THE SENSITIVITY OF EXPECTED UTILITY VIOLATIONS TO THE EXPERIMENTAL DESIGN: HOW CONTEXT AFFECTS RISKY CHOICE

by

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ABSTRACT

Expected Utility Theory is tested under different question contexts. It is hypothesized that previously cited independence violations may result from experimental biases rather than a shortcoming of the Theory. An experimental survey presents risky choice questions as lotteries and as "real life" scenarios to test the relative frequency of independence violations under different test conditions. Simple proportion-difference test statistics show that some choice pairs elicit significantly different choices under the scenario contexts. A more sophisticated analysis, using logit regression models, finds that the scenario contexts reduce choice biases caused by the similarity of the alternatives. Choices over scenario-contexts are found to be consistent with Expected Utility Theory. Violations of Expected Utility Theory over lottery contexts are attributed to the similarity of the alternatives.

CHAPTER 1

INTRODUCTION

How do people make decisions when prospective alternatives have uncertain consequences? Traditional economic analysis clearly describes how price and quantity *levels* affect people's choices, but what can economists say about the effects of random *variability* about these levels? Variability (or risk) may affect even the behavior of people who choose between risky alternatives by maximizing *expected* profit (or wealth). If people do not simply maximize expected profit, have different attitudes toward risk, and generally demand significant risk premiums for riskier but otherwise equivalent alternatives, then specification of comparative static changes in a risky environment is more complicated than that assumed by the expected value criterion . Because the world is indeed a risky place, economists need to be concerned with these possible effects.

For example, if government bans a key pesticide used on a particular crop, the ban may both reduce farmers' average yield and increase yield variability for that crop.[1] The change in yield variability will potentially affect even risk-neutral farmers (those who maximize expected profits) on two grounds: (1) covariance between yield and prices may affect farmers' average

[1]A pesticide ban would increase yield variability only if pesticides are risk-reducing inputs (i.e. variance reducing inputs). Horowitz and Lichtenberg (1993) find empirical evidence suggesting that both fertilizer and pesticides actually may be risk-increasing inputs. Other work, including that by Antle (1988,1989), finds that pesticides are risk-reducing.

profits (Newbery and Stiglitz, 1985, chapter 5), and (2) larger variability may increase the likelihood of a costly bankruptcy (Benjamin, 1978; Atwood and Watts, 1994). For farmers who are not risk neutral (i.e. risk averse or risk loving farmers), the change in profit variability itself also affects utility. In making predictions on the magnitudes of these possible effects, economists have made strong assumptions regarding individuals' criteria for choosing among risky alternatives. This thesis focuses on some criticisms that have surfaced regarding economists' assumptions in modeling these possible effects of risk for individuals who are not necessarily risk neutral.

Because of the strong normative appeal and general usefulness of Expected Utility Theory (EU), it has become the paramount assumption in almost all theoretical and empirical research on risk. For example, theoretical investigations by Sandmo (1971) and Newbery and Stiglitz (1985) use EU as a benchmark to make comparative static predictions over changes in risk with regard to input use. Antle (1987, 1989) also assumes EU in his study on the welfare implications of pesticide regulation. Restrictions on the utility function have led to further extensions of EU (e.g., Tobin,1955-56); Arrow (1958, 1974); Pratt (1964); Friedman and Savage (1948)). For a detailed overview on the theoretical implications of risk and EU theory see Newbery and Stiglitz (1985).

Although many economists consider EU quite useful in studying the implications of risk, the theory has seen substantial criticism. Allais (1953) and Kahneman and Tversky (1979) find that subjects' choices over hypothetical lotteries systematically violate EU's axioms. If in fact EU theory does not reasonably approximate people's choices, another model should be

considered for descriptive use. Consequently, some economists concerned about EU's apparent lack of descriptive accuracy have proposed generalizations to EU (generalized expected utility theories, or GEU) that allow for the behavior generally observed in experimental findings. Systematic violations of GEU models, however, have also been documented (e.g. Camerer, 1992).

The difficulties in modeling choices under risk have arisen due to the ambiguity of the objective function. The neoclassical economic model for consumer choice asserts that individuals maximize their utility subject to constraints (e.g. income and prices). But how can utility be specified with regard to uncertain consequences of choice? The expected value criterion (EV) assumes utility functions are strictly linear with respect to wealth. This strict cardinal limitation on the utility function is inflexible compared to modern ordinal interpretations of utility--EU is more general. Under EU, the utility function is not subject to the cardinal limitations of EV; only the probabilistic *weighting* of utility is assumed to be linear. GEU models generalize the objective function further to allow for a non-linear probabilistic weighting of utility. The non-linear probabilistic weighting of utility in GEU models, however, is difficult to interpret.

Could there be another explanation for EU violations besides a misspecification of the objective function? Following general suggestions by Rubinstein (1988), Azipurua et al (1993), and Leland (1992a, b), Buschena (1992) develops a framework of costly decisions, where the accuracy of choice depends on the costs and benefits of choice, roughly approximated by their "similarity." The similarity models suggest that *preferences* may indeed be

consistent with EU, but that *choices*, especially in experimental settings, can sometimes be biased relative to the marginal costs and marginal benefits of decision-making. The explanation follows the notion of *bounded rationality.* Bounded rationality asserts that the costs of decision-making create bounds to the accuracy of decisions, creating "rational" choices that may differ from true preference. Rather than propose an objective function different from EU to account for violations, these models suggest that decisions are constrained by individuals' "choice functions" that include, perhaps among other variables, the similarity of the alternatives. Thus the similarity models move towards *explaining* EU violations through costly decisions and the marginalist paradigm.

While Buschena finds that the similarity model provides a more robust explanation and empirical support for the choices people make over hypothetical lotteries, more research is needed to investigate other factors that may affect the costs and benefits of choice; that is, economists need to better understand the variables that may enter people's choice functions.

While experimental EU violations and the theories used to account for them have given many insights into risky decision making, large gaps remain between the experimental design and the "real world" types of decisions that economists have interest in modeling. Choices over hypothetical gambles of arbitrary lotteries may not reasonably reflect, say, farmers' choices on pesticide use or crop rotations. In particular, the hypothetical lotteries used in most experiments lack real money payoffs and a context that is pertinent to decisions of interest. Could these differences between the experimental

and "real world" decisions change the nature of the costs and benefits of choice?

Psychologists have found that question context and framing significantly affect peoples' choices in experimental risky choice research (Hershey and Schoemaker ,1981; Heath and Tversky 1991; Kahneman and Lovallo, 1993). Could it be that context and frame are variables that enter choice functions along with similarity? If so, why? Psychologists contend that normative or prescriptive theories like EU fail as a *description* of behavior (Kahneman and Tversky; 1979; Plous, 1993), arguing that real world decisions are too complex to systematically apply EU theory to choices. Rather, people rely on heuristics, or rules of thumb, to simplify the vastly complex decisions made in real world. Presumably, the experimental violations of EU result from an exploitation of people's heuristics. Choices, therefore, may also be affected by the decision-maker's familiarity with the context of the choice dilemma. What the decision-maker learns from context may provide information about the consequences of choice at a relatively low cost in time and effort. Indeed, Heath and Tversky (1991) show that people prefer choosing over risky alternatives in a familiar context than over equivalent alternatives in a simple lottery context.

This thesis incorporates survey responses from a class of undergraduate students and a group of Montana seed potato producers in a study on the effects of context on choice. Using these data, the thesis attempts to address the following questions:

(1) How does question context affect choice (e.g. more risk-loving, more risk- averse, more or less consistent with EU theory)?

(2) How does context affect the influence of similarity as defined by Buschena?

(3) What can economists learn from context and similarity effects in their efforts to understand people's decisions under risk?

(4) Can economists find reasonable risk attitude estimates using experimental choices over hypothetical risky situations? What reservations should economists hold regarding such estimates?

Chapter 2 reviews the relevant literature on EU, GEU models, similarity models, and the effects of context. Chapter 3 motivates and describes the experimental method used in the thesis and outlines the hypotheses tested in Chapter 4. Chapter 5 summarizes the results and discusses implications and extensions of this research.

CHAPTER 2

LITERATURE REVIEW

This chapter reviews some of the expansive literature on risky choice. The discussion begins with a short history describing the development of Expected Utility Theory (EU) and the axioms that characterize EU and its implications, followed by a discussion of the types of experimental violations that have questioned its applicability. The chapter then reviews the many theories offered to explain these violations. These alternative theories include the generalizations to EU (GEU theories) that weaken EU's independence axiom, and the similarity hypothesis that offers a bounded rationality explanation for the patterns of experimental EU violations.

The Expected Utility Hypothesis

Before the adoption of EU, the maximum expected value (EV) criterion was used to describe decision making under risk. The expected value of an investment is characterized by its mean or average return. Over a n-dimensional discrete set of outcomes,

$$EV = \sum_{i}^{n} p(x_i)x_i \tag{1}$$

where $p(x_i)$ is the probability density function (pdf) over the payoffs, x_i, in each state i. Over a continuous pdf,

$$EV = \int_x p(x)x\partial x. \qquad (2)$$

The EV criterion places no consideration on variability (or risk). For example, a sure $100 is equivalent to a fair coin toss for $200, which is also equivalent to a one in 100 chance for $10,000.

Early probability theorists Cramer (1738) and Bernoulli (1738/1954) felt that EV did not capture people's true preferences. In particular, they observed individuals generally preferring less risky alternatives over riskier ones with the same expected value. Their observations of people's apparently risk-averse preferences were supported by an interesting occurrence known as the "St. Petersburg Paradox," offered by Bernoulli's brother Nicholas, and described below.

> Consider a risky investment that will return 2^n, where n is determined by the number of fair coin tosses until a "head" appears.
>
> The EV of the St. Petersburg gamble is given by
>
> $$EV = \sum_{i=1}^{\infty}(0.5)^i(2)^i = \sum_{i=1}^{\infty}(0.5 \bullet 2)^i = \sum_{i=1}^{\infty} 1 = \infty$$
>
> However, contrary to the EV criterion, most individuals say they are willing to buy or sell the investment for just $25 to $30.

The St. Petersburg Paradox and casual observations of preferences over risky transoceanic trading ventures led Bernoulli (1738/1954) to propose a utility function that was non-linear with respect to wealth. Specifically, Bernoulli and Cramer (1738) found that observed risk-aversion could be explained by a decreasing marginal utility function in wealth. Bernoulli (1738/1954) and Cramer (1738) proposed an investment evaluation method that assigns cardinal measures to the utility of potential payoffs, a proposal

that became philosophically precarious during the ordinal revolution pioneered by Edgeworth (1881), Fisher (1930), Hicks (1946), Slutsky (1952), Pareto (1906), and others nearly two centuries later.[2]

Von Neumann and Morgenstern (1953) proposed EU theory, and the axioms that characterize its validity, as a cardinal representation of ordinal preferences over risky payoffs. While EU places no cardinal restrictions on the form of the utility function, it does assume a linear probabilistic weighting of utility. For a n-dimensional discrete set of payoffs the EU of an investment alternative is:

$$EU = \sum_{i}^{n} p(x_i)U(x_i), \tag{3}$$

and over a continuous set of payoffs:

$$EU = \int_{x} p(x)U(x)\partial x, \tag{4}$$

---

2 There could be other explanations for the St. Petersburg Paradox. Because the investment itself could never exist, it may be difficult to interpret bids to buy and sell the investment. There is a positive probability for infinitely large payoffs. No entity could guarantee payoffs larger than the world's wealth. Equivalently, no individual could offer a bid for the investment larger than the world's wealth, because the funds would not be available to borrow.

Still, the hypothetical bids seem quite small relative to the world's wealth. But suppose the gamble were capped at some very large payoff, say $\$10^{15}$ (one thousand trillion dollars). For the St. Petersburg game, if "heads" first appeared on the 50th trial, the payoff would be greater than $\$10^{15}$, so in the capped gamble, if the first heads appeared on the 50th flip or after, the payoff would be just $\$10^{15}$. It can be easily verified that the expected value for the capped game would be only about $51. Thus, wealth is a very considerable constraint in the St. Petersburg gamble. A bid of $25 is the EV equivalent to St. Petersburg gamble capped at $1,677,216; a bid of $30 is the EV equivalent to the gamble capped at $536,870,912. Thus, the "phenomenon" could merely be attributable to peoples' confidence in the solvency of the gamble's underwriter.

where p(x) is the pdf over the payoffs x, and U(x) is the utility function over potential payoffs x.

Jensen (1967) showed that three axioms, taken together, form sufficient and necessary conditions for EU preference ordering over risky gambles across a fixed payoff vector **X**. See Jensen (1967), von Neumann and Morgenstern (1953), and Fishburn (1988) for a more thorough discussion.

A1. Ordering axiom: Individuals have a complete and transitive preference ordering ($\succ$) of probability distributions over **X** (indifference allowed). The preference ordering is a weak ordering, implying that $\succ, \succeq$, *and* $\approx$, defined as strong preference, weak preference, and indifference respectively, are transitive, and also that

$$[p \approx q, q \succ r] \Rightarrow [p \succ r] \text{ and } [p \succ q, q \approx r] \Rightarrow [p \succ r]$$

A2. Continuity axiom: Individuals do not infinitely prefer any outcome over another. Given axiom A1, and assuming that the individual is not indifferent between all payoffs in **X**, let X_W and X_b denote the worst and best possible payoffs in **X**. In a gamble over X_W and X_b the individual prefers a higher probability on X_b. Also, the individual is indifferent between any certain payoff X_i in **X** and *some* gamble over X_W and X_b. Stated formally, if p, q, and r are distributions over **X**, and{$\succ$} indicates preference, then

$$[p \succ q, q \succ r] \Rightarrow [\{\alpha p + (1-\alpha) r \succ q\} \;\&\; \{q \succ \beta p + (1-\beta) r\}] \quad \text{for some } \alpha, \beta \in \{0, 1\}$$

A3. Independence axiom: Given a probability distribution over **X**, if one piece of the distribution is replaced with a new piece, and the individual likes the new piece just as well as the old, then the individual will like the new probability distribution over **X** just as well as the old. Stated formally,

$$[p \approx q] \Leftrightarrow [\alpha p + (1-\alpha) r \approx \alpha q + (1-\alpha) r], \text{ and } 0 < \alpha < 1.$$

Also:

$$[p \succ q] \Leftrightarrow [\alpha p + (1-\alpha) r \succ \alpha q + (1-\alpha) r].$$

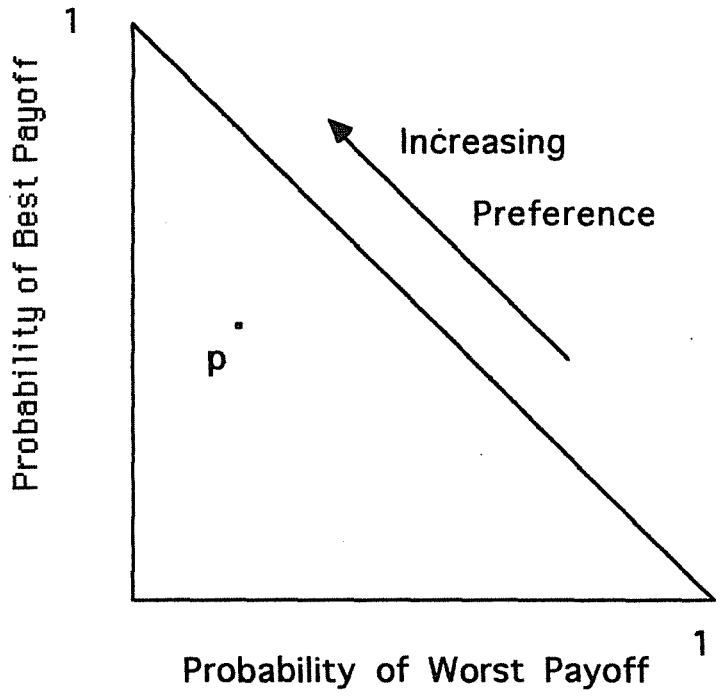
The independence axiom has received the greatest scrutiny from behavioral psychologists and some economists. More on the nature of the axiom's restrictions and how observed behavior violates the axiom will be discussed later in this chapter.

The Risk Triangle

If the payoff vector **X** is limited to three discrete payoffs, a triangular diagram can be used to represent gambles over **X** and graphically represent the implications of EU and other risky choice theories. The triangle was originally developed by Marshack (1950), and put to good use by Machina (1982, 1987) to represent EU violations and the testable implications of EU and other risky choice models.

All gambles can be represented using discrete, three dimensional probability distributions that represent a subspace of the $\Re^3$ vector space (Euclidean 3-space). Consider an arbitrary gamble, say $\mathbf{p} = (p_w, p_m, p_b)$. Because the sum of the three elements must obey the laws of probability and sum to one, only two elements must be specified explicitly to represent the gamble. The probability of the worst payoff, p_w, is plotted along the horizontal axis; the probability of the best payoff, p_b, is plotted along the vertical axis; the probability of the middle payoff, $p_m = (1 - p_b - p_w)$, is shown only implicitly. Thus, all possible gambles over **X** must lie on or within the triangle in Figure 1.

Figure 1
The Risk Triangle



Along each boundary of the triangle one payoff has a zero probability, hence these gambles simplify to two payoff gambles. The hypotenuse, for example, represents all gambles where ($p_b + p_w = 1$), and thus ($p_m = 0$). Each of the three vertices on the triangle represent points where two payoffs have zero probability, and therefore represent a sure return of the remaining third payoff. Let X_w, X_m, and X_b represent the worst, middle, and best possible payoffs over **X**. Thus, a sure payoff of X_w is represented by the probability vector (1, 0, 0) and corresponds to the lower right vertex. Likewise, X_m for sure is given by (0, 1, 0), and corresponds to the lower left vertex; and X_b for sure is given by (0, 0, 1) and corresponds to the upper left vertex. All gambles besides the vertices have some risk or variability

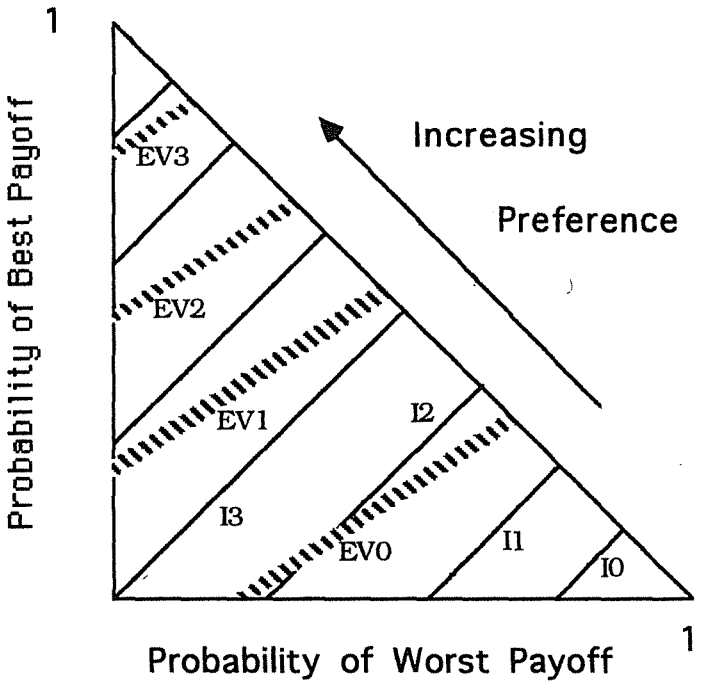
associated with them. All gambles on the interior of the triangle represent gambles with non-zero probabilities on all three payoffs.

Monotonicity (utility increases with wealth, or $U(x_2) \geq U(x_1)$ if $x_2 > x_1$) implies that preference increases as gambles tend from the worst payoff for sure (1, 0, 0), at the lower right vertex, toward the best payoff for sure (0, 0, 1), at the upper left vertex; therefore, indifference curves should slope upward. The axioms of EU theory place further limitations on the shape of the indifference curves. A1, the *ordering axiom*, says that indifference curves can never cross. A2, the *continuity axiom* says that preference increases along the hypotenuse towards the upper-left direction, and that some point along the hypotenuse is indifferent to the origin; the axiom also implies that indifference curves should be continuous, without "holes." A3, the *independence axiom,* says that the indifference curves must be straight lines (known as the *betweenness property*) and be parallel to one another. See Fishburn (1988), Camerer (1992) and Buschena (1992) for a more thorough discussion.

The solid upward sloping lines in Figure 2 (I0, I1, ...) are conceptual indifference curves for EU choices on a risk triangle; the dashed lines represent iso-expected value lines (EV0, EV1, ...). Notice that as gambles tend from the origin towards the hypotenuse along the indifference curves, p_m becomes smaller while both p_b and p_w become larger: hence the variance increases and gambles become riskier. These indifference curves represent the preferences of a risk averter because they are steeper than the iso-expected value lines. These indifference curves show that a risk-averter is indifferent between a lower expected value, lower variance alternative, and a

higher expected value, higher variance alternative. Conversely, a risk lover's indifference curves would be flatter than the iso-expected value lines.

Figure 2
EU Indifference Curves for a Risk Averter



Expected Utility Violations

This section reviews several classic types of EU violations that are documented in the literature. Most of the literature finds fault with the independence axiom. The widely-cited independence violations have taken on names like "the Allais Paradox," "the certainty effect," "the common consequence effect," and "the common ratio effect." In some instances, even transitivity violations have been documented. This briefly reviews these

types of phenomena; the reader is sometimes referred to original works for more detailed discussions.

Independence Violations

Allais first noted a systematic EU violation, frequently referred to as the "Allais Paradox," which has also been labeled the "common consequence effect." In an experimental survey, Allais asked subjects to hypothetically choose their preference over the following two pairs of lotteries.[3]

Pair #1	Lottery A	Lottery B
	1 Million for sure	1/100 Chance of Nothing 89/100 Chance of 1 Million 10/100 Chance of 5 Million
Pair #2	Lottery A*	Lottery B*
	89/100 Chance of Nothing 11/100 Chance of 1 Million	90/100 Chance of Nothing 10/100 Chance of 5 Million

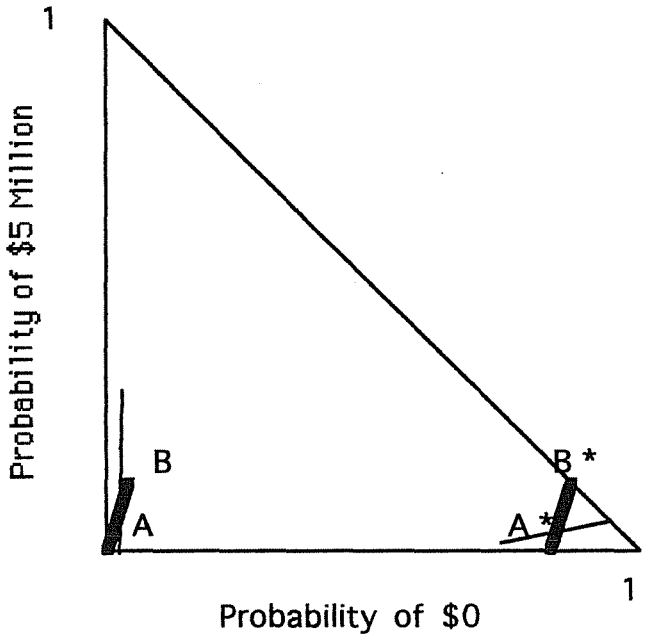
There are four possible pairs of responses from the two choices: AA*, BB*, AB*, and BA*. For example, AA* means choosing A in Pair #1 and A* in Pair #2. EU theory predicts that choices should be either AA* or BB*; choosing AB* or BA* violates the independence axiom of EU theory. To see why, merely apply the independence axiom to Pair #1 to obtain Pair #2. The common piece of "89/100 Chance of $1 Million" is removed from the both lotteries in Pair #1 and replaced with a common piece of "89/100 Chance of

---

3 Allais used 1952 French francs. In current U.S. dollars, the 1 million payoff is about $12,500 and the 5 million payoff is about $62,500. The conversion is derived by converting 1952 francs to U.S. dollars using the 1952 exchange rate of 300 francs to the dollar, and then converting current dollars using the GNP Implicit Price Deflator.

Nothing" to obtain the gamble in Pair #2. Because identical pieces are exchanged in both lotteries, independence says that preference should not change.[4] But when respondents were presented with the two choice pairs, the most frequent response was AB,* in violation of EU theory.

Figure 3
The Allais Paradox on the Risk Triangle



The risk triangle in Figure 3 shows the Allais Paradox graphically. The thick lines represent nodes connecting the alternative lotteries in each choice pair. Because the nodes are parallel, and indifference curves are supposed to be parallel under EU, subjects should be consistent in their responses over the two choice pairs; that is, they should choose the less risky

[4] To obtain the second choice pair from the first using the formal definition of the independence axiom (A3), simply take $\mathbf{p} = (0, 1, 0)$ and $\mathbf{q} = (.01, .89, .10)$ for the payoff vector $\mathbf{X} = (0, 1 \text{ mil.}, 5 \text{ mil.})$ from the first choice pair and then set $\alpha = 0.11$ and $r = 0$ to obtain the second choice pair.

for both choice pairs (AA*) or choose the riskier for both choice pairs (BB*). The thin lines on the triangle represent possible indifference curves for the subjects that chose AB*. Because these indifference curves cannot be parallel, the independence axiom is violated.

Kahneman and Tversky (1979) present a thorough critique of EU and its limitations. Kahneman and Tversky use a number of Allais-type lottery choice pairs with somewhat more realistic (smaller) payoffs to investigate different types of EU violations. Kahneman and Tversky also propose their own model for risky decisions, called "Prospect Theory," that is reviewed briefly in the following section of this chapter.

A well known example by Kahneman and Tversky exploits a pattern they call a "certainty effect." Their example, which is also used as the basis for empirical work in this thesis, follows.[5]

Pair #3	Lottery C	Lottery D
	3,000 for sure	8/10 chance for 4,000 2/10 chance for 0
Pair #4	Lottery C*	Lottery D*
	25/100 Chance for 3,000 75/100 Chance for 0	20/100 Chance for 4,000 80/100 Chance for 0

Much like the Allais Paradox above, choices CC* and DD* are consistent with EU while CD* and DC* violate EU. In this example, 75% chance of $0 is

---

[5] Kahneman and Tversky used middle 1970's Israeli shekels for payoffs. Converting to current dollars, 3,000 I.S. ≅ $750 and 4,000 I.S. ≅ $1,000. Note, however that a considerable number of monetary reforms make these numbers somewhat inexact.

added proportionally to both alternatives in Pair #3 to obtain Pair #4.[6] In Kahneman and Tversky's survey, 80 of 100 subjects said they would choose C over D in Pair #3, while 65 of 100 said they would choose D* over C*. The modal individual preference also tends to be CD*, in violation of EU.

The certainty effect asserts that people strongly prefer a sure thing very differently than *almost* a sure thing. Thus, people prefer $3,000 for sure over an 80% chance at $4,000 in Pair #3. But when *both* alternatives have uncertain returns, as in Pair #4, there is no longer a strong bias towards the less risky alternative. Where EU implies that only relative probabilities are important, Kahneman and Tversky's certainty effect suggests that this is not so, especially between certain and almost certain alternatives. Kahneman and Tversky's logic presumably could be extended to reflect the similar phenomenon observed in the Allais Paradox.

