Research in Brief

Modeling Ambiguity in Decisions Under Uncertainty

BARBARA E. KAHN
RAKESH K. SARIN*

We present a model for predicting consumers' choices under conditions of uncertainty and ambiguity. We use the term ambiguity to distinguish the class of risky decisions for which the odds of an uncertain event are not precisely known. We show that our model predicts different decisions for individuals who are ambiguity averse, ambiguity seeking, or ambiguity indifferent, thus relaxing the constraint imposed on preferences by subjected expected utility theory.

Some of the most important decisions consumers make involve ambiguity and uncertainty. The timing of purchase and choice of brand are clearly uncertain processes in a marketplace involving proliferation of brands and frequent introduction of new brands. One cannot be certain when purchasing a used automobile that it will not break down in the very near future. One can never be certain when considering a loan for a new home whether a fixed or a variable plan will be more effective.

For the most part, consumers have learned to cope with uncertainty and ambiguity, particularly in high involvement decisions (Zaichkowsky 1985). Because of the prevalence of such decisions, many researchers have studied the processes consumers use to make decisions under uncertainty. The approaches have been quite diverse, ranging from descriptive studies of how consumers perceive risk (e.g., Bettman 1979; Cox 1967) to studies of how consumers resolve the dissonance that often occurs following risky decisions (Calder 1981).

Although a number of formal models have been proposed to represent decision-making under uncertainty, the ones that are most widely used are those that follow from subjective expected utility theory, SEU (e.g., Bonoma and Johnston 1979; Currim and Sarin 1983, 1984; Hauser and Urban 1977, 1979). In this approach, risk is modeled by reflecting the decision-maker's response to uncertain outcomes defined in terms of specific probabilities of risk. For example, one might model a consumer's utility for a used car given there is a 25 percent chance that the car will break down in the next year.

In real settings, however, exact probabilities cannot always be assigned to events; for example, one can say only that the probability the car will break down in the next six months lies between 10 percent and 40 percent. In these types of situations, the probabilities are ambiguous or, in effect, there is "uncertainty about the uncertainty."

Subjective expected utility theory predicts that the presence of ambiguity in probabilities should not affect how consumers make decisions; one should make the same decision whether the probability of risk is stated as 25 percent or somewhere between 10 percent and 40 percent. However, empirical evidence in the behavioral decision literature has indicated that consumers make decisions differently if there is ambiguity about the uncertainty than if there is no ambiguity, even if the expected risk is the same.

The purpose of this article is to present a model for analyzing choices under ambiguity. We use the term ambiguity to distinguish the class of decisions under uncertainty for which the odds of an uncertain event are not precisely known. We will show that our model predicts different decisions for individuals who are ambiguity averse, ambiguity seeking, or ambiguity

* Barbara E. Kahn is Assistant Professor of Management, Anderson Graduate School of Management, University of California, Los Angeles, CA 90024. Rakesh K. Sarin is Professor of Business Administration, Fuqua School of Business, Duke University, Durham, NC 27706. Partial support for this research was provided by a UCLA Academic Senate Research Grant to Barbara E. Kahn and by a National Science Foundation grant (SES 84-08914) to Rakesh K. Sarin. The authors would like to thank João Assunção and João Becker and three anonymous reviewers for their valuable assistance with this article.

indifferent, thus relaxing the constraint imposed on preferences by the SEU model. In the consumer behavior context, our work advances the previous work by Hauser and Urban (1977, 1979) to situations where probabilities cannot be precisely specified. More generally, this model provides an organized way of thinking about ambiguity and a framework for discussing related issues.

PREVIOUS RESEARCH ON AMBIGUITY

Early Discussion on Ambiguity

Ellsberg (1961) was one of the first to discuss how ambiguity in probabilities could affect choices. He proposed that when the information given was highly ambiguous, many otherwise reasonable people may neither wish nor tend to conform to the axioms of the SEU model. His classic illustration of this behavior, the "Ellsberg Paradox," is that subjects often prefer to bet on the event that a red (or black) ball will be drawn from an urn containing 50 red and 50 black balls than on the same event if the ball would be drawn from an urn containing an unknown proportion of red and black balls. In the latter situation, the probability of the event that a red ball will be drawn is itself a random variable.

