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POLICY ANALYSIS AND BENEFIT EVALUATION FOR
ENVIRONMENTAL REGULATION

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Executive Summary for Risk Valuation Results

1. The risk valuation segment of this study used a sample of 783 adults recruited from a mall in Greensboro, North Carolina.

2. Three chronic diseases thought to be related to exposure to environmental pollutants were analyzed in the valuation study, peripheral neuropathy (a nerve disease) and a terminal and a curable form of lymphoma (cancer of the lymph system with 100 percent and 10 percent chances of survival, respectively). Since most subjects were not familiar with the consequences of contracting these diseases, the questionnaire began with a long segment which educated subjects about the disease consequences.

3. We used the contingent valuation method to value the reductions in the risks of contracting these diseases. Subjects were asked to compare a series of locations that differed from their current place of living in two dimensions, the risk of contracting the disease (either nerve disease or lymph cancer) and a numeraire good. In some questions, the numeraire good was another familiar risk (specifically, the risk of dying in an automobile accident in that location) and in others it was money (as measured by differences in the costs of living in the two locations).

4. An interactive computer program tailored the questions asked of each subject to lead them to a point of indifference between two locations, thus enabling us to derive their rates of trade-off of reductions in the disease risk for increases in either their risk on an automobile death or their cost of living.

5. The median subject was willing to trade-off a 2.5 times greater reduction in the risk of nerve disease for an equivalent increase in the risk of an automobile death. For curable lymph cancer, the median subject was willing to trade-off a 1.6 times greater reduction in its risk for an equivalent increase in the risk of an automobile death, and for terminal lymph cancer the median rate of trade-off against automobile death risk was one for one. Using a four million dollar value of a statistical life as an example, this translates into median values per case avoided of $1.6 million for nerve disease, $2.5 million for curable lymph cancer, and $4.0 million for terminal lymph cancer.

6. In an early portion of the questionnaire, subjects were asked to rate their levels of aversion to each of the major consequences of the three diseases. We found strong correlations between these relative aversion scores and the risk-risk measures for the three diseases, indicating that the risk-risk trade-off rates are accurately reflecting differences in risk reduction values across subjects.

7. Direct elicitation of risk-dollar trade-off rates for nerve disease was shown to yield rates that were highly influenced by the specific choices presented in the initial questions posed of the subjects. Median risk-dollar trade-off rates ranged from $2.1 million to $50 million. The inordinately high values appear to reflect an inability of subjects to fully internalize the units of risk (l/l,OOO,OOO) being traded. In addition, the risk-dollar trade-off rates were found to be uncorrelated with the relative aversion scores for the diseases. These results indicate that the choice task posed of subjects was too complex for them to give answers which accurately reflect their preferences for reducing the risks of the three diseases.

8. We carried out an exploratory study of the application of the conjoint measurement technique to the valuation of health states. The study attempted to estimate utility values for the consequences of diseases that could be used to construct an index of disutility for

each disease. While the disutility values estimated for eight generic disease consequences appear to order the consequences correctly, not enough of the specific consequences of each of the diseases were able to be valued, and thus the indices derived from the conjoint measures did not reflect the relative values of the different diseases. Future research with a more complete coverage of the disease consequences is necessary to more accurately test the ability of the conjoint approach to yield accurate measures of the values of disease risk reductions.

Executive Summary for Risk Communication Results

1. The risk communication segment of this study utilized a sample of 646 adults from the Greensboro, North Carolina area.

2. The risk communication study instrument informed the respondents of either the risks of nerve disease or the risks of lymph cancer, which arose from environmental risks that they would face if they moved to a new area. The respondents were informed that these risks were less than in their present locale so as to avoid alarmist responses to increases in the risk.

3. The risk information presented to respondents consisted of information for two studies pertaining to Area A, which had differing risk implications because of the scientific uncertainties. The respondents' task was to establish the precise risk in Area B that they viewed as being equivalent to the uncertain risks posed by Area A, where the extent of this uncertain risk had to be determined based on their processing of the risk information.

4. An interactive computer program established the point of indifference of the respondents. In particular, it ascertained the precise probability of disease in Area B that the respondent viewed as being equivalent to the uncertain risk in Area A that was implied by the two risk studies that had been undertaken.

5. The overall results suggest that the respondents do learn and process the risk information. Many of the features of this learning process are consistent with a rational (Bayesian) learning model. These positive aspects of the results provide support for use of risk communication as a policy mechanism.

6. Respondents do, however, exhibit what we have termed "ambiguous belief aversion." If there is a large spread in the risks implied by two studies, respondents will assess the risk as being higher even though the mean risk level implied by the two studies may not differ from another study pair for which the scientific estimates are more tightly clustered. Individuals consequently are reluctant to incur situations involving scientific uncertainties, and this reluctance cannot be captured using a standard Bayesian learning framework. This departure from standard learning models suggests that there is an additional ambiguity aversion influence that must be taken into account. Moreover, the extent of this ambiguity aversion is particularly large in situations in which there are substantial downside risks, i.e., the potential for a very bad outcome.

7. Respondents weight the first study mentioned to them more than the second study even though there is no temporal difference in the presentation, only a difference in which the respondents read about the two studies. This result reflects a cognitive limitation of the respondents who appear to be less attentive to the first study mentioned to them than the second. In practice, one might expect this tendency to be even greater to the extent that there is a temporal lag between the presentation of the information pertaining to the first and the second studies.

8. In situations in which there is a temporal order to the studies, one would want respondents to weight the second study more than the first because it presumably extends the initial study and is based on more advanced scientific knowledge and techniques. One observes an effect of this type, as respondents place approximately twice as much weight on the second study as the first study mentioned in situations in which an explicit temporal order to the studies is indicated.

9. These results rule out extreme models of responses. There is no evidence of

alarmist behavior in terms of individuals placing a weight on the risk information they receive that is too great and which cannot be reconciled with a rational learning process. Nor is there evidence of zero responses to the risk information. Moreover, none of the respondents viewed the risk as being the extreme of either a zero risk or a risk that was a certain outcome. Nevertheless, there were systematic biases in behavior that must be taken into account.

10. Our results suggest that risk communication policies can succeed in conveying scientific uncertainties to individuals. However, considerable care is needed in terms of the presentation of the risk information and in the selection of the particular risk information that will be conveyed. In undertaking such policies one must also recognize the cognitive limitations that individuals have in processing the risk information and which will influence the effect this information will have on their perceptions, which may be quite different from the risks that are stated by the government.

Chapter 1

Issues in Valuing Health Risks: Applications of Contingent Valuation and Conjoint Measurement to Nerve Diseases and Lymphoma

by

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Abstract

This study assesses the ability of the contingent valuation method to value reductions in the risks of long-term health effects caused by environmental pollutants. We use a computer-based survey approach to elicit choices among locations to live that differ for the subjects in attributes such as their risks of contracting a chronic disease, their risks of dying in an automobile accident, and their costs of living. From paired comparisons of different locations, we infer respondents' rates of trade-off between reducing the risks of chronic diseases and the automobile death risk as well as their rates of trade-off of disease risks with the cost of living. The value of reducing the risks from both a nerve disease (peripheral neuropathy) and lymphoma (cancer of the lymph system) are measured.

The results indicate that most people consider nerve disease and a curable form of lymph cancer (with a 10 percent chance of death) to be less onerous than death from an automobile accident, although a few people find these diseases to be so undesirable as to be a worse fate than death. Subjects were evenly split as to which was more undesirable, the risk of a fatal form of lymph cancer (with a 100 percent chance of death) or an equivalent risk of an automobile death. The median subject found a reduction in the risk of nerve disease to be worth 0.40 times the value of an equivalent reduction in the risk of an automobile death, with the median subject indicating the curable form of lymph cancer to be 0.625 times the value of an equivalent reduction in the risk of an automobile death. Using a $4 million estimate of the value of a statistical life as an illustration, our median results suggest a value of avoiding a case of nerve disease of $1.6 million, a value of preventing a case of curable lymph cancer of $2.5 million, and a value of avoiding a case of terminal cancer of $4.0 million.

We also asked each subject to rate his or her aversion to each of the major consequences of contracting these diseases and found a strong positive correlation between the risk-risk trade-off values and relative aversion scores, providing further support that the

risk-risk trade-off values measure subjects' values of reducing the risks of the three diseases.

Results on direct elicitation of trade-off rates between disease risks and dollars suggest that many subjects were unable to make consistent choices involving this trade-off. The risk-dollar trade-off rates were not correlated with the relative aversion scores. These results do not provide support for using direct elicitation of risk-dollar trade-offs for benefits, such as chronic disease risk reductions, that require complex choices to be made in the elicitation task.

Finally, the study also explored the use of conjoint analysis as a mechanism of valuing the individual consequences of contracting diseases (as opposed to the disease itself). The results indicate internal consistency among the disease consequences whose disutility values were measured, but it appears that not enough consequences of each of the three diseases in the study were included in the conjoint measurement exercise to obtain good measures of the disease values themselves. Further research will be necessary to determine if a more complete conjoint analysis is capable of measuring the value of disease risk reductions.

I. Introduction

Efficient and effective environmental regulation requires that the benefits of environmental protection be compared with the costs of protection, and that resources devoted to environmental protection produce the most valuable benefits possible. Since many of the benefits of improvement in the environment accrue through reduced incidence of diseases and death, considerations of efficiency and cost-effectiveness call for measurement of the value of reducing the health risks to society that are caused by exposure to environmental pollutants. This paper applies two benefit estimation techniques that are particularly appropriate for valuing health risks, contingent valuation and conjoint measurement, to two fairly representative examples of environmentally caused health risks, lymphoma (cancer of the lymph system) and peripheral neuropathy (a nerve disease attacking the extremities of the body).

The contingent valuation approach was developed over the last twenty-five years as a way to measure the willingness to pay for public goods which are not traded in existing markets. It relies upon establishing a hypothetical choice environment in which subjects are asked to either directly state their willingness-to-pay for the goods being valued or else make a choice from which their willingness-to-pay can be inferred. Applications of the technique have been made to a large variety of goods including atmospheric visibility (Schulze et al., 1983, Rowe et al., 1980, Brookshire et al., 1976), congestion in wilderness areas (Cicchetti and Smith, 1973, Walsh and Gilliam, 1982), freshwater quality (Smith and Desvouges, 1986, Sutherland and Walsh, 1985, Loomis, 1987), forest preservation (Kristom, 1990) elk hunting (Brookshire et al., 1980, Sorg and Nelson, 1986), beach use (McConnell, 1977), acid deposition (Navrud, 1989) and the

disposal of toxic wastes (Bumess et al., 1983). Although the approach still has its skeptics, it has been approved for applications in benefits analysis by organizations such as the U.S. Environmental Protection Agency, the Department of Interior, the U.S. Army Corps of Engineers, and the Water Resources Council. By 1984, the contingent valuation method had developed far enough to justify a national conference on assessing the method (see Cummings et al., 1986), and in 1989 Carson and Mitchell published their landmark treatise of the method, summarizing and evaluating many of the applications to date.

While the contingent valuation method has occasionally been used to estimate the value of a statistical life (Jones-Lee, 1976, Frankel, 1979, Hammerton et al., 1982), the method has been only applied a few times to the valuation of the benefits of health risk reductions (Acton, 1973, Rowe and Chestnut, 1984, Tolley and Babcock, 1986, Magat, Viscusi and Huber, 1988, and Viscusi, Magat, and Huber, 1991). Given that health benefits are one of the most important categories of benefits from environmental regulation, and that health risk reductions are not directly traded in markets, health benefit valuation is potentially one of the most important applications of contingent valuation, AU of the contingent valuation studies of health benefits have involved short-term effects, such as coughing and asthma attacks. One of the main purposes of this study is to extend the contingent valuation methodology to the valuation of long-term health benefits from reducing the risks of chronic diseases such as cancer.

Occasionally the data is available from natural experiments to use market behavior to infer the values of health and safety risk reductions (e.g., Viscusi, 1983,

Moore and Viscusi, 1990). However, in most instances non-market approaches are necessary. Within the class of survey-based approaches to benefit valuation, the health state utilities approach (Kaplan et al., 1976, Rosser and Kind, 1978, and Sackett and Torrance, 1978) has been suggested as an alternative to the use of contingent valuation. While there is wide variation in the specific measurement techniques used in this approach, the basic idea is to decompose an illness into separate attributes of the health states, question people to derive a utility value for each attribute and a relative importance weight for all attributes, and then calculate the weighted sum of the utility values of all attributes to derive a total utility of contracting the disease. This measure of total utility can be compared to the utility of other diseases, as well as of good health. For example, Sintonen (1981) uses the disease attributes of moving, hearing, speaking, seeing, working, breathing, incontinence, sleeping, eating, intellectual or mental functioning, social participation, and perceived health, weighting each of their utility values by a relative importance rating of between 0 and 10. For a review of this literature, see Torrance (1986).

If this health states decomposition approach were capable of accurately measuring the willingness-to-pay for improvements in health status, then it would provide a relatively inexpensive and fast method of health benefit valuation. However, there are several potential problems with its application. Perhaps of most concern, people may not value the disutility of having a disease, such as lung cancer, as equal to sum of the disutilities of suffering each of its attributes. The values may also be highly sensitive to how those attributes are defined and how completely they represent the disease. In

addition, this approach has some difficulty in handling death as one possible consequence of the disease. More fundamentally, it utilizes an *ex post* approach in which people are asked to imagine that they actually suffer from the disease attribute, whereas for most benefit analyses the *ex* ante approach more appropriately reflects the fact that environmental programs produce reductions in the *risk* of adverse health effects to a population, without identifying which individuals will actually contract the disease or experience the disease attributes.

Magat, Viscusi, and Huber (1988) introduced the conjoint measurement technique to environmental benefit valuation literature as a way of inferring benefit values from choices made by subjects which, although hypothetical, are similar to choices they actually do or could be asked to make in their daily lives. In that article, we used conjoint analysis to estimate subjects' relative preferences for money and for the reduction of morbidity risks. This allowed us to derive willingness-to-pay estimates for morbidity risks. In this study we apply conjoint analysis to the problem of measuring long-term health risk valuations.

Like the health states decomposition approach, the conjoint approach works by decomposing the utility of a given health status, or the disutility of a disease, into component parts, deriving a utility weight for each component attribute, and then summing the utilities of the attributes. However, it avoids many of the problems of the health states decomposition approach by deriving the utilities of the attributes of diseases from choices between two diseases which differ among the possible attributes of a disease. In other words, the attributes are valued by making choices among diseases

rather than choosing directly among different values for a single attribute. The properties of the utility model behind the approach are also more consistent with standard economic models of consumer behavior than the somewhat ad hoc rating scales used in some of the health states decomposition approaches.

There are two major research questions that this paper addresses. First, we assess the ability of the contingent valuation method (CVM) to value reductions in the risks of long-term health effects caused by environmental pollutants. Our approach is to study two different diseases thought to be related to be exposure to various environmental contaminants, peripheral neuropathy (nerve disease) and lymphoma (cancer of the lymph system). The former disease is non-fatal in most cases and not related to cancer, while the latter disease is a form of cancer and occurs in both a form that is fatal and one that has a highly probability of recovery.

Although there are many potential causes of peripheral neuropathy, it is thought by some researchers to be linked to environmental pollutants such as lead (e.g., from smelters and batteries), acrylamide, organophosphate pesticides (such as parathion), industrial compounds (such as hexane 2 hexanone), and solvents (such as carbon disulfide). Lymphoma is closely related to leukemia (blood cancer), which has been thought to be one possible consequence of exposure to high levels of toxic chemicals such as formaldehyde and benzene, and toxics such as methylene chloride, dioxin, and acrylomide are also thought to cause various forms of cancer.

We derive values of the benefits of reducing the risk of these diseases in two metrics, dollars and another risk (specifically, the risk of dying in an automobile

accident). We follow the approach of Viscusi, Magat, and Huber (1991) in employing two different metrics for measuring health risk benefits. The risk-risk trade-off rates can be translated into dollar values by assigning values to death avoidance, for example, through wage hedonic studies.

The second major research question is whether conjoint analysis can be used to decompose the value of disease risk avoidance into component parts that represent the characteristics of the disease. As explained above, if the health states decomposition approach is a workable one, then there are reasons to suspect that the conjoint approach will allow more accurate measurement of the component utility values.

In addition to exploring the use of the contingent valuation and conjoint approaches to benefit valuation, we also measured each subject's rating of his or her aversion to eight characteristics of lymph cancer and ten characteristics of nerve disease. These relative aversion scores are useful as a method of checking the extent to which the CVM and conjoint values accurately measured individual values of the health risk reductions, since they can be correlated with both the CVM values and the conjoint values.

Section Two of the paper describes our research methodology, while Section Three presents our results. The final section offers conclusions and implications for future research.

