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HOPES AND FEARS:
THE CONFLICTING EFFECTS OF RISK AMBIGUITY

ABSTRACT. The Ellsberg Paradox documented the aversion to ambiguity in the probability of winning a prize. Using an original sample of 266 business owners and managers facing risks from climate change, this paper documents the presence of departures from rationality in both directions. Both ambiguity-seeking behavior and ambiguity-averse behavior are evident. People exhibit 'fear' effects of ambiguity for small probabilities of suffering a loss and 'hope' effects for large probabilities. Estimates of the crossover point from ambiguity aversion (fear) to ambiguity seeking (hope) place this value between 0.3 and 0.7 for the risk per decade lotteries considered, with empirical estimates indicating a crossover mean risk of about 0.5. Attitudes toward the degree of ambiguity also reverse at the crossover point.

1. INTRODUCTION

Few risks are known with precision. Investors in the stock market earn highly uncertain returns on their investments. Insurers venturing into novel areas of insurance, such as toxic torts or environmental liability, may lack a firm statistical basis for writing coverage. Consumers likewise make risky decisions, in some instances after receiving highly divergent risk information.

The introduction of risk ambiguity into choices under uncertainty adds an additional level of complexity that has been well-documented. In particular, the presence of aversion to ambiguous risks is a well-documented violation of expected utility theory.[1] This violation, commonly referred to as the 'Ellsberg Paradox', arises when people prefer certain, or known, probabilities of winning a prize over uncertain, or ambiguous, probabilities. In the classic basic case, subjects prefer to take a chance on winning a prize with draws from an urn with a specified mixture of balls as opposed to taking a

chance with a subjective probability that is equivalent, but ambiguous. One practical example of this phenomenon is that a person who knows nothing about tennis might prefer to bet on his ability to predict the outcome of a coin toss rather than on the outcome of a professional tennis match, although each prediction offers a fifty-fifty chance of coming true.[2] Such a person is said to be ambiguity-averse, as there is a preference for the known probability gamble over the ambiguous gamble.

Numerous studies have detected aversion to ambiguous probabilities.[3] This preference for the known probability is most prevalent for low probability losses and high probability gains. Other researchers have found instances in which there is a preference for ambiguity. Behavior that is ambiguity-seeking, or at least reflects a reduction in the extent of ambiguity aversion, is exhibited at the opposite extremes: situations involving high probability losses and low probability gains.

The degree of ambiguity may intensify these effects. Several studies have suggested that the degree of ambiguity affects the strength of these responses, as subjects show greater aversion to increasing levels of uncertainty. However, the studies that have established this aversion to increasing degrees of ambiguity have focused only on situations in which subjects are likely to be averse to ambiguous risks in general. For situations involving probabilities and outcomes for which ambiguity is desirable, increasing the degree of ambiguity may be preferable as well. Simply put, if subjects dislike ambiguity, they should dislike higher levels of ambiguity. Similarly, if subjects like ambiguity, as they sometimes do for low probability gains and high probability losses, they might prefer a higher degree of ambiguity.

The phenomenon we will examine here is the reversal in attitudes toward ambiguity as the mean risk rises.[4] Consider a situation in which there is the risk of a loss. The plausibility of reversals in attitudes toward ambiguity is apparent in the following medical example. Suppose that a doctor tells you that there is some low probability that you have a form of fatal cancer. Would you rather face this precise low probability or face the same mean risk but have an ambiguous risk situation in which some doctors think the risk is much greater and others believe that it is less? At low probabilities

of a loss, we hypothesize that the 'fear' of the high risk effect is dominant and that people are ambiguity-averse.

In contrast, suppose you were told that you had a high probability of having a fatal form of cancer. In that instance, the presence of ambiguity in which some experts believe that the risk is substantially lower and some believe that it is higher might be attractive. Ambiguity in this instance generates a 'hope' effect by offering a chance of avoiding the adverse event. Although these hope and fear effects are plausible, each of them violates expected utility theory, as do risk ambiguity effects more generally. In addition to documenting the presence of these influences, we will estimate the switch point at which the ambiguity effect turns from hope to fear.

The context used for our study has aspects of ambiguity that are of policy importance as well as of economic interest. In particular, we will examine how coastal North Carolina managers and business owners respond to the ambiguous risks of storm damage posed by risks of climate change. These businesses are particularly vulnerable to losses caused by hurricanes, rises in the sea level, and other climatic phenomena linked to global warming. This sample consequently consists of individuals facing potentially substantial financial risk because of the presence of environmental risk ambiguities. Understanding the character of their attitudes toward risk ambiguity is pertinent to understanding better what precautionary self-protective responses will result in response to these climatic uncertainties.