Fellner (1961) suggested that subjective probability judgments relating to various choice processes were not strictly comparable. In his article (1961) and later in his book (1965), he argued that the observable decision weights that these decision-makers attached to risky prospects were in many cases not on par with probabilities, but were derived from such probabilities by means of a "slanting" or "distortion" process.

Smith (1969) believed that decision-makers regarded probabilities as probabilities, but changed their values for the utility associated with ambiguous choices. For example, if a decision-maker knows nothing about the stock market, then the ambiguity in the Dow Jones averages may generate anxiety when gambling on such contingencies and consequently lower the utility. Sherman (1974) suggested that the willingness of a person for taking a gamble with ambiguous odds is related to his/her psychological tolerance for ambiguity.

Empirical Investigations of Ambiguity

Several researchers, including Slovic and Tversky (1974) and MacCrimmon and Larsson (1979), empirically tested Ellsberg's hypotheses about ambiguity avoidance and found strong support for his results. Becker and Brownson (1964) tested and confirmed two extensions to Ellsberg's hypotheses: (1) individuals are willing to pay money to avoid actions involving ambiguity, and (2) some people behave as if they associate ambiguity with the range of the second-order distributions of the relative frequency of an event—where the greater the range of the distribution, the greater the ambiguity implied.

Yates and Zukowski (1976) and Larson (1980) empirically tested whether the ambiguity a person perceived and avoided in a decision situation was completely reducible to the range of the induced subjective second-order probability distribution. Both studies found clear evidence against this conclusion.

Curley and Yates (1985) investigated how varying the centers and the ranges of the intervals of possible imprecise probabilities of winning (i.e., ambiguous probabilities of winning) affected decisions. They found that ambiguity avoidance increased with the expected probability of winning, but only when the range of possible probabilities in the ambiguous choice situation included a zero probability of winning. However, the authors cautioned that such a strong interpretation of this interaction effect was premature.

Summary

As the literature shows, considerable empirical evidence has indicated that the SEU model should be generalized to predict preferences under ambiguity. Recently, some researchers have turned their attention to developing alternative models that may account for preference patterns observed in the empirical data. Einhorn and Hogarth (1985) present a descriptive model of how people modify probabilities of ambiguous events. Their model is based on an anchoring and adjustment strategy for assessing probabilities. The initial estimate of the probability provides the anchor, which is then adjusted based on the amount of ambiguity perceived in the situation and the individual's attitude toward ambiguity. Schmeidler (1984), Fishburn (1983), and Luce and Narens (1985) provide an axiomatic approach to generalize the SEU model to incorporate ambiguity. In this article, we propose a model, which generalizes the SEU model, for analyzing consumers' choices under ambiguity. We will show that our model, which nests the SEU model, provides a significant improvement in the prediction of choice.

AN OPERATIONAL DEFINITION OF AMBIGUITY

When evaluating decisions under uncertainty, two components have traditionally been examined: the relative desirability of the possible payoffs and the relative likelihood of the events affecting the payoffs. When we consider the effect of ambiguity in this research, we are adding a third dimension, the nature of the information—or as Ellsberg (1961) writes, "the ambiguity of the information, a quality depending on the amount, type, reliability, and 'unanimity' of information and giving rise to one's degree of 'confidence' in the estimate of relative likelihoods."

Although the ambiguity associated with the likelihood of an event is a subjective variable, it is possible to differentiate between decisions in which ambiguity exists and decisions in which ambiguity does not exist. For example, whereas there is no ambiguity associated with a coin toss, there is a great deal of ambiguity associated with new product technology, computer hardware obsolescence, or the timing of a purchase relative to the next price cut. Unlike with the coin toss, the probability of the event occurring cannot be specified with precision for the consumer decisions. We can only say, for example, that the probability that a video cassette recorder will break down in a year is somewhere between 5 and 30 percent.

We define ambiguity operationally by second-order uncertainty or, in other words, by a probability distribution for the perceived frequencies. This "uncertainty about uncertainty" has been considered previously (e.g., Marschak 1975), but second-order probabilities have never been incorporated specifically in a model of ambiguity. As mentioned earlier, there have been empirical tests associating ambiguity with the range of second-order distributions or the relative frequency of an event (Becker and Brownson 1964; Larson 1980; Yates and Zukowski 1976), but these studies do not propose a model for predicting preferences under ambiguity.

