 5 (CONT.): EXPLANATORY VARIABLES FOR THE LOGISTIC CHOICE REGRESSIONS USING FITTED DISSIMILARITY.

COMBINATION QUESTION/INDIVIDUAL VARIABLES:

DISSIMILARITY ESTIMATE * UNDERGRADUATE INDICATOR,
DISSIMILARITY ESTIMATE * NON-ACADEMIC INDICATOR,
BASE CHOICE*UNDERGRADUATE INDICATOR
BASE CHOICE*NON-ACADEMIC INDICATOR.
THE DIFFERENCE IN THE TWO EXPECTED VALUES * UNDERGRADUATE INDICATOR,
THE LOWER OF THE TWO EXPECTED VALUES * UNDERGRADUATE INDICATOR,
THE DIFFERENCE IN THE TWO EXPECTED VALUES * NON-ACADEMIC INDICATOR,
THE LOWER OF THE TWO EXPECTED VALUES * NON-ACADEMIC INDICATOR,
RATIO OF THE RELATIVE DIFFERENCE IN EXPECTED VALUES* UNDERGRADUATE INDICATOR,
RATIO OF THE RELATIVE DIFFERENCE IN EXPECTED VALUES* NON-ACADEMIC INDICATOR,

TABLE 6: LOGISTIC REGRESSION MODEL 1, SELECTION OF THE RISKIER ALTERNATIVE.

VARIABLE	ESTIMATED COEFFICIENT	ASYMPTOTIC STANDARD ERROR	T-RATIO
QUESTION CHARACTERISTICS:			
EST. DISSIMILARITY	-0.58908	0.07238	-8.1383
ORDER	-0.59E-02	0.31E-02	-1.9009
MINIMUM EV	-0.64E-04	0.53E-04	-1.1939
EV DIFFERENCE	-0.26E-02	0.11E-02	-2.3792
EV DIFF./MIN EV	3.82964	4.4141	0.86759
PERSONAL CHARACTERISTICS:			
BASE CHOICE	1.1333	0.15059	7.5257
GENDER	0.31014	0.08781	3.5320
MARRIAGE	-0.21037	0.15825	-1.3294
CHILDREN	0.16501	0.13132	1.2565
AGE	-0.03122	0.50E-02	-6.2310
EDUCATION LEVEL 3	0.21677	0.34526	0.62786
EDUCATION LEVEL 4	-0.94837	0.37479	-2.5304
EDUCATION LEVEL 5	-0.25056	0.38616	-0.64886
NON-ACADEMIC IND.	0.42033	0.57613	0.72958
UNDERGRADUATE IND.	-0.95628	0.60599	-1.5781
LOTTERY TICKET IND.	-0.01997	0.11750	-0.16992
TEST GROUP1	-0.16163	0.09983	-1.6191
TEST GROUP2	0.20990	0.09561	2.1954
INCOME LEVEL 2	0.03949	0.16383	0.24105
INCOME LEVEL 3	-0.02055	0.21965	-0.93E-02
INCOME LEVEL 4	0.73358	0.23073	3.1794
INCOME LEVEL 5	0.39380	0.24807	1.5875

TABLE 6 (CONT.): LOGISTIC REGRESSION FOR A RISKIER GAMBLE SELECTION

VARIABLE	ESTIMATED COEFFICIENT	ASYMPTOTIC STANDARD ERROR	T-RATIO
EST. DISS.*UNDER.	0.05735	0.09563	0.59975
EST. DISS.*NON-AC.	0.01239	0.11390	0.11390
[EV DIFF/MIN EV]*UN	-2.77076	5.8362	-0.47474
[EV DIFF/MIN EV]*NA	2.6706	7.2541	0.36815
MIN EV*UNDER.	0.12E-04	0.63E-04	0.19671
MIN EV*NON-ACAD.	0.87E-04	0.74E-04	1.1791
EV DIFF.*UNDER	0.52E-03	0.15E-02	0.35966
EV DIFF*NON-ACAD.	-0.22E-02	0.19E-02	-1.1313
BASE*UNDER	-0.02681	0.22396	-0.11971
BASE*NON-AC.	-0.66535	0.23904	-2.7834
CONSTANT	3.6956	0.57221	6.4585

LOG-LIKELIHOOD(0) = -2475.3
LOG-LIKELIHOOD FUNCTION = -2188.3
LIKELIHOOD RATIO TEST = 573.970 WITH 32 D.F.

PREDICTION SUCCESS TABLE

		ACTUAL 0	ACTUAL 1
	0	1847.	800.
PREDICTED	1	393.	653.