The Kahneman and Tversky certainty effect example, illustrated in Figure 4, is a special case of the "common ratio effect." The principal difference between the "common ratio effect," as Figure 3 shows with the "Allais Paradox," and the "common consequence effect" is that the nodes connecting the two lottery pairs on the risk triangle are no longer the same length (Figure 4). Because all lotteries in the Kahneman and Tversky example lie on a border of the triangle, there are just two possible payoffs for each lottery. The "common ratio" name comes from the simple observation that the ratio of the probabilities over the non-zero outcomes is the same for

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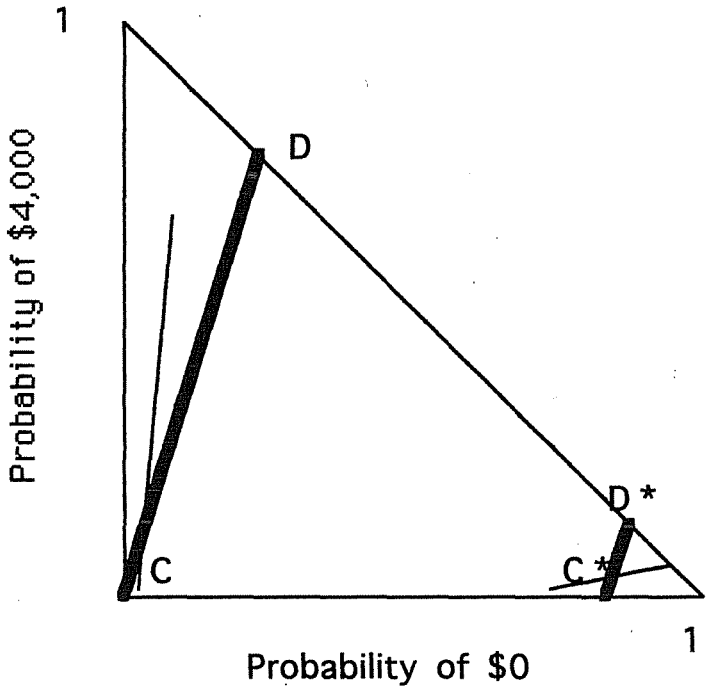
6 To derive Pair #4 from Pair #3 using the formal definition of independence (A3), set $\alpha = 0.25$ and r = 0 and use the alternatives C and D for probability vectors p and q, respectively.

both lottery pairs (re. 0.80/1 = 0.20/0.25 = 4/5). Note that common ratio type violations also occur for gambles without certain alternatives.

Figure 4
Common Ratio Effect on Risk Triangle



Order Violations

Other EU violations tend to encompass phenomena that apparently contradict even the more basic theories of risky choice. These violations find choices inconsistent with EU's first axiom of ordering (A1), and are also contrary to the assumption of preference ordering that is fundamental to consumer choice theory. Intransitivity of preferences and "framing effects" are principal among these phenomena.

Tversky (1969) demonstrated that many subjects have intransitive choice patterns over some sets of hypothetical lottery gambles. Tversky's

study asked subjects to select between each of the five following pairs over five lottery gambles; the lottery gambles are labeled A, B, C, D, E. The off chance for each of the five gambles has a $0 payoff (e.g. gamble A is 7/24 Chance of $5.00 and 17/24 Chance at $0). Experimental choice patterns over the gambles are illustrated by $\{\succ\}$.

Pair #1	7/24 Chance of $5.00 (A) vs. 8/24 Chance of $4.75 (B) A $\succ$ B	Pair # 4	10/24 Chance of $4.25 (D) vs. 11/24 Chance of $4.00 (E) D $\succ$ E
Pair #2	8/24 Chance of $4.75 (B) vs. 9/24 Chance of $4.50 (C) B $\succ$ C	Pair # 5	7/24 Chance of $5.00 (A) vs. 11/24 Chance of $4.00 (E) E $\succ$ A
Pair #3	9/24 Chance of $4.50 C) vs. 10/24 Chance of $4.25 (D) C $\succ$ D		

Summarizing the most common preferences over gambles A through E:

$$A \succ B \succ C \succ D \succ E \succ A.$$

This pattern violates transitivity.

Many noted "framing effects" find apparent preferences between identical alternatives that are distinguished from one another only by the words used to couch each alternative. Such findings are analogous to a preference for a "half glass full" over a "half glass empty," and reflect the simplest form of intransitivity. Tversky and Kahneman (1981) present a rather striking framing effect for a hypothetical choice dilemma paraphrased as follows:

Six hundred people have contracted a fatal disease with only two possible treatment methods. If the first method is adopted, 400 people will die and 200 will live; if the second method is adopted, there is a 2/3 probability that all will die and a 1/3 probability that all will live.

One group of subjects preferred the first treatment method over the second by a ratio of 2.6:1 when the two alternatives were stated in terms of lives saved, while a second group preferred the second treatment method over the first by a ratio of 3.5:1 when the two alternatives were stated in the number of lives lost. For instance, the lives-saved frame stated: "200 lives saved versus a 1/3 probability that 600 lives will be saved;" the lives-lost frame stated: "400 die versus a 2/3 probability that 600 will die and a 1/3 probability that none will die."

Framing effects can also be found in arbitrary lottery gambles like those reviewed above. Consider the same two Kahneman and Tversky choice pairs described previously in this chapter (C vs. D and C* vs. D* from the certainty effect above). In their survey, a majority of respondents preferred a sure $3,000 over an 80% percent chance of $4,000, but then violated the EU independence axiom by preferring a 20% chance of $4,000 over a 25% chance of $3,000. Kahneman and Tversky found that people chose quite differently when the second gamble was framed instead as a two stage problem: a 25% chance to receive a lottery ticket with the subject's choice of a certain $3,000, or an 80% chance of $4,000 and a 20% of $0. Though taken together the two stages are the same as choosing between 25% of $3,000 and 20% at $4,000 (0.25 x 100 = 25% and 0.25 x 80 = 20%), when the problem was staged in this

alternative manner, respondents tended to choose 25% of $3,000 rather than the 20% of $4,000 chosen in the original compound gamble.[7]

Accounting for EU Violations

Economists and psychologists have proposed several models to explain or otherwise account for the EU violations discussed in the previous section. Generalized Expected Utility (GEU) models relax the independence axiom to allow for most observed phenomena but do not allow for intransitivity. Alternatively, Leland (1992a, b), Rubinstein (1988), Azipurua et. al. (1993), and Buschena (1992) offer models that suggest cognitive limitations in decision-making. Their research suggests that cognitive limitations create decision costs that may bias choice away from true preference in a systematic manner. Their models postulate that these limitations are exploited in the certainty effect and the Allais Paradox, giving rise to choice patterns that seemingly violate EU. This section reviews a few of these models and the literature that tests their empirical strength. Because the GEU models are not central to the implications of this thesis, and because some of them tend to be rather mathematically tedious, the discussion focuses only on the models' testable implications. The interested reader can see the original papers or the reviews by Fishburn (1988), Camerer (1992), and Machina (1987) for more thorough discussion of the GEU models.

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[7] Note that the two stage problem illustrates the independence transformation, where $\alpha = 0.25$ and r = 0 in the axiom definition. Recalling the formal definition of independence,

$$[p > q] \Leftrightarrow [\alpha p + (1-\alpha)r > \alpha q + (1-\alpha)r].$$

Generalizations of EU Theory

Many alternative choice theories have been offered amid the experimental violations to EU described in the previous section. The recent work by Camerer (1992) and Harless and Camerer (1993) has shown, however, that even these models fall short of encompassing all types of risky choice phenomena encountered. The implied indifference curves suggested by some of the most prevalent GEU models are portrayed on risk triangles in figures 5 through 12. All of these models preserve some aspects of the ordering (A1) and continuity (A2) axioms, so indifference curves are continuous, upward sloping lines that do not cross on the risk triangle.

The GEU models usually exploit some type of mathematical transformation of the original EU theory. Rather than assuming a linear probabilistic weighting of utility, the GEU models weight the probability function relative to the payoffs or by a nonlinear function of the probabilities.

Weighted Expected Utility theory (Chew and MacCrimmon 1979, Chew 1983) weakens the independence axiom to imply that indifference curves fan in or fan out from the lower right to upper left of the risk triangle and meet at some point outside the triangle (see figures 5 and 6). "Fanning out" says that indifference curves become steeper as gambles tend toward the upper left (become more risk-averse); "fanning in" says that indifference curves become less steep as gambles tend toward the upper left (become more risk-loving). The probabilistic weight in the *Weighted Expected Utility* models does not depend on the probabilities, therefore satisfying betweenness (i.e. that indifference curves are straight lines). A variation of Weighted Expected Utility, *Disappointment Aversion* (Gul, 1991; Neilson, 1992), shown in figure

7, holds that indifference curves fan out for the lower right section of the triangle and fan in for the upper left section. *Implicit EU* (Dekel, 1986), shown in figure 8, is a more general form of weighting through outcomes, assumes only betweenness and does not restrict indifference curves to fanning in, fanning out, or being parallel.

Other GEU models also relax the betweenness property of EU. *Rank Dependent EU* (Quiggin, 1982, 1985; Segal, 1987, 1989; Yaari, 1987) weights the probabilities prior to calculation of the expected utility-- hence, indifference curves are no longer straight lines (see figures 9 and 10). Kahneman and Tversky's *Prospect Theory* (1979), easily the greatest departure from EU, suggests an over-weighing of very low probabilities, and an under-weighting of larger probabilities. Furthermore, if the probability weighting function is highly non-linear near 0 and 1 (due to the certainty effect), the indifference curves will dramatically change in slope, shape, and may even become discontinuous near the edges of the triangle (figure 11). *Prospect Theory* also asserts that people make approximations to simplify alternatives, akin to the effects of similarity, decision costs, and bounded rationality discussed in the following section. The effects of these general approximations, however, are not shown on *Prospect Theory's* indifference curve map.

Most GEU models fall short of describing a reason or an explanation of the behavior implied by their indifference curves; the models merely attempt to add more flexibility to EU so that observed experimental choices are allowed. A noted exception to this "ad hoc" approach to fitting choice theories to observed phenomena is Machina's fanning out hypothesis (figure 12).

Machina's hypothesis (1982) suggests that EU does well at predicting choices in a localized region of the triangle, but that as gambles become better (in terms of stochastic dominance), risk aversion increases. Machina's indifference curves are not restricted to straight lines because the theory also allows for choice approximations that may lead to errors. Fanning out is also rejected in experimental findings (e.g. Conlisk, 1989).

Figure 5
Weighted Utility Fanning Out

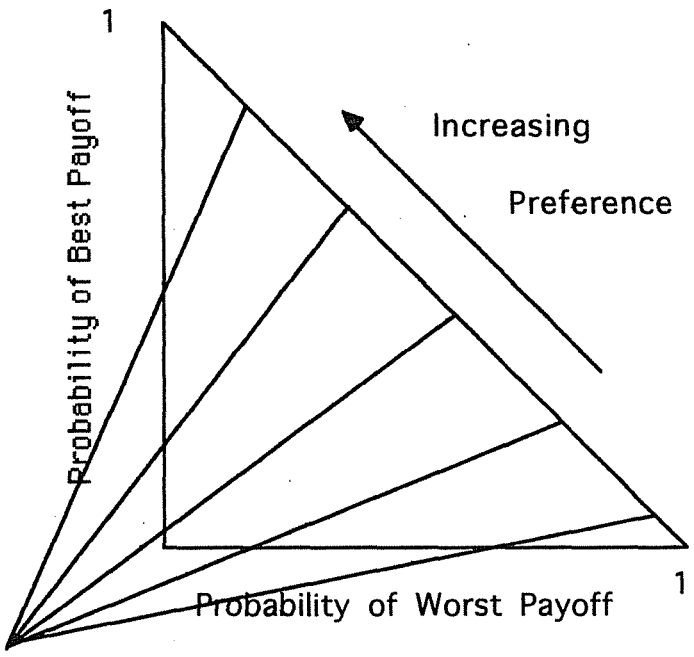


Figure 6
Weighted Utility Fanning In

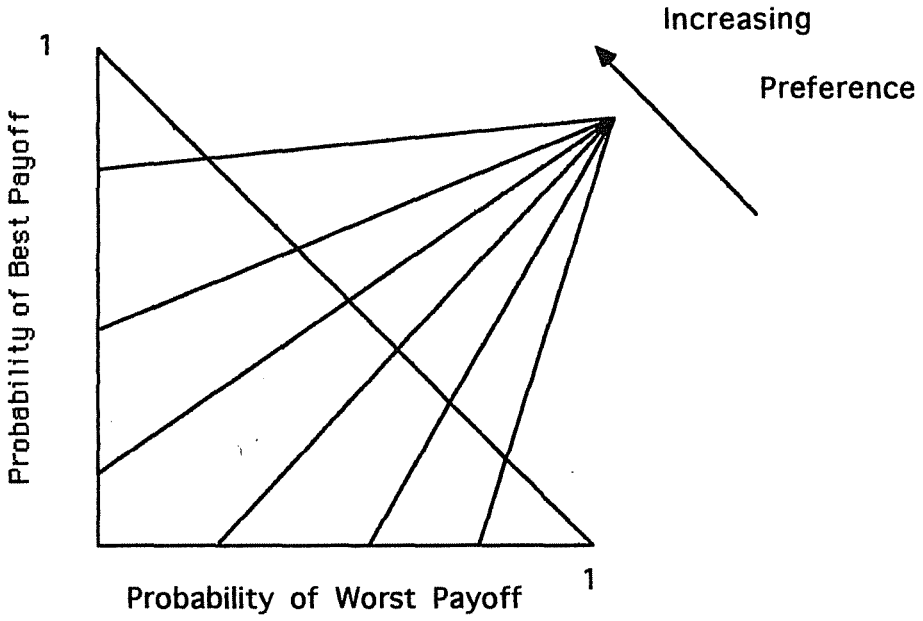


Figure 7
Disappointment Aversion, Mixed Fanning

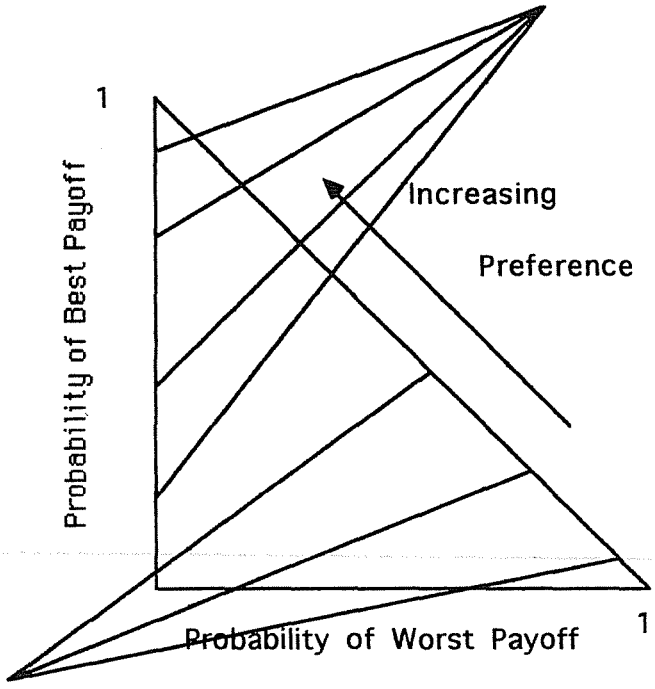


Figure 8
Implicit EU

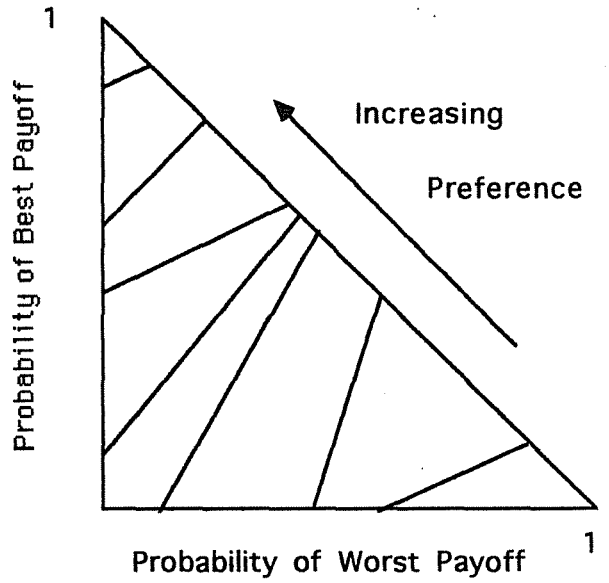


Figure 9
Segal's Rank Dependent EU

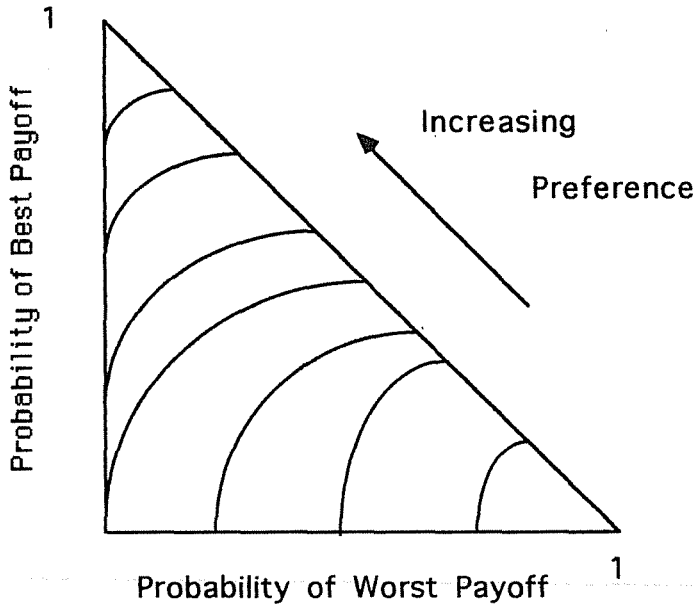


Figure 10
Quiggin's Rank Dependent EU

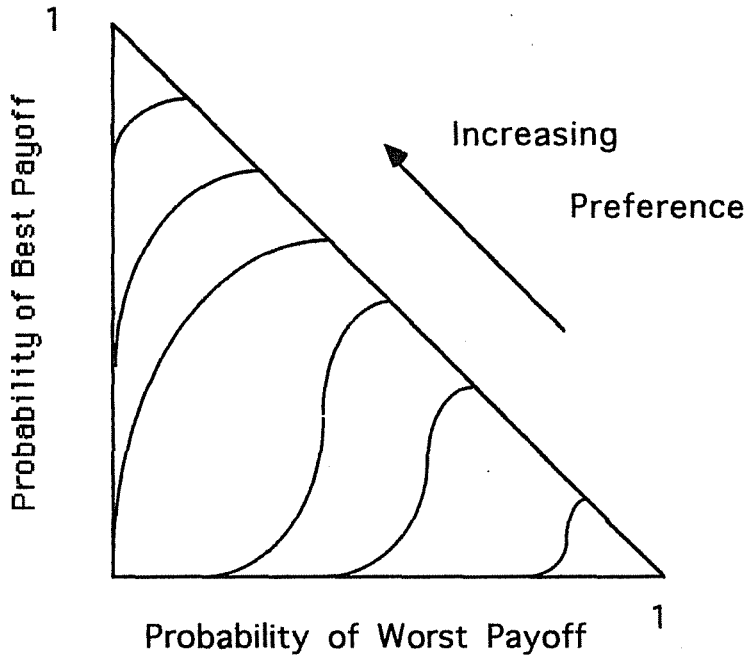


Figure 11
Prospect Theory

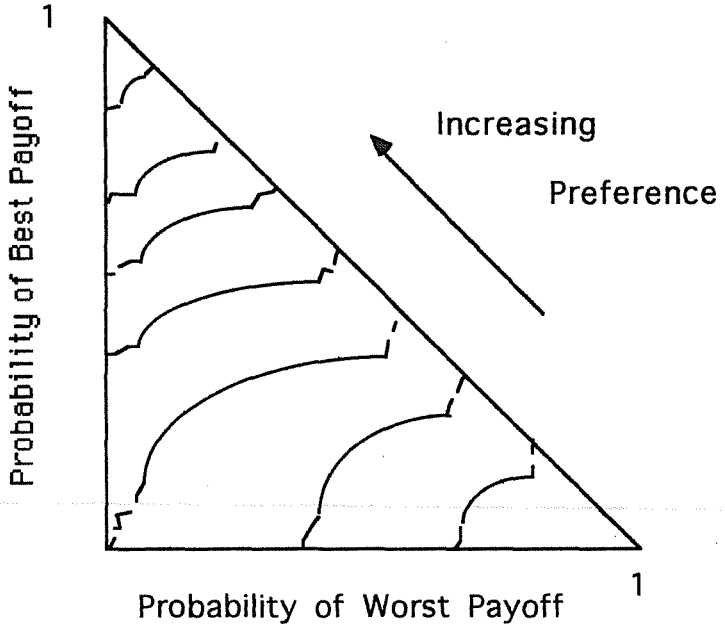
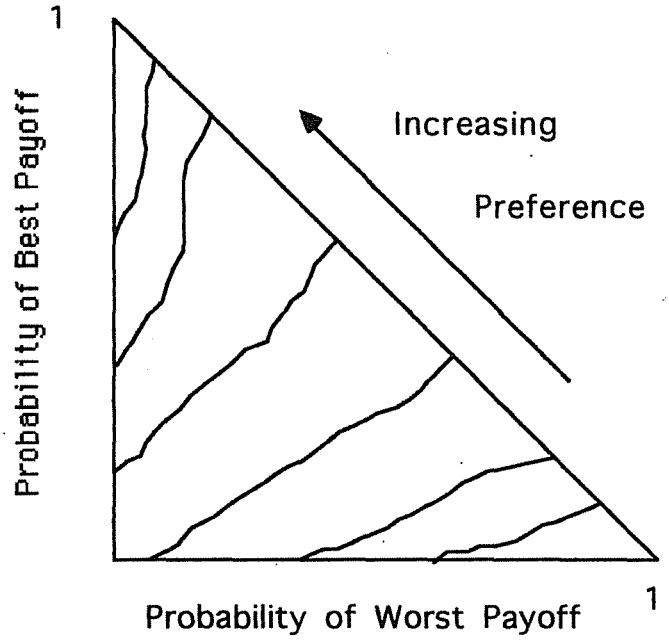


Figure 12
Machina's Fanning Out



Recent Empirical Tests

Recent works by Conlisk (1989) and Camerer (1989, 1992) explore choices over different regions of the risk triangle to test the GEU models discussed above. Conlisk investigates three variants of the Allais paradox.[8] The first variant changes the frame of Lotteries A* and B* in Pair #2 to expose the pairs relationship to A and B in Pair #1 through the independence axiom (A3), much like Kahneman and Tversky's two stage gamble.

8 Conlisk used 1988 dollars where Allais used 1953 French francs. The payoffs used in Conlisk's variants are therefore much larger.

Original Allais Example:

Pair #1	Lottery A	Lottery B
	\$1 Million for sure	1/100 Chance of Nothing 89/100 Chance of \$1 Million 10/100 Chance of \$5 Million
Pair #2	Lottery A*	Lottery B*
	89/100 Chance of Nothing 11/100 Chance of \$1 Million	90/100 Chance of Nothing 10/100 Chance of \$5 Million

Conlisk's First Variant:

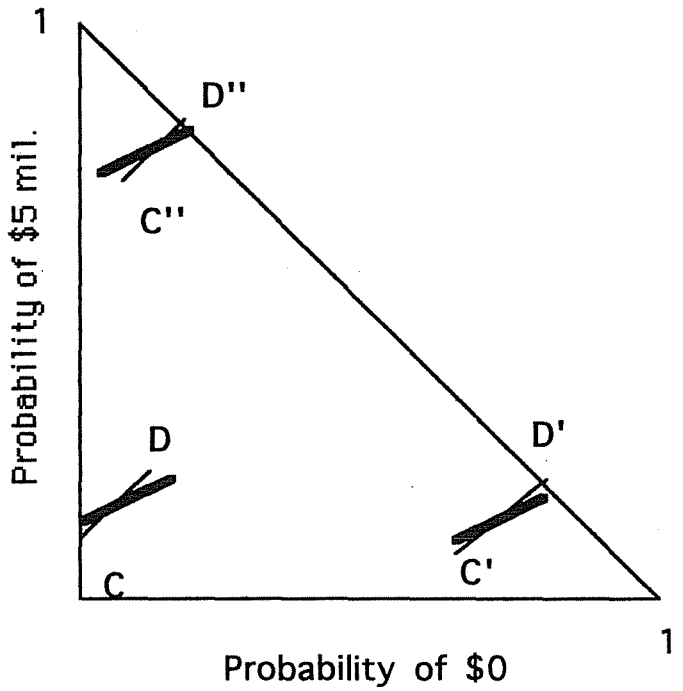
Pair #3	Lottery I	Lottery I*
	\$1 Million for sure	1/11 Chance of Nothing 10/11 Chance of \$5 Million
Pair #4	Lottery A	Lottery B
	11/100 Chance of Lottery I 89/100 Chance of \$1 Million	11/100 Chance of Lottery I* 89/100 Chance of \$1 Million
Pair #5	Lottery A***	Lottery B**
	11/100 Chance of Lottery I 89/100 Chance of \$1 Million	11/100 Chance of Lottery I* 89/100 Chance of \$1 Million

Note that Pair #1 and Pair #2 have the same probability distributions and payoffs as Pair #4 and Pair #5 respectively; only the frames of the choice pairs differ. Conlisk's first variant substantially reduces the number of EU violations, and eliminates the systematic nature of EU violations observed in the original Allais example.

Conlisk's second and third variant examine different regions of the risk triangle. The second variant moves both of the choice pairs slightly to the

interior of the triangle (C,D) and (C',D'), the third variant tests responses in the upper left region of the triangle to test fanning out (C",D"). Figure 13 shows the second and third variant graphically on the risk triangle. Conlisk finds that choices over the pairs just on the interior of the triangle are consistent with EU (AD vs. C'D'). The third variant rejects fanning out because fewer people choose the less risky gamble in pair (C"D") than in both pair (AB) and pair (C'D').

Figure 13
Conlisk 2nd and 3rd Variant of the Allais Paradox



Camerer (1992) uses data collected from his own research and from several others, including Conlisk (1989), Battalio et al. (1990), Prelec (1990), Starmer and Sugden (1987), Chew and Waller(1986), MacCrimmon and Larsson (1979), Looms (1991), and Hogarth and Einhorn (1992), to compare

the predictability of the GEU models. Camerer (1992) asserts six stylized facts about the nature of the empirical findings in this body of literature. The stylized facts provide useful generalizations that summarize experimental findings on risky choice.

Stylized fact #1: EU is not violated for choice pairs that sit exclusively on the inside of the risk triangle.

Stylized fact #2: The slope and shape of indifference curves change around a reference point. That is, risk aversion seems to change around a reference point, usually zero (e.g., risk aversion for losses is less than for gains).

Stylized fact #3: Fanning out is systematically violated.

Stylized fact #4: Betweenness is systematically violated (indifference curves are not straight lines).

Stylized fact #5: EU violations depend on the size and sign of payoffs

Stylized fact #6: EU violations have cross-species robustness with regard to 1-5 above. Studies have shown that rats and pigeons (with payoffs in food) violate EU just as humans do.

Cognitive Limitations (Decision Costs)

There has been a general resistance by economists to use GEU theories in applications to the study of risk. There are many reasons for this resistance. If EU is not an appropriate model, which GEU model should be used? Every GEU model is systematically violated over carefully chosen gambles. And if a GEU model could be selected, its implications would be more difficult to solve for than with EU. Perhaps most importantly, GEU models lack the general normative appeal of EU; GEU models generally lack a coherent explanation of how people actually make decisions. GEU models merely propose new objective functions to fit observed choice. Rather than

objective function to allow for observed violations as in the GEU models, the models reviewed in this section suggest that violations are caused by subjects' cognitive limitations that create decision costs.

The risky choice criteria reviewed thus far, including EV, EU, and the GEU models, suggest various functional forms that might be used to model peoples' *preferences* over risky gambles. These theories, and the experimental studies that test for their consistency, suggest that there are no costs to decision-making and, therefore, that systematic violations of EU must imply that the EU functional form for preference is incorrect, or choice is equivalent to preference. In other words, these models imply that people never make mistakes, choosing alternatives they do not actually prefer. Another plausible explanation for the EU violations is that EU does indeed model people's preferences, but that systematic *mistakes* result from approximations or rules of thumb used relative to the costs and benefits involved with the decision, coupled with clever experimental manipulation meant to expose these approximations.