A MODEL FOR DECISIONS UNDER AMBIGUITY

Consider lottery L where one wins x dollars if event E occurs and zero dollars if it does not. We denote $u(x)$ as the utility of outcome x with $u(0) = 0$ and p as the probability of event E, which is a random variable with density $\phi(p)$. An interpretation of $\phi(p)$ is the probability distribution over the frequency of occurrence of event E. For example, suppose the probability of event E occurring was determined by tossing a coin and having it land heads up. In this case, $\phi(p) = 1$ for $p = 0.5$. In contrast, suppose the probability of event E occurring was determined by the tossing of a thumbtack and having it land point down. In this case, we may not have as precise an idea of the probability of the event occurring. For example, it may be that $\phi(p) = 1/0.2$ for $0.4 \leq p \leq 0.6$, which implies that the probability of a thumbtack landing point down is uniformly distributed between 0.4 and 0.6. Of course, $\phi(p)$ is subjective and will vary with each individual. We will not discuss assessment of $\phi(p)$; however, the literature for assessing subjective probability distributions (e.g., Winkler 1967) is relevant in developing appropriate interrogation procedures or protocols.

The SEU model for evaluating the lottery L is:

$$\begin{aligned} \mathrm{SEU}(L) &= \int_{p=0}^{1} p\phi(p)dp\, u(x) \\ &= \bar{p}u(x) \end{aligned} \qquad \mathbf{(1)}$$

where $\bar{p}$ is the average probability of occurrence for event E.

Our model departs from the SEU model by assigning a decision weight to event E, denoted $w(E)$. Thus, the value function for lottery L is given by:

$$V(L) = w(E)u(x). \qquad \mathbf{(2)}$$

The decision weight for event E depends on the entire $\phi(p)$ rather than on $\bar{p}$ as in Equation 1.

Attitude toward ambiguity and the amount of ambiguity in the situation enter in the model through this decision weight. We define this decision weight as follows:

$$w(E) = \bar{p} + \int_{p=0}^{1} (p - \bar{p})e^{[-\lambda(p-\bar{p})]/\sigma}\, \phi(p)dp \qquad \mathbf{(3)}$$

where λ reflects an individual's attitude toward ambiguity in a given context and $\sigma = \sqrt{\int_{p=0}^{1} (p - \bar{p})^2\phi(p)dp}$ is the standard deviation of the random variable p.

An interpretation of the decision weight given by Equation 3 is that the average probability is adjusted based on the amount of ambiguity and the attitude toward ambiguity. Note that if there is no ambiguity in a situation, then $w(E) = \bar{p}$. Similarly, if the subject does not care about the presence of ambiguity reflected by his value of $\lambda = 0$, then again $w(E) = \bar{p}$. Therefore the model reduces to the SEU model if there is no ambiguity in a situation or if a subject has a neutral attitude toward ambiguity.

When $\lambda \neq 0$, and $\phi(p)$ is not degenerate, the $(p - \bar{p})$ measures the amount of "disappointment" or "elation" each possible value of p represents relative to the average value of p. So, if the average probability of the event occurring was 0.5, then a probability of the event occurring equal to 0.8 would be better and the amount of "elation" would equal 0.3. This "disappointment" or "elation" is weighted by $e^{[-\lambda(p-\bar{p})]/\sigma}$, where $\frac{(p - \bar{p})}{\sigma}$ is a normalization factor. If λ is positive, then the individual is ambiguity averse and the potential "disappointment" experienced by the possibility of probabilities smaller than the average probability is higher than the potential "elation" experienced by the possibility of probabilities larger than the average probability. These ideas of "disappointment" and "elation" are analogous to those Bell (1982, 1985) described about utilities in his theories.

The model reduces, as a first-order approximation, to a simple variant of the mean-variance model, which is seen by taking a first-order Taylor approximation of $e^{[-\lambda(p-\bar{p})]/\sigma}$ and substituting it in Equation 3. Using this substitution, we get:

$$w(E) = \bar{p} - \lambda\sigma. \qquad \mathbf{(4)}$$

Clearly, an ambiguity averse individual ($\lambda > 0$) will dislike higher variance. In both the thumbtack game and Ellsberg's urn with the unknown proportion of balls, the variance of the probability of winning is higher than the alternative choices that have known probabilities and thus no variance. This greater variance alone may account for the observed majority of preferences. However, we do not advocate the use of Equation 4 in favor of Equation 3 because the former model may be insufficient in more complex situations (involving skewness).