II. Methodology

A. Sample

The sample was recruited from a blue collar mall in Greensboro, North Carolina, a city which is often used in survey research because its citizens are fairly representative of the United States population. Table One lists the mean, standard deviation, minimum, and maximum values of all the demographic questions asked of the subjects, as well as their responses to questions about their familiarity with the two diseases under study. About 56 percent of the sample were women, average family size was 2.7, respondents averaged in their thirties (all were over 20 years of age), income averaged over $40,000, the average subject had completed some college education without graduating, and 58 percent were married. The questions about subjects' familiarity with nerve disease and lymph cancer were included both because they are possible correlates with the valuation responses and because they increased the subjects' involvement with the disease description parts of the questionnaire. Most subjects were not familiar with the consequences of contracting the two diseases under study, requiring us to include a section at the beginning of the questionnaire that educated subjects about these disease characteristics. We interspersed questions about familiarity with the two diseases with these descriptions in order to reinforce the information about the diseases as well as to increase subjects' involvement with the questionnaire.

B. Research Design

Our primary mechanism for eliciting health risk reduction valuations was the use of paired comparison questions about a familiar choice, namely, a residential location

decision. In each question, subjects were asked to choose between two locations that differed along two dimensions, the risk of contracting the disease (either nerve disease or lymph cancer) and a numeraire good. In some questions the numeraire good was money (as measured by differences in the cost of living in the two locations) and in other questions this good was another familiar risk (specifically, the risk of dying in an automobile accident in that location). Their responses to these paired comparison questions allowed us to infer each subject's rate of trade-off of either money or automobile death risk reduction for a reduction in the risk of contracting the disease.

They were informed that the two new locations in each question were identical in all other respects to the places they now live, and that the risks of contracting the disease or dying in an automobile accident were lower in both of the new locations than where they currently lived. This context allowed them to ignore the many other attributes which enter into a location decision and focus on the health, automobile death, and cost-of-living differences between the two locations. It also avoided the extreme reaction which often occurs when people are asked to accept increases in health risks (see viscusi and Magat, 1987).

The questionnaire was administered on a personal computer using an interactive program that adjusted the questions asked of each subject based on his or her previous responses. This approach has been successfully used by the authors in several previous studies, most recently Viscusi, Magat, and Huber (1991). By tailoring the questions to each subject, fewer questions need to be asked of each subject, thus economizing on the time available with each subject. As well, this approach avoids potential problems with

interviewer bias and induces subjects to more honestly reveal their preferences. The use of a computer also tends to engage subjects better than when the same questions are asked by interviewers, yielding results which reflect a higher level of attention paid by the subjects to the interview task.

Interviewers were used to introduce the subjects to the survey and to the use of the personal computer. In addition, the interviewers assisted in educating the subjects about the consequences of contracting the two diseases, since most of them were not familiar with the exact consequences of the diseases. The interviewers gave subjects the short descriptions of the diseases contained in Appendices A and B and read this description out loud. As described above, the computer program reinforced this initial education by asking subjects a long series of questions about each of the consequences of contracting the disease (e.g., nerve disease does not affect life expectancy).

For each separate experimental treatment, subjects were given a series of paired comparison questions and for each question they were asked to indicate on a nine-point scale whether they preferred Area A, they preferred Area B, or they were indifferent between the two areas. See, for example, the initial question displayed at the bottom of Table Four which was asked of subjects trading off the risk of lymph cancer and the risk of an automobile death. If the subject preferred Area A on the previous question, the subsequent question was designed to modify one of the risks in Area A or Area B to make Area A less attractive. Similarly, if the subject preferred Area B on the previous question, the subsequent question modified the risks to make Area B less attractive. This process continued until the risks in the two locations made the subject indifferent

between them. From this indifference point we then inferred the subject's rate of trade-off between the two risks (or, in the case of the cost-of-living question, between the disease risk and money).

Based on pre-testing with several different values of the risks in the initial question, we chose values for that questions which corresponded to the likely median responses of subjects. In this way we were able to minimize the number of iterations of the question before reaching the point of indifference, thus economizing on interview time and reducing any effects on subjects' responses of the iterative process used to find their points of indifference.

In addition to the paired comparison questions, we also asked some subjects to answer some questions about generic disease characteristics which we then analyzed using conjoint analysis, a technique for measuring consumer preferences developed in the marketing literature and introduced to the environmental risk valuation literature in Magat, Viscusi, and Huber (1988). The results from this analysis were used to measure preferences for reductions in the risk of contracting diseases that are characterized by the consequences valued in the conjoint questions.

Figure One lays out the complete research design for our study. Note that subjects were randomly divided into eight separate groups labelled A through H. Subjects within each group were all asked the same sets of questions as listed in columns (2) through (9), in this order. Note that each group answered some, but not all of the eight sections of questions in the survey. For example, only groups C through H answered the conjoint questions. This paper analyzes the valuation results derived from

segments of the questionnaire corresponding to columns (2), (3), (5), (6), and (7). The questions described in columns (4), (8), and (9), as well as portions of column (5), were used to explore responses to ambiguity about the underlying risks of contracting the diseases. These results are analyzed in Chapters Two and Three.

III. Results

Our valuation results can be divided into three parts, those using contingent valuation, those using the relative aversion scores for different generic disease characteristics, and those derived from conjoint analysis. In addition., we analysis the correlations among the responses to these three methods of inferring values for environmental risk reductions.

A. Contingent Valuation

Risk-Risk Estimates

As explained above, we asked subjects to select between two locations that differed, first, in the risk of one disease, either lymphoma (cancer of the lymph system) or the nerve disease (peripheral neuropathy), and, second, in the risk of dying in an automobile accident. Table Two provides results on two forms of lymph cancer, "curable" lymph cancer, which has a 90 percent chance of complete recovery if detected early, and "terminal" lymph cancer, which, as the name implies, is always fatal. Part A displays the curable lymph cancer results, Part B gives the terminal lymph cancer results, and Part C lists the within-subject rates of trade-off between the two forms of lymph cancer. The mean trade-off rates are always larger than the median rates because of the

existence of large values for some subjects and the lower bound of zero for responses. For this reason, the medians provide a more useful summary statistic of the entire distribution of trade-off rates.

The tables also provide separate results for subjects which answered the questions about *curable* lymph cancer before responding to the questions about terminal lymph cancer (i.e., corresponding to column six in the research design of Figure One and then column seven) and for subjects which answered the *terminal* lymph cancer questions first (i.e., column seven followed by column six). Since the order effect was small, we will focus on the responses for all subjects.

The median subject was willing to tradeoff a reduction in the risk of curable lymph cancer of 1.6/1,000,000 for a 1/1,000,000 increase in the risk of an automobile death, which implies that a one in a million reduction in the risk of curable lymph cancer is worth 0.625 times a one in a million reduction in the risk of an automobile death. A few subjects did value reducing the curable lymph cancer risk more than reducing the auto death risk (minimum trade-off rate equals 0.4), while some subjects indicated a considerably lower value for reducing the risk of curable lymph cancer than an automobile death (maximum equals 40).

These results appear to capture the subjects' true preferences for reduction in the two risks. We would expect that for most people curable lymph cancer would be a serious disease, but less onerous than death. Because of the dread associated with cancer, a few people may well prefer to lower their risk of lymph cancer, even the curable type, than to lower their risk of a fatal automobile accident. Part of the

dispersion of values may also be caused by differences in what the subjects perceive as their own risks and those described in the questions, despite the fact that the questionnaire asked them personal characteristics, such as driving mileage and skill, and emphasized that these characteristics were used to estimate the subjects own risks.

The terminal lymph cancer results show the median subject to be indifferent between death from lymph cancer and death from an automobile accident, although some subjects found the lymph cancer death worse and others found an automobile death worse. This dispersion reflects the comparative values that people place on the pain and suffering associated with cancer death versus the benefits of remaining alive with cancer rather than dying immediately in an automobile accident. Because terminal lymph cancer differs from curable lymph cancer only in the likelihood of dying (100 percent versus 10 percent), it is to be expected that the median and mean trade-off rates reflect a higher relative value placed on terminal lymph cancer than curable lymph cancer.

To test this relationship further, we also calculated each subject's ratio of his or her terminal lymph cancer trade-off rate to his or her curable lymph cancer trade-off rate. The median ratio is 0.75, indicating that the terminal lymph cancer risk is 1.33 worse than the risk of curable lymph cancer, a result which is broadly consistent with the median trade-off rates reported in Parts A and B.

The results in Table Three on the nerve disease - automobile death trade-off rates indicate that nerve disease is also considered to be a serious disease, but less undesirable than either form of lymph cancer. The majority of our subjects asked to

choose between locations that differed in nerve disease and automobile death rates were given a ***single*** estimate of the nerve disease risks in each of the two locations (Group One). The median subject found a **2.5/1,000,000** reduction in the risk of nerve disease to be equivalent to a **1/1,000,000** reduction in the risk of an automobile death. This implies that a reduction in the risk of contracting nerve disease is worth 0.4 times an equivalent reduction of the risk of an automobile death.

Fifty subjects were placed in a separate group (Group Two) to explore the effect on trade-off rates of the number of studies used to estimate the nerve disease risks. Group Two subjects were told that ***two*** separate studies had shown the same nerve disease risk, while Group One subjects were given the results of only a single study. The Group Two median is somewhat higher than the Group One median, but its mean is lower, indicating that this manipulation had little effect.

For benefit-cost studies it is useful to translate these results about disease risk-automobile death risk trade-off rates into dollar values. While the literature on the value of a statistical life gives a fairly wide range of estimates, recent work (Moore and Viscusi, 1990) suggests a value of about four million dollars. Using this number for purposes of illustration, our median results suggest a value of avoiding a case of nerve disease of $1.6 million, a value of preventing a case of curable lymph cancer of $2.5 million, and a value of avoiding a case of terminal lymph cancer of $4.0 million.

Fisk-Dollar Estimates

Table Four provides results on the rates of trade-off between reductions in the risk of contracting nerve disease and increases in the cost of living, that is, money.

Subjects were divided into eight groups which differ according to their nerve disease risks and their costs of living. For each group we report the median and mean values of the cost-of-living/nerve disease trade-off rate as measured in units of dollars per l/1,000,000 reduction in the risk of nerve disease.

The median values differ across groups according to both the cost-of-living and the nerve disease risk differences in the initial questions posed to the different groups. The higher the cost of living difference in the initial question, the higher the median trade-off rate. Also, the larger the nerve disease risk difference between the two areas, the lower the trade-off rate. This variation in responses across groups with variations in the initial question' suggests that subjects had **difficulty** answering this form of question, and that their rates of trade-off were influenced by the figures in the initial question.

In addition, when translated into implied values per case of nerve disease avoided, even the medians (and especially the means) imply inordinately high valuations. For example, the median value of 2.5 dollars per **1/1,000,000** reduction in the risk of nerve disease for Group One implies a value of $2.5 million per case avoided, and six of the other seven groups have even higher values. The translation of willingness-to-pay per **1/1,000,000** reduction in risk into excessively high values per case of nerve disease avoided suggests that subjects did not fully internalize the one over a million unit of risk reduction. These results imply that care must be taken in using risk-dollar trade-off values which are derived ***directly*** from trade-offs between disease risks and a dollar measure such as the cost of living. The results reported in the next sections further

supports this conclusion in that relative aversion scores are more closely associated with risk-risk trade-off values than risk-dollar values.

B. Relative Aversion Scores

Part of the introductory section in the questionnaires about both nerve disease and lymph cancer described the disease characteristics and then asked respondents to specify how important they felt it was to avoid each aspect of the disease. Eight of the main consequences of contracting lymph cancer were identified, as well as ten of the main consequences of nerve disease. These ratings were made on a **9-point** scale with "least important to avoid," "somewhat important to avoid," and "most important to avoid" providing the verbal anchors for scores 1, 5, and 9, respectively. Thus, the larger numbers indicate greater aversion to the consequences of the diseases.

Table Five presents the means and standards deviation of the mean of this relative aversion score for the main consequences of contracting the two diseases (with the exception of the probability that the disease will be fatal, which is the only characteristic that differs across the two forms of lymph cancer, curable and terminal). It is interesting to examine the order of these mean relative aversion scores.

For lymph cancer, respondents were most averse to "mild bleeding problems with skin and joints," which had an aversion score of 8.02 on a **9-point** scale. Given that respondents were told of the mild nature of this bleeding, the level of aversion is surprising. It is possible hat the lack of familiarity attached to bleeding of the joints increases the fear associated with this consequence; one knows how to deal with sweating (6.70) or weight loss **(6.71),** but not bleeding of the joints. This result is consistent with

those of other researchers who. have found that aversion to unfamiliar events like an explosion in a nuclear power plant tends to be greater than their factual characteristics might justify.

The next most averse consequences of lymph cancer were infections (7.95) and depression (7.77), both of which imply a vulnerability to the environment for which relatively few defenses exist. By contrast, the less averse consequences - swelling (7.31), fever (6.99), weight loss (6.1), and sweating (6.70) - may be uncomfortable, but are those kinds of misfortunes for which most of us have well-developed mechanisms for coping.

Considering next nerve disease, its most averse consequence is loss of strength (8.19), followed by an inability to move easily (7.97) and constant pain (7.91), all of which imply a reduction in one's ability to cope with the world. Depression is lower in rank order (sixth) for nerve disease than for lymph cancer (third), but their mean aversion scores are quite close (7.75 and 7.77). The relatively low aversion to having to quit work (7.39) or restricting recreational activity (7.22) may be attributed to the presence in our sample of significant numbers of people who do not work or do not engage in active recreational activities. Finally, the two prescriptions for people with nerve disease, a need to take medication (6.61) and to restrict exercise (6.17), are the least aversive consequences for our sample, perhaps indicating that for this group the cure is better than the disease.

Since the risk-risk and risk-dollar trade-off values described in the above section and the relative aversion scores for a disease's consequences both are constructed to indicate the strength of an individual's preferences to reduce the risk 'of a disease such as

nerve disease or lymph cancer, they should be closely correlated. By regressing the trade-off rates against the mean aversion scores averaged over all of a disease's consequences, we can test the joint hypothesis that the two variables ***both*** measure the strength of preferences for risk reduction. The absence of a correlation would indicate that either one or the other, or both variables do not measure the preferences for risk reduction. Given that there are different numbers of consequences for the two diseases and these consequences appear to be more or less independent, we use the mean aversions scores averaged across all of the disease's consequences as a measure of the strength of preference shown by the responses to the aversion rating responses.

Equations 1 through 4 in Figure Two display the results of these simple regressions. The automobile death equivalent values for nerve disease and the two forms of lymph cancer are all closely correlated with the average of the mean aversion scores. All of the coefficients in equations 1, 3, and 4 are positive, as expected, and significant at more than a 99 percent confidence level. These results suggest that both measures, the risk-risk trade-off values and the average of the mean aversion scores, are measuring the subjects' true values of reducing the risks of the diseases.

Note, however, that the within-subject ***differences*** in the two measures do not have a statistically significant relationship, although the signs of the coefficients in equations 5 and 6 take the correct sign The fact that the differences in the 'two measures for the two diseases are not as closely correlated as the absolute magnitudes of the two measures for each disease indicates that there is some noise in one or the other of the measures, but this differences test requires a greater degree of consistency across

measures than simply comparing the two measures for each disease one disease at a time.

In contrast to the strong correlations between the automobile death risk trade-off rates for all three diseases and the averages of the mean aversion scores, equation 2 indicates that the dollar-denominated measure of nerve disease, i.e., the trade-off between a higher cost of living and a lower risk of nerve disease, is not correlated with the average of the mean aversion scores for the consequences of nerve disease. The contrast between the significantly positive correlations with the risk-risk measures and insignificant correlations with the risk-dollar measure for nerve disease suggests that risk-risk measure more'accurately represents the subjects' values of risk reduction than the risk-dollar measure.

C. Conjoint Assessment

In addition to answering the questions about aversion to particular consequences of lymph cancer and nerve disease, part of our sample also answered a set of eight questions designed to assess aversion to an (unnamed) generic disease. Each of the eight questions asked the respondent to compare two diseases that differed along four dimensions, where these four dimensions, or disease consequences, were chosen from a set of eight dimensions and varied from question to question. Through judicious design of the eight questions we were able to then use conjoint analysis to analyze every subject's utility for each of the eight disease consequences.

The eight generic disease consequences are listed in Table Six. Each question took the form of the following example.

SYMPTOMS	DISEASE A	DISEASE B
CHANCE OF **DEATH** IN 5 YEARS	0%	10%
EXTENSIVE HOSPITAL VISITS	NO	YES
CONSTANT PAIN	NO	YES
OCCASIONAL NAUSEA AND LOSS OF ENERGY	YES	NO

WHICH DISEASE IS WORSE?

DISEASE A									DISEASE B
is far worse	1	2	3	4	5	6	7	8	9 is far worse
				About the same					

CHOOSE THE NUMBER THAT BEST EXPLAINS
HOW YOU FEEL ABOUT THE TWO DISEASES...