For example, in Kahneman and Tversky's "common ratio" EU violation, both choices CD* and choices DC* violate EU, but because choices CD* are observed much more frequently than DC*, a significant choice bias exists. While the GEU models discussed previously assume that this bias implies something systematically wrong with EU, the models described in this section suggest that people make systematic mistakes in judgment resulting from cognitive or perceptive limitations. In particular, Rubinstein (1988), Leland (1992a, b), Azipurua et al. (1993)and Buschena (1992), suggest

that these biases are attributable to the relative similarity of the choice alternatives.

Can systematic mistakes be rational? Yes, if decision making is *costly* and only a selected group of choices reflecting the most dramatic effects of these costs are observed. Making the decisions that would be optimal if making decisions were not costly is often difficult with positive decision costs. To the degree that decisions are difficult or costly, observed choices could be (rationally) less correct. The idea follows directly from the notion of costly or bounded rationality originally put forth by March (1978) and Simon (1960).

Rubinstein (1988) introduces alternative similarity as a characteristic that may lead to decision costs. Leland tests a more generalized form of Rubinstein's axiomatic framework and finds that a significant percentage of choice patterns support this similarity model over GEU models. These models relate to earlier work by Luce (1961). The similarity models hold that individuals may use cost-saving approximation methods that weigh dissimilar aspects between alternatives more heavily than similar aspects, perhaps leading to biased choice relative to EU

Similarity depends on both the probability differences and the payoff differences between two risky alternatives. The effect of similarity can be illustrated using the following common ratio example.

Pair #1	Lottery A	Lottery B
	90/100 Chance of $3,000 10/100 Chance of Nothing	45/100 Chance of $6,000 55/100 Chance of Nothing
Pair #2	Lottery A*	Lottery B*
	2/1000 Chance of $3,000 998/1K Chance of Nothing	1/1000 Chance of $6,000 999/1K Chance of Nothing

In experimental surveys, subjects violate EU by tending to choose alternative A in Pair #1 and B* in Pair #2. Similarity may explain the violation as follows. Because both the probabilities and the payoffs in Pair #1 are very different (or dissimilar), the costs of evaluation are relatively small and subjects will tend to choose the less risky Lottery A (their true preference). In Pair #2, however, the probabilities in Lottery A* and B* are very similar while the payoffs remain very different. Subjects tend to choose Lottery B* because they focus on the dissimilar payoffs of $6,000 and $3,000, largely ignoring the very small absolute difference in the probabilities. Furthermore, because the stakes are considerably smaller in Pair #2, and because the utility *difference* between the two alternatives in Pair #2 likely is small, the subject has little incentive to judge his or her decision very carefully. The similarity hypothesis suggests: (1) choices between two dissimilar choice pairs generally will be consistent with EU; (2) choices between similar and dissimilar choice pairs likely will violate EU; and (3) choices between two similar choice pairs may or may not violate EU.

The dissertation by Buschena generalizes Leland and Rubinstein's similarity models to find a more general and continuous measure of similarity. While Rubinstein's similarity hypothesis has clear implications

for choice pairs like the common ratio example above, clear implications of similarity have not been established for gambles with three payoffs. To address this problem, Buschena elicits similarity judgments from the subjects themselves and then fits them to objective characteristics of the choice pairs. These objective characteristics include measures such as the distance between the probabilities of the two alternatives (PDM), their difference in expected value (EVD), and indicator variables for choice pairs with a "quasi-certain" alternative and those with "equal dimensional support."[9] "Quasi-certain" (QC) alternatives are those with no probability of a zero payoff (i.e., those that lie on the vertical axis of the risk triangle). Choice pairs with "equal-dimensional-support" (EDS) are those in which both alternatives have a positive probability on all three payoffs. EDS choice pairs are those corresponding to Camerer's (1992) *Stylized fact #1* that refers to choice pairs that sit exclusively on the inside of the risk triangle.

Similarity judgments between alternative gambles were elicited in Buschena's study by having subjects mark a slash on a similarity scale following each of several choice pairs in each survey. The scale marking method allows for a continuous measure of subjects' perceptions of similarity. A GLS estimate found PDM, EVD, and QC to be negatively related with the subjects' similarity judgments, and EDS to be positively related with the subjects' similarity judgments. The results therefore indicate that alternatives closer together on the risk triangle, with smaller absolute expected value differences, or where both alternatives sit exclusively on the interior of the risk triangle, are more similar. The significance of QC

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[9] These variables will be defined more formally in Chapters 3 and 4.

indicates that Kahneman and Tversky's "certainty effect" significantly reduces perceived similarity.

In general, Buschena found that more similar alternatives were more likely to elicit the riskier response, while dissimilar alternatives were more likely to elicit the less risky response for risky pairs comparable through EU's independence axiom. The model extends Rubenstein's hypothesis of similarity effects: the more similar the probabilities the more likely the subject will choose the riskier choice for a fixed set of payoffs. The similarity model therefore predicts that sufficiently risk averse subjects may systematically violate EU by choosing the less risky alternative on a very dissimilar choice pair and choosing the riskier alternative on a very similar choice pair for EU comparable choice pairs. Buschena finds his similarity model to explain choices more robustly than any of the GEU models discussed previously.

Because the similarity model moves towards a plausible *explanation* for choices that differ from EU and has stronger empirical support as compared to the GEU models discussed previously, the model is applied to the research in this thesis to gauge the effect of context on choice.

Context Effects on Choice

As noted earlier in this chapter, "framing effects" are risky choice dilemmas that elicit very different responses depending only on how the question is worded. The term "context" is used somewhat differently. A different "context" refers to a different situation and circumstance of a risky dilemma rather than just a trivial variation in words used to couch the same gamble. For example, two competing risky contexts might be gambling in

Las Vegas versus investing in the stock market, as opposed to the "lives saved" vs. "lives lost" framing example discussed previously.

Hershey and Schoemaker (1981) study choices in an insurance context as compared with choices in a standard lottery context. They surveyed two groups of subjects for their preferences between a sure loss versus a small probability of a much larger loss. One group was presented with the series of risky choice dilemmas under the context of a standard lottery-type gamble; a second group was presented with the same risky choice dilemmas under the context of choosing whether or not to buy an insurance premium to protect against a potential loss (no particular type of insurance was specified). The insurance and lottery contexts elicited significantly different responses. Table 1 summarizes Hershey and Schoemaker's results.

Table 1 shows the eighteen choice pairs (Q1-Q18 in column one), the probability of the large loss (in column two), the amount of the larger loss (in column three), the alternative sure loss (in column four), and the percent choosing the sure alternative under both contexts (in columns five and six).

Table 1. Hershey and Schoemaker Tests for Effect of Insurance Context

Question	Risky Alternative		Sure Loss Alternative	% Preferring Sure Alternative with Insurance Context	% Preferring Sure Alternative with Lottery Context
	probability	$Loss			
Q1	0.001	$10,000	$10	70.7%	56.1%
Q2	0.005	2,000	10	75.6	61.0
Q3	0.01	1,000	10	80.5	56.1
Q4	0.05	200	10	56.1	58.5
Q5	0.10	100	10	43.9	46.3
Q6	0.20	50	10	36.6	43.9
Q7	0.001	10,000	10	80.5	53.7
Q8	0.01	10,000	100	65.9	46.3
Q9	0.10	10,000	1,000	58.5	29.3
Q10	0.50	10,000	5,000	39.0	31.7
Q11	0.90	10,000	9,000	34.1	24.4
Q12	0.99	10,000	9,900	26.8	22.0
Q13	0.999	10,000	9,990	17.1	17.1
Q14	0.01	100	1	68.3	63.4
Q15	0.01	1,000	10	68.3	46.3
Q16	0.01	10,000	100	63.4	39.0
Q17	0.01	100,000	1000	75.6	36.6
Q18	0.01	1,000,000	10,000	61.0	29.3

Both alternatives in all risky choice pairs have equal expected values. That is, the sure loss alternative is an actuarially fair insurance premium. Therefore, globally risk averse individuals should always prefer the sure loss over the risky loss. Subjects given the insurance context appear significantly more risk-averse (i.e., more likely to choose the sure loss) over some gambles, but not over others. Hershey and Schoemaker assert that the insurance context has a greater effect for more "realistic" insurance situations. Hershey and Schoemaker describe "realistic" insurance contexts as those with both large potential losses ($\geq$ $1,000) and probabilities "low enough to invoke an insurance atmosphere" ($p \leq 0.1$).

Unfortunately, their study does not allow direct tests of the EU independence axiom. Rather, their paper questions whether people's basic tastes and preferences can be represented through a utility function (in

wealth) that may in turn be reasonably applied to the EU framework. Assuming EU were true, the implied utility function would have at least one inflection point, which implies both risk-loving and risk-averting regions. Because Hershey and Schoemaker find the inflection point difficult to explain, and because the insurance context elicits significantly different responses than the simple lottery context, they find their data to be more consistent with Kahneman and Tversky's Prospect Theory.[10]

Hershey and Schoemaker do not explain *why* a "realistic" insurance context invokes different responses. The risky gambles that they describe as "realistic" are presumably gambles and contexts that are more familiar to the subjects. Recent work by Heath and Tversky (1991) and the overview by Kahneman and Lovallo (1993), examine how a subject's familiarity with the context of the risky gamble affects their choice. In particular, they report that "holding judged probability constant, people prefer to bet in a context where they consider themselves knowledgeable or competent than in a context where they feel ignorant or uninformed" (Heath and Tversky, p. 7). They propose the "competence hypothesis" that suggests that the consequences of each choice include the credit or blame associated with the outcome as well as the monetary payoff. This hypothesis is motivated by empirical findings that have come to be called an ambiguity effect. The

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10 Hershey and Schoemaker's assertion that their results are more in line with Kahneman and Tversky's *Prospect Theory* is somewhat tenuous. Their experimental data rejects the existence of EU coupled with the assumption that people are *globally* risk averse, or that their utility function is *globally* concave in wealth. Friedman and Savage (1948) and Friedman (1989) offer a utility function explanation and cognitive limitations to describe the same behavior.

simplest example of this effect, originally put forth by Ellsberg (1961), follows.

> There are two boxes: one contains 50 red balls and 50 green balls, whereas the second contains 100 red and green balls in unknown proportion. A subject draws a ball blindly from the box of his or her choice and guesses the color. A correct guess wins $20. Although people are indifferent between guessing a red or green ball, people generally prefer to bet on the 50/50 box over the box with the unknown composition of balls.

Hence, the competence hypothesis asserts that people prefer the 50/50 box because the additional information adds to their self-perception of "competence," even though the two alternatives are qualitatively identical.

The study by Heath and Tversky goes on to test the effect of knowledge on betting. Subjects were first asked a series of questions in two different categories, like history, sports, or geography. The subjects rated their confidence in their answers for each question. For example, with a self-rating of 60%, a subject said he or she was 60% confident in giving the correct response. The subjects could then choose between betting on their answers or on lottery gambles in which the probability of winning was equal to their stated confidence. For example, if an individual gave a confidence rating of 70%, he or she could choose from betting that his or her answer was correct, or betting on 70% chance lottery, defined by drawing a chip numbered 1-70 from a box filled with 100 numbered poker chips.

The results of the experiment were twofold. First, people tended to bet on their answer when their confidence was high (> 65%), but tended to choose the lottery when their confidence was low to moderate. Second, people were generally overconfident in their ability to answer correctly. Several other experiments by Heath and Tversky yielded similar results. Subjects paid, in

effect, as much as a 20% premium to bet on familiar propositions with equivalent chances.

Patrick, Musser, and Ortmann (1993) use context-based questions to elicit relative risk attitude measures from corn belt farmers. They test whether the farmers' responses could be related to farm characteristics. The farmers responses are also compared with those of non-farmers. The study finds little correlation between survey responses and farm characteristics, and finds little difference between farmer and non-farmer responses. While this thesis incorporates context-based questions somewhat similar to Patrick, Musser, and Ortmann, their paper does not allow for testing within an EU framework as does this thesis.

Conclusions and Comments

The literature reviewed in this chapter encompasses many perspectives on risky choice, some of which present quite disturbing results for the theoretical and applied economist. All of the studies, however, use experimental data that typically reflect only hypothetical situations and incentives; questions ask subjects what they *would* choose under arbitrarily prescribed circumstances. The obvious criticism of such experimental work is its questionable relation to the "real world." Do hypothetical decisions between arbitrary risky lotteries reflect *real* decisions made under risk and uncertainty?

With very few exceptions, the questions used in these experimental surveys fail to incorporate a risky context that may compare more reasonably with the actual risky situations subjects face everyday; most risky choices made in the "real world" are not over arbitrary lotteries. Yet framing and

Hershey's and Schoemaker's insurance context produce significantly different responses. How sensitive are people's choices to the context of the risky dilemma? Which contexts more accurately reflect people's "real world" choices? More to the point, do the EU violations that appear so prevalently in experimental findings also appear in the decisions people make everyday?

The first part of Chapter 3 discusses some of these sensitive issues involved with the experimental design used to test EU theory: its relevance to the study of risk, what economists can and cannot learn from market data, and the motivation for the experimental framework used in this study. The second part of Chapter 3 details the experimental design used and the hypotheses to be tested in Chapter 4.

CHAPTER 3

MOTIVATION & EXPERIMENTAL DESIGN

Motivation

This section discusses some sensitive issues involved with the gap that lies between research that uses market data and research that uses experimentally generated data. The experimental methods used in the research reviewed in Chapter 2 report a number of interesting results, some of which counter common assumptions used in economics. To what extent do these phenomena result from the experimental methods used to expose them as opposed to the inaccuracy of the EU objective function? While most aspects of the experimental testing approach must realistically be maintained for direct tests of EU, the context of the hypothetical gambles can be varied to test for the effects of experimental bias. This section also comments on how and why context may affect choice. The following section further develops these possible effects of context and presents the experimental design used to test for these effects.

What Economists Can Expect to Learn From Market Data

Because nearly all research on the consistency of EU and GEU models has been experimental in nature, it is pertinent to ask what economists can expect to learn about EU and GEU models from market decisions. Unfortunately, it seems unlikely that powerful tests between risky choice

models using market data could be formulated. Because most risky choice models yield similar predictions under most situations, the null hypothesis of any risky decision model, perhaps even a well crafted expected profit model, would be difficult to reject using market data. A large and comprehensive data set would be required. Complications could arise if the investigating economist could not obtain all information available to the decision makers, making isolation of risk preferences difficult. With the exception of Bar-Shira (1992), the EU hypothesis has not been tested with market data. Although Bar-Shira's work does not reject EU, the power of the test is poor.

Risky market decisions become more obscure because most are also made under some degree of uncertainty. The distinction between risk and uncertainty is an important one. Risk is strictly defined for conditions where the probability distribution over payoffs is known and is objective; uncertainty corresponds with the more realistic condition where the probability distribution is unknown and is subjective. Experimental research on risky choice therefore assumes that the study of choice under risk gives insight into the more realistic condition of choice under uncertainty. While economists can estimate probability distributions using market data, estimates would have to be very accurate to enable a distinction between the different risky choice theories, most of which can be very sensitive to small changes in the probability density function. These different theories are sensitive because the effects of risk focuses on the second and higher moments of the probability distribution function, and the difference between EU and GEU models pertains mostly to the third and higher moments of the

distribution function. The magnitudes of these higher moments are generally very small.

Even if an excellent approximation of the probability density function can be estimated with market data, one would still have difficulty testing between risky choice theories. To see this, consider the following generalized functional form for risky gamble valuation:

$$U^* = \sum_i f[x_i, p(x_i)]U(x_i) \tag{5}$$

where U* is the individual's value of the gamble, $U(x_i)$ is the utility of prospective payoffs x_i, and $f[x_i, p(x_i)]$ is the weighting function of utility with respect to the payoffs x_i and the probability density function $p(x_i)$. The different risky choice theories assume different forms of the function $f[x_i,p(x_i)]$, while an individual's attitude toward risk is implied by the utility function $U(x_i)$. To estimate the form of $f[x_i, p(x_i)]$, a functional form of $U(x_i)$ must be assumed; conversely, to estimate the form of $U(x_i)$, the form of $f[x_i,p(x_i)]$ must be held constant. It is difficult to isolate the parameters of one function unless assumptions are made over the form of the other because both x_i and $p(x_i)$ will vary in most market data. In an experimental framework, one can hold the payoff vector **X**, and, therefore, $U(x_i)$ constant for all probability distributions. It seems unlikely that one could find market data with multiple distributions over a fixed payoff vector. Risk analysis across a producer population becomes more complicated because the utility functions (i.e., risk preferences) of different producers may also vary.

The Experimental Approach--Is it Realistic?

An appropriate experimental design avoids many of the problems encountered when using market data. Such an experimental design allows for isolation of the probabilistic weighting function of utility. Because an experiment allows for testing of multiple gambles over a fixed and discrete set of payoffs, there is no need to specify the form of the utility function--it can reasonably be assumed to be the same for all gambles under EU. Furthermore, there is no need to estimate the probability density function, nor a need to account for a lack of precision in the estimate. Hence, the experimental approach is particularly useful for examining how people value alternatives under risk because mitigating variables are either removed or held constant.

There are, of course, limitations to the experimental testing approach. While the experimental approach allows for a more manageable analysis with objectively defined risk, it could be that objectively defined probability distributions are too unrealistic to accurately represent the "real world" case of choice under uncertainty. In addition, when experimental alternatives offer only hypothetical payoffs, subjects suffer no opportunity costs for a poor choice. Because all true choices necessarily entail costs, economists may argue that such decisions should not be taken to represent true economic behavior.

Still, more than a lack of real payoffs seems to affect choice in experimental studies. If violations were merely due to subjects not taking the survey seriously due to the lack of real payoffs, one would likely observe EU violations to be more random than the systematic *biases* toward particular

types of violations that regularly appear in experimental research. While economists have no theory regarding people's choices when there are no opportunity costs to their decisions, the systematic nature of violations is still perplexing and damaging to EU.

Furthermore, some research involving real incentives shows the same effects found in surveys with hypothetical incentives (although sometimes these effects are diminished). For example, Meyerowitz and Chaiken (1987, from Plous, 1993) show clear effects of framing for a group of college-aged women given pamphlets on self-examinations for breast cancer (BSE). Different frames on the pamphlets induced different rates of continued practice of breast self-examination. Hence, framing appears to affect choice even with real risks.

Only a few tests of the EU independence axiom have been performed over real payoffs (e.g., Smith and Walker (1993)). The present body of research pertains to relatively small payoff levels and has had mixed findings. Clearly more study using real money payoffs is required. Buschena and Zilberman (1994) show, however, that their experimental study offering only hypothetical payoffs appears to be consistent with research offering real money payoffs. In particular, the overall rate of population inconsistency (percent of subjects that reversed their choice on a repeated question) was only 23%, which compares favorably to the rates of 32% and 26.5% in real money experiments by Camerer (1989) and by Starmer and Sugden (1987), suggesting that subjects regarded the questions seriously even without money incentives.

Still, if peoples' true preferences are relatively consistent with EU, but their choices are biased due to approximations and similarity effects as described by Buschena (1992), Rubinstein (1988), Leland(1992a,b), and Azipurua et al. (1993), it may be expected that these biases would be exaggerated when payoffs were hypothetical. While the costs (in time and effort) of making the best choice are the same for hypothetical and real payoffs, the benefits for correctly choosing the EU maximizing choice are very different. At the margin, less effort should be applied to choice pairs under hypothetical payoffs and hence the subjective bias (from similarity, perhaps) would be larger. For the case of real payoffs, one could hypothesize more decision effort and, therefore, a smaller bias. Hence, if decision costs affect choice giving rise to experimental EU violations, and we wish to investigate the *causes* of the perceptual biases that bring about these violations, it may be acceptable to use hypothetical payoffs. Further study with money payoffs is required, however, to investigate the effects of decision effort on choice.

The Role of Context and Experience in Decision Making

Experimental tests of risky choices have been placed in a context very different from the contexts that economists generally have interest in assessing. Choices between arbitrary gambles for money may be very different from risky choices on irrigation, pesticide, and fertilizer inputs made by farmers; or an individual's choice to drive a car and risk an accident, or go skiing and risk a broken leg. To what extent does the lack of realistic and pertinent context affect choice in experimental risky choice analyses?

As described in Chapter 2, research by Heath and Tversky (1991) and Kahneman and Lovallo (1993) find that people prefer familiar risky gambles

over unfamiliar but otherwise equivalent risky gambles. Because risky decisions modeled by economists usually involve contexts familiar to the decision-makers (e.g., it can be reasonably assumed that Montana seed potato farmers are quite familiar with the risks involved with seed potato production), and choices over familiar contexts have been shown to be quite different from choices over unfamiliar or arbitrarily defined lottery gambles, it seems likely that tests of the consistency of EU and other risky choice theories might differ when carried out using contexts familiar to the subjects.

A familiar context may cause the subject to recall previous decision making experience. The degree that a subject is familiar with a gamble may reduce the subject's costs of evaluating his or her preferred choice. This rationale could explain the findings of Heath and Tversky (1991) reviewed in Chapter 2 showing that people prefer to choose between familiar gambles over unfamiliar gambles. If EU does indeed indicate true *preference* for risky gambles, then economic theory suggests that individuals would tend towards EU-consistent behavior, but does not preclude the existence of errors resulting from decision costs. Where the similarity hypothesis suggests that these costs bias choice away from EU between pairs of gambles with large differences in similarity, a familiar context may reduce these costs and therefore reduce the bias. A "rational" decision-maker may make judgment errors. Such judgment errors may even be quite predictable. Economists would hope, however, that over the long run decision-makers would come to a better understanding of the costs and benefits of risky choice and make choices more consistent with EU, whether or not they have an intimate understanding of probability. Hence, in competitive markets systematic EU

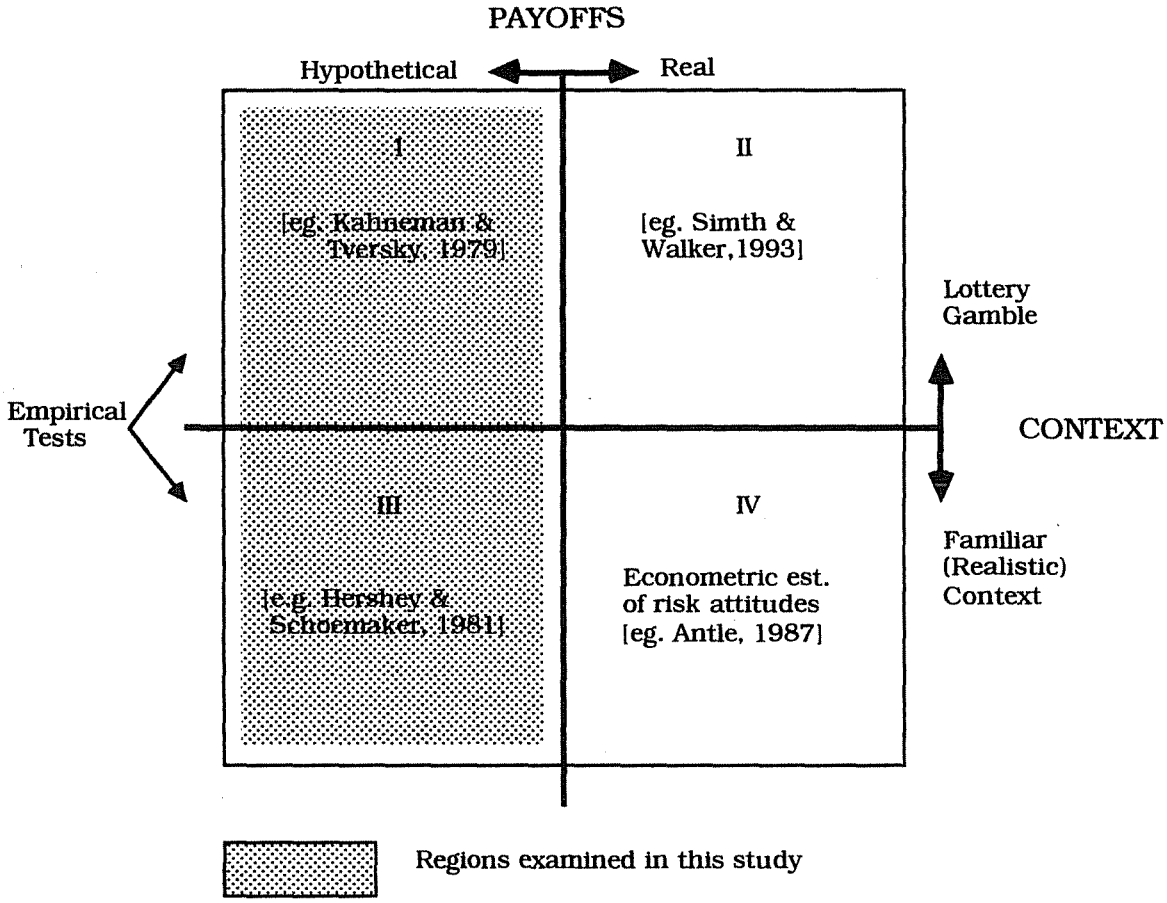
violations should be less frequent, as noted by Knez, Smith, and Williams (1985) and Coursey, Hovis, and Schultze (1987).

Here the risky choice investigator comes to his or her own dilemma: testing between risky choice theories using market data is very difficult, yet experimental situations can never perfectly duplicate the context, experience, and uncertainty associated with actual market decisions. A simplified experiment may be too far removed from real world choices to insure accurate representation. Use of market data would be preferable, but in using it one must either make assumptions about people's risk preferences or make assumptions about the functional form that weights their preferences, both of which are under inquiry. Use of hypothetical survey data, on the other hand, assumes that the experiment reasonably approximates real world decisions.

Figure 14 shows a graphical representation of the two dimensions of risky choice evaluation methods. While researchers may investigate quadrants I, II, and III using experimental data, quadrant IV must rely strictly on market data, and therefore must make assumptions about the functional form for choice (or utility). This thesis intends to take a small step toward bridging the two risk attitude evaluation methods by testing for the effects of context on the frequency and nature of EU violations in quadrants I and III. The testing method is still experimental, so the payoffs are only hypothetical, and therefore may only give insight to the actual effects of context and experience in market decisions. While results from the experimental study may not accurately reflect "real world" choices, the effect of the context may indicate the direction that hypothetical choices deviate from actual market decisions. If the incidence of EU violations is sensitive to

a change in context, it suggests an explanation for the violations that differs from the "ad hoc" invocation of new objective functions as proposed by the various GEU models.

Figure 14
Risky Attitude Evaluation Dimensions



Experimental Design

Effects of Context

The potential impacts of context on risky choice were discussed in the previous section. This thesis proposes that a familiar context may give the

subject a better understanding of the probabilities and stakes involved. Past decision-making experience in a similar context may shed light on the alternatives. To the extent that the familiarity of the context reduces costs of preference evaluation, it is hypothesized that the similarity biases are reduced relative to unfamiliar gambles. If similarity effects lead to EU violations, then the EU violations normally predicted by similarity should also be less likely under familiar contexts. Put another way, as compared to standard, presumably unfamiliar lottery-context choice pairs, more "realistic" scenario-context risky choice pairs with very dissimilar alternatives should elicit a greater number of riskier responses, and those very similar choice pairs should elicit fewer riskier responses.