Estimation

There are three components of the model to estimate: $u(x)$, λ, and $\phi(p)$. The preference function, $u(x)$, is measured externally using standard utility theory methods (i.e., lotteries). In our testing of the model, we provide the subjects with the second-order probability distribution, $\phi(p)$, but this can also be estimated by eliciting median and quartile approximations from the subjects and fitting a suitable distribution, such as the beta distribution.

To estimate λ, each subject can be asked to indicate the known probability of winning that would make him/her indifferent between the known urn and the ambiguous urn. For example:

> There are two urns containing red and black balls. A ball will be chosen randomly from one of the urns; if the ball is red, you will win \$100. Urn 1 has an unknown proportion of red and black balls totaling 200. How many red balls (total of red and black balls equals 200) would you put in Urn 2 to make you indifferent between the two urns?

In the preceding example, if the subject indicates that 83 red balls and 117 black balls would make him/her indifferent between the two urns, then solving the following equation would yield a value for λ:

$$0.415 = 0.5 + \int_0^1 (p - 0.5)e^{[-\lambda(p-0.5)]/(1/\sqrt{12})}\,\phi(p)dp,$$

where $\phi(p)$ equals one because the distribution of p in Urn 1 is assumed to be a uniform distribution between 0 and 1, the most general assumption. In this case, λ equals $1/\sqrt{12}$. This example shows the "irrational" nature of ambiguity avoidance. For example, if an ambiguity averse subject chooses less than 100 red balls to indicate indifference, then s/he is limiting his/her opportunity of winning to gain the false sense of security of thinking s/he knows more about the outcome. It is true that the subject knows more about the process of winning in the first urn than in the second urn, but s/he does not know any more about the probability of the outcome, information s/he mistakenly thinks s/he is "buying" by sacrificing the number of red balls in choosing an indifference value.

TESTABLE IMPLICATIONS INHERENT IN THE MODEL

Decision-Makers Consider Ambiguity When Making Choices Under Uncertainty

The first assumption of the proposed model is that people consider ambiguity when making decisions under uncertainty. Clearly, previous empirical work (e.g., Becker and Brownson 1964; Ellsberg 1961; Larson 1980; MacCrimmon and Larsson 1979; Slovic and Tversky 1974) provides support for this assumption. Thus, the SEU model can be rejected as a descriptive model of decision-making as our model will provide significantly better predictions for decisions that involve ambiguity.

People's Attitudes Toward Ambiguity Vary

By allowing the parameter λ in our model to be positive, negative, or zero, we are allowing the possibility of ambiguity avoidance, proneness, and indifference. If $\lambda > 0$, then the subject is ambiguity averse in that context and $w(E)$ will be less than $\bar{p}$; if $\lambda = 0$, then the subject is ambiguity neutral and $w(E) = \bar{p}$; and if $\lambda < 0$, then the subject is ambiguity prone and $w(E)$ is greater than $\bar{p}$. For an ambiguity averse subject, a higher weight is attached to a given degree of disappointment than that attached to the same degree of elation. Further, a proportionately larger weight is attached as the degree of disappointment increases.

Several researchers (Einhorn and Hogarth 1985; Ellsberg 1961) have suggested that ambiguity proneness might exist, although it is not as prevalent as ambiguity avoidance. For example, Einhorn and Hogarth (1986) found that, in a sample of 274 MBA students at the University of Chicago, 47 percent showed ambiguity avoidance, 34 percent showed ambiguity indifference (perhaps reflecting business school training), and 19 percent showed ambiguity proneness in their choices.

Consumers Are Willing to Pay for Differences in Ambiguity in Choices

Our model also suggests that consumers not only consider ambiguity in making decisions under uncertainty, but are willing to pay to avoid it or to seek it. This willingness is obvious in our parameterization of λ. In our previous example, the subject is giving up or paying 17 red balls of opportunity of winning to avoid ambiguity. As λ changes, the amount people are "willing to pay" varies. Empirically, Becker and Brownson (1964) found that subjects would pay to avoid ambiguity.