Respondents were asked to specify how much worse Sickness B is compared to Sickness A. This kind of question was repeated for eight different pairs of disease profiles. Assuming the "about the same" response reflects indifference, then the raw response, less 5, measures how much each Sickness B profile is perceived to be worse than Sickness A. This preference (or aversion) difference is assumed to be an additive function of the difference in the generic consequences of the disease. For example, the question above measures the **(dis)utility** of a 10 percent increase in the chance of dying, plus the impact of required hospitalization, plus the aversion to constant pain, minus the impact of occasional nausea and loss of energy. We used regression analysis to derive

estimates of the disutility of the eight generic disease consequences. The mean values of these disutility indices are listed in Table Six.

As the results in Table Six indicate, the greatest mean aversion is to a 10 percent increase in the chance of death (1.56). Hospitalization (1.19) and surgery (0.84) form the next most aversive group. After these consequences come constant pain (0.39), the loss of mobility outside the home (0.38), and the loss of strength and feeling (0.24), all of which reflect less absolute limits on normal activities than do hospitalization and surgery. Finally, restricted recreational activity (0.13) and occasional nausea and loss of energy (.0.07) are the least aversive generic consequences.

Under the conjoint model, these numbers form an additive scale, implying, for example, that occasional nausea and loss of energy plus surgery (0.07 + 0.84 = 0.91) is marginally more aversive on average, than is the loss of mobility outside the home plus the loss of strength and feeling (0.38 + 0.24 = 0.62). Thus, *if* diseases can be decomposed into their generic consequences, one could compare the disutility of any two diseases by summing the disutility indices of their specific consequences and comparing these two sums.

While appealing in principle, this procedure requires that people evaluate diseases as the additive sum of the disutilities of their consequences, independently of the which specific disease comprises any given set of consequences. It may be the case that people find some diseases, such as cancer, more aversive than others above and beyond any differences in the disutilities they hold for the specific consequences of these diseases.

On a more practical note, this procedure requires estimation of the disutilitities of the ***entire*** set of possible consequences of any diseases which are to be compared. Even for two diseases, such as nerve disease and curable lymph cancer, the number of consequences' disutilities which need to be estimated quickly becomes very large. In this example, out of the 8 consequences of curable lymph cancer and the 10 consequences of contracting nerve disease, only one overlaps, thus requiring the estimation of 17 disease consequence disutilitites. Since respondents can only compare four consequences of a disease at most, the number of questions required to estimate the disutilities of each of the generic disease consequences quickly becomes unmanageably large.

Even though we did not estimate the disutilities of all 17 disease consequences comprising both curable lymph cancer and nerve disease, we can roughly test the ability of the conjoint model to measure overall disease disutilities by summing the disutilities of the specific consequences whose disutitites were measured. Thus, for curable lymph cancer this index (CLCINDEX) is comprised of the sum of each individual's disutility of a 10 percent chance of death, plus hospitalization, plus occasional nausea and loss of energy. Similarly, for nerve disease the index (NDINDEX) is formed by summing the disutilities of the loss of mobility outside the home, plus constant pain, plus loss of strength, plus occasional nausea and loss of energy. While these indices formed from an assessment of the generic consequences do not include all of the properties of each specific disease, if the other unmeasured consequences are randomly distributed, the indices should be correlated with overall aversion to the diseases.

Equations 7 through 11 in Figure Two test whether the two indices formed from the conjoint disutitilty indices, CLCINDEX and NDINDEX, are correlated with either the automobile death trade-off rates for curable lymph cancer and nerve disease or their relative aversion scores. None of the coefficients in these simple regression equations is statistically significant. Since both the automobile death trade-off rates and the relative aversion cores are closely correlated, it is likely the conjoint disutility indices are poor measures of the values of avoiding nerve disease and curable lymph cancer.

This lack of significance could be due to several possible reasons. The indices comprise less than half of the consequences of each disease, and thus may be missing important consequences that are imperfectly correlated which those which are included in the indices. Also, people's preferences for avoiding disease risks may not be formed by summing the disutilites of a disease's consequences, that is, independently of the overall effect of having the disease. Finally, the conjoint measurement procedure may not be measuring the values of individual disease consequences accurately. Since the ordering of the mean disutility indices in Table Six makes good intuitive sense, it is unlikely that the last reason explains the lack of significance. We suspect that the first reason, that is, the omission of several key consequences of the two diseases, explains the lack of correlation between the conjoint indices and both the automobile death equivalent trade-off values and the relative aversion scores. However, more research will be necessary to fully resolve this issue.

IV. Conclusions

This paper has explored the use of the contingent valuation method to estimate the values that people place on reducing their risks from contracting chronic diseases such as those caused by exposure to environmental pollution. We focused on two diseases with long-term effects, a nerve disease (peripheral neuropathy) and two forms of lymphoma (cancer of the lymph system), one that is fatal and another with a high chance of survival. In previous work (Viscusi, Magat, and **Huber,** 1991) we developed a computer-based methodology to elicit values for avoiding short-term health risks, and this paper extends that approach to the valuation of reducing the risks of contracting diseases with long-term health effects, including possible death and the other aspects of cancer.

In addition, we developed a more rigorous application of the health states decomposition approach (Torrance, 1986) to valuing disease avoidance than has generally been used and conducted some preliminary tests of the effectiveness of that approach to accurately measure values. Our method of application of this approach involved the use of conjoint analysis to recover the disutilities associated with the different characteristics of a disease, such as loss of energy and the need for hospitalization.

The contingent valuation approach elicited values for reducing the risks of **nerve** disease and lymph cancer using two metrics, another familiar risk (specifically, the risk of dying in an automobile accident) and money. The automobile-death-risk-denominated values appear to be accurately measuring preferences for risk avoidance. The median

subject found that reducing the risk of contracting nerve disease to be 0.4 times as valuable as reducing the risk of an automobile death. In contrast, the median value of reducing the risk of contracting curable lymph cancer was 0.625 times the values of avoiding the risk of an automobile death, and the median subject was indifferent between reducing the risk of terminal lymph cancer and reducing his or her automobile death risk. Both the magnitudes of these risk-risk trade-off values and their relative values are consistent with objective evaluation of the consequences of contracting the three diseases.

As a test of the extent to which these risk-risk values measure subjects' true values of reducing the risk of contracting the diseases, we correlated them with an independent measure of their aversion to the major consequences of contracting each of the diseases. These relative aversion scores for each subject were found to be positively and significantly related to their risk-risk values, adding additional support to the confidence that we can place in the risk-risk values.

In contrast to the risk-risk values, the dollar-denominated values of nerve disease derived from the subjects' responses do not appear to accurately represent their values of averting the risk of nerve disease. They are overly sensitive to the specification of the original trade-off question in the elicitation program, and they appear to be fairly insensitive to the units used to measure risk In addition, unlike the risk-risk measures, they are not correlated with the relative aversion scores that subjects attached to consequences of contracting nerve disease. Based on these results, we concluded that many of our subjects were unable to accurately respond to the location choice question

that required them to trade-off lower nerve disease risk in one location in exchange for a higher cost of living. For complex valuation tasks such as valuing the benefits of reduced risks of disease, subjects appear to be much more capable of making the risk reduction trade-offs if they are posed in terms of a trade-off with another familiar risk than if they are framed as a trade-off with money.

These results suggest some important questions for future research. It would be useful to study the sensitivity of the responses to various design parameters in the study, such as the levels of the risks being avoided. Also, the contingent valuation method needs to be applied to other long-term health risks besides nerve disease and lymph cancer. Finally, there are many unanswered questions about the use of the conjoint analysis in the health states decomposition approach. While we were able to implement the approach using conjoint, a valid test of its accuracy requires that all the major consequences of contracting a disease be included in the disutility scores associated with each disease. As well, it would be useful to condition each consequence of the disease to the specific disease causing that consequence and test whether subjects' disutility values of the consequences are truly independent of the disease causing them to occur.

TABLE ONE

Demographic and Disease Knowledge Characteristics of Sample

A) Summary Statistics

Variable	N	Mean	Std. Dev.	Min	Max
SEX	727	1.443	0.497	1.000	2.000
NOPEOP	727	2.704	1.202	1.000	5.000
NOCHILD	617	5.144	3.173	1.000	8.000
KNOW-ND	727	2.083	0.453	1.000	3.000
KNOW_LS	727	1.834	0.373	1.000	2.000
WORKING	727	1.224	0.417	1.000	2.000
KNOW-HS	727	1.839	0.368	1.000	2.000
LOST-AD	720	1.503	0.814	1.000	9.000
MILES	714	3.398	1.444	1.000	6.000
TIMEDRV	706	2.727	1.892	1.000	9.000
RATEDRV	677	6.858	2.161	1.000	9.000
AGE	599	3.105	1.582	1.000	7.000
KNOW_LC	727	2.050	0.538	1.000	3.000
CLC_REC	725	1.843	0.364	1.000	2.000
KNOW_RAD	725	1.720	0.449	1.000	2.000
TLC-FAT	727	1.510	0.500	1.000	2.000
CHEMO	727	1.520	0.500	1.000	2.000
LIFE-INS	727	1.576	0.766	1.000	3.000
EDUCATN	727	3.820	1.303	1.000	7.000
MARRIED	727	1.425	0.495	1.000	2.000
INCOME	727	1.645	0.731	1.000	3.000
INC_LOW	369	2.894	1.075	1.000	5.000
INC_HI	180	3.211	2.265	1.000	8.000

TABLE ONE (Cont.)

Demographic and Disease Knowledge Characteristics of Sample

B) Variable Definitions

Variable	Definition	Coding.
SEX	Sex	1 = Female, 2 = Male
NOPEOP	No. people at home?	No. = l-5, 5 = 5 or more
NOCHILD	No. children at home?	No. = l-a, 7 = 7 or more, 8 = none
KNOW-ND	Know anyone with nerve disease (ND)?	1 = Yes, 2 = No, 3 = Not Sure
KNOW_LS	Know ND shortens lifespan?	1 = Yes, 2 -No
WORKING	Currently working for pay?	1 -Yes, 2 = No
KNOW-HS	Know hospitalization required for ND?	1 -Yes, 2 = No
LOST-AD	Lost friend in auto death?	1 = Yes, 2 = No
MILES	Estimated miles you travel in a car per week	1 = o-19, 2 = 20-99, 3 = 100-199, 4 = 200-299, 5 = 300-400, 6 = 400+
TIMEDRV	Always the driver?	1 = Always, 2 = Usually, 3 = Half the time, 4 = Usually passenger, 5 = Always passenger
RATEDRV	Rate yourself as driver	1 = Poor, 5 = Average, 9 = Superior
AGE	Age	1 = 21-25, 2 = 26-30, 3 = 31-40, 4 = 41-50, 5 = 51-60, 6 = 61-70, 7 = 70+
KNOW_LC	Know anyone with lymph cancer (LC)?	1 = Yes, 2 = No, 3 = Not Sure
CLC_REC	Know that curable LC has 90% recovery rate?	1 -Yes, 2 = No
KNOW_RAD	Know that radiation treatment required for CLC?	1 -Yes, 2 -No
TLC-FAT	Know that terminal LC fatal?	1 = Yes, 2 = No
CHEMO	Know that radiation and chemotherapy required for TLC?	1 -Yes, 2 -No
LIFE-INS	Family member has life insurance?	1 = Yes, 2 = No, 3 = Not Sure

TABLE ONE (Cont.)

Demographic and Disease Knowledge Characteristics of Sample

B) Variable Definitions (Cont.)

Variable	Definition	Coding
EDUCATION	Education level	1 = Grades 0-8, 2 = Grades 9-11, 3 = Grade 12, 4 = Some college, 5 = College grad., 6 = Some grad. work, 7 = Grad. degree
MARRIED	Married now?	1 -Yes, 2 -No
INCOME	Annual family income	1 = Less than $40,000, 2 = More than $40,000, 3 = No answer
INC_LOW	Annual family income below $40,000	1 = Under $10,000, 2 = $10,000 - $19,999, 3 = $20,000 - $29,999, 4 = $30,000 - $39,999, 5 = No answer
INC_HI	Annual family income above $40,000	1 = $40,000 - $49,999, 2 = $50,000 - $59,999, 3 = $60 000 - $69,999, 4 = $70,000 - $74,999, 5 = $80,000 - $89,999, 6 = $90,000 - $99,999, 7 = Over $100,000, 8 = No answer

TABLE TWO

Lymph Cancer (LC) - Automobile Death (AD) Equivalents

A) Curable Lymph Cancer (CLC)

Treatment	N	CLC/AD Trade-off Rate				
		Median	Mean	Std. Error of Mean	Min	Max
All Subjects	783	1.600	2.845	0.209	0.04	40
Subjects answering CLC questions before TLC questions	477	1.780	2.918	0.266	'0.04	40
Subjects answering TLC questions before CLC questions	306	1.600	2.731	0.339	0.04	40

Jnitial Question:

Risk	Rate (x 1/1,000,000)	
	Area A	Area B
Curable lymph cancer	140	100
Auto death	150	170

TABLE TWO (Cont.)

Lymph Cancer - Automobile Death Equivalents

B) Terminal Lymph Cancer (TLC)

Treatment	N	TLC/AD Trade-off Rate				
		Median	Mean	Std. Error of Mean	Min	Max
All Subjects	789	1.000	1.614	0.130	0.03	30
Subjects answering TLC questions before CLC questions	312	1.000	1.551	0.210	0.03	30
Subjects answering CLC questions before TLC questions	477	1.000	1.655	0.165	0.03	30

Initial Question:

Risk	Rate (x 1/1,000,000)	
	Area A	Area B
Terminal lymph cancer	130	100
Auto death	150	170

TABLE TWO (Cont.)

Lymph Cancer - Automobile Death Equivalents

C) Within-Subject Trade-off Rate for Two Types of Lymph Canoer: **TLC/CLC**

Treatment	N	**TLC/CLC** Trade-off Rate				
		Median	Mean	Std. Error of Mean	Min	Max
All Subjects	769	0.750	1.037	. 0.088	0.00075	37.5
Subjects 'answering CLC questions before TLC questions	468	0.750	0.966	0.075	0.005	25.0
Subjects answering TLC questions before CLC questions	301	0.750	1.147	0.193	0.00075	37.5

TABLE THREE

Nerve Disease (ND) - Auto Death (AD) Trade-off Rates[a]

Group Number	Initial Question: Area A ND	Initial Question: Area A AD	Initial Question: Area B ND	Initial Question: Area B AD	N	ND/AD Trade-off Rates[b]: Median	Mean	Std. Error of Mean	Min (#)	Max (#)
1	175	150	100	170	128	2.50	4.917	1.096	0.075 (15)	75.000 (3)
2[c]	175	150	100	170	50	3.20	3.999	1.467	0.075 (8)	75.000 (1)

[a] Nerve disease risks and auto death rates are both in units of 1/1,000,000 per year.

[b] The ND/AD trade-off rates are measured in units of increases in the per 1/1,000,000 risk of nerve disease per 1/1,000,000 decrease in the risk of an auto death.

'Group two subjects received the same questions as those in group one with the exception that group two subjects told there vere two studies both estimating an identical 175/1,000,000 risk of nerve disease in Area A.

TABLE FOUR

Nerve Disease (ND) - Cost of Living (COL) Trade-off Rates[a]

Group Number	Initial Question: Area A ND	Initial Question: Area A COL	Initial Question: Area B ND	Initial Question: Area B COL	N	COL/ND Trade-off Rates[b]: Median	Mean	Std. Error of Mean	Min (#)	Max (#)
1	200	same	100	250	58	2.500	20.912	9.993	0.050 (2)	500.000 (1)
2	200	same	100	500	27	8.000	87.877	50.704	0.800 (1)	1,000.000 (2)
3	150	same	100	250	73	5.000	69.869	26.745	0.300 (1)	1,000.000 (4)
4	150	same	100	500	28	10.000	172.257	98.329	1.200 (1)	2,000.000 (2)
5	240	same	100	250	23	2.143	52.975	25.328	0.214 (1)	357.143 (3)
6	240	same	100	500	25	5.710	97.531	46.667	0.072 (1)	714.290 (3)
7	110	same	100	250	24	25.000	366.292	236.412	0.500 (1)	5,000.000 (1)
8	110	same	100	500	27	50.000	818.444	510.575	2.000 (1)	10,000.000 (2)

[a] Nerve disease risks are measured in units of 1/1,000,000 per year. Cost of living measures the difference between the annual cost of living in the subject's current location and that in Area A or Area B.

[b] Measured in dollars per 1/1,000,000 reduction in the risk of nerve disease.