NUMBER OF RIGHT PREDICTIONS = 0.250E+04
PERCENTAGE OF RIGHT PREDICTIONS = 0.67696

TEST BASE+BASENA = 0
TEST VALUE = 0.46792
STANDARD ERROR OF TEST VALUE 0.19574
ASYMPTOTIC NORMAL STATISTIC = 2.3905370

TABLE 7: LOGISTIC REGRESSION MODEL 2 FOR CE PATTERN VIOLATIONS

VARIABLE	ESTIMATED COEFFICIENT	ASYMPTOTIC STANDARD ERROR	T-RATIO
QUESTION CHARACTERISTICS:			
EST. DISSIMILARITY	-0.81209	0.13561	-5.9884
ORDER	-0.68E-02	0.37E-02	-1.8214
MINIMUM EV	-0.15E-03	0.75E-04	-1.9954
EV DIFFERENCE	-0.33E-02	0.31E-02	-1.0776
EV DIFF./MIN EV	3.7154	8.1586	0.45540
PERSONAL CHARACTERISTICS:			
BASE CHOICE	1.1573	0.19220	6.0214
GENDER	0.44135	0.11093	3.9787
MARRIAGE	-0.16204	0.20075	-0.80717
CHILDREN	0.24196	0.16551	1.4619
AGE	-0.03803	0.63E-02	-5.9957
EDUCATION LEVEL 3	0.27467	0.43794	0.62718
EDUCATION LEVEL 4	-0.82944	0.47417	-1.7493
EDUCATION LEVEL 5	-0.27281	0.49014	-0.55661
NON-ACADEMIC IND.	0.38332	1.1465	0.33434
UNDERGRADUATE IND.	-1.78387	1.0559	-1.6894
LOTTERY TICKET IND.	0.04789	0.14722	0.32530
TEST GROUP1	-0.22477	0.12597	-1.7843
TEST GROUP 2	0.18829	0.12046	1.5631
INCOME LEVEL 2	0.01393	0.20833	0.06687
INCOME LEVEL 3	-0.16594	0.27915	-0.59446
INCOME LEVEL 4	0.84712	0.29250	2.8961
INCOME LEVEL 5	0.41896	0.31245	1.3409

TABLE 7 (CONT.): LOGISTIC REGRESSION MODEL 2 FOR CE PATTERN VIOLATIONS

VARIABLE	ESTIMATED COEFFICIENT	ASYMPTOTIC STANDARD ERROR	T-RATIO
EST. DISS.*UNDER.	0.25250	0.17569	1.4372
EST. DISS.*NON-AC.	0.10893	0.21201	0.51379
EV DIFF.*UNDER	0.41E-02	0.40E-02	1.0140
EV DIFF*NON-ACAD.	0.58E-02	0.48E-02	1.2155
MIN EV*UNDER.	0.19E-05	0.97E-04	0.01981
MIN EV*NON-ACAD.	-0.30E-04	0.12E-03	-.25438
[EV DIFF/MIN EV]*UN	-15.679	10.758	-1.4575
[EV DIFF/MIN EV]*NA	-23.785	13.177	-1.8051
BASE*UNDER	-0.09146	0.28238	-0.32632
BASE*NON-ACAD.	-0.55155	0.30268	-1.8222
CONSTANT	5.0141	0.91994	5.4505

LOG-LIKELIHOOD(0) = -1560.5
LOG-LIKELIHOOD FUNCTION = -1378.2
LIKELIHOOD RATIO TEST = 364.685 WITH 32 D.F.