We ran an informal experiment and also found that subjects were willing to pay to avoid ambiguity. We asked 54 MBA students to assume they were playing the following game. Either a fair coin or a thumbtack would be flipped. They were to choose heads or tails (for the tack choose point up or point down). If they won the flip, they would win \$500; if not, they would win nothing. We first asked them to indicate the admission price they would pay to play with the coin and then asked them the price they would pay to play with the tack. In this case, the fair coin represented the unambiguous case, where the probability of winning equals 0.5 exactly, and the tack represented the ambiguous case. Of the 54 subjects, 18 said they would pay more to play with the coin than with the tack. These 18 people agreed to pay an average of \$172.37 to play with the coin and \$60.28 to play with the tack. There were 21 people who said they would pay more to play with the tack than with the coin. This group may represent some people who would pay to seek ambiguity, but does represent some people who believe that they have more information about the probability of winning with the tack and, hence, will pay more for that information. Fifteen people were indifferent between the two and would pay the same for both games.

Mean and Variance Alone May Not Account Completely for Choices

In our model, we are incorporating the entire distribution of second-order probabilities, i.e., $\phi(p)$, because we are assuming that the mean and variance alone do not account completely for choices. This is consistent with Einhorn and Hogarth (1985), who also argue that mean and variance are not sufficient to account for people's choices under ambiguity.

This assumption has been supported in part by Yates and Zukowski (1976) and Larson (1980), who found empirically that ambiguity was not considered in decision-making simply through the range of the induced subjective second-order probability distribution. In fact, Larson (1980) hypothesized as a result of his empirical studies that future work in this area should consider incorporating the entire second-order distribution.

Summary

Thus, the published empirical literature provides support for four properties of our theoretical model: (1) people consider ambiguity in making choices, (2) people are willing to pay for differences in ambiguity in their choices, (3) different people have different attitudes toward ambiguity, and (4) a simple mean-variance model is not sufficient to understand choices made when the associated probabilities are ambiguous. Therefore, we have shown that for predicting consumers' choices our model is significantly better than the subjective expected utility model, which is nested in it, because the SEU model cannot account for any of the four results listed here.

EXTENSIONS OF CURRENT MODEL

Impact of Expected Probability of Risky Event Occurring

As described earlier in this article, our model predicts that a subject is "disappointed" or "elated" at various values of p (the probability that event E occurs) depending on their distances from $\bar{p}$. Our model does not presently predict that attitudes toward ambiguity vary with $\bar{p}$. In other words, our model does not allow for a difference in attitude toward ambiguity depending upon whether the expected probability of the event occurring is 90 percent or 5 percent. The model can be refined, if such an effect were desirable, by letting λ be a function of $\bar{p}$. We designed an experiment to examine whether there was a need to generalize the model in this way.

The study was run on 63 undergraduate students who were paid \$10 to participate. Subjects were told to assume that they would be reaching into an urn and drawing a ball. If the ball were red, the subject would win \$10; if the ball were black, the subject would win nothing or lose \$5 depending upon the context assignment.

Under both contexts, each student was asked 15 times to choose between two urns. We were therefore collecting repeated measures per individual, but we randomized the order of the questions to diminish an order effect. In each case, the proportion of red and black balls in one urn was specified exactly and the exact number of red balls (and hence black balls) in the other urn was not known—but the range within which the number of red balls would fall was known. Both urns had the same expected number of red balls. The students were asked to choose with which urn they would prefer to play the game and then to indicate how they would change the composition of the fixed urn so that they would be indifferent between the two urns. We used these answers to develop a dependent measure of their attitude toward ambiguity and called it the ambiguity premium.[1]

The results of this study indicated a significant effect of range ($F = 7.97$, $p < 0.0004$), which justifies the use of the $(p - \bar{p})$ term in the model to represent "disappointment" or "elation." In addition, we found a significant effect of $\bar{p}$ on attitude toward ambiguity ($F = 16.78$, $p < 0.0001$). This result suggests that the weight on the "disappointment" or "elation" should be a function of $\bar{p}$. One way to incorporate this result would be to allow λ to be a linear function of $\bar{p}$. Thus, in a refined model

$$w(E) = \bar{p} + \int_{p=0}^{1} (p - \bar{p}) e^{[-(a+b\bar{p})(p-\bar{p})]/\sigma} \phi(p) dp, \quad (5)$$

where a and b are parameters reflecting attitude toward ambiguity. This refinement of the model also allows for an interaction effect between mean and