TABLE FIVE

Relative Aversion Scores
(g-point scale: 9 most averse, 1 least averse)

A) Lymph Cancer Consequences

Rank	Consequence	Mean Aversion Score	Standard Deviation of Mean
1	Bleeding	8.02	0.06
2	Infections	7.95	0.06
3	Depression	7.77	0.07
4	Loss of Energy	7.47	0.07
5	Swelling	7.31	0.08
6	Fever	6.99	0.08
7	Weight Loss	6.71	0.09
8	Sweating	6.70	0.09

B) Nerve Disease Consequences

Rank	Consequence	Mean Aversion Score	Standard Deviation of Mean
1	Loss of Strength	8.19	0.06
2	Inability to move easily	7.97	0.07
3	Constant pain	7.91	0.07
4	No cure	7.88	0.08
5	Weak muscles	7.79	0.07
6	Depression	7.75	0.07
7	Must quit work	7.39	0.09
8	Must restrict recreational activity	7.22	0.08
9	Medications required	6.61	0.09
10	Must restrict exercise	6.17	0.10

N = 755

TABLE SIX

Aversion to Generic Consequences of Diseases (n = 266)

Generic Consequences	Mean Conjoint Disutility Index	Std. Error of Mean
10% Chance of Death	1.56	0.17
Hospitalization	1.19	0.13
Surgery	0.84	0.11
Constant Pain	0.39	0.11
Loss of Mobility Outside the Home	0.38	6.11
Loss of Strength and Feeling	0.24	0.11
Restricted Recreational Activity	0.13	0.11
Occasional Nausea and Loss of Energy	0.07	0.12

FIGURE ONE

Experimental Design

(1) Group	(2) Conjoint Questions about Generic Disease Characteristics	(3) Dollars vs. Nerve Disease (ND) - One ND Risk Study	(4) One Area with ND Risk Study vs. Another Area with Two ND Risk Studies	(5) Auto Deaths (AD) vs. ND	(6) AD vs. Curable Lymph Cancer (CLC)[f]	(7) AD vs. Terminal Lymph Cancer (TLC)[f]	(8) TLC - One Area with with One Risk Study vs. Another Area with Several Risk Studies	(9) AD vs. TLC - Several Cancer Risk Studies
A	No	Yes	Yes (2nd study shows **lower** risk; small difference between 2 risk estimates)[a]	Yes (**two** ND risk studies; 2nd study shows lower risk; small difference between 2 risk estimates)[a]	Yes	Yes	No	No
	No	Yes	Yes (2nd study shows **higher** risk; small difference between 2 risk estimates)[a]	Yes (**two** ND risk studies; 2nd study shows higher risk; small difference between 2 risk estimates)[a]	Yes	Yes	No	No
	No	No	No	Yes (**one** ND risk study showing risk equal to **mean** of two risk estimates in each of other groups)[e]	Yes	Yes	Yes (**mean** risk in 2nd area same as in last question; **asymmetric** range; range skewed to **right**)[g]	Yes (**mean** risk same in last question; **asymmetric** range; range skew to **right**)[g]

FIGURE ONE (Cont.)

Experimental Design

(1) Group	(2) Conjoint Questions about Generic Disease Characteristics	(3) Dollars vs. Nerve Disease (ND) - One ND Risk Study	(4) One Area with ND Risk Study vs. Another Area with Two ND Risk Studies	(5) Auto Deaths (AD) vs. ND	(6) AD vs. Curable Lymph Cancer (CLC)[f]	(7) AD vs. Terminal Lymph Cancer (TLC)[f]	(8) TLC - One Area with with One Risk Study vs. Another Area with Several Risk Studies	(9) AD vs. TLC - Several Cancer Risk Studies
D	No	No	No	Yes (one ND risk study showing risk equal to mean of two risk estimates in each of other groups)[e]	Yes	Yes	Yes (mean risk in 2nd area same as in last question; asymmetric range; range skewed to left)[h]	Yes (mean risk same in last quest ion; asymmetric range; range skew to left)[h]
E	Yes	No	Yes (2nd study shows lower risk; large difference between 2 risk estimates)[b]	Yes (two ND risk studies; 2nd study shows hieher risk; large difference between 2 risk estimates)[b]	Yes	Yes	No	No
F	Yes	No	Yes (2nd study shows hieher risk; large difference between 2 risk estimates)[b]	Yes (two ND risk studies; 2nd study shows lower risk; large difference between 2 risk estimates)[b]	Yes	Yes	No	No

FIGURE ONE (Cont.)

Experimental Design

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Group	Conjoint Questions about Generic Disease Characteristics	Dollars vs. Nerve Disease (ND) - One ND Risk Study	One Area with ND Risk Study vs. Another Area with Two ND Risk Studies	Auto Deaths (AD) vs. ND	AD vs. Curable Lymph Cancer (CLC)[f]	AD vs. Terminal Lymph Cancer (TLC)[f]	TLC - One Area with with One Risk Study vs. Another Area with Several Risk Studies	AD vs. TLC - Several Cancer Risk Studies
G	Yes	No	Yes (no temporal order of 2 studies; small difference between 2 risk estimates)[c]	Yes (two ND risk studies; no temporal order of 2 studies: small difference between 2 risk estimates)[c]	Yes	Yes	No	No
H	Yes	No	Yes (no temporal order of 2 studies; large difference between 2 risk estimates)[d]	Yes (two ND risk studies; no temporal order of 2 studies; laree difference between 2 risk estimates)[d]	Yes	Yes	No	No

FOOTNOTES

[a]**Lower risk** = 150/1,000,000, higher risk = 200/1,000,000, difference = 50/1,000,000.

[b]**Lower** risk = **100/1,000,000**, higher risk = **240/1,000,000**, difference = **130/1,000,000**.

[c]**Two** risk estimates are **150/1,000,000** and **200/1,000,000**, difference = **50/1,000,000**.

[d]**Two** risk estimates are **110/1,000,000** and **240/1,000,000**, difference = **130/1,000,000**.

[e]**Mean** risk equals **175/1,000,000**. While most subjects were given the results of a single study, some were informed that studies estimated the identical risk.

[f]Subjects were randomly assigned, with half answering Section 6 before Section 7 and half answering in reverse order.

[g]**Mean** risk = **130/1,000,000**, risks range from **125/1,000,000** to **155/1,000,000**.

[h]**Mean** risk = **130/1,000,000**, risks range from **105/1,000,000** to **135/1,000,000**.

FIGURE TWO

Regression Analyses of Relative Aversion Scores,
Conjoint Disutility Indices, and
Auto Death (AD) and Cost-of-Living (COL)
Trade-off Rates

Equation Number	Dependent Variable	Independent Variable	Coefficient (Std. Error)	Prob. Value
1	AD/ND	ND-AVE	0.298 (0.093)	0.002
2	COL/ND	ND-AVE	11.39 (39.30)	0.77
3	AD/CLC	LC-AVE	0.693 (0.170)	0.0001
4	AD/TLC	LC-AVE	1.715 (0.280)	0.0001
5	(AD/ND - AD/CLC)	(ND-AVE - LC-AVE)	0.081 (0.162)	0.618
6	(AD/ND - AD/TLC)	(ND-AVE - LC-AVE)	0.276 (0.304)	0.364
7	NDINDEX	ND-AVE	-0.024 (0.174)	0.890
8	CLCINDEX	LC-AVE	-0.074 (0.133)	0.578
9	AD/ND	NDINDEX	0.087 (0.142)	0.540
10	AD/CLC	CLCINDEX	-0.237 (0.379)	0.533
11	(AD/ND - AD/CLC)	(NDINDEX - CLCINDEX)	-0.086 (0.180)	0.633

APPENDIX A

LYMPHOMA (LYMPH CANCER)

There are several types of lymph cancer which can attack the lymph system of the human body, Your lymph system uses lymph vessels to transport lymph fluid throughout your body, much like your blood vessels transport blood. Located in this system are lymph nodes which filter the lymph fluid. There are several types of lymph cancer which share the same symptoms, but they differ in the likelihood that the disease will be fatal.

If you were to get this disease, your symptoms may include painless swelling of your lymph nodes, fevers, night sweats, tiredness, weight loss, and itching skin. As a result of these symptoms and the side effects of the treatment, some people suffer periods of depression.

The treatment of lymph cancer includes radiation therapy which requires frequent visits to a clinic or doctor's office on an outpatient basis. This treatment may result in the following adverse effects: fatigue, redness and dryness of your skin, dry and sore throat, shortness of breath, nausea, vomiting, and diarrhea.

Certain types of lymph cancer also require chemotherapy (drug therapy) as a part of the treatment. During treatment by chemotherapy, you may experience some of the following side effects: hair loss, lowered resistance to infections, loss of appetite, nausea, vomiting, and mouth sores.

If you work outside of your home, you would still be able to continue working, and you would not lose any wages or salary. Through medical insurance plans and/or Medicare and Medicaid Programs, you would not have to pay for large medical expenses for the treatment of the disease.

APPENDIX B

PERIPHERAL NEUROPATHY (NERVE DISEASE)

A nerve disease called peripheral neuropathy is a serious and, at times, painful disease. If you contracted it, you would have the disease for the rest of your life. Fortunately, this nerve disease does not change how long you will live. In other words, peripheral neuropathy is never fatal.

One characteristic of this nerve disease is a loss of strength and feeling in your hands and feet. As a result, you would find walking difficult, and you would need to use a cane. You may also have difficulty with routine tasks such as opening jars. This loss of strength would limit your ability to participate in strenuous recreational activities. Many people would experience periods of depression due to these restrictions on physical activity.

In the beginning stages of the disease, you would be able to work at your job regularly, but could not do difficult physical work. As the disease worsened, you would become unable to work. For most people, the government's Social Security Disability Program would make up for any lost salary and wages. Also, through medical insurance plans and/or Medicare and Medicaid Programs, most people would not have to pay for large medical expenses.

Your treatment for this nerve disease would require occasional visits to your doctor, taking several medications daily, and a regular exercise program.

REFERENCES

Acton, Jan P. 1973. "Evaluating Public Programs to Save Lives: The Case of Heart Attacks," Research Report R-73-02, Rand Corporation, Santa Monica, California.

Brookshire, David S. 1976. "The Valuation of Aesthetic Preferences," *Journal of Environmental Economics and Management,* vol. 3, no. 4, pp 325-346.

Brookshire, David S. et al. 1980. "Valuing Increments and Decrements in Natural Resource Service *Flows," American Journal of Agricultural Economics,* vol. 62, no. 3, pp. 478-488.

Bumess, H.S. et al. 1983. "Valuing Policies Which Reduce Environmental Risk," *Natural Resources Journal,* vol. 23, pp. 675-82.

Cicchetti, Charles J., and V. Kerry Smith. 1973. "Congestion, Quality Deterioration, and Optimal Use: Wilderness Recreation in the Spanish Peaks Primitive Area," *Social Science Research,* vol. 2, pp. 15-30.

Cummings, Ronald G. et al. 1986. *Valuing Environmental Goods: A State of the Arts Assessment of the Contingent Method* (Totowa, N.J., Rowman and Allenheld).

Frankel, M. 1979. "Opportunity and the Valuation of Life," Preliminary Report for the Department of Economics, University of Illinois, Urbana-Champaign.

Hammer-ton, M. et al. 1982. 'The Consistency and Coherence of Attitudes to Physical Risk: Some Empirical Evidence," *Journal of Transport Economics and Policy,* May, pp. 181-199.

Jones-Lee, Michael W. 1976. The Value of Life: An Economic Analysis (Chicago, University of Chicago Press).

Kaplan, Robert M., et al. 1976. "Health Status: Types of Validity and the Index of Well-Being," *Health Services Research,* Winter, pp. 478-507.

Kristrom, Bengt. 1990. *Valuing Environmental Benefits Using the Contingent Valuation Method* (Umea, Sweden, University of Umea Press).

Loomis, John B. 1987. "An Economic Evaluation of the Public Trust Resources of Mono Lake," Institute Report No. 30, College of Agricultural and Environmental Sciences, University of California, Davis.

Magat, Wesley A. et al. 1988. "Paired Comparison and Contingent Valuation Approaches to Morbidity Risk Valuation," ***Journal of Environmental Economics and Management, vol.*** 15, pp. **395-411.**

McConnell, Kenneth E. 1977. "Congestion and Willingness to Pay: A Study of Beach Use," ***Land Economics,*** vol. 53, no. 2, pp. 185-195.

Mirchell, Robert Cameron, and Richard T. Carson. 1989. Using ***Surveys to Value Public Goods: The Contingent Valuation Method*** (Washington, D.C., Resources for the Future).

Moore, Michael J., and W. **Kip** Viscusi. 1990. ***Compensation Mechanisms for Job Risks: Wages, Workers' Compensation, and Product Liability*** (Princeton, NJ., Princeton University Press).

Navrud, Stale. 1989. "Estimating Social Benefits of Environmental Improvements from Reduced Acid Depositions: A Contingent Valuation Survey," in ***Valuation Methods and Policy Making in Environmental Economics,*** H. Folmer and E. Van Ierland (Amsterdam, Elsevier Science Publishers).

Rosser and Rind. 1978. "A Scale of Valuations of States of Illness: Is There a Social Concensus?," ***International Journal of Epidemiology,*** vol. 7, no. ***4,*** pp. 347-358.

Rowe, Robert D, and Lauraine G. Chestnut. 1983. "Valuing Environmental Commodities Revisited," ***Land Economics,*** vol. 59, pp. 404410.

Rowe, Robert D. et al. 1980. "An Experiment on the Economic Value of Visibility," ***Journal of Environmental Economics and Management, vol. 7,*** pp. 1-19.

Sackett, D.L. and George W. Torrance. 1978. 'The Utility of Different Health States as Perceived by the General Public," ***Journal of Chronic Diseases,*** vol. 32, no. 11, pp. 697-704.

Schulze, William D. et al. 1983. "Methods Development in Measuring Benefits of Environmental Improvements: Experimental Approaches for Valuing Environmental Commodities," vol. 2, Draft Manuscript of a Report to the Office of Policy Analysis and Resource Management, U.S. Environmental Protection Agency, Washington, D.C.

Sintonen, Harri. 1981. "An Approach to Measuring and Valuing Health States," ***Social Science and Medicine,*** vol. **15C,** pp. 55-65.

Smith, V. Kerry, and William H. Desvouges. 1986. ***Measuring Water Quality Benefits*** (Boston, Kluwer-Nijhoff).

Sorg, Cindy F., and Louis J. Nelson. 1986. "Net Economic Value of Elk Hunting in Idaho," Resource Bulletin RM-12, Rocky Mountain Forest and Range Experiment Station, U.S. Forest Service, Fort Collins, Colorado.

Sutherland, Ronald J., and Richard G. Walsh. 1985. "Effect of Distance on the Preservation Value of Water Quality, " ***Land Economics,*** vol. 1, no. 3 pp. 281-291.

Tolley, George S., and Lyndon Babcock. 1986. "Valuation of Reductions in Human Health Symptoms and Risks, University of Chicago, Final Report to the Office of Policy Analysis, U.S. Environmental Protection Agency.

Torrance, George A. 1986. "Measurement of Health State Utilities for Economic Appraisal: A Review," ***Journal of Health Economics,*** vol. 5, pp. l-30.

Viscusi, W. Kip et al. 1991. "Pricing Environmental Health Risks: Survey Assessment of Risk-Risk and Risk-Dollar Trade-Offs for Chronic Bronchitis," ***Journal Of Environmental Economics and Management,*** vol. **21,** no. 2.

Viscusi, W. Kip. ***1983. Risk by Choice: Regulating Health and Safety in the Workplace*** (Cambridge, Mass., Harvard University Press).

Walsh, Richard G., and Lynde 0. Gilliam. 1982. "Benefits of Wilderness Expansion with Excess Demand for Indian Peaks," ***Western Journal of Agricultural Economics,*** vol. 7, pp. 1-12.

Chapter 2

Communication of Ambiguous Risk Information

by

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Abstract

This paper reports on the responses of 646 individuals to environmental risk information involving different forms of risk ambiguity. Recipients of more than one set of risk information do not simply average the risk levels provided. Rather, a variety of aspects of the nature of the risks that are communicated influence their probabilistic beliefs. Individuals' perceptions of the risk levels to which they are exposed are likely to be greater: i) for more ambiguous risks, ii) for risks for which the unfavorable risk evidence is presented last even when there is no temporal order, iii) for risks for which the most unfavorable risk studies have been performed most recently, and iv) for risks where there is asymmetry in the risk ambiguity that imposes substantial potential downside risks. Although these effects are modest for the median individual, the potential for extreme responses that reflect only the most adverse or the most favorable piece of information provided is quite prevalent. These findings are of interest more generally in that they indicate how individuals form their risk perceptions in the presence of risk ambiguity.

1. Ambiguity and Risk Communication

Risk communication efforts provide risk information to individuals so that they can make more informed decisions about the risks they face.' Informational policies can affect behavior when there is a difference in the risk information of the two parties. One party, typically the government or the producer, has more information about a particular risk than does the individual exposed to the risk. The purpose of risk communication policies is to transfer this information to the parties that can use the information to improve their decisions.