> *Hypothesis:* A scenario-context should reduce the biasing effects of similarity. As compared with a simple lottery context, subjects will be more likely under a "realistic" scenario-context to choose the riskier alternative for very dissimilar alternatives and more likely to choose the less risky alternative for very similar alternatives, and will therefore choose more consistently with Expected Utility Theory.[11]

Subjects may draw further inferences from the particulars of each scenario, perhaps biasing choice towards either the riskier or less risky alternative in a way not anticipated by the experimenter. The empirical tests in Chapter 4 attempt to isolate the above hypothesis from these possible

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[11] The predictions in this hypothesis are with regard to choice pairs that can be related to each other through EU's independence axiom. Furthermore, the predictions for the likelihood of riskier or less risky choice relate to cross-sectional or population proportions as found in previous research on risky choice. The likelihood that any *individual* will choose the less risky or riskier alternative can not be predicted because individuals' preferences with regard to risk are not observable. The hypothesis does predict, however, that individual choices are less likely to systematically violate EU under a "realistic" scenario-context.

effects. For example, if a scenario presents a situation that subjects might expect to see a number of times, the stakes of the gamble become quite different from a gamble that subjects might expect to see just once. Akin to the risk-reducing effects of investing in a portfolio of assets rather than just one, playing a risky gamble multiple times will reduce the variance of the expected return. As the number of plays tends to infinity, the higher expected value alternative will tend to stochastically dominate the lower expected value alternative, regardless of the difference in variability; i.e., for an infinite number of plays risk does not matter. Thus, to the degree that a subject perceives a gamble as having multiple opportunities, the subject may be more likely to choose the riskier choice. It is important to consider these possible effects in testing the above hypothesis.

Empirical work in Chapter 4 also accounts for the effects of context on subjects' similarity judgments. While it is hypothesized that a context may affect the influence of similarity, it is somewhat unclear how a scenario-context will affect subjects' evaluation of similarity itself. The effects of context on choice may act separately from the effects of similarity, or perhaps context could act in conjunction with similarity. These possible effects involve the functional form of people's choice functions and are therefore empirical questions. They are not the primary question of interest, however, so they are not stated through a formal hypothesis.

The Experimental Survey

The design of the experimental survey and the empirical work in Chapter 4 largely follows that of Buschena (1992). Buschena's similarity model is applied to hypothetical choice surveys that also include different

contexts: simple lottery context gambles consistent with those used in Buschena and other research on risky choice, and a series of "real life" type scenarios that attempt to describe gambles using a context more familiar to the subjects. Two subject groups were used: a large undergraduate economics class and a group of Montanan seed potato farmers. Unfortunately, only 18 surveys were returned by the farmers, a sample too small for useful interpretation of their responses. The results in Chapter 4 therefore discuss only the responses from the 171 undergraduate students.

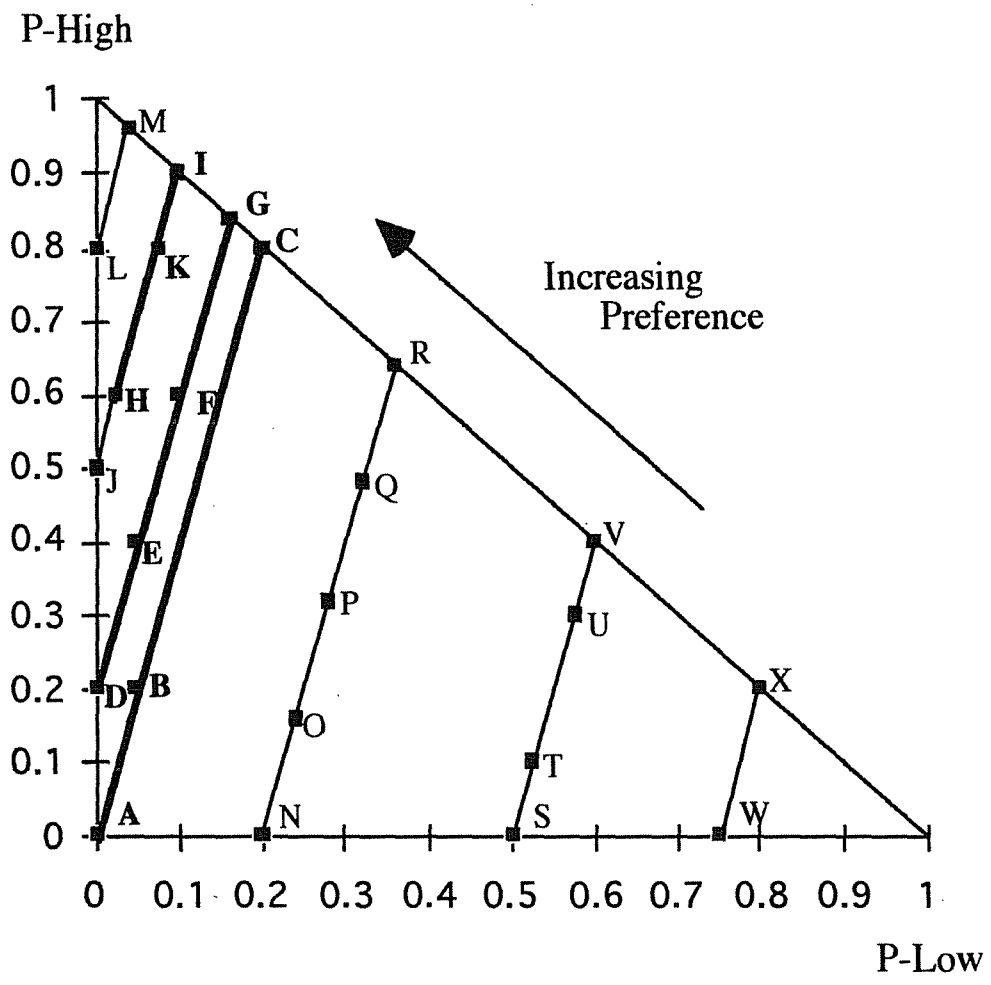
Recognizing that experience may play an important role in decision-making, the scenarios include situations somewhat like those the students and farmers may have previously faced or considered. There were four scenarios for each group, each with two different sets of probabilities and payoffs. The scenarios for both groups are given in Appendix C. In addition to the four scenarios, each subject received 18 lottery-type choice dilemmas, akin to those used in previous research on risk, for a total of 22 risky choices in each survey.

The students received four scenarios, referred to in the following discussions as "Career Job," "Used Car," "Part Time Job," and "Grandmother." The scenario "Career Job" is a choice dilemma between two full time job offers, one with a large, reputable company offering a modest salary but greater job security, the other with a newer, less reputable company offering a potentially higher salary but less job security. "Used Car" is a choice dilemma between two risky offers on the sale of a used car. "Part Time Job" is a risky choice dilemma between two part time jobs.

"Grandmother" is a choice dilemma between two risky investment options for an inheritance from the subject's grandmother.

The probabilities associated with the gambles were chosen from a set of 20 vectors, each representing a choice pair of gambles. The gambles are listed in Table 2 and are shown graphically on a risk triangle in figure 15. The choice pairs in boldface print, and with thicker lines connecting them in the figure, portray alternatives that appeared as both lotteries and scenarios; the gambles in standard print, and with thinner lines connecting them, appeared only as lotteries. Each subject received a question for each vector of probabilities plus two repeated questions: an early scenario question repeated as a lottery question later in the survey, and an early lottery question repeated as another lottery question later in the survey. The repeated questions tested for choice reversals.

Figure 15. All Gambles as Viewed on Risk Triangle



Notice that all of the choice pairs in Table 2 connect to make parallel nodes on the risk triangle in figure 15. This construction allows testing of choices for consistency with EU. As discussed in Chapter 2, EU implies that indifference curves should be parallel on the risk triangle. Because all choice pairs connect gambles to form parallel nodes, an individual who chooses consistently with EU should choose the riskier alternative for all choice pairs or the less risky alternative for all choice pairs. Choosing the less risky

alternative for one choice pair and the riskier alternative for another pair violates EU.

Table 2. All Gambles Appearing in Survey

Choice Pair	P_{LOW} Payoff	P_{MID} Payoff	P_{HIGH} Payoff	Q_{LOW} Payoff	Q_{MID} Payoff	Q_{HIGH} Payoff
(1) E vs. G	**0.05**	**0.40**	**0.55**	**0.16**	**0.00**	**0.84**
(2) E vs. F	**0.05**	**0.40**	**0.55**	**0.10**	**030**	**0.60**
(3) A vs. C	**0.00**	**0.00**	**1.00**	**0.20**	**0.00**	**0.80**
(4) B vs. C	**0.05**	**0.20**	**0.75**	**0.20**	**0.00**	**0.80**
(5) A vs. B	**0.00**	**0.00**	**1.00**	**0.05**	**0.75**	**0.20**
(6) D vs. E	**0.00**	**0.20**	**0.80**	**0.05**	**0.55**	**0.40**
(7) H vs. I	**0.025**	**0.60**	**0.375**	**0.10**	**0.00**	**0.90**
(8) F vs. G	**0.10**	**0.60**	**0.30**	**0.16**	**0.00**	**0.84**
(9) L vs. M	0	0.20	0.80	0.04	0.00	0.96
(10) H vs. K	0.075	0.375	0.60	0.075	0.125	0.80
(11) T vs. U	0.525	0.375	0.10	0.575	0.125	0.30
(12) T vs. V	0.525	0.375	0.10	0.60	0.00	0.40
(13) S vs. V	0.50	0.50	0.00	0.60	0.00	0.40
(14) W vs. X	0.75	0.25	0.00	0.80	0.00	0.20
(15) N vs. O	0.20	0.80	0.00	0.24	0.60	0.16
(16) O vs. P	0.24	0.60	0.16	0.28	0.40	0.32
(17) P vs. Q	0.28	0.40	0.32	0.32	0.20	0.48
(18) Q vs. R	0.32	0.20	0.48	0.36	0.00	0.64
(19) N vs. R	0.20	0.80	0.00	0.36	0.00	0.64
(20) J vs. K	0.00	0.50	0.50	0.075	0.125	0.80

Note: The choice pairs in boldface are those that were presented as both lotteries and scenarios. The standard print choice pairs were presented only as lotteries.

The gambles represent a variety of regions and characteristics on the risk triangle. These different characteristics pertain to the variables that

Buschena found to significantly affect subjects' perceptions of similarity. Recall, for example, that some choice pairs include "quasi-certain" (QC) gambles that lie on the vertical axis--those that represent gambles with a zero probability of a $0 payoff, while other choice pairs include only gambles on the interior of the triangle. In Chapter 2 it is explained that choice pairs sitting exclusively on the interior of the triangle have "equal dimensional support" (EDS) because they have positive probabilities for every payoff for both alternatives. The distance between the gambles on the risk triangle also varies extensively among the various choice pairs, corresponding to the PDM variable defined by Buschena (PDM is defined formally in Chapter 4).

As discussed in Chapter 2, Buschena's similarity model is applied to this thesis for three reasons: (1) similarity can be used to isolate the effect of context; (2) the similarity model moves toward a plausible explanation for those choices that systematically differ from EU; and (3) the similarity model has stronger empirical support than the GEU models reviewed in Chapter 2. The similarity model predicts that choice is biased toward the riskier alternative for similar pairs and, therefore, that EU violations are most likely to occur over choice pairs with large differences in perceived similarity. An EU violation presumably results due to a sufficiently risk-averse individual choosing the less risky alternative on a dissimilar choice pair and choosing the riskier alternative on a similar choice pair, where the choice pairs are related to each other through EU's independence axiom (A3). The hypothesis stated earlier in this chapter proposes that this tendency toward EU violations caused by similarity is reduced with a "realistic" scenario-context.

For example, the similarity hypothesis predicts that choice pair A vs. C (shown in Figure 15 and Table 2) is likely to have the lowest proportion of individuals choosing the riskier alternative because a large distance separates the two gambles on the risk triangle, and also because the pair includes the certain alternative "A." Buschena found that choice pairs such as these were perceived as very dissimilar. Choice pair A vs. C is the same as that used by Kahneman and Tversky to show the "certainty effect" or the first pair used to show the "common ratio effect" as they were described in Chapter 2. Other choice pairs, such as "F vs. G" and "W vs. X," compare gambles that lack a certain alternative and are much closer to each other on the risk triangle. The similarity hypothesis predicts that choice pairs such as these will have a much larger percentage of riskier choices. Because all of the choice pairs are comparable through the EU independence axiom, comparison of individual choices over very dissimilar choice pairs, like A vs. C, with more similar choice pairs, like F vs. G, are more likely to violate EU than over two dissimilar pairs such as A vs. C and N vs. R. The empirical work in Chapter 4 shows that the scenario context reduces this tendency towards EU violations predicted by the similarity hypothesis.

The choice pair surveys were extensively randomized to remove or otherwise account for subtle biases in choice that might have resulted from extraneous variables such as question order. The order of choice pairs and of alternatives within each choice pair were chosen randomly for each survey. The payoffs associated with each choice pair (except the scenarios) were randomly selected from a set of three vectors, ($0, $300, $400), ($0, $3,000, $4,000), and ($0, $21,000, $28,000), with the first, second, and third element

corresponding to the low, middle, and high payoffs respectively. The particulars of each scenario determined the appropriate payoff level each; the Grandmother and Career Job scenarios incorporated the ($0, $21,000, $28,000) payoff vector and the Used Car and Part Time Job scenarios incorporated the ($0, $3000, $4000) payoff vector.

In addition, there were four test formats, each with a different ordering of scenarios and lotteries.[12] Also, seven randomly chosen choice pairs elicited each subject's judgment of similarity between the alternatives as in Buschena (1992) and Buschena and Zilberman (1994). The subject made his or her similarity judgment by marking a slash on a continuous line. The subjects' slashes on the similarity scales were later measured and recorded on a scale of 0.1 to 10.0 (the numbers on the above scale are arbitrary because each judgment was measured on a ruler not shown). An example of the scale used to elicit a subject's similarity judgment between two risky alternatives "A" and "B" follows.

```
How similar do you find options "A" and "B" above?

0_____________________________________________9
very          somewhat        somewhat      very
dissimilar    dissimilar      similar       similar
```

The similarity scale is much like that used by Buschena (1992) and described in Chapter 2. By marking a slash along a line rather than giving discrete

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[12] The four format orderings were: (1) 2 scenarios, 18 lottery gambles, 2 scenarios; (2) 9 lottery gambles, 4 scenarios, 9 lottery gambles; (3) 1 scenario, 3 lottery gambles, 1 scenario, 6 lottery gambles, 1 scenario, 3 lottery gambles, 1 scenario, 6 lottery gambles; and (4) 3 lottery gambles, 1 scenario, 6 lottery gambles, 1 scenario, 3 lottery gambles, 1 scenario, 6 lottery gambles, 1 scenario.

numbers (e.g. 3.4), the subjects can easily give an accurate representation of their perceived similarity.

A complete sample survey is given in Appendix D. The construction of the surveys was accomplished using a PASCAL computer program written by the author. The code for the program is given in Appendix B.

CHAPTER 4

EMPIRICAL RESULTS

This chapter explains the empirical results of the experiment outlined in Chapter 3. First, a summary of the general results is presented along with simple test statistics that suggest the circumstances under which context affects choice. The implications of context suggested by the summary statistics are then confirmed through more comprehensive logistic regression models that account for the effects of similarity. The results show that, while similarity significantly biases choice away from EU, these biases are reduced when gambles are placed into a scenario context. Moreover, the results show that the EU hypothesis cannot be rejected for choices over scenario gambles.

Summary Statistics

The clearest indication of a context effect is shown by comparing the percentage of subjects choosing the riskier alternative when the pairs differ only in context. Table 3 shows the percentage of subjects choosing the riskier alternative for each of the eight scenario-context choice pairs and each of the corresponding lottery-context choice pairs. The corresponding lottery pair in each row has the same probabilities and payoffs as those in the scenario. The table shows the scenarios, the choice pairs that correspond to those in table 2 and figure 15, the frequency of selection for each alternative, and the proportion of subjects choosing the riskier alternative for each scenario pair

and its equivalent lottery pair. The right hand columns show the changes in the proportion of riskier choice and Z statistics that test for a significant difference between the proportion of riskier choices in each lottery-scenario comparison. Appendix A gives a summary of responses for the remaining choice pairs that correspond only to lotteries.

The Z test statistic is based on the standard normal distribution and follows from the convergence properties of the maximum likelihood estimate of a binomial distribution (see Bain and Engelhardt, 1992). For large sample sizes (usually > 30), if the true population proportion of riskier choice were the same for lotteries and scenarios, then

$$Z = \frac{\hat{\rho}_S - \hat{\rho}_L}{\sqrt{\hat{\rho}(1-\hat{\rho})(1/n_L + 1/n_S)}} \sim N(0,1) \qquad (6)$$

where $\hat{\rho}_L$ is the proportion of riskier choices over lotteries, $\hat{\rho}_S$ is the proportion of risky choices over scenarios, $\hat{\rho}$ is the pooled proportion of riskier choices over both lotteries and scenarios, and n_L and n_S are the number of riskier plus less risky choices for lotteries and scenarios respectively ("indifferent" choices were skipped for purposes of this test).[13] The null hypothesis of an equal population proportion of riskier choice between a particular scenario context and the equivalent lottery context is rejected for sufficiently large magnitudes of Z, whether they be positive or negative. A significantly negative Z indicates a smaller proportion of riskier choice for

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13 $\hat{\rho}$ = (riskier scenario choices + riskier lottery choices)/(n_L + n_S).

Table 3. Lottery-Scenario Comparisons for Percent Riskier Choice

Scenario Context	Choice Pair	Lottery Gambles				Scenario Gambles				Change in % Risky	Z Test for Different % Risky
		N*	Less Risky Choices	Riskier Choices	Percent Risky	N*	Less Risky Choices	Riskier Choices	% Risky		
CAREER JOB	(1) E vs. G	49	36	10	21.7	85	51	32	38.6	16.9	1.952**
CAREER JOB	(2) E vs. F	58	37	19	33.9	85	52	31	37.3	3.4	0.412
USED CAR	(3) A vs. C	54	52	2	3.7%	94	66	26	28.3%	24.6%	3.639***
USED CAR	(4) B vs. C	54	37	15	28.8	77	56	18	24.3	-4.5	-0.568
PART TIME JOB	(5) A vs. B	47	35	10	22.2	87	46	39	45.9	23.7	2.648***
PART TIME JOB	(6) D vs. E	62	44	17	27.9	84	60	23	27.7	-0.2	-0.021
GRANDMOTHER	(7) H vs. I	52	30	22	42.3	95	63	31	33.0	-9.2	-1.123
GRANDMOTHER	(8) F vs. G	51	25	25	50.0	76	59	15	20.3	-29.7	-3.474***

* The sum of the "Less Risky" and "Riskier" responses is often less than "N." The difference between the two correspond to those indifferent between the two alternatives.

$$Z = \frac{\hat{\rho}_S - \hat{\rho}_L}{\sqrt{\hat{\rho}(1-\hat{\rho})(1/n_L + 1/n_S)}} \sim N(0,1) \text{ for large sample size}$$

Where: $\hat{\rho}_L$ =proportion of risky choices over lotteries

$\hat{\rho}_S$=proportion of risky choices over scenarios

$\hat{\rho}$ =pooled proportion of risky choices over both lotteries and scenarios = (Riskier Scenario Choices + Riskier Lottery Choices)/(n_L + n_S)

n_L and n_S are the number of risky + less risky choices for lotteries and scenarios respectively

scenarios; a significantly positive Z indicates a larger proportion of riskier choice for scenarios.

The Z statistics in Table 3 show clear differences between the Used Car "A," Part Time Job "A," and Grandmother "B" scenarios and their lottery-context equivalents. Career Job "A" shows a marginally significant difference in choice. For the remaining scenarios, Career Job "B," Used Car "B," Grandmother "A," and Part Time Job "B," the difference in the proportion choosing the riskier alternative is clearly insignificant. Upon first inspection, it is difficult to discern a pattern for the effects of scenarios on choice. For example, although Used Car "A" elicits significantly more riskier responses than its lottery counterpart, Grandmother "B" elicits significantly fewer riskier responses. In addition, although one rendition of each scenario "story" shows a significant difference, the second rendition of each story is insignificant. There does not seem to be an overall effect of the scenarios towards riskier or less risky choices, nor a clear pattern in significance across stories. Rather, the effects seem to depend on the characteristics of the gamble in conjunction with a scenario-context because they differ across both stories and gambles.

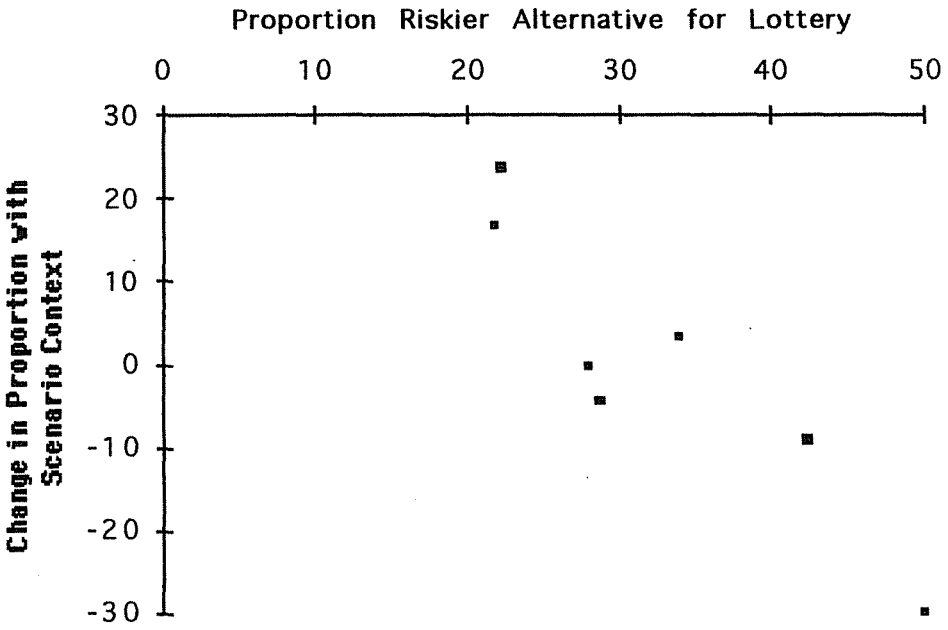
In Chapter 3 it was hypothesized that "real life" scenario-contexts may reduce the effects of similarity on choice, and hence reduce the biases in choice suggested by the similarity models. Specifically, the hypothesis stated that the scenario-context should increase the number of riskier choices for very dissimilar choice pairs (e.g. A vs. C), and decrease the number of riskier choices for very similar choice pairs (e.g. F vs. G). The Z tests in Table 3 and

the plot and regression in Figure 4 indicate this type of an effect from the scenario-contexts.

Notice that for the lottery eliciting the lowest proportion of riskier responses (choice pair A vs. C at 3.7%), the corresponding Used Car scenario (at 28.3%) elicits the most significant positive effect on the proportion of riskier choice. Conversely, for the lottery eliciting the greatest proportion of riskier responses (choice pair F vs. G at 50%), the corresponding Grandmother scenario (at 20.3%) elicits the largest absolute negative effect on the proportion of riskier choice. Hence, it seems that the scenarios may balance the proportion choosing the riskier alternative relative to the choice proportions for lotteries with the same probabilities and payoffs. To illustrate this effect, Figure 15 shows a plot of the percentage of subjects choosing the riskier alternative under the lottery context against the change in this percentage with the introduction of the scenario contexts (the 6th and 11th columns in Table 3). Figure 15 also includes the estimated parameters from a linear regression that fits the plot quite well. The t-ratios, with the corresponding p-values shown in the parentheses below the coefficients, show strong significance.[14]

[14] The true significance of the variables are difficult to interpret because each observation corresponds to many observations in Table 3. Figure 15 and the regression are meant only for illustrative purposes to motivate the remainder of the analysis.

Figure 16
Scatter Plot: Change in Percent Risky Choice Introduction of Scenario



Fitted Linear Regression with 8 Observations:

$$\%\text{ Riskier Choices for Lotteries} = \underset{(0.000)}{30.96} - \underset{(0.002)}{0.687} \times \%\text{Change}$$

$R^2 = 0.8104$ R^2- Adj. = 0.7788

Chapter 3 also suggested that subjects may draw further, unplanned inferences from some scenarios, perhaps biasing choice towards either the riskier or less risky alternative, clouding the similarity-reducing effects. An example was given in Chapter 3 relating to scenarios that might be understood as having multiple opportunities for play, which might increase the relative value of the riskier alternative for those scenarios. Although the scenarios "Career Job," "Part Time Job," and perhaps "Used Car" are gambles that subjects might understand as having multiple opportunities, the

"Grandmother" scenario is just a one-time opportunity. Therefore, the ""Career Job," "Part Time Job," and "Used Car" scenarios may elicit a greater percentage of riskier choices relative to the "Grandmother" scenario, and perhaps the lottery gambles. With the possible exception of the "Grandmother" scenario, the summary statistics in Table 3 show no clear indication of this type of effect. It is important, however, to distinguish possible effects resulting from any nuances of the scenario stories and possible similarity-reducing effects of scenario-contexts. For example, the "Grandmother" scenario may be showing either a reduction in the effects of similarity or a multiple opportunity effect, or both. Because these two types of effects may be confounding one another, further analysis is required to distinguish between them. Moreover, there is a need to account for differences in individual preferences with regard to risk. Nevertheless, even these simple test statistics show that subjects' choices in an experimental setting are often sensitive to the context of the alternatives.

Estimating Similarity

The similarity of the choice pairs must first be estimated in order to test for the effects of similarity on choice, and to test for how context may affect the influence of similarity on choice. As described in Chapter 2 and Chapter 3, little is understood about similarity in three dimensions of payoffs. The model used in this thesis therefore follows that of Buschena fitting the subjects' judgments of similarity to objective measures over the gambles. These measures include PDM, EVD, EDS, and QC as they were described in Chapter 3. Subjective similarity judgments were elicited from seven randomly selected choice pairs on each twenty-two question survey. The

subjects made their judgments by marking a slash along a continuous line (see Chapter 3 or the sample survey in Appendix D for an example). These judgments were later measured along a scale of 0.1 to 10.0, with 0.1 corresponding to the subject viewing the alternatives as "very dissimilar" and 10.0 corresponding to "very similar." These judgments make up the dependent variable for this estimate.

Several models were estimated to fit the subjects' similarity judgments to objective characteristics of the choice pairs as in Buschena (1992). As in Buschena's work, a generalized least squares (GLS), or weighted least squares (WLS), method of estimation was used to account for different variability in responses by different subjects.[15] It is suspected, *a priori*, that heteroscedasticity exists across individuals. That is, different individuals likely will have different spreads of responses across the similarity scale illustrated in Chapter 3. Moreover, each individual may have a different "mean" similarity estimate--where some individuals may place all similarity judgments relatively high on the scale, others may place all judgments relatively low on the scale. To adjust for this possible variation in the subjects' similarity scales, dummy variables representing each individual were also included in each model. These estimates allow for specification of the objective characteristics that pertain to the subjects' judgments of

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[15] The GLS heteroscedasticity adjustment uses the maximum likelihood (ML) estimate of each individual's standard error from an ordinary least squares regression. The ML estimate is a biased but consistent estimator of each individual's standard error. An unbiased estimator would use the square root of the sum of squared errors over each individual divided by the number of similarity judgments (in this case 7) minus the number of right hand side variables used in the regression (in this case 18); the estimate used here simply divided by 7. The unbiased estimate is obviously infeasible.

similarity between choice pairs. The regressions also allow for similarity estimates to be applied to observations where a subjective judgment was not elicited.

Several GLS regressions were estimated to view the robustness and sensitivity of the results. These regressions used different variables to account for the variation in similarity judgments across choice pairs. A list of definitions for the explanatory variables is given in Table 4. The GLS similarity estimate used in the analyses to follow is shown in Table 5. The estimate in Table 5 uses general descriptive measures of the choice pairs along with dummy variables for the scenarios. Note that the summary statistics for key variables used in these similarity regressions and the regressions to come later in this chapter are given in Appendix A.