[1] Ambiguity premium is the dependent measure of attitude toward ambiguity. If the ambiguity premium is negative, it suggests that the consumer is ambiguity averse and would "pay" to avoid ambiguity. If the ambiguity premium is positive, it suggests that the consumer is ambiguity seeking. If it is zero, it suggests ambiguity neutrality. The ambiguity premium correlates with λ in the model. For more detail on the experiment, see Kahn and Sarin (1987).

range, which empirical results also suggest is desirable ($F = 11.19$, $p < 0.0001$). Finally, the results suggest that the context of the bet, in this instance winning only or winning and losing, has an effect ($F = 5.11$, $p < 0.02$) on attitude toward ambiguity. This effect of context was further investigated in another experiment described next.

Attitude Toward Ambiguity as a Function of Context

The model currently implies that λ is constant for an individual in a given context. Attitude toward ambiguity quite possibly could differ from one context to another. When probabilities are objective, risk attitude often depends on the context (see Kahneman and Tversky 1979). However, context effects are not well understood at this time, and exploring the relationship between the characteristics of a context and its influence on attitude toward ambiguity would be worthwhile. In the following experiment, we test the effect of ambiguity over several consumer choice contexts. The subjects were 60 MBA students who were told that 25 percent of them would be chosen randomly to paticipate in a lottery when they finished answering the questions. Their choices in the lottery would come from their responses to the questionnaire. As a result of the lottery, they would be paid $3, $5, or $7. Everyone not chosen to participate in the lottery would be paid $5.

Specifically, in this experiment, we tested:

- Context effects: We examined decision settings that represent the type of situations that students as consumers might actually face. Each subject was asked to make several decisions involving risk across the following consumer contexts: (1) radio warranty decisions, (2) pharmaceutical decisions involving either allergy drugs given during pregnancy or skin rash drugs that could cause some side effects, and (3) service decisions involving either quality of food at a restaurant or dependability and time of film processing. In each case, the subject was asked to choose between two products or services, one described with unambiguous probabilities and one with ambiguous probabilities.
- Win/loss payoff effects: Many consumer decisions involve choices between status quo and a potential loss or between status quo and a potential gain. We examine how a win or loss framing would affect risky decisions with ambiguous probabilities.
- Mean and range effects: We test the effects of mean probabilities and of ranges of probabilities on attitudes toward ambiguity in consumer choice contexts.

Results

In the Table, the ambiguity premiums are reported for each of the contexts in our study for fixed levels of mean probability ($\bar{p} = 0.5$) and range (0.4 to 0.6). The absolute value of the ambiguity premium is the largest for the pregnancy context. The average premium is negative (ambiguity averse) for the pregnancy and the film processing contexts and positive for the restaurant, skin rash, and radio warranty contexts. Although these directional observations point to a context effect, it cannot be statistically confirmed because of the relatively small range (0.4 to 0.6).

TABLE

AMBIGUITY PREMIUMS FOR ALTERNATIVE CONTEXTS

Level of context	N	Mean	SD
Pregnancy	21	–.0319	.1503
Film processing	21	–.0200	.0486
Restaurant	20	.0290	.0924
Skin rash	19	.0105	.1186
Radio warranty	19	.0158	.0709

NOTE: Mean = 0.50 and range = 0.20.

The restaurant and film processing contexts can be directly compared across many levels of range as a function of the experimental design. Here, we do find a significant context effect ($F = 12.30$, $p < 0.0007$). We observe overall ambiguity aversion for the film processing context (mean premium = –0.0317) and ambiguity seeking for the restaurant context (mean premium = 0.0556).

The most interesting result, besides the context effect discussed in the preceding paragraph, is the presence of a significant mean × win/loss payoff interaction ($F = 4.79$, $p < 0.01$). In the gains domain, there is ambiguity seeking at low mean probabilities and ambiguity aversion at high mean probabilities. In the loss domain, a reflection effect occurs with ambiguity aversion at low mean probabilities and ambiguity seeking at high mean probabilities. These results parallel those observed for risk aversion. A possible explanation for the close resemblance between the findings on risk aversion and ambiguity aversion may be that the same psychological factors are responsible for both effects. Therefore, the presence of ambiguity may accentuate the attitude toward risk (aversion or seeking). In our study, we controlled for risk aversion by using the identical payoffs for the two choices in each pair of questions.