In situations in which the provider of the risk information has perfect knowledge, the question is.primarily one of conveying this knowledge to the user in the most effective way possible. In many important instances of risk communication, however, even the better informed party does not have perfect information. There will necessarily be considerable uncertainty regarding the exposure level of the affected individuals and differences in the risk according to individual sensitivity. Even more fundamentally, there may be underlying scientific uncertainty.

Suppose, for example, that the government believes that there is a potential risk of cancer from a particular environmental exposure, but it is not sure of the extent of the risk. Some studies indicate that the risk is small, but others indicate a larger risk. How should the government attempt to convey this information? Should it indicate the upper end of the risk range? Should the government communicate the lower end of the risk range? Should it simply provide the mean or the median

estimate of the risk value and not indicate that there is ambiguity pertaining to the risk?

Choosing among these various alternatives often creates important problems from the standpoint of long-term credibility. If we tell individuals of a specific risk now and then must change our risk assessment in the future, then the credibility of the information provider will be undermined. Moreover, the manner in which this credibility is undermined may depend on whether the subsequent information provided is more or less favorable than was originally given. Truthful disclosure of information would require that we convey the presence of ambiguity pertaining to the risk, but the danger is that individuals may not be able to process ambiguous risk information reliably, and thus their resulting decisions will not be sound.

The problem in communicating ambiguous risks stems from the difficulties individuals have in dealing with probabilities that are not known with precision. The paper by **Ellsberg (1961),** for example, highlighted the potential role of individual aversion to ambiguous probabilities of winning a prize, as compared with comparable probabilities known with **precision.**[2] In the case of environmental risks, the reference point is not hypothetical lotteries but instead scientific studies. More importantly, the ambiguity pertains not to the chance of winning a positively valued outcome as in the **Ellsberg** experiment, but the chance of suffering a neaatively valued loss. It also may be that individuals' attitude toward ambiguity depends on whether they

are facing gains or losses.

From the standpoint of a single decision, individuals seeking to maximize subjective expected utility should be indifferent to a probability of a particular outcome irrespective of whether the probability is known with precision. However, in sequential decision context, individuals should actually display a preference for probabilities that are not known with precision. This result is the basis of the classic two-armed bandit problem whereby individuals will prefer the slot machine with the uncertain probability because it offers the opportunity for learning and adaptive behavior. The individual can stay with the machine if it turns out to be favorable or he can quit and switch to a slot machine with known properties if the outcomes are unfavorable. In this sequential decision context, individuals should have a preference for risk ambiguity.

The literature on the role of ambiguity and how it affects decisions often has led to conflicting implications. Some studies indicate a preference for ambiguity, while others indicate an aversion to ambiguity. Since we review this literature elsewhere,3 we will focus on the new original research findings in this paper rather than providing a detailed overview of the literature. What should be emphasized is that our concern is with ambiguity regarding probabilities, not ambiguity regarding payoffs. Thus, the major issue is how ambiguity concerning the precision of the probability affects attitudes towards lotteries, not how ambiguity in terms of **the**

spread of outcomes influences behavior. To the extent that individuals are averse to ambiguity, we will refer to this aversion as "ambiguous belief aversion" to distinguish it from what we would term "ambiguous payoff aversion," which is the normal type of ambiguity that accounts for the usual risk aversion phenomenon.

The organization of our paper is as follows. Section 2 introduces the study and provides the basic elements of the test of whether ambiguity matters. In section 3 we indicate how the order of presentation of the ambiguous information influences attitudes toward the risk. Section 4 introduces an additional complication. Not only may the order of presentation of the risk information differ, but there also may be a temporal order with which the studies are undertaken. In such contexts, do individuals weight more recent studies more heavily than studies carried out previously? Later studies presumably should receive more weight if they have a more refined scientific basis or are more pertinent to current risk exposures; In section 5 we extend our analysis of ambiguous risk beliefs to consider the role of skewness in the risk information that is provided. Section 6 summarizes our principal conclusions pertaining to risk ambiguity. The extent and character of the risk ambiguity greatly affect the risk that respondents believe is equivalent to the ambiguous risk.

2. Does Ambiguity Matter?

To analyze the effects of risk ambiguity we undertook a survey of individual responses to alternative information presented to them. The sample used for the study consists of 646 subjects who were recruited at a Greensboro, North Carolina shopping mall.[4] After being recruited for the study, these subjects participated in a computer-administered survey in which they indicated their willingness to move to different areas depending on the risks. The particular risks considered in the study were those of non-fatal nerve disease and lymph cancer, where each of these diseases were linked to environmental pollution. The experiment focused on a decision to move to one of the two areas, Area A and Area B, which differed in their risks of contracting one of these two diseases. Subjects were told that the two new locations were otherwise identical to where they now live. They were also informed that in both areas, the risk of nerve disease (or lymph cancer) was less than in their current loaction. The interviewer also read the subjects a short description of the diseases and asked them several questions to reinforce their understanding of the consequences of contracting them.

Individuals were asked to choose which of these two areas they would prefer if they had to move. Subjects were given risk information pertaining to Area A, for which the risk levels were ambiguous, and they were asked whether they preferred the uncertain risks of Area A to the precise risks of Area B. The

known risk for Area B was subsequently altered until the respondent viewed the Area B risk as being equivalent to the ambiguous risks they would face in Area A.

The nature of the survey task can be best illustrated within the context of the information in Table 1. Panel 1 of the table presents information concerning the initial test of risk ambiguity. Subjects were told that there had been two studies of the risks of nerve disease posed by exposure in Area A. One study indicated a risk level of 150 cases per 1 million population, whereas a second study indicated a risk of 200 cases per 1 million population. They were then asked precisely what risk level in Area B would they view as being equivalent to the risks posed in Area A. This process involved a series of iterative paired comparisons which were modified until indifference was reached. In each case, all aspects of the two areas were held constant other than the one particular risk, which in the case of Panel 1 was nerve disease.

For all of the results considered in the first 4 tables in this paper, the midpoint of the risk range for Area A is always 175.[5] If individuals simply average the risk information provided for Area A, which is what they would do if they placed equal weight on the two studies, then the risk level in Area B that is equivalent to Area A will be 175 for all of the first 4 tables of results. Consequently, the test of risk ambiguity will always be the extent to which the responses for Area B differ from 175.

As is indicated in the results in Panel A of Table 1, for the risk combination (150, 200), the median risk response is simply the average of these two risk levels -- 175. However, the mean is somewhat greater than 175 -- 178.35 -- which in this case is significantly different from 175 at the usual confidence levels because of the tight standard error of the mean. As is indicated in the table, one respondent was most influenced by the minimum of the risk range, and a second respondent was at the opposite extreme, but for the most part the respondents were at or somewhat above the average of the two risk levels provided.

If, however, we increase the extent of the risk ambiguity, the effect becomes more pronounced. In the case of Panel 2 in Table 1, the size of the spread in the two studies has increased from 50 to 130. This increase in risk ambiguity raises the median risk that is viewed as equivalent to Area A to a value of 180, and the mean risk response increases to 191. Perhaps most strikingly, 13 respondents indicate that the risk in Area B that is equivalent to Area A is 240 cases per million --.the high end of the risk range reported for Area A. The fraction of respondents at this extreme is over 20 percent of the sample.

What the results in Panel 2 suggest is that in situations where there is substantial risk'ambiguity there will be strong ambiguous belief aversion, as individuals will view a pair of risks with a substantial spread as being more unfavorable than if they have been told the risk was at the midpoint of the range. The way in which people react to risk ambiguity will also be

strikingly different, as some individuals may react in an extreme manner. Indeed, in this example the substantial number of extreme responses is consistent with the often alarmist responses that we observe to publicly provided risk information, such as information pertaining to medicine tamperings or food contamination. The risk that people perceive as being equivalent to imprecise risks varies with the extent of imprecision so that alarmist responses to dimly understood but potentially substantial hazards may be quite prevalent.

3. Does the Order of Presentation Matter?'

In the risk communication experiment described in Table 1, subjects were given information pertaining to two risk assessments for Area A, where the low risk assessment appeared first and the high risk assessment was second. It may be that what we are observing is not purely an ambiguity effect, but rather the influence of the order of presentation. In particular, even though no explicit temporal order was indicated, individuals may place a greater weight on the second study listed.

There are two reasons why we might observe such an effect. The first is a **recency** effect. When individuals are provided with risk information over time, the more recently provided information should have a greater salience. Although there is not an important time dimension with information provided **simultaneously** over a computer, if individuals read this

information from left to right there is perhaps somewhat greater salience of the second piece of information that is read. More importantly, in all likelihood there is an implied temporal order even though the survey instrument indicated quite explicitly that there were simply two studies and that no temporal order was necessarily to be inferred.

To analyze the effects of temporal order, one must compare the results in Table 1 with the same outcome and the same nerve disease risk pairs except that the order of the risk information presented is reversed. These results appear in Table 2.

For Risk Pair 1 (150, 200), the temporal order appears to make no substantial difference in terms of the median risk that is equivalent to the risk pair, the mean risk response, or the frequency of individuals at the two extremes. The overall result is that there is modest evidence of ambiguity belief aversion in each of the two cases.

Once the spread between the two risk studies is increased from 50 cases per million in Risk Pair 1 to 130 cases per million in Risk Pair 2, the potential role of the order of presentation becomes more apparent. In the case of the risk pair (110, 240), the median risk response of 180 is a bit above the midpoint of the range. With the presentation order reversed to be (240, 110), the median response is exactly at the midpoint of 175. The divergence of the responses is even greater with respect to the means. The mean risk equivalent to (110, 240) is 191, as compared with a mean risk equivalent of 170 for the risk pair

(240, 110). Reversing the order of presentation produces a striking difference in the means. This effect can be traced in large part to the outliers in the distribution. For the risk pair (110, 240), 13 of the 58 respondents indicated a risk equivalent of 240, which is the maximum value of the range, as contrasted with only one of the 29 respondents receiving the risk pair (240, 110). Moreover, in the case of the risk pair of (240, 110), 4 of the 29 respondents viewed this risk as 'being equivalent to the low end of the range -- a risk value of 110 cases per million.

Particularly when there is a substantial spread between the risk estimates, the order of presentation appears to be of substantial consequence. The respondents place a greater weight on the second of the risk values presented. If this weight on the second study is sufficient, as it was in the case where there is a large spread in the risk values for Risk Pair 2, the order of presentation effect can dominate the influence of ambiguous belief aversion.

In all of the cases in Table 2, there is a danger of people gravitating to extremes at both ends of the spectrum. Whenever individuals are given a risk range, some individuals may be at one or the other extreme. The great majority of the respondents will be clustered in the middle of the distribution near the midpoint of the range, but the frequency of extreme responses is certainly not negligible. Indeed, 25 of the 172 respondents who are captured in the samples reflected in Table 2 are either at

the high or low value of the risk pairs that were presented to them. Some individuals consequently take both pieces of information into account when processing the risk information, whereas others select one of the two pieces of information as being more credible and focus exclusively on that piece of information. Because clustering at an extreme response is greatest when the second piece of information provided is unfavorable, risk ambiguity aversion is particularly likely to be evident when the worst information is presented last.

4. Does the Temporal Order Matter?

If individuals receive risk information over time, presumably they should place greater weight on the second study. In addition to being more recent in their memory, the second study also should provide a more reliable index of the actual extent of the risk to the extent that it is based on superior scientific studies or more pertinent environmental exposure information. By presenting information to respondents regarding the sequence of studies, but presenting the information at the same time, we can isolate the temporal order effect from the **recency** in memory effect. Thus, the focus of this section is on the extent to which indicating a temporal order for the two studies is of consequence.

Table 3 summarizes the effects of temporal order for four different nerve disease risk pairs. Consider first the risk pair (150, **200),** where the first group of respondents listed in Table

3 did not view these studies as being in any particular temporal order, whereas in the second case an **explicit** temporal order was given. In each case, the study indicating a risk of 200 cases per million was the second in the sequence.

Temporal order has a modest effect on the respondents' mean risk assessment, raising it from 178 in the case of no temporal order to 182 with temporal order. In addition, the extent to which individuals were at the extreme upper end of the range increases substantially in the case of temporal order, in which 12 of the 97 respondents view the risk as being equivalent to 200 cases per million. The overall effect of temporal order is to augment the effect of ambiguous belief aversion, as the respondents place greater weight on the second higher risk study, thus increasing their perceived risk in Area A.

In contrast, if it is the second study that indicates the lower level of the risk, as in the case of Risk Pair 2 (200, 150), we observe essentially the opposite effect. When no temporal order indicated, the assessed risk level is slightly greater than the midpoint of the range of 175. Once there is a temporal order indicated, individuals place somewhat greater weight on the second of the two pieces of risk information given, thus eliminating the ambiguous belief aversion effect; the mean risk response of 174 is not significantly different from the midpoint value of 175. There is in addition greater clustering of individuals at the low end of the risk range of 150, as 6 of the 82 respondents assess the risk at being at the minimum of the

risk range.

Expanding the stated spread of risk values from 50 to 130 in Risk Pair 3 (110, 240) greatly intensifies these effects. Indicating a temporal order for this rising risk sequence boosts the median risk assessment, the mean risk assessment, and most dramatically increases the number of respondents who are at the upper end of the risk range. Overall, 23 of the 94 respondents assess the risk as being 240, as the indication of a temporal order in the studies leads one-fourth of the sample to consider only the second of the two studies as being informative.

Much the same effect, but in the opposite direction, is observed if there is temporal order but the order of the studies is reversed to be (240, 110). In that situation, indication of temporal order leads to a mean risk assessment value of 159, which is below the midpoint value of 175. In addition, 18 of the 74 respondents give a risk equivalent value of the low end of the risk range, 110. Although the tendency to place substantial weight on the second study is somewhat less when the second study indicates a low risk value as opposed to a high risk value, there is still a substantial effect in that direction that more than offsets the influence of ambiguous belief aversion. The substantial size of the spread for this risk pair accounts for the strength of these effects. Overall, the indication of temporal order increases the weight on the second study, increasing the effect of risk ambiguity aversion when the disparity in studies is great.

5. Does the Symmetry of the Risk Spread Matter?

Thus far, all the experimental manipulations have provided risk information centered around a common midpoint of 175. The only variation has been to change the order of presentation of the risk studies and to increase the size of the spread around this risk value.

An interesting economic question is the extent to which individuals also react to the symmetry of the spread. In particular, do they place greater weight on the worst case outcome and what might be termed the down-side potential of the risk?

To analyze these effects experimentally, two different risk scenarios involving terminal lymph cancer were devised. In each situation, the survey informed respondents that the average risk indicated by these studies was 130. However, the high and low end of the range of risk studies differed. In the first case listed in Table 4, the high study observed was 155, and the low study was just below the average of 130, as it was 125. In the second of the two instances, the asymmetry in the risk is in the opposite'direction, as the high end of the risk studies observed was 135, which is just above the average of 130. In that instance, the low risk value indicated by the studies was 105, thus producing an asymmetry in the risk range below the average risk value. In each case the risk spread from the low to high study was the same -- 30 cases per million.

Although the median respondent focuses primarily on the

average risk value indicated, the mean values differ. In the case of risk study distributions that are skewed in a manner so that the lowest risk estimate is well below the average, there appears to be little role for risk ambiguity aversion. Respondents focus primarily on the average risk amount.

In contrast, if there is skewness that indicates that the potential risk may be much higher than the average amount, the mean response is much greater than the average. The mean risk values associated with the risk range (155, 125) is significantly greater than the mean risk assessment equivalent to the risk range (135, 105) even though the average risk values indicated were the same. Moreover, it is striking that these differences were generated using only a risk spread of 30 cases per 1 million respondents, which is a much tighter distribution than was needed to generate the risk ambiguity effects considered in Tables l-3. These results indicate that the potential source of much of the ambiguous belief aversion is the fear of the worst case outcome rather than simply concern with the risk spread.[6] Asymmetry in the risk spread accentuates the impact of the ambiguous belief aversion when the asymmetry indicates the potential of a much higher risk level.

6. Conclusion

Individual processing of risk information consists of more than simply giving equal weight to the various pieces of information that have been received. The potential for extremist

responses and alarmist reactions is quite pronounced. Although there is the possibility of individuals focusing at either end of the risk extremes that are presented, several systematic patterns of risk perception responses were identified.

First, there is evidence of ambiguous belief aversion. As the extent of the spread indicated by the alternative risk measures increases, individuals raise their risk assessment. In forming these risk assessments, individuals place a greater weight on the last risk value given to them even if no temporal order in the risk values is indicated. However, if there is an explicit temporal order, there is a much more substantial weight given to the final risk study than to'the initial risk study. Consideration of the role of skewness in the risk distribution highlights the factors driving the ambiguous belief aversion. In particular, it is the fear of the worst case scenario that seems to be of greatest concern to respondents. This influence is also reflected in the extreme values of the risk responses, as respondents are much more likely to indicate that the high end of the risk range is the risk equivalent value than they are to indicate that the low end of the risk range is the actual risk level.