The idea of the similarity estimate is to fit subjects' perceptions of similarity to objective measures that show the "closeness" of the alternatives. The variable PDM, for example, is an objective measure showing the relative distance between the alternatives on the risk triangle. Technically, PDM is the distance between the probability vectors in Euclidean 3-space, or

$$PDM = \sqrt{(p_{low} - q_{low})^2 + (p_{mid} - q_{mid})^2 + (p_{high} - q_{high})^2} \qquad (7)$$

where the probability vectors **p** and **q** represent each of the alternatives in a risky choice pair (see Buschena, 1992).

Table 4. Definition of Variables in GLS Similarity Estimate

Variable Name	Variable Definition
S1 (Career Job "A")	Dummy variable for Career Job scenario with gambles E vs. G
S2 (Career Job "B")	Dummy variable for Career Job scenario with gambles E vs. F
S3 (Used Car "A")	Dummy variable for Used Car scenario with gambles A vs. C
S4 (Used Car "B")	Dummy variable for Used Car scenario with gambles B vs. C
S5 (Part Time Job "A")	Dummy variable for P.T. Job scenario with gambles A vs. B
S6 (Part Time Job "B")	Dummy variable for P.T. Job scenario with gambles D vs. E
S7 (Grandmother "A")	Dummy variable for Grandmother scenario with gambles H vs. I
S8 (Grandmother "B")	Dummy variable for Grandmother scenario with gambles F vs. G
PDM	Probability distance measure in Euclidean 3-space
PDM^2	PDM squared
PDM^3	PDM cubed
EVD	Difference in expected value of alternatives
MEV	Minimum expected value of alternatives
EVR	Expected value difference ratio = EVD/MEV
EDS	Equal dimensional support = 1 if positive probability for all three payoffs in both alternatives, 0 otherwise.
QC	Quasi-certainty = 1 if zero probability of at a zero payoff on less risky alternative, 0 otherwise
Question Number	Order of question as the subject saw on the survey

Table 5. GLS Similarity Estimate

Variable Name	Coefficient	Standard Error	T-Ratio	P-Value
S1 (Career Job "A")	0.84111	0.3967	2.120	0.034
S2 (Career Job "B")	-0.19572	0.3530	-0.5545	0.579
S3 (Used Car "A")	-0.15979	0.4618	-0.3460	0.729
S4 (Used Car "B")	-0.46175	0.3859	-1.197	0.232
S5 (Part Time Job "A")	-0.42011	0.3314	-1.267	0.205
S6 (Part Time Job "B")	0.22469E-01	0.3434	0.6542E-01	0.948
S7 (Grandmother "A")	-0.19829	0.3527	-0.5622	0.574
S8 (Grandmother "B")	1.0727	0.3366	3.187	0.001
PDM	-21.302	4.988	-4.270	0.000
PDM^2	33.832	11.93	2.837	0.005
PDM^3	-20.463	8.776	-2.332	0.020
EVD	-0.19757E-03	0.2013E-03	-0.9817	0.327
EVR	44.640	3.873	11.53	0.000
EDS	0.73847	0.1428	5.170	0.000
QC	-0.69888	0.1550	-4.508	0.000
Question Order	0.14695E-01	0.7031E-02	2.090	0.037
Constant	6.9352	0.7583	9.146	0.000

Dependent Variable: Subjective similarity judgments measured from scale.

Also, not shown, are 170 dummy variables representing each individual.
An F-test for their joint significance equals 2.27 with 170 & 980 D.F. The corresponding p-value is less than 0.001.

An F test for the joint significance of the 8 scenario dummies equals 2.31 with 8 & 980 D.F. The corresponding p-value equals 0.02.

1167 Observations, 979 degrees of freedom

$R^2 = 0.7961$ R^2-Adj. = 0.7571

Except for the scenario dummy variables, the qualitative results of the coefficient estimates in Table 5 are much like that of Buschena (1992). The probability distance measures, PDM, PDM^2, and PDM^3, have roughly the same significance as in Buschena's estimate, showing a general cubic relation

of PDM on similarity. The total effect of the PDM measures act in a negative relationship to similarity over the entire range of PDM; that is, similarity increases as the distance between the alternatives on the risk triangle decreases.[16] The cubic PDM relationship implies that similarity decreases at an decreasing rate with respect to PDM for values of PDM less than 0.55, and decreases at an increasing rate for values of PDM greater than 0.55. Thus, the cubic relationship allows for a nonlinear relationship of similarity with PDM.

The equal dimensional support (EDS) dummy variable in Table 5 (equals 1 when both alternatives lie exclusively on the interior of the risk triangle) is significantly positive, indicating that such pairs are perceived as more similar. The quasi-certainty variable (QC) shows that choice pairs with one of the alternatives lying on the vertical axis (i.e., an alternative having a zero probability of a $0 payoff) are significantly less similar.

The variables measuring expected values, EVD and EVR capture differences between different payoff levels. EVD is also somewhat collinear with PDM, hence the coefficient estimate should be interpreted with care. The EVR variable seems to capture the relative position on the risk triangle. Larger EVR values for a given EVD or PDM represent choice pairs further toward the lower right region of the risk triangle; smaller EVR values represent choice pairs further toward the upper left region of the risk triangle. The EVR variable may be capturing the relative similarity of the

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16 $\partial SIM / \partial PDM = -21.3 + 67.7(PDM) - 61.4(PDM)^2$; maximizing the differential: $\max(\partial SIM / \partial PDM) \cong -2.66$ $@PDM \cong 0.55$ hence, $\partial SIM / \partial PDM < 0$ over all PDM.

highest and middle payoff, although its interpretation remains unclear.[17] The signs of the remaining variables appear to be consistent with the hypothesis of similarity reviewed in Chapter 2.

In Chapter 3, it was suggested that the context of the gamble may also affect the subjects' perceptions of similarity.[18] While the data used here do not allow clear tests for these effects, two of the scenarios, Career Job "A" and Grandmother "B," clearly influence the subjects' similarity judgments in a positive direction. A Wald F-test on the joint significance of the eight scenario dummy variables equals 2.31 with 8 and 980 degrees of freedom and is significant with approximately 98% confidence.

Several other GLS models were also estimated. Instead of using general characteristic measures like PDM, these alternative estimates incorporated a series of dummy variables to represent each choice pair (two alternative estimates are given in Appendix A). While the dummy variable estimates should more accurately model the subjects' similarity judgments for this experiment, they do not indicate the types of characteristics that lead to perceived similarity, nor do they allow for application of the similarity hypothesis to more general circumstances. These alternative estimates are

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[17] Because the middle and highest payoffs are relatively close to each other as compared to the middle and low payoffs [re. $3,000 and $4,000 as compared to $3,000 and $0], subjects could find greater similarity between alternatives with small probability differences between the high and middle payoffs. The PDM variable does not capture this possible effect, but it may be captured somewhat by EVR. A superior measure would be to compare the absolute differences in the cumulative density functions of the two alternatives as in Buschena (1992). The measures here are used for the sake of simplicity, and because of the strong fit as compared to the dummy variable GLS estimations in Appendix B.

[18] Note that context affecting similarity is different from the idea in the Hypothesis proposed in Chapter 3 that context may reduce the *influence* of similarity.

therefore used only as a benchmark to measure the performance of the more general GLS estimate in Table 5. The fit of the more general similarity model, as measured by the adjusted R^2, compares well with those of the alternative dummy variable models in Appendix A (Tables 19 and 20), which have R^2 values of 0.79 and 0.74.

Logit Models For Likelihood of Riskier Choice

A more rigorous analysis is needed to examine why and how context affects subjects' choices. Two logit regression models are used to explain subjects' discrete choices over risky pairs with various characteristics of the pairs. The dependent variable in these regressions equals 1 when the riskier alternative is chosen and equals 0 when the less risky alternative is selected. The explanatory variables include a measure of individual risk preference, fitted similarity from the regression in Table 5, and dummy variables representing the different contexts. These models allow for isolation of the context and similarity effects that was lacking in the previous analyses.

The logit model is based on the cumulative logistic probability function:

$$P_i = F(Z_i) = \frac{1}{1 + e^{-Z_i}} \tag{8}$$

where P_i equals the likelihood (or the cumulative probability) that an individual (i) will choose the riskier alternative, and Z_i is an index that measures the subject's attitude toward a risky choice pair, so that the higher the value of Z_i, the greater the likelihood of choosing the riskier alternative. The logistic function is particularly attractive because it can transform a linear function Z, that can vary from negative infinity to positive infinity, into

a likelihood function ranging from zero to one. The inverse of equation (7) can be solved for Z_i:

$$Z_i = \log\left(\frac{P_i}{1-P_i}\right) \tag{8}$$

Hence, the dependent variable of a linear regression on choice is simply the logarithm of the odds that the riskier choice will be made. Because, however, we only observe subjects' choices and not their odds for choosing the riskier alternative, a maximum likelihood estimation must be used. Note that when Z_i equals zero, the likelihood of choosing the riskier alternative, P_i, equals 0.5, hence a less risky choice and a riskier choice are equally likely to occur. This note helps for interpretation of the coefficients and t-ratios in the following regressions.

The logit regression models in Tables 8 and 9, (with variable definitions in Tables 6 and 7, respectively) shed further light on the simple statistics given in Table 3. The first logit model in Table 8 merely tries to account for other variables that may be affecting choice in the simple proportion difference tests from Table 3. The second logit model in Table 9 moves toward explaining how context affects choice. Note that the first logit model in Table 8 includes the entire sample, while the second only includes choice pairs that were seen as both scenarios and lotteries in the experiment. The sample is restricted for the second logit model to remove any biases resulting from the selection of gambles used for the scenarios; that is, because all scenario choice pairs lie in the upper-left region of the triangle, the choice pairs in the lower right are skipped.

The first logit model uses the general measures that were explanatory variables in the GLS similarity estimate together with a mean response variable to represent the general preferences of each subject.[19] This variable is simply the average of each respondents choices, where choices are either 0 for a less risky choice, 0.5 for and indifferent choice, and 1 for a riskier choice. Thus, the mean response variable has a range from 0 to 1. The larger this variable, the more often the subject generally selected the riskier alternative. Under strict adherence to EU, the mean response variable should be the only significant variable.

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[19] Individual dummy variables could also be used in place of the mean individual response variable. Several such regressions produced results nearly identical to those presented here, but were much more costly to estimate in computer time.

Table 6. Variable Definitions Logit Model #1 for Riskier Choice

Variable Name	Definition
Mean Individual Response	Mean answer for each individual, where riskier choice = 1, less risky = 0, and indifferent = 0.5
S1 (Career Job "A")	Dummy variable for Career Job scenario with gambles E vs. G
S2 (Career Job "B")	Dummy variable for Career Job scenario with gambles E vs. F
S3 (Used Car "A")	Dummy variable for Used Car scenario with gambles A vs. C
S4 (Used Car "B")	Dummy variable for Used Car scenario with gambles B vs. C
S5 (Part Time Job "A")	Dummy variable for P.T. Job scenario with gambles A vs. B
S6 (Part Time Job "B")	Dummy variable for P.T. Job scenario with gambles D vs. E
S7 (Grandmother "A")	Dummy variable for Grandmother scenario with gambles H vs. I
S8 (Grandmother "B")	Dummy variable for Grandmother scenario with gambles F vs. G
PDM	Probability distance measure in Euclidean 3-space
PDM^2	PDM squared
PDM^3	PDM cubed
EVD	Difference in expected value of alternatives
MEV	Minimum expected value of alternatives
EVR	Expected value difference ratio = EVD/MEV
EDS	Equal dimensional support = 1 if positive probability on for all three payoffs for both alternative, 0 otherwise.
QC	Quasi-certainty = 1 if zero probability of at a zero payoff on the less risky alternative, 0 otherwise
Payoff Level #1	Dummy Variable = 1 for payoff vector ($0, $3,000, $4,000)
Payoff Level #2	Dummy Variable = 1 for payoff vector ($0, $21,000, $28,000)

Table 7. Variable Definitions for Logit Model #2 for Riskier Choice

Variable Name	Variable Definitions
Mean Individual Response	Mean answer for each individual, where riskier choice = 1, less risky = 0, and indifferent = 0.5
Similarity × Lottery	GLS similarity estimate from Table 5 × dummy variable for a lottery context
Similarity × Scenario	GLS similarity estimate from Table 5 × dummy variable for a scenario context
Scenario	Dummy variable = 1 for all scenarios, = 0 for all lotteries
Lottery	Dummy variable f= 1 for all lotteries, = 0 for all scenarios
Payoff Dummy #1	Dummy variable for payoff vector ($0, $3,000, $4,000)
Payoff Dummy #2	Dummy variable for payoff vector ($0, $21,000, $28,000)

Table 8. Logit Model #1 for Prediction of Riskier Choice

Variable Name	Coefficient	Standard Error	T-Ratio
Mean Individual Response	5.5824	0.24362	22.915
S1 (Career Job "A")	0.36630	0.30016	1.2203
S2 (Career Job "B")	-0.46344	0.27783	-1.6681
S3 (Used Car "A")	1.9045	0.46984	4.0535
S4 (Used Car "B")	0.31541	0.34372	0.91763
S5 (Part Time Job "A")	0.55704	0.26942	2.0676
S6 (Part Time Job "B")	-0.11715	0.29503	-0.39709
S7 (Grandmother "A")	-0.21650	0.28493	-0.75986
S8 (Grandmother "B")	-1.4371	0.34077	-4.2171
PDM	0.83732	3.2876	0.25469
PDM^2	-2.9723	5.2421	-0.56700
PDM^3	0.87551	2.5304	0.34599
EVD	0.20969E-04	0.43020E-03	0.48742E-01
MEV	0.22574E-05	0.16338E-04	0.13816
EVR	-3.2932	4.2177	-0.78080
EDS	0.16510	0.12284	1.3441
QC	-0.47999	0.13889	-3.4558
Payoff Level #1	0.34342E-03	0.11868	0.28935E-02
Payoff Level #2	0.53422E-01	0.37916	0.14089
Constant	-2.3335	0.58456	-3.9918

Dependent Variable: 0 for less risky choice, 1 for riskier choice

Likelihood Ratio Test = 850.4 with 19 Degrees of Freedom

A chi-square test on joint significance of scenario dummies equals 46.8 with 8 D.F; the corresponding p-value is less than 0.001.

Prediction Success Table:

		Actual	
		0	1
Predicted	0	2012	670
	1	305	567

Percentage of Right Predictions = 0.72566

Table 9. Logit #2 Prediction for Riskier Choice

Variable Name	Coefficient	Standard Error	T-Ratio
Mean Individual Response	5.6950	0.37375	15.237
Similarity × Lottery	0.82971	0.14770	5.6175
Similarity × Scenario	-0.16466	0.14733	-1.1176
Scenario	-2.3498	0.65492	-3.5879
Lottery	-6.5400	0.67015	-9.7590
Payoff Dummy #1	0.41012E-01	0.20009	0.20497
Payoff Dummy #2	0.16946	0.20282	0.83549

Dependent Variable: 0 for less risky choice, 1 for riskier choice

Note that this regression only includes observations with choice pairs that were seen as both lotteries and scenarios.

Likelihood Ratio Test = 335.7 with 7 Degrees of Freedom

Prediction Success Table:

		Actual	
		0	1
Predicted	0	959	287
	1	109	201

Percentage of Right Predictions = 0.74550

Notice that the t-ratios in Table 8 for the scenario dummy variables qualitatively mirror the significance and direction of Z statistics in Table 3--the Used Car "A," Part Time Job "A," and Grandmother "B" scenarios significantly affect choice in the same direction implied by the Z statistics. A Wald chi-squared test on the joint significance of the 8 scenarios equals 46.8 with 8 degrees and is significant with more than 99.99% confidence. Hence, the effects of the scenarios seem to be robust to a more complete model.

The logit model in Table 9 directly tests the hypothesis proposed in chapter 3 and implied by the previous analysis. Although similarity biases choice by increasing the likelihood of a riskier choice, it was hypothesized that context reduces this bias, creating choices more consistent with EU. The

specification in Table 9 differs from that in Table 8 in three respects. First, the fitted similarity estimate from Table 5 is used rather than the objective measures used to fit similarity in the first place; second, the effect of similarity is measured separately for scenarios and lotteries; and lastly, a single dummy variable representing all scenarios is used rather than one for each scenario choice pair. Hence, the regression in Table 9 allows for testing of the similarity-reducing effect of the scenarios.[20]

As hypothesized by Buschena (1992), the fitted similarity variable is positively related with the likelihood of riskier choice for the lottery context (Lottery× Similarity); holding other variables constant, the more similar the two alternatives, the more likely a riskier choice when the choice pair is in a lottery context . In support of the hypothesis proposed in Chapter 3, the similarity variable for scenarios (Scenario× Similarity) does not significantly influence choice.

There is no constant term for the logit regression in Table 9. Rather, the dummy variables Scenario and Lottery represent the constant term for

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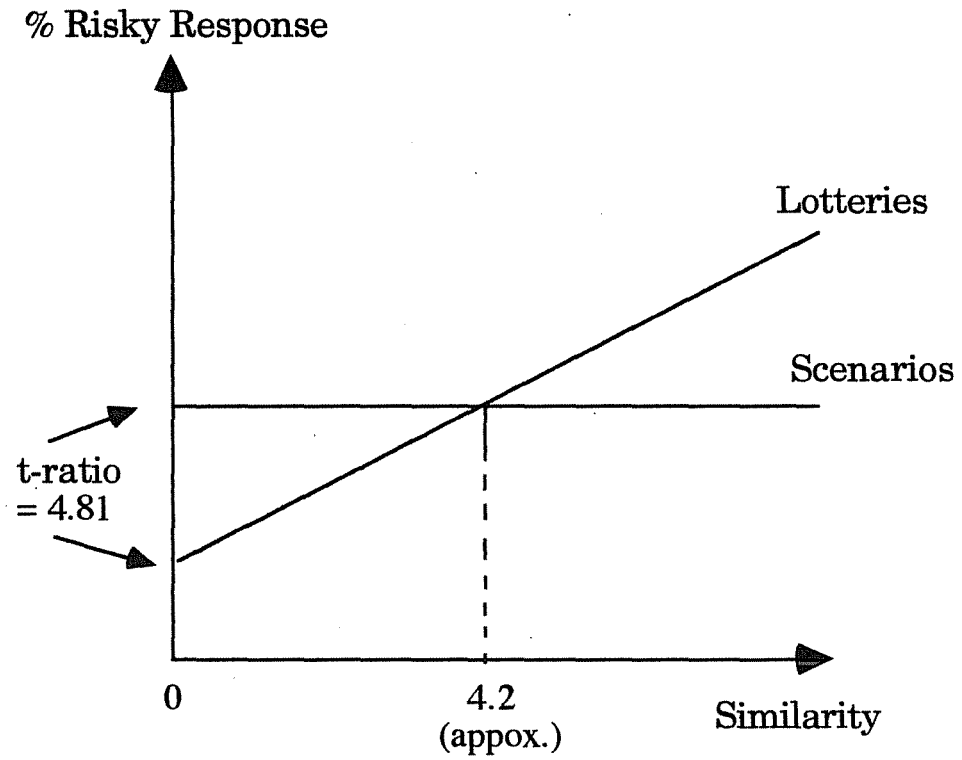
20 A similar regression was run that used dummies representing each "story" rather than a single dummy variable for all scenarios (there were two scenarios, "A" and "B," for each "story"). This alternative estimate is important because it allows for testing of any nuances in the stories that may bias choice, and cloud the true similarity-reducing effects of the scenarios. After taking the effects of similarity into account, this alternative estimate, shown in Appendix B, finds the four different stories to have the same affect on choice. In this alternative estimate, however, fitted similarity has a significantly *negative* effect on choice. Because there are only two different gambles for each story, and because this bias is no longer significant when the four stories are collapsed into a single dummy variable, it seems the significance of this negative bias is spurious and results from a confounding of the story dummy variables and the fitted similarity variable; that is, there is not enough variance between the similarities of the two scenarios for each story for the regression to distinguish them perfectly from the fitted similarity measure.

each type of context. Both scenario and lottery dummies are significantly less than zero, indicating that the representative subject is more likely to choose the less risky alternative than the riskier alternative when two are dissimilar. The coefficient for Lottery is significantly more negative than the coefficient for Scenario (t-ratio for a significant difference equals 4.81 with p-value less than 0.0001). Hence, for very dissimilar alternatives, the representative subject is more likely to choose the riskier alternative under a scenario-context than in a lottery-context. This result is also consistent with the hypothesis in Chapter 3. To see why, refer to Figure 16. It was hypothesized that under the scenario context subjects would be more likely to choose the riskier alternative for very dissimilar alternatives and less likely to choose the riskier alternative for very similar alternatives. Thus, although the percent choosing the riskier alternative is positively related to similarity for lotteries (as shown by the upward sloping "Lotteries" line in Figure 16), there should be no such relationship for scenarios (shown by the horizontal "Scenarios" line)--or at least the similarity effect should be diminished. The significant difference between the Scenario and Lottery dummy variables indicates a significant difference in the intercept of the "Scenarios" line and the "Lotteries" line. Thus, individuals view scenarios and lotteries differently.

Figure 17
Risky Response and Similarity Relationships



The analyses thus far, and specifically the logit regression in Table 9, indicate that both similarity and context affect choice. It is clear that greater similarity increases the likelihood of a riskier choice for lotteries, and that for scenario-contexts affects this relationship. The relative flatness of the "Scenarios" line, indicated by the insignificant "Similarity × Scenario" coefficient in Table 9, also suggests that scenarios are roughly consistent with EU. With these data, however, the representative individual's true preference remains unclear. Similarity may bias choice over lotteries in several ways. For instance, very similar alternatives may bias choice toward the riskier alternative, indicating that true preference is toward the less risky

alternatives; or very dissimilar alternatives may bias choice toward the less risky alternative, indicating true preference is toward the riskier alternative; or finally, there could be a bias in both these directions, indicating that choice is closest to true preference when alternatives are moderately similar. There could be many plausible explanations for the differences in choice, but because actual preferences are not observable, isolating true preference is difficult.[21]

Expected Utility Violations

The analysis has thus far focused on the effects of similarity and context on the likelihood of riskier choice. While the previous analysis is interesting and has specific implications for possible violations of EU, the experimental design allows for direct comparison of the individual subjects' choices to test for the frequency and causes of actual violations. All choices by an individual over the same payoff vector should elicit the same choice under EU: either all riskier or all less risky. Therefore, rather than look cross-sectionally at the likelihood of a riskier choice, the analysis in this section uses a different data set constructed by comparing choices over pairs that should elicit the same response under EU. Moreover, these analyses pay close attention to the *type* of violation. As discussed in Chapters 2 and 3, the existence of EU violations is not particularly damaging to the theory; rather, it is the systematic *bias* toward a type of violation that indicates a possible

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[21] The problems presented in the last footnote make these inferences even less clear. Under ideal circumstances, an experiment should include many different scenario stories (e.g. "Grandmother"), each with many different choice pairs. In this experiment, however, there were only four stories, each with just two choice pairs. If the data set were large enough, perhaps some inferences could be made as to the risk preferences across the population.

shortcoming of the theory. Thus, the analysis in this section looks closely at the relative bias of choices over lotteries as compared to choices over scenarios.

The Effect of Similarity on EU Violations

Before modeling the occurrences of EU violations, a benchmark needs to be established to gauge their relative frequency. After all, people naturally make mistakes, and only after their natural rate of choice variability is known can inferences be made on the frequency and type of EU violations. A natural rate of variability for the subject population was estimated by taking the percent of subjects switching their choice on a repeated lottery choice pair. The tested choice pair appeared as the first or second lottery on the survey and again as the last or the penultimate lottery pair on the survey. Because the order of the choice pairs was randomized, so were the probability vectors for the repeated pair. The error choice reversal rate was 32%, which is relatively close to previous research with real money payoffs, including that by Camerer (1989) at 32% and Starmer and Sugden (1987) at 26.5%. Hence, for any two choice pairs over the same vector of payoffs, there is a 32% chance the representative subject will violate EU merely due to natural variability in their responses.[22]

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[22] The variability rate of 32% corresponds to an natural error rate of 20% for each question. The rate of 32% shows inconsistency over *two* choice pairs. There are two ways for a person to show this inconsistency: by choosing correctly on the first pair and choosing incorrectly on the second pair, or by choosing incorrectly on the first pair and correctly on the second pair. Thus, the error rate of 20% corresponds to the variability rate of 32% (2 x (0.8)(0.2) = 0.32).

A PASCAL program was written to compare all pairs of individual choices over a common payoff vector. As described in Chapter 3, the experiment was designed such that any two choice pairs with the same payoff vector should elicit the same preference under EU (either both riskier or both less risky). The program evaluated each pair of choices for their consistency with EU and measured their difference in fitted similarity and in other general characteristics. For pairs that violated EU, the program also evaluated the type of violation relative to that predicted by the similarity hypothesis. As reviewed in Chapter 2, the similarity hypothesis predicts that subjects will violate EU by choosing the riskier alternative on the more similar pair and selecting the less risky alternative on the less similar pair. Thus, the PASCAL program determined the type of violation per the fitted similarity estimates from the regression in Table 5. In the analysis to follow, violations of the type predicted by the similarity hypothesis are denoted by "Type A" and violations contrary to that predicted by the similarity hypothesis are denoted by "Type B."

Tables 10 and 11 report the number and type of EU violations. Because the natural error rate suggests that 32 percent of the pairs should violate EU "naturally," the observed number of 38.8 percent is not especially large. The test statistic, calculated using the same proportion difference test statistic given in the first section of this chapter, is 1.76. There are slightly more violations than expected; this difference, however, is significant with about 4 percent confidence with a single tailed test.

Table 11 shows, however, that there is a strong bias towards the type of violation predicted by similarity, denoted by "Type A."[23] Moreover, Table 12, which compares the expected and observed number of violations implied by the natural error rate, shows that the excess violations are due entirely to those predicted by the similarity hypothesis.[24] The t-statistics in Table 12 are calculated using the same proportion test statistic given earlier in this chapter. While the t-statistic of 2.16 shows a significantly greater number of "Type A" violations with about 1.5% confidence, the t-statistic of 0.07 shows that there is clearly no significant difference between the expected and observed number of "Type B" violations. Thus, the similarity hypothesis explains all EU violations not accounted for by the natural error rate.

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[23] This test statistic is that derived by Conlisk (1989) to show the violation bias in his three variants of the Allais example as reviewed in Chapter 2.

Formally: $$Z = \frac{(S_A - 1/2)\sqrt{N-1}}{\sqrt{(1/4V) - (S_A - 1/2)^2}} \sim N(0,1)$$

Where S_A equals the proportion of violations that are of "Type A," V equals the proportion of question pairs that are violations, and N equals the number of question pairs.

[24] The expected number of violations is derived from the natural error rate assuming that natural errors will be perfectly random; that is, the chance of being "Type A" equals that of being "Type B." Thus, where the natural error rate implies that 32% of the choice pairs will be in violation of EU, randomness of violations implies that there will be 0.32/2 = 0.16, or 16% violations of each type.