Summary

As a result of our empirical testing, we found two significant effects that suggest future directions for research on ambiguity. First, we found a significant context effect, which indicates that attitude toward ambiguity in risky decisions varies from context to context. Finding a significant context effect implies in our modeling structure that λ is individual and context specific.

Second, we found a significant mean × win/loss payoff interaction. Generally, we found a reflection effect for ambiguity that parallels the reflection effect found for the value function in Prospect Theory (Kahneman and Tversky 1979). Paralleling the reflection effect from Prospect Theory suggests that ambiguity will accentuate the effects of risk aversion or risk proneness and will not cancel it out. Our model needs to be extended to include this effect. One possible way, as mentioned earlier, is to allow λ to be a linear function of $\bar{p}$. In addition, further empirical work is needed to see how context would affect this interaction.

CONCLUSIONS

In consumer research, many of the decisions made under uncertainty involve probabilities that cannot be specified exactly and hence are ambiguous. For example, in consumer durable purchase decisions, there is uncertainty about potential breakdown or technological obsolescence of the product. As mentioned earlier, in major purchases, such as a car or a home purchase, the probabilities of various risks are generally not defined explicitly. Similarly, in services, there is uncertainty and ambiguity involved in choosing among health care services, in deciding among universities, or in choosing among careers.

In this article, we have provided new theoretical and empirical research showing that the subjective expected utility model is not general enough to describe fully such decisions. We have postulated a model that can describe how choices are made when probabilities are ambiguous. Our model shows a significant improvement in explanatory power over the SEU model, which is nested in it, when ambiguity is present.

Our main purpose has been to define the nature of ambiguity and to develop a formal framework for evaluating its effects. In this regard, our model can be compared to Einhorn and Hogarth's (1985) model of ambiguity. Both models are descriptive models of behavior. Einhorn and Hogarth's model extends the anchoring and adjustment paradigm of behavior. Our model generalizes expected utility theory, which offers a few advantages. First, the model we propose generalizes the subjective expected utility model while only adding one more parameter in the simple version and two more in a refined version.[2] Second, in terms of disappointment and elation, the model has a behavioral justification, which parallels some related work in risk theory. Third, the model reduces to a variant of the mean-variance model, which is appropriate to use in many common circumstances and reduces to the SEU model when there is either no ambiguity in a choice situation or the subject is indifferent about the presence of ambiguity.

Empirically, we have found that the consumer context, payoffs involved (win or loss), and the amount of ambiguity (range effects) and risk (mean effects) present in the decision affect the overall attitudes toward ambiguity. Our findings suggest that if ambiguity is present in consumer decisions, the overall attitude toward risk may be accentuated.

[*Received February 1987. Revised February 1988.*]

[2] Einhorn and Hogarth (1986) have a discussion about how their model also can be viewed as an extension of SEU, although extending the SEU model was not the original starting point in their modeling framework.

REFERENCES

Becker, Selwyn W. and Fred O. Brownson (1964), "What Price Ambiguity? Or the Role of Ambiguity in Decision Making," *Journal of Political Economy*, 72 (February), 62–73.

Bell, David E. (1982), "Regret in Decision-Making Under Uncertainty," *Operations Research*, 30 (5), 961–982.

——— (1985), "Disappointment in Decision-Making Under Uncertainty," *Operations Research*, 33 (1), 1–27.

Bettman, James R. (1979), *An Information Processing Theory of Consumer Choice*, Reading, MA: Addison–Wesley.

Bonoma, Thomas V. and Wesley J. Johnston (1979), "Decision Making Under Uncertainty: A Direct Measurement Approach," *Journal of Consumer Research*, 6 (September), 177–191.

Calder, Bobby J. (1981), "Cognitive Consistency and Consumer Behavior," in *Perspectives in Consumer Behavior*, eds. Harold H. Kassarjian and Thomas S. Robertson, Glenview, IL: Scott, Foresman, 258–269.