What these results suggest is that the communication of ambiguous risk information is a quite sensitive policy process. More fundamentally, individual decisions in contexts in which risks are not defined precisely will be quite sensitive to the character of the information that is available. Being able to

predict individual responses will require more than simply knowing which pieces of information individuals have received. We also must know the order in which they have received it and various other aspects of the nature of the risk information that individuals have processed in order to be able to reliably predict behavior. Perhaps the most reassuring aspect of the results is that the median respondent generally weights the information provided equally. The danger is that the responses of the individuals at the extremes may greatly influence the overall societal response to the risk.

Table 1

Risk Ambiguity Aversion and the Size of the Nerve Disease Risk Spread

Panel 1: Risk Ambiguity

Risk Levels in Area A	Sample Size	Median	Mean	Std. Error of Mean	Min (#)	Max (#)
150, 200	65	175.00	178.35	1.24	150.50 (1)	200.00 (1)

Panel 2: Size of Spread Effect

Risk Levels in Area A	Sample Size	Median	Mean	Std. Error of Mean	Min (#)	Max (#)
110, 240	58	180.00	191.08	3.95	115.00 (1)	240.00 (13)

Table 2

Presentation Order Effects for Nerve Disease Risks

Risk Levels in Area A	Sample Size	Median	Mean	Std. Error of Mean	(#)I	(#)X
Risk Pair 1:						
150, 200	65	175.00	178.35	1.24	150.50 (1)	200.00 (3)
200, 150	20	175.00	177.88	2.67	150.00 (1)	200.00 (2)
Risk Pair 2:						
110, 240	58	180.00	191.08	3.95	115.00 (1)	240.00 (13)
240, 110	29	175.00	170.35	5.78	110.00 (4)	240.00 (1)

Table 3

Temporal Order Effects for Nerve Disease Risks

Risk Levels in Area A:	Temporal Order	Sample Size	Median	Mean	Std. Error of Mean	Min (#)	Max (#)
Risk Pair 1:							
150, 200	No	65	175.00	178.35	1.24	150.50 (1)	200.00 (3)
150, 200	Yes	97	177.50	181.67	1.10	150.00 (1)	200.00 (12)
Risk Pair 2:							
200, 150	No	20	175.00	177.88	2.67	150.00 (1)	200.00 (2)
200, 150	Yes	82	175.00	174.13	1.18	150.00 (6)	200.00 (1)
Risk Pair 3:							
110, 240	No	58	180.00	191.08	3.95	115.00 (1)	240.00 (13)
110, 240	Yes	94	185.00	197.45	2.95	130.00 (1)	240.00 (23)
Risk Pair 4:							
240, 110	No	29	175.00	170.35	5.78	110.00 (4)	240.00 (1)
240, 110	Yes	74	175.00	159.19	3.84	110.00 (18)	235.00 (1)

Table 4

Asymmetric Risk Spread Effects for Lymph Cancer

Risk Studies for Area A: Hish	Low	Ave.	Sample Size	Median	Mean	Std. Error of Mean	(#)n	(#)x
155	125	130	59	130.00	134.90	1.07	128.5 (1)	155.00 (2)
135	105	130	68	130.00	130.38	0.39	112.5 (1)	135.00 (2)

Footnotes

1. For a review of risk communication issues, see Viscusi and Magat (1987) and the National Research Council (1989).

2. This literature did not end with the original paper by Ellsberg. See, among others, Curley and Yates (1985), Einhorn and Hogarth (1985), Hogarth and Kunreuther (1989), Kahn and Sarin (1988), Kunreuther and Hogarth (1990), Viscusi (1989), and Viscusi and O'Connor (1984).

3. Our review of the literature on ambiguity appears in Magat, Viscusi, Huber, and Payne (1990). See, for example, the studies cited in footnote 2, supra, for an overview of this research.

4. This study was undertaken for the U.S. Environmental Protection Agency. A similar sample was used in Viscusi and Magat (1987). In that work we describe in detail the representativeness of that sample, which utilized the same shopping mall intercept to recruit the experimental subjects. It should be noted that because of its representativeness, Greensboro, North Carolina is often the test site for national consumer marketing efforts as well as studies by Federal government agencies, such as the Environmental Protection Agency.

5. All the results in the tables in this paper are for the sample population which gave consistent responses. Only 56 subjects were eliminated from the sample because they exhibited incomplete or inconsistent responses. Four subjects gave incomplete responses. Seventeen respondents indicated the following type of inconsistency. They indicated a preference for Area A through the sequence of iterations of the questionnaire and then when they were forced to restart the paired comparisons they preferred Area B on the first question or were indifferent. Twenty-nine respondents indicated that they were indifferent to the two areas on every "first" comparison that appeared in the questionnaire. Five respondents preferred Area A on all of the iterations through to the last question and then on the last question when the risk levels of Area B dominated those of Area A, indicated that they were indifferent or preferred Area A. Finally, five of the responses were incomplete because of missing demographic information.

6. This risk spread is much smaller than the risk ranges considered in Tables l-3. If one were to expand the risk spread as in those earlier studies, one would expect the effect of the skewedness of the risk distributions to become more pronounced.

References

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

Einhorn, Hillel J., & Robin M. Hogarth, "Ambiguity and Uncertainty in Probabilistic Inference," Psychological Review 92 (4), 433-461 (1985).

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

Hogarth, Robin M., and Howard Kunreuther, "Risk, Ambiguity, and Insurance," Journal of Risk and Uncertainty, 2, 5-35 (1989).

Kahn, Barbara E., and Rakesh K. Sarin, "Modeling Ambiguity in Decisions Under Uncertainty," Journal of Consumer Research, 15, 265-272 (1988).

Kunreuther, Howard, and Robin M. Hogarth, "How Does Ambiguity Affect Insurance Decisions?" Working Paper, Wharton School of Business, University of Pennsylvania (1990).

Magat, Wesley A., W. Kip Viscusi, Joel Huber, & John Payne, "Ambiguity and Health Risks," Working Paper, Duke University

(1990).

National Research Council, Improving Risk Communication, Washington, D.C.: National Academy Press, 1989.

Viscusi, W. Kip, "Prospective Reference Theory," Journal of Risk and Uncertainty, 2 (4), 235-264 (1989).

Viscusi, W. Kip, & Wesley A. Magat, Learning About Risk: Consumer and Worker Responses to Hazard Information, Cambridge: Harvard University Press, 1987.

Viscusi, W. Kip, Wesley A. Magat, & Joel Huber, "Pricing Environmental Health Risks: Survey Assessments of Risk-Risk and Risk-Dollar Trade-Offs for Chronic Bronchitis," Working Paper, Duke University (1990), forthcoming in Journal of Environmental Economics and Manaaement.

Viscusi, W. Kip, and Charles O'Connor, "Adaptive Responses to Chemical Labeling: Are Workers Bayesian Decision Makers?" American Economic Review, 74, 942-956 (1984).

Chapter 3

Bayesian Expected Utility with Ambiguous Belief Aversion

by

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Abstract

This study examines the effect of ambiguous environmental risk information on lottery preferences using a sample of 646 adults. The learning process is consistent with features of a Bayesian expected utility model in terms of the overall magnitude and sign of the weights that respondents place on the risk information. Significant ambiguous belief aversion is also evident, where the extent of this aversion increases with the size of the risk spread, but at a decreasing rate. These results are consistent with both probability-based and preference-based models of risk ambiguity. The findings also indicate the presence of cognitive limitations in the processing of risk information, but lead to rejection of more extreme models in which individuals respond in alarmist fashion or do not learn at all.

1. Risk Ambiguity and Economic Decisions

A substantial economic literature has documented a variety of anomalies in decisions under uncertainty.' Individuals making such decisions often have risk perceptions that are biased in a systematic manner. Responses to increases in the risk may be inconsistent with preferences suggested by responses to decreases in the risk. In addition, there are a wide variety of inconsistencies that have been observed with respect to individual choice behavior.

One of the most long-standing and prominent anomalies in choice under uncertainty has been the Ellsberg (1961) Paradox. Consider a situation in which you will win a prize if you can correctly guess the color of a ball that will be drawn from an urn. Urn 1 contains 50 red balls and 50 black balls. Urn 2 contains an unknown mixture of red and black balls, but you have the option of selecting the color of the ball that may be drawn. Subjects generally prefer picking a ball from Urn 1 with the hard probabilities to drawing from the urn with an uncertain mixture. As Raiffa (1961) observed, this preference for precise probabilities is not rational since an individual could convert the "soft" probability for Urn 2 into a hard probability by flipping a fair coin and relying on the outcome of this coin toss to select the color of the ball to be drawn.

Notwithstanding the irrationality of this aversion to soft probabilities of winning a prize for one-shot lotteries such as this, this behavior has been borne out in a number of other studies of individual attitudes toward ambiguous risks.[2]

Moreover, it has given rise to a series of alternative models of choice under uncertainty that are intended to model behavior that is inconsistent with conventional models of expected utility. In some instances these alternative theories relax the additivity assumption for probabilities,[3] in other analyses the authors speculate that the participant in the study believes that the experiment is being manipulated against him in the case of the urn with uncertain properties;' and a final class of models hypothesize that the probabilities are additive but that there'is an additional component of a multi-attribute utility function pertaining to additivity, such as regret or blame associated with ambiguous choices.'

Although the Ellsberg Paradox indicates that in situations of winning a prize individuals would prefer a hard probability of success to an equivalent soft probability, in situations in which individuals will incur a loss rather than experience a gain would individuals prefer a sure probability of a loss or a less precisely understood probability of equivalent magnitude? Evidence presented in the insurance context by Kunreuther and Hogarth (1989, 1990) suggests that there is aversion to ambiguous probabilities in the case of losses.

The character of the risk ambiguity may also be of consequence. Heath and Tversky (1991), for example, found that ambiguity was of particular concern when decision maker competence was an issue.

A variety of frameworks have been suggested to capture the

empirical aspects of this behavior. Einhorn and Hogarth (1985a,b) have explored attitudes toward ambiguous risks using an anchoring and adjustment model whereby individuals initially set their probability at some anchor value, and then alter this probability depending on the information that has been received. Although this response to ambiguous probabilities potentially does violate standard expected utility models, the anchoring and adjustment process is very similar in character to a Bayesian learning procedure. Their anchor and adjustment model hypothesizes that individuals' assessed probabilities are non-additive, which is not consistent with a Bayesian framework. The studies by Kunreuther and Hogarth (1989, 1990) examine this formulation within a series of experiments pertaining to insurance. Kunreuther and Hogarth's (1990) experimental study found that insurers added an ambiguity premium when setting insurance rates for hypothetical ambiguous risks. This behavior does not necessarily contradict the expected utility model since the insurance industry in heavily regulated and there are, for example, constraints imposed on reinsurance and related aspects of the ratemaking process. Moreover, insurers are dealing with multiple risks and risk sequence of lotteries over time. Heath and Tversky (1991) likewise find support for risk ambiguity, but the role of individual knowledge of the lottery context leads them to dismiss not only Bayesian models, but post-Bayesian sub-additive probability models as well.

The most distinctive feature of the study is that the

empirical reference point that will serve as the basis of the hypothesis tests will be a model of expected utility that incorporates a Bayesian learning process. The character of the risk information provided will take into account the multiplicity of informational sources that may influence individuals probabilistic beliefs.

The nature of risk ambiguity that will be of particular concern here is the effect of receiving conflicting risk information. Contexts in which there is ambiguous risk information occur frequently as various scientific and technical studies have different implications for the magnitude of a risk. How do individuals process this risk information and act upon it when making their decisions, and can this behavior be reconciled with standard models of expected utility? The model we will develop will also recognize the fact that when dealing with experimental studies individuals may not necessarily take the stated probabilistic information at face value, as has been noted in Viscusi (1989). Thus, we will explicitly estimate the weight that individuals place on the risk information presented to them and, using the results of this analysis, assess whether there are anomalies in individual responses to ambiguous risks that are not consistent with the Bayesian expected utility model. These weights will also reflect the role that individual knowledge and competence has in a Bayesian context so that the incremental role of ambiguous belief aversion will be distinguished from the effect of individual knowledge. The approach in this paper

consequently differs from much of the literature, which typically identifies a role of risk ambiguity but does not formally test whether a Bayesian expected utility model can be reconciled with this behavior.

Based on these responses of 646 adults to a series of questions regarding locational risks, this paper will address two broad classes of issues. First, how do individuals process multiple pieces of risk information? In particular, what is the character of the learning process and the weighting of the information that individuals receive? Do individuals ignore the risk information, respond in an alarmist manner, or follow a Bayesian learning process? Our framework will explicitly account for the role of cognitive limitations in information processing, which we will find to be consequential. Second, is there an aversion to ambiguous risk beliefs once one takes into account the Bayesian decision context? The empirical results we will generate indicate that there is a significant effect of this type, which we designate as "ambiguous belief aversion" to distinguish it from aversion to ambiguity in the payoffs. The extent of the ambiguous belief aversion increases with the extent of risk ambiguity, but at a diminishing rate. Section 2 of the paper outlines the model of decision that will be tested, and Section 3 discusses the estimating equation. Section 4 presents the empirical results.

2. The Lottery Structure and Implications for Expected Utility

In the case of the Ellsberg model, the uncertain decision

context involved an unspecified mixture of balls in a Bernoulli urn. Our focus will be somewhat different. In particular, the ambiguity in the risk information will arise because of conflicting scientific information that the individual has received about an environmental risk. Particularly in the case of dimly understood health risks, there is a range of scientific evidence with different risk implications. If individuals receive different pieces of risk information, how do they process this information in forming their risk judgments and in making their decisions? Moreover, is there evidence of ambiguous belief aversion? If, for example, individuals were presented with two studies indicating risks of 140 x 10^{-6} and 160 x 10^{-6}, would this information be viewed as more or less favorable than two studies indicating risks of 100 x 10^{-6} and 200 x 10^{-6}? The median risk level is the same, but the spread between the two risks is greater. If the assessed risk is higher in the latter case, individuals are said to exhibit ambiguous belief aversion. In testing for the presence of ambiguous belief aversion, the analysis below will take into account the different weights that individuals may place on risk information depending on the order of presentation of the information as well as the temporal order of the studies.

Individuals participating in this study received a computer-administered survey that addressed their willingness to move to different areas that differed in terms of the risks they posed.[6] More specifically, individuals had a choice of moving to Area A

or Area B, which differed in terms of their environmental risks. Part of the sample encountered a risk of non-fatal nerve disease, and in other cases the risk context was lymph cancer. In each case the risk was specifically linked to environmental pollution. The survey informed the subjects that the areas were otherwise identical to the areas in which they now lived. Moreover, subjects were told that the risk levels were less than in their present location, thus avoiding possibly alarmist responses to increases in the risks that have been observed in some studies: After receiving a short description of the diseases, the subjects answered several questions that were intended to reinforce their understanding of the health consequences of the ailments.

The overall structure of the decision took the following form. The survey indicated that there had been two studies of the risk levels in Area A, where these studies had different implications. The interactive computer program then informed individuals of the risk in terms of the total number of cases of the disease per one million population that was implied by each of the studies. They were then asked what precise risk in Area B would be equivalent to the risks posed in Area A, for which they had received two pieces of risk information. The equivalent risk in Area B was ascertained through a series of iterative paired comparisons that were modified until indifference was reached. The survey established this equivalence by, in effect, determining the hypothetical reference lottery that the respondent viewed as being indifferent to the lottery with

ambiguous risks.

To make the survey procedure more explicit we will utilize the following notation.. Let U(Y) be the utility of good health with income Y, and V(Y) be the utility of ill health with income Y, where U(Y) > V(Y). The respondent receives information about two studies pertaining to the risk in Area A, where each study i has associated illness frequency rate r_i and informational content ξ_i, where i=1,2. The risk level r_i is provided to the respondent, and the informational content ξ_i is a parameter that must be estimated. Thus, study i is equivalent to observing ξ_i trials in which the disease may occur, where the disease occurs in a fraction r_i of these trials. After receiving this risk information, the respondent forms an assessed probability of illness $p(r_1,\xi_1,r_2,\xi_2)$ in Area A. The objective of the survey is to ascertain the precisely understood probability of illness s that establishes indifference between Area A and Area B. The value of s satisfies

(1) $p(r_1,\xi_1,r_2,\xi_2)V(Y) + (1-p(r_1,\xi_1,r_2,\xi_2))U(Y) = sV + .(1-s)U(Y)$,

or, upon simplification,

(2) $$s = p(r_1,\xi_1,r_2,\xi_2).$$

The function of the reference lottery is to establish the assessed probability of illness'that the respondent has after being given the risk information.