Table 10. Summary of EU Violations

	Number	Percent of Total
Consistent with EU	4622	61.2
Violation of EU	2928	38.8
Test Statistic for Difference from Natural Error Rate of 32%	1.76	

Table 11. Summary of Violation Types

	Number	Percent of Total
Violation Type "A"	1733	59.2
Violation Type "B"	1195	40.8
Test Statistic for Significant Bias in Violation Type	10.01	

Table 12. Observed and Expected Violations

	Number Observed/Expected	Percent of Total Observed/Expected	T-Ratio for Difference
Consistent with EU	4622/5134	61.8/68.0	1.76
Violation Type "A"	1733/1208	23.0/16.0	2.16
Violation Type "B"	1195/1208	15.8/16.0	0.07

The Effect of Context on EU Violations

The preceding shows that similarity causes choices to be biased away from EU. But because context affects the influence of similarity on risky choice, context should also affect the bias towards the type of violations that similarity predicts. Specifically, the hypothesis in Chapter 3 proposes that a

scenario-context should reduce the bias toward the "Type A" violations. Logit regression models are used to test if context does indeed affect the frequency and type of EU violations.[25]

Table 13. Variable Definitions for EU Violation Logit Models

Variable Name	Definition
Strength of Preference	Absolute value of (0.5 - Mean Individual Response) where Mean Individual Response is as previously defined in Tables 6 and 7.
Similarity Difference	Difference in fitted similarity from GLS regression
Average Similarity	Average fitted similarity of the two alternatives
Difference in EVD	Difference in EVD (expected value difference) as defined previously
Difference in MEV	Difference in MEV (minimum expected value as defined previously
Scenario vs. Scenario (SS)	Dummy Variable = 1 when both pairs are in a scenario context
Lottery vs. Lottery (LL)	Dummy variable = 1 when both pairs are in a lottery context
LL × Sim. Difference	LL× difference in fitted similarity
LL × Ave. Similarity	LL× average fitted similarity
SS × Sim. Difference	SS × difference in fitted similarity
SS × Ave. Similarity	SS × average fitted similarity

A logit model isolating the *bias* of violations, as in Table 11, is needed. The following logit models therefore estimate the likelihood of a "Type A" violation. In these regressions, all observations consistent with EU are skipped and the type of violation is specified by the values of the dependent variable. The dependent variable equals 1 for violations of "Type A" and

25 The logit models for the likelihood of an EU violation are given in Appendix B. These regression are very weak, presumably because most violations result from the natural error rate and are therefore purely random. Because the *bias* towards the "Type A" violation is the issue of most interest, the discussion focuses on these logit regressions.

equals 0 for violations of "Type B." Thus, if EU accurately represented people's choices, both types of violations would be equally likely and no explanatory variables could predict the type of violation. Recall from the description of the logit regression model earlier in this chapter (equation 7) that when Z_i equals zero, the likelihood function equals 0.5; that is, if the likelihood function is regressed only on a constant, and the estimated constant value equals zero, then a 1 and 0 are equally likely.

A logit regression model regressing just a constant on violation type is therefore very similar to the bias test shown in Table 11. The simple logit model in Table 14 is just this kind of regression. Rather than regress on just a constant, however, the constant value is divided into two dummy variables: one for lotteries and one for scenarios. Thus, while Table 11 tests for a similarity induced bias over the entire sample, the regression in Table 14 tests for similarity-induced bias over lotteries and scenarios separately. As the similarity model predicts, the Lottery vs. Lottery constant term shows strong significance toward the type of violation predicted by similarity. For the Scenario vs. Scenario variable, however, the bias is negative, indicating a greater likelihood of a "Type B" violation, although the t-ratio of 1.18 is clearly insignificant. Hence, for this simple logit model, EU cannot be rejected over scenario-contexts.

Table 14. Logit Model #1 for Likelihood of EU Violation Type "A"

Variable Name	Coefficient	Standard Error	T-Ratio
Scenario vs. Scenario (SS)	-0.49597E-01	0.18187	-0.27270
Lottery vs. Lottery (LL)	0.38739	0.38460E-01	10.073

Dependent Variable: 0 for EU violation of "Type B," 1 for violation of "Type A"

Likelihood Ratio Test = 2.8 with 1 D.F. (relative to constant term only)

Prediction Success Table:

		Actual	
		0	1
Predicted	0	62	59
	1	1135	1672

Percentage of Right Predictions = 0.59221

The logit model in Table 14 fails to account for different magnitudes of similarity differences. Although the similarity hypothesis predicts that excessive EU violations will occur due to subjects choosing the less risky alternative on the less similar choice pair and choosing the riskier alternative on the more similar choice pair, for similarity differences that are very small, the bias will likely be very small. Clearly, a more rigorous model is needed to account for the relative differences in similarity and to test whether the scenarios reduce the relative effect of similarity. The logit model in Table 15 accounts for the effects of relative similarity differences. Several additional variables are included in this model as compared to the simple model in Table 14 to shed further light on the cause of violation biases, or lack thereof.

Table 15. Logit Model #2 for Likelihood of EU Violation Type "A"

Variable Name	Coefficient	Standard Error	T-Ratio
Strength in Preference	1.4508	0.37200	3.9001
LL × Sim. Difference	0.35536	0.52779E-01	6.7329
LL × Ave. Similarity	-0.92593E-01	0.61607E-01	-1.5030
SS × Sim. Difference	0.46231	0.44534	1.0381
SS × Ave. Similarity	-0.23582	0.11326	-2.0822
Difference in EVD	0.80049E-03	0.21214E-03	3.7734
Difference in MEV	-0.36283E-04	0.10297E-04	-3.5237
Constant	0.23790	0.31299	0.76009

Dependent Variable: 0 for EU violation of "Type B," 1 for violation of "Type A"

Likelihood Ratio Test = 90.6 with 7 D.F.

Prediction Success Table:

		Actual	
		0	1
Predicted	0	225	194
	1	972	1537

Percentage of Right Predictions = 0.60178

The Strength of Preference variable is a proxy for the variability in each subject's choices.[26] The interpretation of Strength of Preference for this regression is rather subtle. When Strength of Preference is small, the subject switches choices quite frequently, presumably because the subject was nearly indifferent between the alternatives or perhaps because the subject did not take the survey very seriously. While subjects with very low Strength of

[26] The Strength in Preference variable equals the absolute value of (0.5-Mean Response). Because all "indifferent" choices are necessarily skipped for this regression, the Mean Response variable becomes the proportion of riskier choices by an individual over the survey. The Mean Response variable can therefore be likened to a binomial distribution. Because a binomial distribution has the greatest variance when the proportion parameter (in this case Mean Response) equals 0.5, and variance decreases as the proportion parameter gets further from 0.5, the larger the value of Strength in Preference, the less the variability in that individual's responses.

Preference will violate EU frequently, their violations will likely be more random. The significantly positive value of Strength of Preference indicates that those with stronger preference (or those that took the survey more seriously) were therefore more likely to violate EU *systematically* as predicted by the similarity hypothesis.

The Similarity Difference variable measures the absolute difference in fitted similarity per the GLS estimate in Table 5. Akin to the logit analysis prediction for the likelihood of a riskier choice, the effect of Similarity Difference is measured separately for scenarios (by the variable SS × Sim. Difference) and lotteries (by the variable LL × Sim. Difference) As the similarity model predicts, the greater the absolute difference in similarity, the more likely a violation of "Type A" for lotteries. For scenarios, however, the difference in similarity does not significantly affect the likelihood of a "Type A" violation, indicating that the bias caused by similarity has been reduced.

Average Similarity measures the average fitted similarity. Recall that alternatives were judged to be similar for larger values of similarity and were judged to be dissimilar for smaller values of similarity. Thus, as both alternatives become more similar, the bias towards the "Type A" violation is reduced. The Average Similarity variable must be interpreted in conjunction with Similarity Difference. If Similarity Difference were not in the regression, Average Similarity would not be significant (per other regressions not shown). Average Similarity is also measured for Scenarios and Lotteries separately ("SS × Ave. Similarity" and "LL × Ave. Similarity," respectively). Both variables show that when both alternatives become more similar, the

implications for choice are obscured. This effect is in line with the similarity hypothesis of Rubenstein (1988) and Buschena (1992). Finally, the variables Difference in EVD (the pairs' expected value differences) and Difference in MEV (the pairs' minimum expected value differences) capture some of the effects of similarity and differences between different payoff vectors.

The constant term is not significantly different from zero. As described earlier, a constant value of zero indicates that a dependent variable of 0 and 1 are equally as likely after accounting for all other variables. For this regression, the insignificance of the constant term implies that both types of errors are equally as likely after accounting for similarity and payoff differences. Thus, the model captures all influences that bias choice away from EU.

Summary of Results

The experimental evidence that finds fault with EU's independence axiom, and the many researchers proposing generalizations to EU that weaken the axiom, believe peoples *preferences* to be more sensitive to changes in probability distribution than the independence axiom suggests. Alternatively, this research finds people's experimental *choices* to be very sensitive the experimental design. In particular, the context of the alternatives significantly affects subjects' choices and substantially reduces their inconsistency with what EU predicts. The choices in this experiment over "real life" scenario-type contexts do not reject the EU hypothesis, while choices over lotteries do. The similarity hypothesis offered by Rubenstein (1988), Leland (1992a,b), Azipurua et al. (1993) and Buschena (1992) explains the bias well for lottery contexts.

CHAPTER 5

CONCLUSIONS & EXTENSIONS

Understanding methodology is material to the interpretation of empirical findings. In economics, perhaps more than in most sciences, research must be clear in its assumptions. Because of the many complications clouding the interpretation of market data, correlation, and especially causation, are difficult to isolate. These complications of the "real world" likely explain why so many economists often come to different conclusions; small differences in assumptions can produce very different results.

An experimental design, such as that used in this thesis and the research reviewed in Chapter 2, therefore has strong appeal. The many complications of the "real world" seem to vanish, and it seems few assumptions are needed. This research shows, however, that economists using experimental data must also pay close attention to their assumptions. Indeed, for the case of experimental risky choices, it may be the departure from the "real world" that causes choices to depart so markedly from those theorized by EU.

The extended footnote in Chapter 2 that discusses another possible explanation for the "St. Petersburg Paradox" is a case in point. In hypothesizing a concave utility function in wealth given subjects' bids to buy and sell the "St. Petersburg gamble," theorists have assumed that people

could envision, and choose in accordance with, alternatives from a world that could never exist. For experimental risky choice research, it is assumed that choices over arbitrary lottery gambles with hypothetical payoffs reasonably approximate "real world" types of risky decisions. While the experiment used for this thesis makes similar assumptions, it modestly attempts to relate the arbitrary gambles to real world types of decisions. Yet this modest change elicits significantly different responses that are contrary to earlier findings questioning the validity of EU. Clearly, experimental EU violations are sensitive to the context of choice pairs.

The sensitivity of the experimental design demonstrates, much like the work on similarity by Rubinstein (1988), Leland (1992a,b), Azipurua et. al (1993), and Buschena (1992), that the accuracy of choice, like all objective functions in economics, is constrained by costs. Decision making is costly, and relates to people's "choice functions" that include many variables such as time, similarity, and as this thesis demonstrates, context. It is likely that other constraints also affect people's choices. But rather than change the objective function in an "ad hoc" manner as in the GEU theories , this thesis moves towards providing an *explanation* for choices that deviate from EU . These GEU theories are not consistent with modern economic methodology. Before the objective function is changed or weakened to account for observed behavior, economists must first determine if they have accounted for all constraints. Contrary to the GEU models, this thesis takes another step towards understanding the constraints people face when making risky decisions.

Summary of the Chapters

Chapter 2 reviews some of the expansive literature on EU violations, the theories used to account for EU violations, including the GEU models and the similarity hypotheses, and context effects on choice. The most widely documented evidence of EU violations use experimental data and are frequently referred to as the "Allais Paradox," the "common consequence effect," the "common ratio effect," and the "certainty effect" (e.g. Allais, 1953; Kahneman and Tversky, 1978). The GEU models propose valuation functions that are more flexible than EU to allow for the responses observed experimentally (e.g. Chew and MacCrimmon, 1979; Chew, 1983; Gul, 1991; Dekel, 1986; Quiggin, 1982, 1985; Segal, 1987, 1989; Yaari, 1987; Kahneman and Tversky, 1979; and Machina, 1982). Recent work by Conlisk (1989), Camerer (1989, 1992), and others, find that the GEU models still do not allow for all types of EU violations. Camerer's work proposes six stylized facts that summarize experimental findings on choice; no GEU model is consistent with all six stylized facts.

Alternatively, the similarity models propose that EU may indeed model people's true *preferences*, but that *choices* may sometimes be biased due to approximation methods that relate to the similarity of the alternatives (Luce, 1956; Rubinstein, 1988; Leland, 1992a,b; Azipurua, 1993; and Buschena, 1992). These hypotheses propose that the similarity of the alternatives affects the costs and benefits of decision making. Thus, the similarity models find that EU violations result from carefully chosen choice pairs that exploit subject's approximation methods. In addition to offering a

plausible explanation for observed EU violations, Buschena (1992) finds his similarity model to have stronger empirical support than the GEU models.

Some work briefly examines possible context effects on choice (e.g. Hershey and Schoemaker, 1980; Heath and Tversky, 1991; and Kahneman and Lovallo, 1993). This work, however, does not relate directly to the incidence of EU violations. This thesis moves toward expanding the current understanding of context on choice, especially with regard to EU violations.

Chapter 3 motivates and explains the experimental design used in this thesis. The chapter discusses issues involved with the difference between research that uses market data, as traditionally used in economic analysis, and research that uses experimentally generated data, like that used to show EU violations. The differences between EU and the GEU models are very small over most gambles. Indeed, EU is a special case within all GEU models. Finding market data strong enough to distinguish between EU and GEU models, or between alternative GEU models, would be extremely difficult. Risky choice research that uses experimentally generated data allows for direct tests between these different risky choice theories.

To what extent do experimental EU violations result from the experimental design that exposes them? The experimental design may be too far removed from the "real world" for market choices to be reasonably represented. Before discarding EU as a reasonable description of people's market choices, the robustness of the violations should be tested across different experimental conditions. Thus, this thesis tests for the robustness of EU violations across different contexts. While the data are still generated experimentally, the test conditions are changed somewhat to include more

"realistic" scenario-contexts along with the lottery contexts used in previous research.

The empirical work reported in Chapter 4 finds that context does indeed affect subject's choices. Simple proportion-difference test statistics show that, relative to lottery-contexts, scenario-contexts elicit a significantly different proportion of riskier responses over certain risky alternatives. The pattern of the effects, however, are not readily apparent. More rigorous analysis, using logit regression models, shows that the scenario-contexts reduce the biasing effects of similarity. While the experimental data strongly support the similarity hypothesis for choices over lotteries, similarity effects are not significant for choices over scenarios. The analysis indicates that the "realistic" scenario-contexts reduce the bias caused by similarity. Moreover, choices over scenario-contexts, and choices over lottery contexts adjusted for the effects of similarity, fail to reject EU.

Extensions

A more carefully designed experiment could yield stronger tests for the effects of context. The scenario-context choice pairs only include those in upper-left region of the risk triangle. These pairs were chosen because it was easier to find more realistic gambles that pertained to this region. It remains unclear if context has the same similarity-reducing effects in the lower-right region of the risk triangle. The statistical analysis also could be strengthened with a greater variety of gambles for each scenario story. This experiment only incorporates two choice pairs for each scenario story. A broader experiment is needed to distinguish more clearly between the similarity-

reducing effects of scenario-contexts and effects resulting from the particulars of each scenario-story.

This thesis was to have also incorporated responses from Montana seed potato farmers. The inadequate sample size, however, did not yield meaningful results. Because most work on risky choice has included only student subjects, experiments still need to be carried out over different subject groups. Agricultural producers would be particularly attractive subjects because most are sole proprietors, are subjected to a great deal of risk (e.g. weather and price variability), and presumably have experience making risky decisions. The rationale for including different subject groups, particularly those that may be more experienced making risky decisions, is like that for including different contexts; that is, to test the robustness of EU violations across different test conditions.

While more work is clearly needed to investigate the descriptive accuracy of EU, this thesis shows that empirical results should be interpreted more carefully, especially when using experimentally generated data. Before changing the objective function, one must first look to other plausible explanations for observed behavior.

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APPENDICES

APPENDIX A

SUPPLEMENTARY TABLES & REGRESSIONS

Summary Tables

Table 16. Summary Statistics of Key Explanatory Variables

Variable Name	Mean	Standard Deviation	Minimum	Maximum
Strength of Preference	0.15794	0.10449	0.00000E+00	0.45500
Similarity Difference	1.1015	0.77739	0.10000E-02	3.8820
Average Similarity	4.9151	0.65824	3.0970	6.9440
Difference in EVD	118.34	213.84	0.00000E+00	1120.0
Difference in MEV	2592.7	4148.5	0.00000E+00	21350.
Fitted Similarity	4.8043	0.97152	2.9300	7.1010
PDM	0.49215	0.29448	0.25923	1.2961
PDM^2	0.32890	0.42524	0.67200E-01	1.6800
PDM^3	0.28473	0.53772	0.17420E-01	2.1775
Expected Value Difference (EVD)	211.39	265.83	4.0000	1400.0
EVR = (EVD/MEV)	0.31360E-01	0.20354E-01	0.10526E-01	0.66667E-01

Table 17. Summary of Lottery Responses

Choice Pair	Payoff Vector	Number Less Risky	Number Riskier	Indifferent Responses	% Risky
1	1	18	11	1	0.379
E vs G	2	36	10	3	0.217
	3	27	7	1	0.206
2	1	21	15	1	0.417
A vs. C	2	37	19	2	0.339
	3	9	10	1	0.526
3	1	52	2	0	0.037
B vs. C	2	21	2	0	0.087
	3	26	3	0	0.103
4	1	37	15	2	0.288
A vs. B	2	20	3	2	0.130
	3	29	10	1	0.256
5	1	35	10	2	0.222
D vs. E	2	23	5	0	0.179
	3	28	9	0	0.243
6	1	44	17	1	0.279
H vs. I	2	16	10	1	0.385
	3	19	7	1	0.269

Choice Pair	Payoff Vector	Number Less Risky	Number Riskier	Indifferent Responses	% Risky
7	1	10	13	1	0.565
F vs. G	2	30	22	0	0.423
	3	16	17	0	0.515
8	1	16	20	0	0.556
L vs. M	2	25	25	1	0.500
	3	19	11	1	0.367
9	1	29	27	2	0.482
H vs. K	2	41	25	1	0.379
	3	37	26	1	0.413
10	1	29	28	0	0.491
H vs. K	2	31	27	3	0.466
	3	32	29	4	0.475
11	1	39	18	6	0.316
T vs. U	2	24	25	8	0.510
	3	24	25	9	0.510
12	1	32	17	5	0.347
T vs. V	2	39	21	8	0.350
	3	41	15	4	0.268
13	1	31	9	7	0.225
S vs. V	2	33	14	9	0.298
	3	44	20	9	0.313
14	1	28	26	13	0.481
W vs. X	2	19	18	11	0.486
	3	34	15	16	0.306
15	1	37	17	4	0.315
N vs. O	2	32	19	1	0.373
	3	36	26	7	0.419
16	1	28	24	2	0.462
O vs. P	2	27	31	1	0.534
	3	38	23	3	0.377
17	1	32	13	5	0.289
P vs. Q	2	24	32	3	0.571
	3	29	34	6	0.540
18	1	22	15	2	0.405
Q vs. R	2	36	22	1	0.379
	3	48	28	4	0.368
19	1	43	5	4	0.104
N vs. R	2	47	12	2	0.203
	3	54	10	4	0.156
20	1	40	17	0	0.298
J vs. K	2	34	17	1	0.333
	3	55	19	0	0.257

Table 18 Summary of Scenario Resopnses

Choice Pair	Payoff Vector	Number Less Risky	Number Riskier	Indifferent Responses	% Risky
1	1				
E vs G	2	51	32	2	0.386
Career Job	3				
2	1				
A vs. C	2	52	31	2	0.373
Career Job	3				
3	1	66	26	2	0.283
B vs. C	2				
Used Car	3				
4	1	56	18	3	0.243
A vs. B	2				
Used Car	3				
5	1	46	39	2	0.459
D vs. E	2				
Part Time Job	3				
6	1	60	23	1	0.277
H vs. I	2				
Part Time Job	3				
7	1				
F vs. G	2	63	31	1	0.330
Grandmother	3				
8	1				
L vs. M	2	59	15	2	0.203
Grandmother	3				

Supplementary Similarity Estimates

Table 19. GLS Similarity Estimate #1

Variable Name	Coeficient	Standard Error	T-Ratio
P2 (Risky Pair E vs. F)	1.527	0.403	3.778
P3 (Risky Pair A vs. C)	-0.392	0.368	-1.065
P4 (Risky Pair B vs. C)	0.251	0.335	0.748
P5 (Risky Pair A vs. B)	-1.008	0.368	-2.738
P6 (Risky Pair D vs. E)	0.370	0.369	1.003
P7 (Risky Pair H vs. I)	0.242	0.384	0.631
P8 (Risky Pair F vs. G)	0.848	0.329	2.585
P9 (Risky Pair L vs. M)	0.665	0.301	2.211
P10 (Risky Pair H vs. K)	1.188	0.325	3.655
P11 (Risky Pair T vs. U)	2.110	0.321	6.566
P12 (Risky Pair T vs. V)	1.012	0.305	3.312
P13 (Risky Pair S vs. V)	2.588	0.326	9.945
P14 (Risky Pair W vs. X)	2.849	0.321	8.865
P15 (Risky Pair N vs. O)	1.145	0.316	3.623
P16 (Risky Pair O vs. P)	2.080	0.307	6.775
P17 (Risky Pair P vs. Q)	2.199	0.357	6.154
P18 (Risky Pair Q vs. R)	1.041	0.323	3.221
P19 (Risky Pair N vs. R)	0.648	0.295	2.198
P20 (Risky Pair J vs. K)	-0.219	0.327	-0.670
Payoff Dummy #1	-0.412	0.115	-3.575
Payoff Dummy #2	-0.366	0.117	-3.126
Constant	4.224	0.562	7.518

Also, not shown, are 170 dummy variables representing each subject.

996 Observations, 807 Degrees of Freedom

$R^2 = 0.8321$ R^2-Adj. = 0.7929

Table 20. GLS Similarity Estimate #2

Variable Name	Coeficient	Standard Error	T-Ratio
P2 (Risky Pair E vs. F)	1.4465	0.3969	3.645
P3 (Risky Pair A vs. C)	-0.39205	0.3805	-1.030
P4 (Risky Pair B vs. C)	0.16509	0.3383	0.48807
P5 (Risky Pair A vs. B)	-1.0660	0.3631	-2.936
P6 (Risky Pair D vs. E)	0.31044	0.3750	0.8278
P7 (Risky Pair H vs. I)	0.16639	0.3887	0.4281
P8 (Risky Pair F vs. G)	0.82691	0.3341	2.475
P9 (Risky Pair L vs. M)	0.58432	0.3011	1.941
P10 (Risky Pair H vs. K)	1.1701	0.3298	3.548
P11 (Risky Pair T vs. U)	2.2418	0.3250	6.897
P12 (Risky Pair T vs. V)	0.98785	0.3123	3.163
P13 (Risky Pair S vs. V)	2.4262	0.3288	7.379
P14 (Risky Pair W vs. X)	2.8735	0.3263	8.807
P15 (Risky Pair N vs. O)	1.1222	0.3169	3.541
P16 (Risky Pair O vs. P)	2.0263	0.3108	6.519
P17 (Risky Pair P vs. Q)	2.2062	0.3539	6.233
P18 (Risky Pair Q vs. R)	1.0713	0.3293	3.254
P19 (Risky Pair N vs. R)	0.61354	0.2995	2.048
P20 (Risky Pair J vs. K)	-0.36159	0.3356	-1.077
S1 (Career Job "A")	0.78127	0.4304	1.815
S2 (Career Job "B")	-0.69344E-01	0.4623	-0.1500
S3 (Used Car "A")	-0.23689	0.4778	-0.4958
S4 (Used Car "B")	-0.28992	0.4411	-0.6573
S5 (Part Time Job "A")	1.0897	0.3967	2.747
S6 (Part Time Job "B")	0.13679E-01	0.4227	0.3236E-01
S7 (Grandmother "A")	-0.15000	0.4425	-0.33906
S8 (Grandmother "B")	0.76208	0.3839	1.985
Question Number	0.15431E-01	0.6992E-02	2.207
Payoff Dummy #1	-0.34624	0.1171	-2.9561
Payoff Dummy #2	-0.30083	0.1216	-2.474
Constant	4.2376	0.4987	8.497

Also, not shown, are 170 dummy variables representing each individual.

1167 Observations, 967 Degrees of Freedom

$R^2 = 0.7882$ R^2-Adj. = 0.7446

Supplementary Logit Regressions

Table 21. Logit #3 Prediction for Riskier Choice

Variable Name	Coefficient	Standard Error	T-Ratio
Mean Individual Response	5.4201	0.23706	22.864
Fitted Similarity	0.34125	0.48594E-01	7.0226
Similarity × Scenario	-0.97761	0.22235	-4.3967
Career Job	0.50789	1.1141	0.45589
Used Car	-0.91005	0.79582	-1.1435
Part Time Job	-0.38261E-01	0.88293	-0.43335E-01
Grandmother	-0.36373	1.0076	-0.36098
Lottery	-4.4175	0.28639	-15.425
Payoff Dummy #1	-0.13858E-02	0.10690	-0.12964E-01
Payoff Dummy #2	0.20676	0.10588	1.9528

Likelihood Ratio Test = 737.0 with 7 Degrees of Freedom

Prediction Success Table:

		Actual	
		0	1
Predicted	0	2021	711
	1	296	526

Percentage of Right Predictions = 0.71666

Table 22. Logit Model #1 for EU Violation

Variable Name	Coefficient	Standard Error	T-Ratio
Strength of Preference	-4.8849	0.20592	-23.723
Similarity Difference	0.50424E-01	0.31416E-01	1.6051
Average Similarity	0.18511	0.36700E-01	5.0438
Difference in EVD	0.26298E-03	0.13063E-03	2.0132
Difference in MEV	0.22915E-04	0.68270E-05	3.3565
Scenario vs. Scenario (SS)	0.11885	0.12777	0.93014
Constant	0.19330	0.66887E-01	2.8900

Dependent Variable: 0 for EU consistent, 1 for EU violation

Likelihood Ratio Test = 671.5 with 6 D.F.

Prediction Success Table:

		Actual	
		0	1
Predicted	0	3698	1928
	1	924	1000

Percentage of Right Predictions = 0.62225

Table 23. Logit Model #2 for EU Violation

Variable Name	Coefficient	Standard Error	T-Ratio
Strength in Preference	-4.8903	0.20601	-23.738
Similarity Difference	0.48461E-01	0.31174E-01	1.5545
Average Similarity	0.19148	0.36808E-01	5.2021
Difference in EVD	0.27046E-03	0.13075E-03	2.0685
Difference in MEV	0.22712E-04	0.68279E-05	3.3264
SS × Sim. Difference	0.10474	0.16031	0.65334
SS × Ave. Similarity	-0.35850	0.22592	-1.5869
Constant	0.19250	0.65777E-01	2.9266

Dependent Variable: 0 for EU consistent, 1 for EU violation

Likelihood Ratio Test = 673.5 with 7 D.F.