PREDICTION SUCCESS TABLE

		ACTUAL 0	ACTUAL 1
	0	1162	507
PREDICTED	1	241	414

NUMBER OF RIGHT PREDICTIONS = 0.158E+04
PERCENTAGE OF RIGHT PREDICTIONS = 0.67814

TEST BASECE+BASENA = 0
TEST VALUE = 0.60574
STD. ERROR OF TEST VALUE 0.24652
ASYMPTOTIC NORMAL STATISTIC = 2.4571415

TABLE 8: LOGISTIC REGRESSION MODEL 3 FOR CRE PATTERN VIOLATIONS

VARIABLE	ESTIMATED COEFFICIENT	STANDARD ERROR	T-RATIO
QUESTION CHARACTERISTICS:			
EST. DISSIMILARITY	-0.78152	0.22745	-3.4360
ORDER	-0.30E-02	0.02564	-0.11546
MINIMUM EV	-0.54E-03	0.10E-03	-5.3353
PERSONAL CHARACTERISTICS:			
BASECRE	3.8824	1.7302	2.2440
GENDER	0.25249	0.35345	0.71435
MARRIAGE	-1.6630	0.74182	-2.2417
CHILDREN	-0.52665	0.45979	-1.1454
AGE	0.29E-02	0.01883	-0.15173
EDUCATION LEVEL 3	0.16183	1.0776	0.15018
EDUCATION LEVEL 4	-1.7431	1.2219	-1.4265
EDUCATION LEVEL 5	-0.80987	1.2939	-0.62591
NON-ACADEMIC IND.	0.78934	1.2771	0.61808
UNDERGRADUATE IND.	-2.1834	1.7045	-1.2809
LOTTERY TICKET IND.	0.47186	0.50060	0.94259
TEST GROUP1	0.24660	0.57021	0.52017
TEST GROUP2	0.86481	0.37705	2.2936
INCOME LEVEL 2	-1.5935	0.78467	-2.0308
INCOME LEVEL 3	0.04146	0.91453	0.04534
INCOME LEVEL 4	-0.51001	1.0209	-0.49956
INCOME LEVEL 5	0.02965	1.1227	0.02641

TABLE 8 (CONT.): LOGISTIC REGRESSION MODEL 3 FOR CRE PATTERN VIOLATIONS

VARIABLE	ESTIMATED COEFFICIENT	ASYMPTOTIC STANDARD ERROR	T-RATIO
EST. DISS.*UNDER.	0.16E-02	0.32053	0.50E-02
EST. DISS.*NON-AC.	0.21035	0.29889	0.70377
BASE*UNDER	-4.4246	2.0863	-2.1208
BASE*NON-ACAM	-2.3250	2.0944	-1.1101
CONSTANT	-5.1213	1.9065	2.6862

LOG-LIKELIHOOD(0) = -213.43
LOG-LIKELIHOOD FUNCTION = -145.56
LIKELIHOOD RATIO TEST = 135.722 WITH 24 D.F.

PREDICTION SUCCESS TABLE ACTUAL

		0	1
	0	146	32
PREDICTED	1	44	95

NUMBER OF RIGHT PREDICTIONS = 241.
PERCENTAGE OF RIGHT PREDICTIONS = 0.76025

TEST BASECRE+BASENA = 0
TEST VALUE = 1.5574 STD. ERROR OF TEST VALUE 1.1862
ASYMPTOTIC NORMAL STATISTIC = 1.3129416
TEST BASECRE+BASEUN = 0
TEST VALUE = -0.54217 STD. ERROR OF TEST VALUE 1.1466
ASYMPTOTIC NORMAL STATISTIC = -0.47283974

TABLE 9: VARIABLES FOR THE REDUCED FORM LOGISTIC MODEL OF RISKY CHOICE

QUESTION CHARACTERISTICS:

METRIC, METRIC SQUARED AND METRIC CUBED,
INDICATOR FOR ZERO PROBABILITY OF THE LOW OUTCOME (PSEUDO-CERTAINTY),
INDICATOR FOR EQUI-DIMENSIONAL SUPPORT
ABSOLUTE DIFFERENCE BETWEEN THE EXPECTED VALUES OF THE ALTERNATIVES,
MINIMUM EXPECTED VALUE OF THE ALTERNATIVES,
RATIO: ABSOLUTE DIFFERENCE OVER MINIMUM EXPECTED VALUE,
THE ORDER OF THE SURVEY QUESTION.

PERSONAL CHARACTERISTICS

BASE CHOICE MEASURE FOR A RELATIVELY DISSIMILAR PAIR,
GENDER INDICATOR (1=MALE),
INDICATOR FOR MARRIAGE,
INDICATOR FOR CHILDREN,
THE AGE OF THE INDIVIDUAL,
EDUCATION LEVEL INDICATORS:
- LEVEL 3 (SOME COLLEGE)
- LEVEL 4 (COLLEGE GRADUATE)
- LEVEL 5 (GRADUATE OR PROFESSIONAL STUDIES),

INDICATOR FOR NON-ACADEMICS (AND NON-UNDERGRADUATES)
INDICATOR FOR UNDERGRADUATES,
INDICATOR FOR LOTTERY TICKET PURCHASE WITHIN THE MONTH,
TEST GROUP 1 (INITIALLY MORE LOW-METRIC MEASURE QUESTIONS),
TEST GROUP 2 (INITIALLY MORE LARGE-METRIC MEASURE QUESTIONS),

TABLE 9 (CONT.): VARIABLES FOR THE REDUCED FORM LOGISTIC MODEL 4 OF RISKY CHOICE

INTERACTION TERMS

BASE CHOICE * UNDERGRADUATE INDICATOR,
BASE CHOICE * NON-ACADEMIC INDICATOR,
METRIC*UNDERGRADUATE INDICATOR
METRIC*NON-ACADEMIC INDICATOR
PSEUDO-CERTAINTY*UNDERGRADUATE INDICATOR
PSEUDO-CERTAINTY*NON-ACADEMIC INDICATOR

TABLE 10: LOGISTIC REGRESSION USING REDUCED FORM VARIABLES FOR SIMILARITY: RISKY CHOICE.