There are two ways in which ambiguous belief aversion could enter the respondent's evaluation of the reference lottery risk s that establishes equivalence with the ambiguous lottery. First,

ambiguous beliefs may affect the assessed probabilities of the outcomes.[7] The Bayesian formulation of $p(r_1, \xi_1, r_2, \xi_2)$ explicitly recognizes that ambiguous risk information will affect risk assessments. Problems arise, however, if the assessed probabilities of the two outcomes are no longer additive. Suppose that in contexts of ambiguous beliefs the individual slants down the assessed probability of the favorable outcome but does not alter the assessed probability of the adverse outcome.' This formulation will generate aversion to ambiguous choices of winning a prize in the case of the Ellsberg experiment and reluctance to incur more ambiguous chances if incurring a loss. Let $a(r_1, \xi_1, r_2, \xi_2)$ be the ambiguity belief aversion value that affects the assessed risks.[9] The reference lottery that is equivalent to the ambiguous risk lottery is defined by

(3) $sV(Y)+(1-s)U(Y) =$

$$p(r_1, \xi_1, r_2, \xi_2)V(Y) + (1-p(r_1, \xi_1, r_2, \xi_2) - a(r_1, \xi_1, r_2, \xi_2))U(Y).$$

Solving for s yields

$$(4) \qquad s = p(r_1, \xi_1, r_2, \xi_2) - \frac{a(r_1, \xi_1, r_2, \xi_2)U(Y)}{V(Y) - U(Y)}.$$

If ambiguous belief aversion enters through the probabilities, then the reference lottery value s differs from the Bayesian risk assessment by the final term, which is dependent on the utility of the two states and the effect of ambiguous beliefs on the assessed risk of the favorable event.

Alternatively, let ambiguity enter the model not through the probabilities but through the utility function. If the adverse

outcome occurs in the case of ambiguous beliefs, let there be some regret or blame associated with the event." If respondents have a multi-attribute utility function for which risk ambiguity is an additively separable component $A(r_1, \xi_1, r_2, \xi_2)$ that reduces the value of the adverse event, then the reference lottery satisfies

(5) $sV(Y)+(1-s)U(Y) =$

$$p(r_1, \xi_1, r_2, \xi_2)\,(V(Y)-A(r_1, \xi_1, r_2, \xi_2)) + (1-p(r_1, \xi_1, r_2, \xi_2))U(Y).$$

Solving for s, we obtain

$$(6) \qquad s = p(r_1, \xi_1, r_2, \xi_2) - \frac{p(r_1, \xi_1, r_2, \xi_2)A(r_1, \xi_1, r_2, \xi_2)}{V(Y) - U(Y)}.$$

Both the probability-based and utility-based models of ambiguous beliefs yield formulations in which the equivalent reference lottery probability s equals the Bayesian probability $p(r_1, \xi_1, r_2, \xi_2)$ minus a complex ambiguous belief aversion term. The effect of the ambiguous belief aversion term depends on the lottery structure and the value of the payoffs. Increases in the value of U(Y), for any given value of V(Y), will increase the magnitude of the effect of ambiguous beliefs on s for each of the two models." In each case, unfavorable outcomes that are more adverse and consequently have been associated with lower values of V(Y) will lead to a greater effect of risk ambiguity on the estimated value of s. The payoff structure has effects on ambiguous belief aversion that are in an identical direction for both the probability-based and preference-based models of ambiguous belief aversion. The role of ambiguous belief aversion

will consequently depend both on the probabilistic structure of the lotteries as well as on the utility of the lottery payoffs. Results that have indicated the dependence of the influence of risk ambiguity on the lottery consequences, such as Kunreuther and Hogarth (1989) and Heath and Tversky (1991), consequently are consistent with each of these formulations.[12]

3. The Empirical Framework

Because of the potentially complex functional form of the risk ambiguity term that affects s, the empirical analysis will estimate an average value of the ambiguous belief term to determine whether there is any significant negative discrepancy between s and $p(r_1, \xi_1, r_2, \xi_2)$. Evidence of a significant negative effect will lead to a rejection of the conventional Bayesian expected utility model, but will not indicate whether the probability-based model or a preference-based model of ambiguous belief aversion has greater validity.

Suppose that respondents have prior risk assessments of disease equal to p_0, with associated precision γ (i.e., respondents act as if they have observed γ trials in forming their prior, where a fraction p_0 of the trials involve occurrence of the disease). For a Bayesian learning model with probability assessments that can be characterized by a beta distribution,[13] the posterior assessed probability of disease p_1 after learning of study 1 is given by

$$p_1 = \frac{\gamma p_0 + \xi_1 r_1}{\gamma + \xi_1}. \tag{7}$$

After receiving information pertaining to study 2, the posterior probability assessment becomes

$$(8) \qquad p_2 = \frac{(\gamma+\xi_1)p_1 + \xi_2 r_2}{\gamma + \xi_1 + \xi_2} = \frac{\gamma p_0+\xi_1 r_1+\xi_2 r_2}{\gamma + \xi_1 + \xi_2}.$$

If we let $\gamma' = \gamma/(\gamma + \xi_1 + \xi_2)$, $\xi'_1 = \xi_1/(\gamma + \xi_1 + \xi_2)$, and $\xi'_2 = \xi_2/(\gamma + \xi_1 + \xi_2)$, then equation 8 can be expressed in terms of a simple weighted average of the prior probability, the risk implied by study 1, and the risk implied by study 2. The weights are the relative informational content associated with each of these components, or

$$(9) \qquad p_2 = \gamma' p_0 + \xi'_1 r_1 + \xi'_2 r_2.$$

It should be noted that the estimates of $\gamma' p_0$ will reflect the relative informational content and level of respondents' prior beliefs. The estimates of ξ_1 and ξ_2 capture the informational content placed on the risk information received and will explicitly take into account the role of respondent knowledge in processing risk information. Differences in individual knowledge have a fundamental role to play within a Bayesian learning model, and the estimates of equation 9 will explicitly recognize this dependence. Heath and Tversky (1991) found that individual competence also influences the role of risk ambiguity. The estimates derived from equation 9 will distinguish the role of risk ambiguity from the influence of risk competence that is a legitimate component of Bayesian learning. Unlike Heath and Tversky (1991), however, we do not also include

experimental treatments for which there will be variations in risk competence that influence the role of ambiguity.

Several learning situations can be distinguished. The first is what will be designated the "naive Bayesian." Respondents may learn (i.e., $\xi_1, \xi_2 > 0$), and in doing so they place an equal weight on the two studies regarding the Area A risk (i.e., $\xi_1 = \xi_2$). For experimental treatments that treat the studies symmetrically, this response is reasonable.

Some of our experimental treatments indicate that there is an explicit temporal order to the scientific studies. In situations in which the second study is undertaken after study 1, one might reasonably conclude that study 2 has greater scientific validity, since it presumably extends study 1. Respondents whom we will designate as "attentive Bayesians" consequently should place a greater weight on the second study if there is an explicit temporal order, or $\xi_2 > \xi_1 > 0$ in these cases.

A third possibility is that of a Bayesian with cognitive limitations. In situations in which information about two studies is acquired and there is no temporal order, the studies should be viewed symmetrically. If this information were provided over a period of time, one would expect individuals to place greater weight on the second study because of a recency effect. However, if the information is presented simultaneously on a computer screen, as in this study, then there should be no recency effect arising from temporal differences in information acquisition. Respondents may, however, place a greater weight on

the first study if they are not attentive to the survey task, or they may weight the second study more highly if they infer a temporal order when none existed. Thus, $\xi_1 \neq \xi_2$, but the direction of the discrepancy depends on the character of the respondents@ cognitive errors.

In each of these instances, the learning process will not satisfy the Bayesian updating process if the response to the information provided is too great. In particular; the sum of the relative informational weights must equal 1 (i.e., $\gamma' + \xi'_1 + \xi'_2 = 1$). In the analysis below, we will be unable to estimate γ', as only $\gamma' p_0$ can. be estimated. Thus, the test for an alarmist learner is whether the relative informational weights on the two studies exceed 1 either individually or collectively (i.e., $\xi_1 > 1$, $\xi_2 > 1$, or $\xi_1 + \xi_2 > 1$). Responses of this type will suggest that individuals overreact to risk information that they receive. Many observers have noted that there are often alarmist responses with respect to publicly identified low probability events, such as the chance of being killed in a terrorist attack while vacationing in Europe or the risk of being poisoned by a Chilean grape tainted with cyanide. Although such responses do not necessarily contradict a Bayesian learning model,[14] they do raise the legitimate issue of whether individuals overreact to risks.

These four learning models capture different variants of learning behavior that reflect modifications that are consistent with the learning model formulated in equation 9 or involve

alternative hypotheses regarding the magnitude and signs of the coefficients. Another class of models pertains to the role of ambiguous belief aversion. For the probability-based ambiguity model (see equation 4) and the preference-based ambiguity model (see equation 6), the equilibrating value of s will differ from $p(r_1, \xi_1, r_2, \xi_2)$ by a complex ambiguous belief term.

In situations in which there is a broad range of scientific evidence regarding the risk, the respondent faces a less precisely understood risk. We will model the role of risk ambiguity through inclusion of a variable equal to the risk range R implied by the studies, where $R = |r_1 - r_2|$. The R term captures the most salient aspect of risk ambiguity and will enable us to estimate the average value of risk ambiguity for the sample. The role of some of the other factors that might affect ambiguous belief aversion will be explored through the use of interaction terms with the risk range R.

To better assess the empirical consequences of this formulation, consider two sets of information. For the information set A, the two studies indicate risks of 100 x 10^{-6} and 200 x 10^{-6}, so that the value of R is 100 x 10^{-6}. Information set B's studies indicate risks of 125 x 10^{-6} and 175 x 10^{-6}, with a risk range of 50 x 10^{-6}. In each case the mean risk is 150 x 10^{-6}, but the value of R is greater for the more ambiguous study pair.

A difference in the assessed value of the risk s that is indifferent to the risk implied by the sets of studies does not

necessarily imply that respondents exhibit ambiguous belief aversion. For the two sets of risk information specified above, there would be no ambiguous belief aversion if the assessed risk s were 150 x 10^{-6}. Suppose, however, that respondents assess the value of s associated with information set A as equalling 166.7 x 10^{-6}, and the assessed value of s for information set B is 158.0 x 10^{-6}. Both pairs of studies had the same median risk and study A had a risk range R of 100 x 10^{-6}, as compared with only 50 x 10^{-6} for study B. The assessed value of s is greater for the pair of studies with a greater risk range. One might conclude from these results that subjects exhibit ambiguous belief aversion in all cases involving imprecisely understood probabilities and that the extent of aversion increases with the size of the risk range R. This conclusion may be too hasty. One will observe this pattern of responses without ambiguous belief aversion if equation 9 takes on the specific functional form

$$p_2 = (1/3)r_1 + (2/3)r_2. \tag{10}$$

Equation 10 is consistent with Bayesian learning for situations in which the respondent places a greater weight on the second study. This example highlights the care one must exercise in testing for the influence of ambiguous belief aversion.

If ambiguous belief aversion is of consequence, then we should rewrite the posterior belief equation 9 to take it into account. Since the role of risk ambiguity may be a nonlinear relationship, we will include both the linear and quadratic risk range terms in the equation, so that we have

(11) $$p_2 = \gamma' p_0 + \xi'_1 r_1 + \xi'_2 r_2 + \psi_1 R + \psi_2 R^2.$$

The hypothesis is that evaluated at the mean risk level, the net effect of R is positive in the presence of ambiguous belief aversion, whereas this term has no role to play in a standard Bayesian learning model. If the influence of ambiguous belief aversion diminishes with the extent of the risk range, then $\psi_1 > 0$ and $\psi_2 < 0$, whereas an increasing incremental effect of ambiguous belief aversion will be indicated by $\psi_1 > 0$ and $\psi_2 > 0$.

A final elaboration on the model is needed, since we do nbt observe p_0 and consequently cannot estimate the value of $\gamma'_0 p_0$. If, however, the individual's prior and the precision of this prior is a function of the respondent's demographic characteristics, so that

(12) $$\gamma'_0 p_0 - a + \sum_{i=1}^{a} \beta_i X_i,$$

then we can rewrite equation 7 as

(13) $$p_2 - \alpha + \sum_{i=1}^{n} \beta_i X_i + \xi'_1 r_1 + \xi'_2 r_2 + \psi_1 R + \psi_2 R^2.$$

Table 1 summarizes the hypotheses associated with the different learning models possibly reflected in equation 11.

It is instructive to contrast this empirical test with earlier test that have appeared in the literature. The **Ellsberg** urn model explicitly highlights the role of ambiguous probabiliites, but may not yield conclusive evidence. One urn is uncertain, whereas another has properties known with precision. Some authors, including **Ellsberg (1961),** have speculated that

respondents may believe the uncertain urn is being manipulated against them so that the stated probabilities will not be treated at face value. The underlying asymmetry in the experimental structure may capture more than risk ambigiuty. Otherwise, these results isolate the role of ambiguous risk beliefs.

More recently, Kunreuther and Hogarth (1989) developed a test of an anchor and adjustment model which they contrast with a Bayesian expected utility model. Their test is not as refined a test of the Bayesian framework as that presented here for two reasons. First, they focus on the behavior of the median respondent rather than developing an explicit statistical analysis of the entire data set. Second, the test they suggest for determining the validity of the Bayesian model-is not conclusive.[15] Their study presents subjects with a single piece of risk information, leading to the formation of $p_1(r_1)$ values that should follow equation 1 if subjects are Bayesian. They hypothesize that one should find that

$$p(r_1) + p(1-r_1) = 1 \qquad (14)$$

if individuals learn in a Bayesian manner. However, if we implement equation 1 we find that the requirement is somewhat different, or

$$p(r_1) + p(1-r_1) = \frac{2\gamma p_0 + \xi_1}{\gamma + \xi_1}, \qquad (15)$$

which only equals 1 if $p_0 = .5$. The hypothesis reflected in equation 14 would be correct if there were a probability .35 of some event and a probability .65 of some complementary event. Their study, however, described separate insurance risks that posed stated risks of .35 and .65, respectively. Respondents will bring to an insurance experiment their prior beliefs concerning the risk.[16] The probabilities of the adverse event may be perceived in a manner quite different than that stated in the experiment. Respondents may still learn in a Bayesian manner and isolate equation 14. Indeed, we would expect such violations except in a very special case. Our formulation is explicitly based on a Bayesian reference point, which will be subjected to a formal empirical test.

4. Empirical Results

The sample used for this study consisted of 646 adults who participated in a survey regarding attitudes toward environmental risks. This sample was drawn at a shopping mall in Greensboro, North Carolina, where the demographic characteristics of this sample are broadly representative of the U.S. population.[17] The average education of the sample was 13.4 years; 49 percent of the sample had household income over $30,000, and the remainder had income below that amount; 57 percent of the sample were married, and 44 percent were males."

Each subject was given a computer-administered questionnaire that elicited preferences with respect to moving to either Area A or Area B. This risk information provided to the subjects

concerning Area A varied, as four different risk pairs were communicated. These risk pairs, which were all in terms of diseases per million population, were the following: (150,200), (120,240), (125,155), and (105,135). The presentation order and the temporal order of these studies was varied so that in all there were ten different distinct sets of information provided to different subjects based on variants of these four sets of risk information. None of the respondents indicated an assessed risk of zero or 1 so that econometric problems arising from observations at a limit did not arise.

Table 2 reports the results of different ordinary least squares estimates of alternative specifications of equation 13 above. Since there was evidence of significant heterskedasticity in the results, the bracketed values in Table 2 present the heteroskedasticity-corrected standard errors based on the procedure developed by White (1980). These adjusted standard errors have similar implications with respect to the significance of the key coefficients of interest. Equation 1 in Table 2 represents the basic version of the learning model in which the intercept captures the role of the prior probability beliefs, and the coefficients of r_1 and r_2 represent the informational weights placed on studies 1 and 2, respectively. The risk ambiguity terms are not included. The intercept term in equation 1 is not statistically significant, which indicates that on average the influence of prior probability beliefs on risk perceptions is not significantly different from zero. This result does not

necessarily imply that the prior risk assessments for these events are not significantly different from zero, although this may in fact be the case since these are very low probability events. Rather, the results suggest that the combined influence of the relative informational weight placed on the prior multiplied by the value of the prior is not significantly different from zero, or $\gamma' \mathbf{p} = 0$.

'The two information weights for the first and second risk studies are each significantly different from zero, as the weight ξ_1 on r_1 has a value of .41, and the value of ξ_2 for r_2 is .55. A somewhat greater weight is placed on the second study mentioned to respondents.