Prediction Success Table:

		Actual	
		0	1
Predicted	0	3701	1923
		921	1005

Percentage of Correct Predictions = 0.62331

APPENDIX B

COMPUTER PROGRAMS

PASCAL Program for Creating Surveys

```
PROGRAM Survey (INPUT, OUTPUT, Pfile, Ofile, S1, S2, S3, S4, S5,
        S6, S7, S8, Test, TestDat);

CONST
   TestNo = 240;
   Pmax = 20;
   Qmax = 22;
   RegPrompt = 'Circle the gamble that you like best.';
   Smax = 4;

TYPE Pmatrix = array[1..PMAX,1..6] of REAL;
   Outmatrix = array[1..3,1..3] of INTEGER;
   Qnum = array[1..Qmax] of INTEGER;
   Pnum = array[1..Pmax] of INTEGER;
   Smatrix = array[1..10, 1..100, 1..80] of CHAR;
   linmat = array[1..10] of INTEGER;
   colmat = array[1..10, 1..100] of INTEGER;

VAR  Pfile : TEXT;
   Ofile : TEXT;
   Prompt : TEXT;
   S1 : TEXT;
   S2 : TEXT;
   S3 : TEXT;
   S4 : TEXT;
   S5 : TEXT;
   S6 : TEXT;
   S7 : TEXT;
   S8 : TEXT;
   Test : TEXT;
   TestDat : TEXT;
   Prob : Pmatrix;
   Out : Outmatrix;
   QN : Qnum;
   PN : Pnum;
   AB : INTEGER;
   Scenario : Smatrix;
   colmax : colmat;
   linmax : linmat;


FUNCTION MTH$RANDOM (Seed : INTEGER) : REAL;
FORTRAN;
```

```
PROCEDURE ReadData(VAR Prob : Pmatrix; VAR Out : Outmatrix;
        VAR Scenario : Smatrix; VAR linmax : linmat;
        VAR colmax : colmat);

VAR  z, x, y, i, j : INTEGER;


BEGIN

OPEN (Pfile,
   FILE_NAME := 'riskprob.dat',
   HISTORY := READONLY);
OPEN (Ofile,
   FILE_NAME := 'outcomes.dat',
   HISTORY := READONLY);
OPEN (S1,
   FILE_NAME := 'scen1.dat',
   HISTORY := READONLY);
OPEN (S2,
   FILE_NAME := 'scen1A.dat',
   HISTORY := READONLY);
OPEN (S3,
   FILE_NAME := 'scen2.dat',
   HISTORY := READONLY);
OPEN (S4,
   FILE_NAME := 'scen2A.dat',
   HISTORY := READONLY);
OPEN (S5,
   FILE_NAME := 'scen3.dat',
   HISTORY := READONLY);
OPEN (S6,
   FILE_NAME := 'scen3A.dat',
   HISTORY := READONLY);
OPEN (S7,
   FILE_NAME := 'scen4.dat',
   HISTORY := READONLY);
OPEN (S8,
   FILE_NAME := 'scen4A.dat',
   HISTORY := READONLY);


RESET (Pfile);
RESET (Ofile);
RESET (S1);
RESET (S2);
```

```
RESET (S3);
RESET (S4);
RESET (S5);
RESET (S6);
RESET (S7);
RESET (S8);

FOR i := 1 TO Pmax DO
   FOR j := 1 TO 6 DO
      READ (Pfile,Prob[i,j]);

FOR i := 1 TO 3 DO
   FOR j := 1 TO 3 DO
      READ (Ofile,Out[i,j]);


   x := 0;
   WHILE NOT (EOF(S1)) DO BEGIN
      x := x+1;
      y := 0;
      WHILE NOT (EOLN(S1)) DO BEGIN
         y := y+1;
         READ(S1, Scenario[1,x,y]);
         END;
      Colmax[1,x] := y;
      READLN (S1);
      END;
   linmax[1] := x;

   x := 0;
   WHILE NOT (EOF(S2)) DO BEGIN
      x := x+1;
      y := 0;
      WHILE NOT (EOLN(S2)) DO BEGIN
         y := y+1;
         READ(S2, Scenario[2,x,y]);
         END;
      Colmax[2,x] := y;
      READLN (S2);
      END;
   linmax[2] := x;

   x := 0;
   WHILE NOT (EOF(S3)) DO BEGIN
      x := x+1;
      y := 0;
      WHILE NOT (EOLN(S3)) DO BEGIN
```

```
        y := y+1;
        READ(S3, Scenario[3,x,y]);
        END;
    Colmax[3,x] := y;
    READLN (S3);
    END;
linmax[3] := x;

x := 0;
WHILE NOT (EOF(S4)) DO BEGIN
    x := x+1;
    y := 0;
    WHILE NOT (EOLN(S4)) DO BEGIN
        y := y+1;
        READ(S4, Scenario[4,x,y]);
        END;
    Colmax[4,x] := y;
    READLN (S4);
    END;
linmax[4] := x;

x := 0;
WHILE NOT (EOF(S5)) DO BEGIN
    x := x+1;
    y := 0;
    WHILE NOT (EOLN(S5)) DO BEGIN
        y := y+1;
        READ(S5, Scenario[5,x,y]);
        END;
    Colmax[5,x] := y;
    READLN (S5);
    END;
linmax[5] := x;

x := 0;
WHILE NOT (EOF(S6)) DO BEGIN
    x := x+1;
    y := 0;
    WHILE NOT (EOLN(S6)) DO BEGIN
        y := y+1;
        READ(S6, Scenario[6,x,y]);
        END;
    Colmax[6,x] := y;
    READLN (S6);
    END;
linmax[6] := x;
```

```
    x := 0;
    WHILE NOT (EOF(S7)) DO BEGIN
       x := x+1;
       y := 0;
       WHILE NOT (EOLN(S7)) DO BEGIN
          y := y+1;
          READ(S7, Scenario[7,x,y]);
          END;
       Colmax[7,x] := y;
       READLN (S7);
       END;
    linmax[7] := x;

    x := 0;
    WHILE NOT (EOF(S8)) DO BEGIN
       x := x+1;
       y := 0;
       WHILE NOT (EOLN(S8)) DO BEGIN
          y := y+1;
          READ(S8, Scenario[8,x,y]);
          END;
       Colmax[8,x] := y;
       READLN (S8);
       END;
    linmax[8] := x;

END;


PROCEDURE RandOrder(VAR Q : Qnum; VAR Outn : Qnum; VAR Seed
:INTEGER);

VAR  Low, High, i, j, N, z : INTEGER;
    Ok : BOOLEAN;
    SV,TP : Qnum;

    PROCEDURE WOReplace(Low, High : INTEGER;VAR Q : Qnum;
                        VAR Seed : INTEGER);

    VAR N : INTEGER;

    BEGIN

    N := High - Low + 1;
    Q[Low] := TRUNC(N*(MTH$RANDOM(Seed)) + Low);

    FOR i := (Low + 1) TO High DO BEGIN
```

```
        Ok := FALSE;
        WHILE NOT(Ok) DO BEGIN
            Ok := TRUE;
            Seed := Seed + 1;
            Q[i] := TRUNC(N*(MTH$RANDOM(Seed)) + Low);
            FOR j := Low TO (i-1) DO BEGIN
                IF  Q[i] = Q[j] THEN
                    Ok := FALSE;
                END;
            END;
        END;
    END; {nested procedure}

BEGIN

Low := 1;
High := Smax;
WOReplace(Low, High, Q, Seed);

FOR i := 1 TO Smax DO BEGIN
    SV[i] := (TRUNC(2*(MTH$RANDOM(Seed)))+(2*i)-1);
    Seed := Seed + 1;
    END;

FOR i := 1 TO Smax DO BEGIN
    z := Q[i];
    Q[i] := SV[z];
    If Q[i] mod 2 = 0 Then
        TP[i+Smax] := Q[i]-1
    Else
        TP[i+Smax] := Q[i]+1;
    END;

FOR i := (2*Smax + 1) TO Pmax DO
    TP[i] := i;

Low := Smax + 1;
High := Pmax;
WOReplace(Low, High, Q, Seed);

FOR i := (Smax + 1) TO Pmax DO
    Q[i] := TP[Q[i]];

Low := 1;
High := Qmax;
WOReplace(Low, High, Outn, Seed);
```

```
FOR i := 1 TO High DO BEGIN
   IF Outn[i] <= Qmax/3 THEN
      Outn[i] := 1;
   IF ((Outn[i] <= Qmax*2/3) AND (Outn[i] > Qmax/3)) THEN
      Outn[i] := 2;
   IF (Outn[i] > 2*Qmax/3) THEN
      Outn[i] := 3;
   END;


END;

PROCEDURE RandAorB (VAR FirstChoice : Qnum; VAR Prob : Pmatrix;
         VAR Seed : INTEGER);

VAR  x, TEMP1, TEMP2, TEMP3 : REAL;
   j, i : INTEGER;

BEGIN

For i:= 1 to Smax DO
   FirstChoice[i] := 0;

FOR i := 1 TO Pmax DO BEGIN

   Seed := Seed + 1;

   FirstChoice[i] := TRUNC(2*MTH$RANDOM(Seed)+1);

   IF FirstChoice[i] = 2 THEN BEGIN
      Temp1 := Prob[i,1];
      Temp2 := Prob[i,2];
      Temp3 := Prob[i,3];
      Prob[i,1] := Prob[i,4];
      Prob[i,2] := Prob[i,5];
      Prob[i,3] := Prob[i,6];
      Prob[i,4] := Temp1;
      Prob[i,5] := Temp2;
      Prob[i,6] := Temp3;
      END;
   END;

END;

PROCEDURE Titlepage (Tnum : INTEGER);

VAR  i : INTEGER;
```

```
BEGIN
   FOR i := 1 TO 24 DO
      WRITELN(Test);
   WRITELN(Test,'                Test Number ', Tnum);
   FOR i := 1 TO 29 DO
      WRITELN(Test);
END;

PROCEDURE RegQuest (z, v : INTEGER; Prob : Pmatrix; Out : Outmatrix;
                          QN : Qnum);

VAR x : INTEGER;

BEGIN
   x := QN[z];
   WRITELN(Test, RegPrompt);
   WRITELN(Test);
   WRITELN(Test,'    A:                          B:');
   WRITELN(Test);

   IF (Prob[x,1] > 0.00 ) THEN
      WRITE(Test, '    ', Prob[x,1]*100:5:1,'% chance at $', Out[v,1]:6,'        ')
      ELSE WRITE(Test,'                                ');
   IF (Prob[x,4] > 0.00) THEN
      WRITELN(Test, Prob[x,4]*100:5:1,'% chance at $', Out[v,1]:6)
      ELSE    WRITELN(Test);
   IF (Prob[x,2] > 0.00) THEN
      WRITE(Test, '    ', Prob[x,2]*100:5:1,'% chance at $', Out[v,2]:6,'        ')
      ELSE WRITE(Test,'                                ');
   IF (Prob[x,5] > 0.00) THEN
      WRITELN(Test, Prob[x,5]*100:5:1,'% chance at $', Out[v,2]:6)
      ELSE    WRITELN(Test);
   IF (Prob[x,3] > 0.00) THEN
      WRITE(Test, '    ', Prob[x,3]*100:5:1,'% chance at $',Out[v,3]:6,'        ')
      ELSE WRITE(Test,'                                ');
   IF (Prob[x,6] > 0.00) THEN
      WRITELN(Test, Prob[x,6]*100:5:1,'% chance at $', Out[v,3]:6)
      ELSE    WRITELN(Test);
   WRITELN(Test);
   WRITELN(Test,'    C:  You are indifferent between "A" and "B"');
   WRITELN(Test);
   WRITELN(Test);
END;

PROCEDURE ScenQuest (VAR z : INTEGER; Scenario : Smatrix; QN :
        Qnum; linmax : linmat; colmax : colmat);
```

```
VAR  k, x, j : INTEGER;

BEGIN
   x := QN[z];
   FOR j := 1  TO linmax[x] DO BEGIN
      FOR k := 1 TO colmax[x,j] DO
         WRITE(Test, Scenario[x,j,k]);
      WRITELN(Test);
      END;
END;

PROCEDURE Similar;

BEGIN
   WRITELN(Test);
   WRITELN(Test,'    How similar do you find options "A" and "B" above?');
   WRITELN(Test);
   WRITELN(Test,'    0_____________________________________________9');
   WRITELN(Test,'    very      somewhat      somewhat      very');
   WRITELN(Test,'    dissimilar dissimilar   similar       similar');
   WRITELN(Test);
   WRITELN(Test);
   WRITELN(Test);
   WRITELN(Test);
END;


PROCEDURE TestA (VAR Tnum : INTEGER; VAR Seed : INTEGER; Prob :
            Pmatrix; Out : Outmatrix; linmax : linmat; colmax : colmat);

   VAR  v, count, i, j, x : INTEGER;
   VAR  PN : Qnum;
   VAR  QN, AB, Tab : Qnum;
   VAR  Outn : Qnum;

BEGIN
   RandOrder(PN, Outn, Seed);
   RandAorB(AB, Prob, Seed);
   FOR i := 1 TO 8 DO BEGIN
      CASE PN[i] OF
         1,2 : Outn[i]:=2;
         3,4 : Outn[i]:=1;
         5,6 : Outn[i]:=1;
         7,8 : Outn[i]:=2;
      END;
   END;
```

```
    FOR i := 1 to 20 DO
            Tab[i] := AB[i];
    FOR i := 1 to 20 DO
            AB[i] := Tab[PN[i]];

FOR i := 1 to 20 DO
    QN[i] := PN[i];
QN[21] := PN[6];
    AB[21] := AB[6];
      Outn[21] := Outn[6];
QN[22] := PN[2];
    AB[22] := AB[2];
      Outn[22] := Outn[2];
FOR i := 1 TO Smax DO
    AB[i] := 0;

Titlepage(Tnum);

count := 0;

FOR j := 1 TO 2 DO BEGIN
    x := j;
    count := count + 1;
    WRITELN(Test, 'Question #',count:3);
    WRITELN(Test);
    ScenQuest(x, Scenario, QN, linmax, colmax);
    WRITE (TestDat, Tnum, QN[x], AB[x], Outn[x],'    1', count);
    WRITELN (TestDat);
    IF (x mod 3) = 0 THEN
        Similar
    ELSE FOR i := 1 TO 10 DO
        WRITELN(Test);
END;

FOR j := 5 TO 22 DO BEGIN
    x := j;
      count := count + 1;
    WRITELN(Test, 'Question #', count:3);
    WRITELN(Test);
    v := Outn[j];
    RegQuest(x, v, Prob, Out, QN);
    WRITELN (TestDat, Tnum, QN[x], AB[x], Outn[x],'    0', count);
    IF (x mod 3) = 0 THEN
        Similar;
    WRITELN (Test);
    WRITELN (Test);
```

```
    END;
    FOR j := 3 TO 4 DO BEGIN
        x := j;
        count := count + 1;
        WRITELN(Test, 'Question #', count:3);
        WRITELN(Test);
        ScenQuest(x, Scenario, QN, linmax, colmax);
        WRITE (TestDat, Tnum, QN[x], AB[x], Outn[x],'     1', count);
        WRITELN (TestDat);
    IF (x mod 3) = 0 THEN
        Similar
    ELSE FOR i := 1 TO 10 DO
        WRITELN(Test);

    END;

END;

PROCEDURE TestB (VAR Tnum : INTEGER; VAR Seed : INTEGER; Prob :
        Pmatrix; Out : Outmatrix; linmax : linmat; colmax : colmat);

    VAR  v, count, i, j, x : INTEGER;
    VAR  PN : Qnum;
    VAR  QN, AB, Tab : Qnum;
    VAR  Outn : Qnum;

BEGIN
    RandOrder(PN, Outn, Seed);
    RandAorB(AB, Prob, Seed);
    FOR i := 1 TO 4 DO BEGIN
        CASE PN[i] OF
            1,2 : Outn[i]:=2;
            3,4 : Outn[i]:=1;
            5,6 : Outn[i]:=1;
            7,8 : Outn[i]:=2;
        END;
    END;

        FOR i := 1 to 20 DO
                Tab[i] := AB[i];
        FOR i := 1 to 20 DO
                AB[i] := Tab[PN[i]];

    FOR i := 1 to 19 DO
        QN[i] := PN[i];
    QN[22] := PN[20];
        AB[22] := AB[20];
```

```
      Outn[22] := Outn[20];
QN[21] := PN[6];
   AB[21] := AB[6];
      Outn[21] := Outn[6];
QN[20] := PN[1];
   AB[20] := AB[1];
      Outn[20] := Outn[1];
FOR i := 1 TO Smax DO
   AB[i] := 0;

Titlepage(Tnum);

count := 0;

FOR j := 1 TO 1 DO BEGIN
   x := j;
   count := count + 1;
   WRITELN(Test, 'Question #',count:3);
   WRITELN(Test);
   ScenQuest(x, Scenario, QN, linmax, colmax);
   WRITE (TestDat, Tnum, QN[x], AB[x], Outn[x],'    1', count);
   WRITELN (TestDat);
   IF (x mod 3) = 0 THEN
      Similar
   ELSE FOR i := 1 TO 10 DO
      WRITELN(Test);
END;

FOR j := 5 TO 10 DO BEGIN
   x := j;
   count := count + 1;
   WRITELN(Test, 'Question #', count:3);
   WRITELN(Test);
   v := Outn[j];
   RegQuest(x, v, Prob, Out, QN);
   WRITELN (TestDat, Tnum, QN[x], AB[x], Outn[x],'    0', count);
   IF (x mod 3) = 0 THEN
      Similar;
   WRITELN (Test);
   WRITELN (Test);
END;
FOR j := 2 TO 2 DO BEGIN
   x := j;
   count := count + 1;
   WRITELN(Test, 'Question #', count:3);
   WRITELN(Test);
   ScenQuest(x, Scenario, QN, linmax, colmax);
```

```
    WRITE (TestDat, Tnum, QN[x], AB[x], Outn[x],'    1', count);
    WRITELN (TestDat);
IF (x mod 3) = 0 THEN
    Similar
ELSE FOR i := 1 TO 10 DO
    WRITELN(Test);
END;

FOR j := 11 TO 13 DO BEGIN
    x := j;
    count := count + 1;
    WRITELN(Test, 'Question #', count:3);
    WRITELN(Test);
    v := Outn[j];
    RegQuest(x, v, Prob, Out, QN);
    WRITELN (TestDat, Tnum, QN[x], AB[x], Outn[x],'    0', count);
    IF (x mod 3) = 0 THEN
        Similar;
    WRITELN (Test);
    WRITELN (Test);
END;

FOR j := 3 TO 3 DO BEGIN
    x := j;
    count := count + 1;
    WRITELN(Test, 'Question #', count:3);
    WRITELN(Test);
    ScenQuest(x, Scenario, QN, linmax, colmax);
    WRITE (TestDat, Tnum, QN[x], AB[x], Outn[x],'    1', count);
    WRITELN (TestDat);
IF (x mod 3) = 0 THEN
    Similar
ELSE FOR i := 1 TO 10 DO
    WRITELN(Test);
END;

FOR j := 14 TO 19 DO BEGIN
    x := j;
    count := count + 1;
    WRITELN(Test, 'Question #', count:3);
    WRITELN(Test);
    v := Outn[j];
    RegQuest(x, v, Prob, Out, QN);
    WRITELN (TestDat, Tnum, QN[x], AB[x], Outn[x],'    0', count);
    IF (x mod 3) = 0 THEN
        Similar;
    WRITELN (Test);
```

```
        WRITELN (Test);
    END;

    FOR j := 4 TO 4 DO BEGIN
        x := j;
        count := count + 1;
        WRITELN(Test, 'Question #', count:3);
        WRITELN(Test);
        ScenQuest(x, Scenario, QN, linmax, colmax);
        WRITE (TestDat, Tnum, QN[x], AB[x], Outn[x],'     1', count);
        WRITELN (TestDat);
    IF (x mod 3) = 0 THEN
        Similar
    ELSE FOR i := 1 TO 10 DO
        WRITELN(Test);
    END;

    FOR j := 20 TO 22 DO BEGIN
        x := j;
        count := count + 1;
        WRITELN(Test, 'Question #', count:3);
        WRITELN(Test);
        v := Outn[j];
        RegQuest(x, v, Prob, Out, QN);
        WRITELN (TestDat, Tnum, QN[x], AB[x], Outn[x],'     0', count);
        IF (x mod 3) = 0 THEN
            Similar;
        WRITELN (Test);
        WRITELN (Test);
    END;

END;

PROCEDURE TestC (VAR Tnum : INTEGER; VAR Seed : INTEGER; Prob :
        Pmatrix; Out : Outmatrix; linmax : linmat; colmax : colmat);

    VAR  v, count, i, j, x : INTEGER;
    VAR  PN : Qnum;
    VAR  QN, AB, Tab : Qnum;
    VAR  Outn : Qnum;

BEGIN
    RandOrder(PN, Outn, Seed);
    RandAorB(AB, Prob, Seed);
    FOR i := 1 TO 4 DO BEGIN
        CASE PN[i] OF
            1,2 : Outn[i]:=2;
```

```
        3,4 : Outn[i]:=1;
        5,6 : Outn[i]:=1;
        7,8 : Outn[i]:=2;
    END;
END;

    FOR i := 1 to 20 DO
            Tab[i] := AB[i];
    FOR i := 1 to 20 DO
            AB[i] := Tab[PN[i]];

FOR i := 1 to 20 DO
    QN[i] := PN[i];
QN[21] := PN[5];
    AB[21] := AB[5];
      Outn[21] := Outn[5];
QN[22] := PN[1];
    AB[22] := AB[1];
      Outn[22] := Outn[1];
FOR i := 1 TO Smax DO
    AB[i] := 0;

Titlepage(Tnum);

count := 0;

FOR j := 5 TO 7 DO BEGIN
    x := j;
    count := count + 1;
    WRITELN(Test, 'Question #', count:3);
    WRITELN(Test);
    v := Outn[j];
    RegQuest(x, v, Prob, Out, QN);
    WRITELN (TestDat, Tnum, QN[x], AB[x], Outn[x],'    0', count);
    IF (x mod 3) = 0 THEN
       Similar;
    WRITELN (Test);
    WRITELN (Test);
END;

FOR j := 1 TO 1 DO BEGIN
    x := j;
    count := count + 1;
    WRITELN(Test, 'Question #', count:3);
    WRITELN(Test);
    ScenQuest(x, Scenario, QN, linmax, colmax);
    WRITE (TestDat, Tnum, QN[x], AB[x], Outn[x],'    1', count);
```

```
    WRITELN (TestDat);
IF (x mod 3) = 0 THEN
    Similar
ELSE FOR i := 1 TO 10 DO
    WRITELN(Test);

END;

FOR j := 8 TO 13 DO BEGIN
    x := j;
    count := count + 1;
    WRITELN(Test, 'Question #', count:3);
    WRITELN(Test);
    v := Outn[j];
    RegQuest(x, v, Prob, Out, QN);
    WRITELN (TestDat, Tnum, QN[x], AB[x], Outn[x],'    0', count);
    IF (x mod 3) = 0 THEN
        Similar;
    WRITELN (Test);
    WRITELN (Test);
END;

FOR j := 2 TO 2 DO BEGIN
    x := j;
    count := count + 1;
    WRITELN(Test, 'Question #', count:3);
    WRITELN(Test);
    ScenQuest(x, Scenario, QN, linmax, colmax);
    WRITE (TestDat, Tnum, QN[x], AB[x], Outn[x],'    1', count);
    WRITELN (TestDat);
IF (x mod 3) = 0 THEN
    Similar
ELSE FOR i := 1 TO 10 DO
    WRITELN(Test);
END;

FOR j := 14 TO 16 DO BEGIN
    x := j;
    count := count + 1;
    WRITELN(Test, 'Question #', count:3);
    WRITELN(Test);
    v := Outn[j];
    RegQuest(x, v, Prob, Out, QN);
    WRITELN (TestDat, Tnum, QN[x], AB[x], Outn[x],'    0', count);
    IF (x mod 3) = 0 THEN
        Similar;
    WRITELN (Test);
```

```
        WRITELN (Test);
    END;

    FOR j := 3 TO 3 DO BEGIN
        x := j;
        count := count + 1;
        WRITELN(Test, 'Question #', count:3);
        WRITELN(Test);
        ScenQuest(x, Scenario, QN, linmax, colmax);
        WRITE (TestDat, Tnum, QN[x], AB[x], Outn[x],'     1', count);
        WRITELN (TestDat);
    IF (x mod 3) = 0 THEN
        Similar
    ELSE FOR i := 1 TO 10 DO
        WRITELN(Test);
    END;

    FOR j := 17 TO 22 DO BEGIN
        x := j;
        count := count + 1;
        WRITELN(Test, 'Question #', count:3);
        WRITELN(Test);
        v := Outn[j];
        RegQuest(x, v, Prob, Out, QN);
        WRITELN (TestDat, Tnum, QN[x], AB[x], Outn[x],'     0', count);
        IF (x mod 3) = 0 THEN
            Similar;
        WRITELN (Test);
        WRITELN (Test);
    END;

    FOR j := 4 TO 4 DO BEGIN
        x := j;
        count := count + 1;
        WRITELN(Test, 'Question #', count:3);
        WRITELN(Test);
        ScenQuest(x, Scenario, QN, linmax, colmax);
        WRITE (TestDat, Tnum, QN[x], AB[x], Outn[x],'     1', count);
        WRITELN (TestDat);
    IF (x mod 3) = 0 THEN
        Similar
    ELSE FOR i := 1 TO 10 DO
        WRITELN(Test);
    END;
END;

PROCEDURE TestD (VAR Tnum : INTEGER; VAR Seed : INTEGER; Prob :
```

```
    Pmatrix; Out : Outmatrix; linmax : linmat; colmax : colmat);

  VAR  v, count, i, j, x : INTEGER;
  VAR  PN : Qnum;
  VAR  QN, AB, Tab : Qnum;
  VAR  Outn : Qnum;

BEGIN
  RandOrder(PN, Outn, Seed);
  RandAorB(AB, Prob, Seed);
  FOR i := 1 TO 4 DO BEGIN
    CASE PN[i] OF
      1,2 : Outn[i]:=2;
      3,4 : Outn[i]:=1;
      5,6 : Outn[i]:=1;
      7,8 : Outn[i]:=2;
    END;
  END;

    FOR i := 1 to 20 DO
        Tab[i] := AB[i];
    FOR i := 1 to 20 DO
        AB[i] := Tab[PN[i]];


  FOR i := 1 to 20 DO
    QN[i] := PN[i];
  QN[21] := PN[1];
    AB[21] := AB[1];
      Outn[21] := Outn[1];
  QN[22] := PN[5];
    AB[22] := AB[5];
      Outn[22] := Outn[5];
  FOR i := 1 TO Smax DO
    AB[i] := 0;

  Titlepage(Tnum);

  count := 0;

  FOR j := 5 TO 13 DO BEGIN
    x := j;
    count := count + 1;
    WRITELN(Test, 'Question #', count:3);
    WRITELN(Test);
    v := Outn[j];
    RegQuest(x, v, Prob, Out, QN);
```

```
      WRITELN (TestDat, Tnum, QN[x], AB[x], Outn[x],'    0', count);
      IF (x mod 3) = 0 THEN
         Similar;
      WRITELN (Test);
      WRITELN (Test);
   END;

   FOR j := 1 TO 4 DO BEGIN
      x := j;
      count := count + 1;
      WRITELN(Test, 'Question #', count:3);
      WRITELN(Test);
      ScenQuest(x, Scenario, QN, linmax, colmax);
      WRITE (TestDat, Tnum, QN[x], AB[x], Outn[x],'    1', count);
      WRITELN (TestDat);
   IF (x mod 3) = 0 THEN
      Similar
   ELSE FOR i := 1 TO 10 DO
      WRITELN(Test);

   END;

   FOR j := 14 TO 22 DO BEGIN
      x := j;
      count := count + 1;
      WRITELN(Test, 'Question #', count:3);
      WRITELN(Test);
      v := Outn[j];
      RegQuest(x, v, Prob, Out, QN);
      WRITELN (TestDat, Tnum, QN[x], AB[x], Outn[x],'    0', count);
      IF (x mod 3) = 0 THEN
         Similar;
      WRITELN (Test);
      WRITELN (Test);
   END;
END;

PROCEDURE  CreateTests (Prob : Pmatrix ; Out : Outmatrix; linmax :
                              linmat;  colmax : colmat; Scenario : Smatrix);

VAR  Seed, x, y, i, FC, Tnum : INTEGER;

BEGIN

OPEN (Test,
   FILE_NAME := 'Survey.out',
   HISTORY := NEW);
```

```
OPEN (TestDat,
   FILE_NAME := 'TestInfo.dat',
   HISTORY := NEW);

REWRITE (TestDat);
REWRITE (Test);

   Seed := 1;
   y := TRUNC(TestNo/4);
   For i := 1 to y DO BEGIN
      Tnum := i;
      TestA (Tnum, Seed, Prob, Out, linmax, colmax);
      Seed := Seed + 1;
      END;
   x := TRUNC(TestNo/4 + 1);
   y := TRUNC(TestNo/2);
   For i := x to y DO BEGIN
      Tnum := i;
      TestB (Tnum, Seed, Prob, Out, linmax, colmax);
      Seed := Seed + 1;
      END;
   x := TRUNC(TestNo/2 + 1);
   y := TRUNC(3*TestNo/4);
   For i := x to y DO BEGIN
      Tnum := i;
      TestC (Tnum, Seed, Prob, Out, linmax, colmax);
      Seed := Seed + 1;
      END;
   x := TRUNC(3*TestNo/4 + 1);
   For i := x to TestNo DO BEGIN
      Tnum := i;
      TestD (Tnum, Seed, Prob, Out, linmax, colmax);
      Seed := Seed + 1;
      END;
END;

{Main Program}

BEGIN
   ReadData(Prob, Out, Scenario, linmax, colmax);
   CreateTests(Prob, Out, linmax, colmax, Scenario);
END.
```