QUESTION CHARACTERISTICS:

METRIC	-2.0674	0.80578	-2.5658
METRIC^2	-0.92086	1.4991	-0.61428
METRIC^3	0.71457	0.80805	0.88432
ORDER	-0.73E-02	0.31E-02	-2.3641
PSEUDO-CERTAINTY	-0.92561	0.16735	-5.5310
EQUI-DIMENSION	0.01528	0.09564	0.15975
MINIMUM EV	-0.43E-04	0.29E-04	-1.4645
EV DIFFERENCE	-0.40E-03	0.65E-03	-0.60810
EV DIFF./MIN EV	15.667	3.2154	4.8913

PERSONAL CHARACTERISTICS:

BASE CHOICE	1.1406	0.15054	7.5768
GENDER	0.30758	0.08827	3.4845
MARRIAGE IND.	-0.01702	0.14577	-0.11675
CHILDREN IND.	0.21723	0.12826	1.6936
AGE	-0.02672	0.45E-02	-5.7875
EDUCATION LEVEL 3	0.31894	0.34711	0.91886
EDUCATION LEVEL 4	-0.41970	0.34698	-1.2096
EDUCATION LEVEL 5	0.16256	0.36502	0.44535
NON-ACADEMIC IND.	0.77367	0.22685	3.4105
UNDERGRADUATE IND.	-0.25416	0.39111	-0.64986
LOTTERY TICKET IND.	0.02009	0.11692	0.17180
TEST GROUP 1 IND.	-0.18220	0.09829	-1.8537
TEST GROUP 2 IND.	0.20520	0.09621	2.1328

TABLE 10 (CONT.): REDUCED FORM LOGISTIC REGRESSION: RISKY CHOICE

VARIABLE	ESTIMATED COEFFICIENT	ASYMPTOTIC STANDARD ERROR	T-RATIO
METRIC*NON-ACAM.	-0.19428	0.28583	-0.67968
METRIC*UNDER.	-0.17302	0.23696	-0.73014
PSEUDO-CERT*UNDER	0.36550	0.20590	1.7751
PSEUDO-CERT*NON-AC	0.15199	0.25452	0.59718
BASE*UNDER	0.88E-02	0.22601	0.39E-01
BASE*NON-ACAM	-0.70753	0.23394	-3.0244
CONSTANT	0.93769	0.43453	2.1579

LOG-LIKELIHOOD(0) = -2475.3
LOG-LIKELIHOOD FUNCTION = -2142.1
LIKELIHOOD RATIO TEST = 666.409 WITH 28 D.F.

PREDICTION SUCCESS TABLE

		ACTUAL 0	ACTUAL 1
	0	1815	769
PREDICTED	1	425	684

NUMBER OF RIGHT PREDICTIONS = 0.250E+04
PERCENTAGE OF RIGHT PREDICTIONS = 0.67669

TEST BASE+BASENA = 0
TEST VALUE = 0.43311 STD. ERROR OF TEST VALUE 0.18701
ASYMPTOTIC NORMAL STATISTIC = 2.3159761

TABLE 11: INTRANSITIVITIES AS SUGGESTED BY SIMILARITY EFFECTS:

PATTERN 1:	PATTERN 2:
E CHOSEN OVER C,	
F CHOSEN OVER E,	F CHOSEN OVER E
D CHOSEN OVER F,	D CHOSEN OVER F
B CHOSEN OVER D,	B CHOSEN OVER D
but C CHOSEN OVER B,	but E CHOSEN OVER B

	N	MEAN	ST. DEV
INTRANSITIVITY PATTERN 1	117	0.094	0.293

T-VALUES,		
	HO: $\mu = 0$	3.47
	HO: $\mu = (.5)^5$	2.32

	N	MEAN	ST. DEV
INTRANSITIVITY PATTERN 2	115	0.096	0.295

T-VALUES,		
	HO: $\mu = 0$	3.48
	HO: $\mu = (.5)^4$	1.22