These results for equation 1 change very little once a series of demographic characteristics are added in equation 2. The values of the two informational weights for ξ_1 and ξ_2 drop to .39 and .52, but are not much affected by inclusion of the demographic variables. The only statistically significant (95 percent confidence level, one-tailed test) demographic variables in equation 2 are whether the respondent is employed, which has a negative effect on risk perceptions, and whether the respondent has an income level above $30,000, which has a positive effect on risk perceptions. These and the other demographic variables are intended to capture differences in prior probability beliefs across different population groups.

Equation 3 in Table 2 constrains the coefficients ξ_1 and ξ_2 to be equal, as it estimates the average informational weight

placed on the sum of the two risks implied by the studies. This estimate yields an average value of .48 as the informational weight on the studies. The appropriate F test suggests that the coefficients ξ_1 and ξ_2 for the two risk variables are statistically different from one another."

The findings of equations 1 and 2 in Table 2 are consistent with a Bayesian learning model. One cannot distinguish at this juncture which particular model of learning receives the strongest support since the empirical analysis for the first two equations in Table 2 only reflects the most rudimentary aspects of learning, We can rule out, however, the model of alarmist learning, since there is no evidence that individuals respond excessively to the risk information presented, as these tests have been defined in Table 1.

Equation 4 recognizes the likely influence of the temporal order of the studies on the informational weights ξ_1 and ξ_2 that the respondents place upon the risk studies. In particular, if one knows that the second study mentioned in the survey also was undertaken after the first study mentioned, then there is reason to believe that the second study extends the initial one or was based on more recent scientific methods and consequently should receive greater weight. A strong effect of this type is in fact observed. The first study presented to the respondents receives a relative informational weight of . 56, but if a temporal order is indicated the weight is .22 less, for a net informational weight of .34. In the case of the second study mentioned, the

weight placed on this study is .40, but if there is an explicit temporal order indicated the second study receives a weight of .62. As a consequence, in situations in which there is an explicit temporal order, the second study receives roughly double the weight as does the first, whereas in situations in which there is no temporal order indicated respondents place a greater weight on the first of the two studies mentioned, perhaps because of its greater prominence.

These results are supportive of several models in Table 1. One can rule out the naive Bayesian since the informational weights are not identical for the studies mentioned. There is evidence in support of the attentive Bayesian in the case of studies presented in which there is a temporal order, as the more recent studies receive the expected greater weight. However, for studies in which there is no temporal order, the respondents behave in a manner that is consistent with a Bayesian who has cognitive limitations. The first study mentioned in the interview will be more prominent for respondents who process the information or incompletely, and consequently the first study receives' greater weight. The overall impression conveyed by these results is one of respondents who act in a manner one would expect given a rational learning process, with the only deviation from full rationality being that they pay more attention to the first study mentioned in the interview.

The final two equations in Table 2 extend the model by including the ambiguous belief aversion terms in the analysis.

In each case the linear risk range term is positive and statistically significant. For equation 5 the results imply that for each additional case per million in terms of the risk spread, the effect is to raise the risk perception by .04. Thus, in the case of the pair of risk studies posing risks per million of (120,240), which is the largest risk spread considered in the experiment, the role of risk ambiguity is to raise the assessed risks per million by 7.1.

The findings in equation 6 indicate that the role of risk ambiguity is positive, but that it diminishes with the extent of the risk spread. In particular, the impact of risk ambiguity displays a strong non-linearity that indicates a diminishing role of ambiguity belief aversion as the extent of the risk spread is increased. Evaluated at the mean risk of the sample of 160×10^{-6}, the findings in equation 6 imply that risk ambiguity raises the assessed risk by 57×10^{-6}. This effect is 34 percent of the value of the dependent variable, which is the risk that the respondent believes is equivalent to the lottery being presented. The potential influence of ambiguous belief aversion is consequently substantial for the quadratic specification in equation 6.

For the specifications including risk ambiguity, individual employment status continues to exhibit a significant positive effect on risk perceptions, and being in a high income group has a negative effect. The lung cancer knowledge variable falls short of statistical significance at the 5 percent level, but not

at the 10 percent level.

Other variations that may reflect variations in the role of risk ambiguity proved to be inconsequential. For example, interactions of the risk range variable with the temporal order variable did not yield a statistically significant effect.** This modification was of potential theoretical interest since the temporal order influences the relative informational weights ξ_1 and ξ_2. The absence of a significant effect of the temporal order interaction suggests that, given the experimental variations in informational content, only the risk range, not the precision, affects the estimates of the ambiguous belief aversion effect. Interactions of the risk variables with demographic characteristics, such as income, also proved not to be statistically significant so that there was no evidence of significant variations in the values of ξ_1 and ξ_2 with these factors.

4. Conclusion

Individual responses to ambiguous risk information suggests that the character of this response is more subtle than most previous treatments have suggested. The perfect learning model captured through a Bayesian framework received some support in that individuals weight the information that they received, and they place a greater weight on the scientific evidence that is more recent and which should be more credible. Moreover, these responses are not so excessive that they indicate alarmist learning responses.

The findings did, however, indicate two limitations in this learning process. First, 'individuals' cognitive limitations **affect the manner** in which they process risk information. The first study presented to them within a survey context has greater prominence and as a consequence receives greater emphasis in forming risk beliefs.

The second departure from the standard learning model pertains to the role of ambiguous beliefs. There is strong evidence of ambiguous belief aversion, even after one takes into account the full ramifications of a Bayesian learning process. This ambiguous belief aversion increases with the extent of the risk range, but at a diminishing rate. What is perhaps most important about this result is that the role of risk ambiguity is found to be significant within the context of an empirical test that utilizes a fully developed Bayesian expected utility model as the reference point for analysis.

These results do not distinguish whether the source of the ambiguous belief aversion stems from a misperception of the probabilities or an omitted aspect of individual preferences. The results do not distinguish which of these models is correct; they only indicate that a Bayesian expected utility model cannot fully capture the influence of ambiguous risk beliefs. The precise probability that establishes indifference in the reference lottery is higher in situations in which one is facing a lottery involving ambiguous risk beliefs. This, effect could arise if risk ambiguity entered negatively as a component of a

multi-attribute utility function or if it affected the perception of these probabilities in a manner that led to a violation of the standard probability axioms.

The findings do, however, suggest that the role of risk ambiguity is not limited to the narrow experimental context addressed in the **Ellsberg** paradox.- In situations in which individuals acquire risk information from diverse and possibly conflicting sources, they will behave in many ways that are consistent with a standard Bayesian learning model. However, there is an additional component to the choice process involving ambiguous risks that cannot be reconciled within a Bayesian expected utility framework. This result is not only of theoretical interest, as it also reflects the imperfect character of the manner in which individuals process risk information and make subsequent decisions under uncertainty. Identification of the systematic errors in this behavior ideally should better enable the providers of risk information to better understand the intervening cognitive linkages between information provision and economic decisions.

Table 1

Hypotheses for Alternative Learning Models

Nature of Learning	Empirical Hypotheses
Naive Bayesian	$\xi_1, \xi_2 > 0$; $1 \geq \xi_1 + \xi_2$; $\gamma' \mathbf{p}_0 \geq 0$.
Attentive Bayesian	$\xi_2 > \xi_1 > 0$ if temporal order; $\xi_1 = \xi_2 > 0$ if no temporal order; $1 \geq \xi_1 + \xi_2$; $\gamma' \mathbf{p}_0 \geq 0$.
Bayesian with Cognitive Limitations	$\xi_1 > \xi_2$ or $\xi_2 > \xi_1$ if no temporal order; $\gamma' \mathbf{p}_0 \geq 0$.
Alarmist Learner	$\xi_1 > 1$, $\xi_2 > 1$, or $\xi_1 + \xi_2 > 1$.
Ambiguous Belief Aversion	$\Psi_1 R + \Psi_2 R^2 > 0$, $\Psi_1 > 0$ If quadratic term excluded.

Table 2

Estimates of the Risk Perception Equation

Independent ariable	Coefficients (std. errors) 1	2	3	4	5	6
Intercept	12.074	16.326	10.601	5.665	11.389	14.812
RISK1 (r,)	0.412 (0.023)	0.390 (0.028)		0.558 (0.034)	0.528 (0.034)	0.195 (0.042)
RISK1 (r_1) xTemporal order				-0.215 (0.028)	-0.213 (0.028)	-0.216 (0.028)
RISK2(r_2)	0.547 (0.016)	0.524 (0.024)		0.401 (0.034)	0.375 (0.034)	0.041 (0.040)
RISK2(r_2) xTemporal order				0.219 (0.031)	0.216 (0.031)	0.213 (0.031)
RISK1(r_1) + RISK2(r_2)			0.476 (0.021)			
RISK RANGE (R)					0.043 (0.025)	3.163 (0.351)
(RISK RANGE)'						-0.017 (0.002)
Education		0.339 (0.335)	0.291 (0.341)	0.337 (0.325)	0.318 (0.322)	0.423 (0.322)
Employed		3.280 (2.198)	3.383 (2.307)	3.711 (1.982)	3.729 (1.988)	3.982 (1.946)
High Income		-3.575 (1.920)	-3.883 (1.997)	-4.734 (1.839)	-4.794 (1.829)	-4.252 (1.821)
Lung Cancer Knowledge		2.366 (3.156)	2.079 (3.228)	3.516 (2.867)	3.439 (2.838)	3.607 (2.818)
Nerve Disease Knowledge		1.115 (3.157	0.767 (3.357)	0.309 (3.091)	0.663 (3.056)	-0.038 (3.081)
R^2	.43	.43	. 39	.51	.51	. 53

*Other variables included in equation 2 are: respondent sex, number of people in household, age, age variable missing dummy variable, life irisurance coverage, and marital status.

Notes

1. For a review of these anomalies, see **Machina** (1987) for an economic perspective and Kahneman and Tversky (1979) for the psychology literature.

2. In some economic models there may be a preference for risk ambiguity. The evidence presented in Viscusi (1979) and Viscusi and O'Connor (1984) indicates that in multi-period job choice contexts workers should have a preference for ambiguous risks. This result is borne out in their study of worker responses to risk information, but it hinges critically on the role of learning in a multi-period adaptive choice context. This paper will focus on single lotteries so that such concerns will not enter.

3. Models along these lines include, among others, Quiggin **(1982), Fishburn** (1983, **1986),** Einhorn and **Hogarth (1985),** Segal **(1987),** Kunreuther and **Hogarth** (1989, **1990),** and Schmeidler (1989) .

4. See **Ellsberg** (1961) and Viscusi (1989).

5. Smith **(1969),** Bell **(1988),** Winkler **(1991),** and Heath and Tversky (1991) develop analyses based upon an effect of ambiguity on preferences.

6. A more complete description of the survey appears in Viscusi, Magat, and Huber (1990).

7. Sophisticated variants of this formulation can be found in Quiggins **(1982), Fishburn (1983,1986),** Segal **(1987),** and Schmeidler (1989).

8. Alternatively, both probabilities may be affected, but altering only one probability simplifies the model.

9. One could also make ambiguity belief aversion a function of the payoffs, but as we will see below the payoffs will affect the equilibrating value of s without this complication.

10. See Smith (1969), Bell (1988), Heath and Tversky (1991), and Winkler (1991) for advocacy of this approach.

11. If we let the utility function in good health be given by cU(Y), where c is a positive constant, one can show that $\partial s/\partial c > 0$ for both models above. The positive effect of increases in V(Y) on s is determined analogously.

12. Their findings are also consistent with the specific models they advocate as well.

13. The beta distribution can assume a wide variety of skewed and symmetric shapes and is ideally suited to analyzing Bernoulli-type processes such as this. It is, for example, more flexible than the normal distribution, which yields the same functional form for the posterior probability function given below. See Viscusi (1979) and Viscusi and O'Connor (1984) for motivation of the particular parameterization of the beta distribution used here.

14. See Viscusi (1989, 1990) for a Bayesian explanation of such behavior.

15. Kunreuther and Hogarth (1989) describe this test in Section 3.4.1 (pp. 18-19) of their paper.

16. See Viscusi (1989).

17. In several earlier studies we used a similar sample drawn from the same shopping mall. The Greensboro, North Carolina area is not the site of a major college and, because of its representativeness, is often used as a national test site for major consumer marketing efforts. Even if this were not the

case, our main concern is with the character of individual behavior, not the specific magnitudes of the responses.

18. The average reported age of the sample members was 32, but 17 percent of the sample did not report the age value because of the sensitivity of this question for older respondents. A missing variable for the respondents without reported age values will be included in the regression.

19. More specifically, the calculated F statistic for the hypothesis that $\xi_1 = \xi_2$ has a value of 43.2, which greatly exceeds the $F_{0.05}$ cutoff of 3.84 and the $F_{0.01}$ test cutoff of 6.63.

20. In particular, the parameter estimate was -0.010, with an associated standard error of .021.

References

Bell, David E., "Disappointment in Decision Making under Uncertainty," in D. Bell, H. Raiffa, and A. Tversky, eds., Decision Making: Descriptive, Normative, and Prescriptive Interactions (Cambridge: Cambridge University Press, 1988), pp. 358-383.

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

Einhorn, Hillel J., and Robin M. Hogarth, "Ambiguity and Uncertainty in Probabilistic Inference," Psychological Review, Vol. 92, No. 4 (1985), pp. 433-461.

Einhorn, Hillel J., and Robin M. Hogarth, "Decision Making Under Ambiguity," Journal of Business, Vol. 59, No. 4, part 2 (1986), pp. S225-S250.

Ellsberg, Daniel, "Risk Ambiguity, and the Savage Axioms," Quarterly Journal of Economics, Vol. 75 (1961), pp. 643-669.

Fishburn, Peter, "Ellsberg Revisited: A New Look at Comparative Probability," Annals of Statistics, Vol. 11 (1983), pp. 1047-1059.

Fishburn, Peter, "A New Model for Decisions under Uncertainty," Annals of Statistics, Vol. 11 (1986), pp. 127-130.

Heath, Chip, and Amos Tversky, "Preference and Belief: Ambiguity and Competence in Choice Under Uncertainty," Journal of Risk and Uncertainty, Vol. 4, No. 1 (1991), pp. 5-28.

Kahn, Barabara E., and Rakesh K. Sarin, "Modeling Ambiguity in Decisions Under Uncertainty," Journal of Consumer Research, Vol. 15 (1988), pp. 265-272.

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

Kunreuther, Howard, and Robin M. Hogarth, "Risk, Ambiguity, and Insurance," Journal of Risk and Uncertainty,, Vol. 2 (1989), pp. 5-35.

Kunreuther, Howard, and Robin M. Hogarth, "How Does Ambiguity Affect Insurance Decisions?" Working Paper, Wharton School of Business, University of Pennsylvania., May 1990.

Machina, Mark J., "Choice Under Uncertainty: Problems Solved and Unsolved," Journal of Economic Perspectives, Vol. 1, No. 1 (1987), pp. 121-154.

Quiggin, John, "A Theory of Anticipated Utility," Journal of Economic and Oraanizational Behavior, Vol. 3 (1982), pp. 323-343.

Raiffa, Howard, "Risk, Ambiguity, and the Savage Axioms: Comment," Quarterly Journal of Economics, Vol. 75 (1961), pp. 690-694.

Schmeidler, David, @@Subjective Probability and Expected Utility without Additivity," Econometrica, Vol. 57 (1989), pp. 572-587.

Segal, Uzi, "The Ellsberg Paradox and Risk Aversion: An Anticipated Utility Approach," International Economic Review, Vol. 28, No. 1 (1987), pp. 175-202.

Smith, Vernon L., "Measuring Nonmonetary Utilities in Uncertain Chores: The Ellsberg Urn," Quarterly Journal of Economics, Vol. 83 (1969), pp. 324-329.

Viscusi, w. Kip, Emnlovment Hazards: An Investiaation of Market Performance (Cambridge: Harvard University Press, 1979).

Viscusi, W. Kip, "Prospective Reference Theory," Journal of Risk and Uncertainty, Vol. 2, No. 4 (1989), pp. 235-264.

Viscusi, W. Kip, "Sources of Inconsistency in Societal Responses to Health Risks," American Economic Review, Vol. 80, No. 2 (1990), pp. 257-261.

Viscusi, W. Kip, and Charles O'Connor, "Adaptive Responses to Chemical Labeling: Are' Workers Bayesian Decision Makers?" Ame ' a Economic Review, Vol. 74 (1984), pp. 942-956.

Viscusi, W. Kip, Wesley Magat, and Joel Huber, "Communication of Ambiguous Risk Information," paper presented at Fifth International Conference on the Foundations and Applications of Utility, Risk, and Decision Theories, 1990. Forthcoming in Theory and Decision.

White, Halbert L., "A Heteroscedasticity - Consistent Covariance Matrix Estimator and a Direct Test for Heteroscedasticity," Econometrica, Vol. 48 (1980), pp. 817-838.

Winkler, Robert, "Ambiguity, Probability, Preference, and Decision Analysis," Journal of Risk and Uncertainty, Vol. 4, No. 3 (1991).