PASCAL Program for Counting EU Violations and Violation Types

```
PROGRAM VIOLATION (INPUT, OUTPUT, DATA);

TYPE        SMATRIX = ARRAY[1..171, 1..22] OF REAL;
            OUTMAT = ARRAY[1..39501] OF REAL;

VAR  DATA : TEXT;
     NDATA : TEXT;
     ANS, SIM, EVD, MEV, PROB, OUT, EDS, SC, SCEN : SMATRIX;
     VIOL, DSIM, ASIM, RDSIM, SSUM, DORD, VTYPE : OUTMAT;
     DEVD, DMEV, AEV, SEDS, SSC : OUTMAT;

PROCEDURE READDATA (VAR ANS, SIM, EVD, MEV, PROB, OUT, EDS, SC,
                                SCEN : SMATRIX);

VAR I, J : INTEGER;

BEGIN

OPEN (DATA,
     FILE_NAME := '101P.DAT',
     HISTORY := READONLY);

RESET (DATA);

FOR I := 1 TO 171 DO BEGIN
  FOR J := 1 TO 22 DO BEGIN
     READ(DATA, ANS[I,J]);
     READ(DATA, SIM[I,J]);
     READ(DATA, EVD[I,J]);
     READ(DATA, MEV[I,J]);
     READ(DATA, PROB[I,J]);
     READ(DATA, OUT[I,J]);
     READ(DATA, SC[I,J]);
     READ(DATA, EDS[I,J]);
     READ(DATA, SCEN[I,J]);
     END;
  END;
END;


PROCEDURE NEWDATA (VAR VIOL, DSIM, VTYPE, ASIM, RDSIM, SSUM,
     DORD, DEVD, DMEV, AEV, SEDS, SSC : OUTMAT; ANS, SIM, EVD, MEV,
     PROB, OUT, SC, EDS,SCEN : SMATRIX);

VAR I, J, K, X : INTEGER;
     DS : OUTMAT;

BEGIN
```

```
X := 1;

FOR K := 1 TO 171 DO BEGIN
   FOR I := 1 TO 21 DO BEGIN
      FOR J := (I+1) TO 22 DO BEGIN
         IF (OUT[K,I] <> OUT[K,J]) OR
         (ANS[K,I]=1.5) OR (ANS[K,J]=1.5) THEN
           VIOL[X] := 0
         ELSE
           IF (ANS[K, I] = ANS [K, J]) THEN
              VIOL[X] := 1
           ELSE
              VIOL[X] := 2;
         DS[X] := SIM[K,I] - SIM[K,J];
         IF VIOL[X] = 2 THEN BEGIN
           IF ((DS[X]>=0) AND (ANS[K,I]=2)) OR
            ((DS[X]<0) AND (ANS[K,I]=1)) THEN
              VTYPE[X] := 2
           ELSE
              VTYPE[X] := 1
           END;
         IF VIOL[X] <> 2 THEN
               VTYPE[X] := 0;
         DSIM[X] := ABS(DS[X]);
         ASIM[X] := (SIM[K,I] + SIM[K,J])/2;
         RDSIM[X] := DSIM[X]/ASIM[X];
         DORD[X] := J-I;
         SSUM[X] := SCEN[K,I] + SCEN[K,J];
         DEVD[X] := ABS(EVD[K,I] - EVD[K,J]);
         DMEV[X] := ABS(MEV[K,I] - MEV[K,J]);
         AEV[X] := (MEV[K,I] + MEV[K,J])/2;
         SEDS[X] := EDS[K,I] + EDS[K,J];
         SSC[X] := SC[K,I] + SC[K,J];
         X := X + 1;
           END;
       END;
  END;
END;

PROCEDURE WRITENEW (VIOL, DSIM, ASIM, VTYPE, SSUM, DORD, DEVD,
                                        DMEV, AEV, SEDS, SSC : OUTMAT);

VAR I : INTEGER;

BEGIN

OPEN (NDATA,
   FILE_NAME := 'EUVIOL.DAT',
   HISTORY := NEW);
REWRITE (NDATA);
```

```
FOR I := 1 TO 39501 DO BEGIN
   WRITE(NDATA, VIOL[I]:5:1);
   WRITE(NDATA, VTYPE[I]:5:1);
   WRITE(NDATA, DSIM[I]:8:3);
   WRITE(NDATA, ASIM[I]:8:3);
   WRITE(NDATA, DEVD[I]:10:1);
   WRITE(NDATA, DMEV[I]:11:1);
   WRITE(NDATA, AEV[I]:10:1);
   WRITE(NDATA, SEDS[I]:5:1);
   WRITE(NDATA, SSC[I]:5:1);
   WRITE(NDATA, SSUM[I]:5:1);
   WRITELN(NDATA, DORD[I]:6:1);
   END;
END;

BEGIN

READDATA (ANS, SIM, EVD, MEV, PROB, OUT, EDS, SC, SCEN);
NEWDATA (VIOL, DSIM, VTYPE, ASIM, RDSIM, SSUM, DORD, DEVD, DMEV,
      AEV, SEDS, SSC, ANS, SIM, EVD, MEV, PROB, OUT, SC, EDS, SCEN);
WRITENEW (VIOL, DSIM, ASIM, VTYPE, SSUM, DORD, DEVD, DMEV, AEV,
      SEDS, SSC);

END.
```

APPENDIX C

SCENARIOS

Career Job "A"

Suppose you have just graduated and you are looking for a job. After interviewing at many companies in the slim job market, just two employers have offered you a position. You find the benefits, working environment, and location satisfactory for both potential employers, and have narrowed your decision criteria to only earning potential.

The first employer, company ABC, is an established, well known company offering a relatively secure entry level position and moderate potential for advancement. Your salary will begin at $21,000 a year. After careful consideration and research of company ABC, you believe there is a 40 percent chance of gaining promotion after the first year, increasing your annual earnings to $28,000 a year, a 55 percent chance you will remain in your entry level position with the $21,000 salary, and just a 5 percent chance you will be laid off due to an economic downturn.

The second employer, company XYZ, is a newer, expanding company which holds greater future earnings potential, but also holds less job security. Your salary will also begin at $21,000 a year and you have been promised a promotion after one year of employment, increasing your annual earnings to $27,000, but you believe there is a chance of 16 percent that you will be laid off in an economic downturn.

Suppose that if you are laid off with either company you will be unemployed for one year, and if you keep your job after the first year, your earnings prospects in future years will be roughly the same for each company. To summarize:

Company ABC: 40% chance of annual salary of $28,000 in one year.
55% chance of annual salary of $21,000 in one year.
5% chance of being laid off in one year.

Company XYZ: 84% chance of annual salary of $28,000 in one year.
16% chance of being laid off in one year.

Which company would you work for?

A: Company ABC B: Company XYZ

C: You are indifferent between the two employers

Career Job "B"

Suppose you have just graduated and you are looking for a job. After interviewing at many companies in the slim job market, just two employers have offered you a position. You find the benefits, working environment, and location satisfactory for both potential employers and have narrowed your decision criteria to only earning potential.

The first employer, company ABC, is an established, well known company offering a relatively secure entry level position and moderate potential for advancement. Your salary will begin at $21,000 a year. After careful consideration and research of company ABC, you believe there is a 40 percent chance of gaining promotion after the first year, increasing your annual earnings to $28,000 a year, a 55 percent chance you will remain in your entry level position with the $21,000 salary, and just a 5 percent chance you will be laid off due to an economic downturn.

The second employer, company XYZ, is a newer, expanding company that holds greater future earnings potential, but also holds less job security. Your annual salary will also begin at $21,000 but you stand a 60 percent chance of gaining promotion to $27,000 after one year, a 30 percent chance of remaining in your entry level position of $21,000, and a 10 percent chance that you will be laid off in an economic downturn.

Suppose that if you are laid off with either company you will be unemployed for one year, and if you keep your job after the first year, your earnings prospects in future years will be roughly the same for each company. To summarize:

Company ABC: 40% chance of annual salary of $28,000 in one year.
55% chance of annual salary of $21,000 in one year.
5% chance of being laid off in one year.

Company XYZ: 60% chance of annual salary of $28,000 in one year.
30% chance of annual salary of $21,000 in one year.
10% chance of being laid off in one year.

Which company would you work for?

A: Company ABC B: Company XYZ

C: You are indifferent between the two employers

Used Car "A"

Suppose you are selling your old car. You no longer use the vehicle and figure you could use the extra money. You have been advertising for several weeks, asking the "best offer" for your car, but only two people, Mr. Moe and Mr. Jack, have made offers that you are willing to accept.

Mr. Moe, a well known and respected man in the community, has unconditionally offered $3,000 cash for your car.

Mr. Jack has offered $4,000 for you car, but you fear that his check may bounce. You have considered the situation carefully and believe there is 20 percent chance Mr. Moe will write you a bad check, skip town, and leave you nothing for your car should you accept his offer.

To summarize:

Selling to Mr. Moe:	You will get $3,000 for your car.
Selling to Mr. Jack:	80% chance at getting $4,000 for your car. 20% chance at getting $0 for your car.

To whom would you sell you car?

A: Mr. Moe B: Mr. Jack

C: You are indifferent between the two offers

Used Car "B"

Suppose you are selling your old car. You no longer use the vehicle and figure you could use the extra money. You have been car, but only two people, Mr. Moe and Mr. Jack, have made offers that you are willing to accept.

Mr. Jack has offered $4,000 for you car, but you fear that his check may bounce. You have considered the situation carefully and believe there is 20 percent chance Mr. Moe will write you a bad check, skip town, and leave you nothing for your car.

Mr. Moe has offered $3,000 for your car, but you also fear that Mr. Moe's check may bounce. After mentioning your concerns to Mr. Moe, however, he gives you three references for his character and promises an extra $1,000 should his check bounce. Suppose you believe there is a 75 percent chance Mr. Moe's check is good, a 20 percent chance the check is bad and Mr. Moe will give you an extra $1,000 for a total of $4,000 for your car, and a 5 percent chance Mr. Moe's check is bad and that he will skip town, leaving you nothing for your car.

To summarize:

Selling to Mr. Jack:	80% chance at getting $4,000 for your car. 20% chance at getting $0 for your car.
Selling to Mr. Moe:	5% chance at getting $3,000 for your car. 20% chance at getting $4,000 for your car. 5% chance at getting $0 for you car.

To whom would you sell you car?

A: Mr. Jack B: Mr. Moe

C: You are indifferent between the two offers

Part Time Job "A"

Suppose you are looking for a part time job to earn some extra spending money during the school year. You have shopped Bozeman's slim part-time job market extensively, but have found just two job offers.

The first job is a sales position at a local department store, the second is an hourly wage job as a clerk for a local investment company. You are indifferent between the working atmospheres' of the two jobs, and since you are only interested in some extra spending cash, you do not value the relative career experience you may gain from either position.

For the sales job you would work 10 hours a week and would be paid only through a commission on your sales. After having spoken with other salespersons at the store and carefully weighing your potential for salesmanship, you believe there is a 5 percent chance you wouldn't perform well as a salesperson and earn nothing, a 75 percent chance you would average $6/hour for $60/week or $3,000/year (assuming a two week, non-paid vacation), and a 20 percent chance you would be a markedly better salesperson and average $8/hour for $80/week or $4,000/year.

For the clerk job you would also work 10 hours a week, but would be paid a steady wage of $6/hour ($60/week, $3,000/year).

To summarize:

The sales job: 5% chance at earning nothing.
75% chance at earning $6/hour for $3,000/year.
20% chance at earning $8/hour for $4,000/year.

The clerk job: You will earn $6/hour for $3,000/year.

Which job would you choose?

A: The sales job B: The clerk job

C: You are indifferent between the two jobs

Part Time Job "B"

Suppose you are looking for a part time job to earn some extra spending money during the school year. You have shopped Bozeman's slim part-time job market extensively, but have found just two job offers.

The first job is a sales position at a local department store, the second is an hourly wage job as a clerk for a local investment company. You are indifferent between the working atmospheres of the two jobs, and since you are only interested in some extra spending cash, you do not value the relative career experience you may gain from either position.

For the sales job you would work 10 hours a week and would be paid only through a commission on your sales. After having spoken with other salespersons at the store and carefully weighing your potential sales, you believe there is a 5 percent chance you wouldn't perform well as a salesperson and earn nothing, a 40 percent chance you would average $6/hour for $60/week or $3,000/year (assuming a two week, non-paid vacation), and a 55 percent chance you would be a markedly better salesperson and average $8/hour for $80/week or $4,000/year.

For the clerk job you would also work 10 hours a week, but would be paid a steady wage of $6/hour ($60/week, $3,000/year). If business picks up through the year, however, you have been promised a retroactive raise to a steady $8/hour ($80/week, $4,000/year). You feel there you have a 20 percent chance of gaining such a raise.

To summarize:

The sales job:	5% chance at earning nothing. 40% chance at earning $6/hour for $3,000/year. 55% chance at earning $8/hour for $4,000/year.
The clerk job:	80% chance at earning $6/hour for $3,000/year. 20% chance at earning $8/hour for $4,000/year.

Which job would you choose?

A: The sales job B: The clerk job

C: You are indifferent between the two jobs

Grandmother "A"

Suppose your grandmother recently passed away leaving you a trust fund. Your grandmother stipulated in her will that you could not touch the money for 5 years. You must invest the money in one of two investments also stipulated in her will: a portfolio of high return, high risk bonds or a managed mutual fund.

The bonds will return 12 percent a year for a total value of about $28,000 five years from now. After extensive conversation with your stockbroker, however, you believe there is 10 percent chance the bond market will bust and the portfolio will be worthless in five years.

The managed mutual fund, though somewhat less risky, may not return as high a yield as the bonds. After extensive conversation with your stockbroker, you believe there is a 60 percent chance the market will rally and you will receive the same 12 percent return as the bonds for a total of $28,000 five years from now, a 37.5 percent chance the market will remain steady and you will receive about 5.74 percent return for a total of $21,000 five years from now, and just a 2.5 percent chance the market will bust and the mutual fund investment will be worthless in five years.

Summarizing the two options:

Bonds:	90% chance at a $28,000 value in five years. 10% chance at being worthless in five years.
Mutual fund:	60% chance at a $28,000 value in five years. 37.5% chance at a $21,000 value in five years. 2.5% chance at being worthless in five years.

Which investment would you choose?

A: The portfolio of bonds B: The mutual fund

C: You are indifferent between the two investments

Grandmother "B"

Suppose your grandmother recently passed away leaving you a trust fund. Your grandmother stipulated that you could not touch the money for 5 years. You must invest the money in one of two investments also stipulated in her will: a portfolio of high return, high risk bonds or a managed mutual fund.

The bonds will return 12 percent a year for a total value of about $28,000 five years from now. After extensive conversation with your stockbroker, however, you believe there is 16 percent chance the bond market will bust and the portfolio will be worthless in five years.

The managed mutual fund, though somewhat less risky, may not return as high a yield as the bonds. After extensive conversation with your stockbroker, you believe there is a 60 percent chance the market will rally and you will receive the same 12 percent return as the bonds for a total of $28,000 five years from now, a 30 percent chance the market will remain steady and you will receive about 5.37 percent return for a total of $21,000 five years from now, and just a 10 percent chance the market will bust and the mutual fund investment will be worthless in five years.

Summarizing the two options:

Bonds:	84% chance at a $28,000 value in five years. 16% chance at being worthless in five years.
Mutual fund:	60% chance at a $28,000 value in five years. 30% chance at a $21,000 value in five years. 10% chance at being worthless in five years.

Which investment would you choose?

A: The portfolio of bonds B: The mutual fund

C: You are indifferent between the two investments

APPENDIX D

A SAMPLE SURVEY

Risky Choice Survey

I am conducting research on how people choose between risky alternatives. This research will contribute to my Master's thesis in economics.

The survey will ask you to choose among hypothetical alternatives with risky outcomes. Some of the questions also present scenarios that may relate to decisions you have made or soon will make in the real world. Although the dollar outcomes in these questions are not real, please make your decisions as if they were. A practice question is given below.

Circle the gamble you like best.

A:	B:
50% chance at $ 0	60% chance at $ 0
50% chance at $ 6,000	40% chance at $ 8,000

C: You are indifferent between "A" and "B"

Since we are interested in both your decision and how you perceive each risky situation, some of the questions (about 1/3) will have a supplementary section that asks how "similar" you find the two choices. If you find the two options very close or "similar" to one another, mark a slash higher on the line. If you find the two options very different, mark a slash lower on the line. An example is given below.

How similar do you find options "A" and "B" above?

0			9
very dissimilar	somewhat dissimilar	somewhat similar	very similar

If you have any questions about the survey, please ask the administrator for clarification.

If you thoroughly complete the survey, Dr. Baquet will give you 5 extra credit points for your effort. Thank you very much for your time!

Test Number **1**

Question # 1

Suppose you have just graduated and you are looking for a job. After interviewing at many companies in the slim job market, just two employers have offered you a position. You find the benefits, working environment, and location satisfactory for both potential employers, and have narrowed your decision criteria to only earning potential.

The first employer, company ABC, is an established, well known company offering a relatively secure entry level position and moderate potential for advancement. Your salary will begin at $21,000 a year. After careful consideration and research of company ABC, you believe there is a 40 percent chance of gaining promotion after the first year, increasing your annual earnings to $28,000 a year, a 55 percent chance you will remain in your entry level position with the $21,000 salary, and just a 5 percent chance you will be laid off due to an economic downturn.

The second employer, company XYZ, is a newer, expanding company which holds greater future earnings potential, but also holds less job security. Your salary will also begin at $21,000 a year and you have been promised a promotion after one year of employment, increasing your annual earnings to $27,000, but you believe there is a chance of 16 percent that you will be laid off in an economic downturn.

Suppose that if you are laid off with either company you will be unemployed for one year, and if you keep your job after the first year, your earnings prospects in future years will be roughly the same for each company. To summarize:

Company ABC: 40% chance of annual salary of $28,000 in one year.
55% chance of annual salary of $21,000 in one year.
5% chance of being laid off in one year.

Company XYZ: 84% chance of annual salary of $28,000 in one year.
16% chance of being laid off in one year.

Which company would you work for?

A: Company ABC B: Company XYZ

C: You are indifferent between the two employers

Question # 2

Suppose your grandmother recently passed away leaving you a trust fund. Your grandmother stipulated in her will that you could not touch the money for 5 years. You must invest the money in one of two investments also stipulated in her will: a portfolio of high return, high risk bonds or a managed mutual fund.

The bonds will return 12 percent a year for a total value of about $28,000 five years from now. After extensive conversation with your stockbroker, however, you believe there is 10 percent chance the bond market will bust and the portfolio will be worthless in five years.

The managed mutual fund, though somewhat less risky, may not return as high a yield as the bonds. After extensive conversation with your stockbroker, you believe there is a 60 percent chance the market will rally and you will receive the same 12 percent return as the bonds for a total of $28,000 five years from now, a 37.5 percent chance the market will remain steady and you will receive about 5.74 percent return for a total of $21,000 five years from now, and just a 2.5 percent chance the market will bust and the mutual fund investment will be worthless in five years.

Summarizing the two options:

Bonds: 90% chance at a $28,000 value in five years.
10% chance at being worthless in five years.

Mutual fund: 60% chance at a $28,000 value in five years.
37.5% chance at a $21,000 value in five years.
2.5% chance at being worthless in five years.

Which investment would you choose?

A: The portfolio of bonds B: The mutual fund

C: You are indifferent between the two investments

Question # 3

Circle the gamble that you like best.

A:	B:
	4.0% chance at $ 0
80.0% chance at $ 28,000	96.0% chance at $ 28,000
20.0% chance at $ 21,000	

C: You are indifferent between "A" and "B"

Question # 4

Circle the gamble that you like best.

A:	B:
20.0% chance at $ 0	36.0% chance at $ 0
	64.0% chance at $ 400
80.0% chance at $ 300	

C: You are indifferent between "A" and "B"

How similar do you find options "A" and "B" above?

0_____9

very dissimilar	somewhat dissimilar	somewhat similar	very similar

Question # 5

Circle the gamble that you like best.

A:	B:
60.0% chance at $ 0	50.0% chance at $ 0
40.0% chance at $ 4,000	
	50.0% chance at $ 3,000

C: You are indifferent between "A" and "B"

Question # 6

Circle the gamble that you like best.

A:	B:
	5.0% chance at $ 0
20.0% chance at $ 4,000	40.0% chance at $ 4,000
80.0% chance at $ 3,000	55.0% chance at $ 3,000

C: You are indifferent between "A" and "B"

Question # 7

Circle the gamble that you like best.

A:	B:
7.5% chance at $ 0	
80.0% chance at $ 4,000	50.0% chance at $ 4,000
12.5% chance at $ 3,000	50.0% chance at $ 3,000

C: You are indifferent between "A" and "B"

How similar do you find options "A" and "B" above?

0_____9

very dissimilar	somewhat dissimilar	somewhat similar	very similar

Question # 8

Circle the gamble that you like best.

A:	B:
32.0% chance at $ 0	36.0% chance at $ 0
48.0% chance at $ 400	64.0% chance at $ 400
20.0% chance at $ 300	

C: You are indifferent between "A" and "B"

Question # 9

Circle the gamble that you like best.

A:	B:
80.0% chance at $ 0	75.0% chance at $ 0
20.0% chance at $ 4,000	25.0% chance at $ 3,000

C: You are indifferent between "A" and "B"

Question # 10

Circle the gamble that you like best.

A:	B:
28.0% chance at $ 0	32.0% chance at $ 0
32.0% chance at $ 28,000	48.0% chance at $ 28,000
40.0% chance at $ 21,000	20.0% chance at $ 21,000

C: You are indifferent between "A" and "B"

How similar do you find options "A" and "B" above?

0			9
very dissimilar	somewhat dissimilar	somewhat similar	very similar

Question # 11

Circle the gamble that you like best.

A:	B:
5.0% chance at $ 0	20.0% chance at $ 0
20.0% chance at $ 400	80.0% chance at $ 400
75.0% chance at $ 300	

C: You are indifferent between "A" and "B"

Question # 12

Circle the gamble that you like best.

A:	B:
28.0% chance at $ 0	24.0% chance at $ 0
32.0% chance at $ 28,000	16.0% chance at $ 28,000
40.0% chance at $ 21,000	60.0% chance at $ 21,000

C: You are indifferent between "A" and "B"

Question # 13

Circle the gamble that you like best.

A:	B:
5.0% chance at $ 0	10.0% chance at $ 0
40.0% chance at $ 28,000	60.0% chance at $ 28,000
55.0% chance at $ 21,000	30.0% chance at $ 21,000

C: You are indifferent between "A" and "B"

How similar do you find options "A" and "B" above?

0_____9

very dissimilar	somewhat dissimilar	somewhat similar	very similar

Question # 14

Circle the gamble that you like best.

A:	B:
2.5% chance at $ 0	7.5% chance at $ 0
60.0% chance at $ 4,000	80.0% chance at $ 4,000
37.5% chance at $ 3,000	12.5% chance at $ 3,000

C: You are indifferent between "A" and "B"

Question # 15

Circle the gamble that you like best.

A:		B:	
10.0% chance at $	0	16.0% chance at $	0
60.0% chance at $	400	84.0% chance at $	400
30.0% chance at $	300		

C: You are indifferent between "A" and "B"

Question # 16

Circle the gamble that you like best.

A:		B:	
52.5% chance at $	0	60.0% chance at $	0
10.0% chance at $	4,000	40.0% chance at $	4,000
37.5% chance at $	3,000		

C: You are indifferent between "A" and "B"

How similar do you find options "A" and "B" above?

0_____9

very dissimilar	somewhat dissimilar	somewhat similar	very similar

Question # 17

Circle the gamble that you like best.

A:		B:	
20.0% chance at $	0	24.0% chance at $	0
		16.0% chance at $	400
80.0% chance at $	300	60.0% chance at $	300

C: You are indifferent between "A" and "B"

Question # 18

Circle the gamble that you like best.

A:		B:	
52.5% chance at $	0	57.5% chance at $	0
10.0% chance at $	400	30.0% chance at $	400
37.5% chance at $	300	12.5% chance at $	300

C: You are indifferent between "A" and "B"

Question # 19

Circle the gamble that you like best.

A:		B:	
20.0% chance at $	0	36.0% chance at $	0
		64.0% chance at $	400
80.0% chance at $	300		

C: You are indifferent between "A" and "B"

How similar do you find options "A" and "B" above?

0_____9

very dissimilar	somewhat dissimilar	somewhat similar	very similar

Question # 20

Circle the gamble that you like best.

A:		B:	
10.0% chance at $	0	2.5% chance at $	0
90.0% chance at $	28,000	60.0% chance at $	28,000
		37.5% chance at $	21,000

C: You are indifferent between "A" and "B"

Question # 21

Suppose you are selling your old car. You no longer use the vehicle and figure you could use the extra money. You have been advertising for several weeks, asking the "best offer" for your car, but only two people, Mr. Moe and Mr. Jack, have made offers that you are willing to accept.

Mr. Moe, a well known and respected man in the community, has unconditionally offered $3,000 cash for your car.

Mr. Jack has offered $4,000 for you car, but you fear that his check may bounce. You have considered the situation carefully and believe there is 20 percent chance Mr. Moe will write you a bad check, skip town, and leave you nothing for your car should you accept his offer.

To summarize:

Selling to Mr. Moe: You will get $3,000 for your car.

Selling to Mr. Jack: 80% chance at getting $4,000 for your car.
20% chance at getting $0 for your car.

To whom would you sell you car?

A: Mr. Moe B: Mr. Jack

C: You are indifferent between the two offers

How similar do you find options "A" and "B" above?

0			9
very dissimilar	somewhat dissimilar	somewhat similar	very similar

Question # 22

Suppose you are looking for a part time job to earn some extra spending money during the school year. You have shopped Bozeman's slim part-time job market extensively, but have found just two job offers.

The first job is a sales position at a local department store, the second is an hourly wage job as a clerk for a local investment company. You are indifferent between the working atmospheres' of the two jobs, and since you are only interested in some extra spending cash, you do not value the relative career experience you may gain from either position.

For the sales job you would work 10 hours a week and would be paid only through a commission on your sales. After having spoken with other salespersons at the store and carefully weighing your potential for salesmanship, you believe there is a 5 percent chance you wouldn't perform well as a salesperson and earn nothing, a 75 percent chance you would average $6/hour for $60/week or $3,000/year (assuming a two week, non-paid vacation), and a 20 percent chance you would be a markedly better salesperson and average $8/hour for $80/week or $4,000/year.

For the clerk job you would also work 10 hours a week, but would be paid a steady wage of $6/hour ($60/week, $3,000/year).

To summarize:

The sales job: 5% chance at earning nothing.
75% chance at earning $6/hour for $3,000/year.
20% chance at earning $8/hour for $4,000/year.

The clerk job: You will earn $6/hour for $3,000/year.

Which job would you choose?

A: The sales job B: The clerk job

C: You are indifferent between the two jobs