Cox, Donald F., ed. (1967), *Risk Taking and Information Handling in Consumer Behavior*, Boston, MA: Division of Research, Graduate School of Business Administration, Harvard University.

Curley, Shawn P. and J. Frank Yates (1985), "The Center and Range of the Probability Interval as Factors Affecting Ambiguity Preferences," *Organizational Behavior and Human Decision Processes*, 36 (2), 273–287.

Currim, Imran S. and Rakesh K. Sarin (1983), "A Procedure for Measuring and Estimating Consumer Preferences Under Uncertainty," *Journal of Marketing Research*, 20 (August), 249–256.

——— and Rakesh K. Sarin (1984), "A Comparative Evaluation of Multiattribute Consumer Preference Models," *Management Science*, 30 (May), 543–561.

Einhorn, Hillel J. and Robin M. Hogarth (1985), "Ambiguity and Uncertainty in Probabilities Inference," *Psychological Review*, 92 (4), 433–461.

——— and Robin M. Hogarth (1986), "Decision Making under Ambiguity," *Journal of Business*, 59 (4) S225–S250, point number 2.

Ellsberg, Daniel (1961), "Risk, Ambiguity, and the Savage Axioms," *Quarterly Journal of Economics*, 75 (November), 643–669.

Fellner, William (1961), "Distortion of Subjective Probabilities as a Reaction to Uncertainty," *Quarterly Journal of Economics*, 75 (November), 670–692.

——— (1965), *Probability and Profit*, Homewood, IL: Richard D. Irwin.

Fishburn, Peter C. (1983), "Ellsberg Revisited: A New Look at Comparative Probability," *The Annals of Statistics*, 11 (4), 1047–1059.

Hauser, John R. and Glen L. Urban (1977), "A Normative Methodology for Modeling Consumer Response to Innovations," *Operations Research*, 24 (4), 579–619.

——— and Glen L. Urban (1979), "Assessment of Attribute Importances and Consumer Utility Functions: von Neumann Morgenstern Theory Applied to Consumer Behavior," *Journal of Consumer Research*, 5 (March), 251–262.

Kahn, Barbara E. and Rakesh K. Sarin (1987), "Modelling Ambiguity in Decisions Under Uncertainty," Working Paper No. 163, University of California, Los Angeles, CA 90024.

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

Larson, James R., Jr. (1980), "Exploring the External Validity of a Subjectively Weighted Utility Model of Decision-Making," *Organizational Behavior and Human Performance*, 26 (September), 293–304.

Luce, R. Duncan and L. Narens (1985), "Classification of Concatenation Measurement Structures According to Scale Type," *Journal of Mathematical Psychology*, 29, 1–72.

MacCrimmon, Kenneth R. and Stig Larsson (1979), "Utility Theory: Axioms Versus 'Paradoxes'," in *Expected Utility and the Allais Paradox*, eds. Maurice Allais and Ole Hagen, Dordrecht, The Netherlands: D. Reidel, 333–409.

Marschak, Jacob (1975), "Personal Probabilities of Probabilities," *Theory and Decision*, 6 (May), 121–153.

Schmeidler, David (1984), "Subjective Probability and Expected Utility Without Additivity," Institute for Mathematics and Its Applications Preprint Series No. 84, University of Minnesota, Minneapolis, MN 55455.

Sherman, Roger (1974), "The Psychological Difference Between Ambiguity and Risk," *Quarterly Journal of Economics*, 88 (February), 166–169.

Slovic, Paul and Amos Tversky (1974), "Who Accepts Savages's Axiom?" *Behavioral Science*, 19 (6), 368–373.

Smith, Vernon L. (1969), "Measuring Nonmonetary Utilities in Uncertain Choices: The Ellsberg Urn," *Quarterly Journal of Economics*, 83 (May), 324–329.

Winkler, Robert L. (1967), "The Assessment of Prior Distributions in Bayesian Analysis," *Journal of the American Statistical Association*, 62 (September), 776–800.

Yates, J. Frank and Lisa G. Zukowski (1976), "Characterization of Ambiguity of Decision-Making," *Behavioral Science*, 21 (January), 19–25.

Zaichkowsky, Judith L. (1985), "Measuring the Involvement Construct," *Journal of Consumer Research*, 12 (December), 341–352.