The results from our original survey of coastal business owners and managers suggest that as the probability of a loss increases, subjects become less ambiguity-averse, reaching a 'crossover point' at which they become ambiguity-seeking. We estimate the value of this crossover point. The findings go beyond indicating a shift from a fear effect to a hope effect. The extent of ambiguity matters as well. At probabilities below this crossover point, subjects dislike ambiguity and dislike higher degrees of ambiguity. At probabilities above the crossover point, subjects prefer ambiguity and higher degrees of ambiguity.

This paper is organized in the following manner. Section 2 briefly describes the results of previous experiments and surveys which are relevant to our study. Section 3 develops the empirical model to test

for a crossover point at which subjects' attitudes toward ambiguity and degree of ambiguity change across probabilities. Section 4 and 5 report empirical estimates that incorporate this crossover point into a model of risk perception under ambiguity, and Section 6 concludes.

2. THE RESEARCH CONTEXT AND SURVEY DESIGN

2.1. *Previous research*

The finding commonly referred to as the 'Ellsberg Paradox' has inspired numerous studies on decision-making with ambiguous risks.[5] Some of this Ellsberg-inspired research has focused on the perceptions of different levels of ambiguity, finding most subjects to be averse to such increases in the amount of the ambiguity. Becker and Brownson (1964) found that subjects were willing to pay more as the possible range of winning balls in the urn increased to avoid playing from the ambiguous urn. Viscusi and Magat (1992) tested the effects of risk range in the loss domain and found that the perceived risk increased with an increase in the risk range, but at a decreasing rate.

The focus of our paper is not on the range alone but on its interaction with the mean probability level. Consider a choice between two gambles which offer the same mean probability of winning, for example 0.5, but with a different range of possible probabilities. The first option might offer a probability of winning which is uniformly distributed between 0.4 and 0.6, while the second option might offer a probability distributed uniformly from 0.3 to 0.7. The second option offers a symmetric increase in the mean-preserving spread. Thus, the second option offers a higher degree of ambiguity. An interactive effect of probability and degree of ambiguity would suggest that attitudes toward risk ranges for gambles with low mean probabilities may be different from that of gambles with high mean probabilities.

Past studies of these influences have yielded mixed results. Larson (1980) found no interaction of range effects and probability levels in the gain domain, whereas Curley and Yates (1985) tested for range and probability effects and found that ambiguity aversion increased when the range of the more ambiguous urn increased or when the range of the less ambiguous option decreased.[6] Kahn

and Sarin (1988) found that larger risk ranges increased ambiguity aversion for high probability gains and increased ambiguity seeking behavior for low probability gains. Their experiments also found their student subjects to be ambiguity-seeking for high probability losses and low probability gains.[7]

The research presented in this paper extends these findings in several ways. First, our survey methodology utilizes a risk-risk scenario to examine the risk perception process.[8] Second, our survey examines the risk of storm damage, an event that either will or will not happen. This scenario is similar to many that people face every day: the risk of cancer and other diseases, the risk of automobile accidents, and so on.[9] Third, our empirical formulation and, in particular, our estimation of the crossover point, is quite different from earlier studies. In particular, we explicitly estimate the crossover point and do so in a manner that uses a Bayesian learning model as the starting point for empirical analysis.

To summarize, previous studies suggest that in the gains domain:
  · Subjects are averse to ambiguity and increased degrees of ambiguity for high probabilities.[10]
  · Subjects prefer ambiguity and increased degrees of ambiguity for low probabilities.[11]

In the loss domain the findings are:
  · Subjects are averse to ambiguity and increasing degrees of ambiguity for low probabilities.[12]
  · Subjects are ambiguity-seeking, and enjoy larger degrees of ambiguity, for high probabilities.[13]

Note the symmetry between these findings for the gains domain and the loss domain. Our survey offering various risk ranges across a wide range of probabilities in the loss domain is used to test systematically for this reversal in effects. Moreover, our analysis explicitly shows a reversal in altitudes as the probability is increased. Many of the researchers in the studies listed above examined only one segment of the probability distribution and recognized that their results did not generalize to other probability levels.

2.2. *Survey design*

The survey we used to test for range effects in the loss domain differs from experiments mentioned above. Our general approach follows that of Viscusi, Magat, and Huber (1991), who established ambiguity by providing conflicting expert estimates of a risk. Subjects give the equilibrating precise risk that they consider to be equivalent to the diverse risk judgments. This manipulation of ambiguity is more 'real-world' than most manipulations, as there are indeed many conflicting sources of risk information available to the public. Urn games, or other such manipulations, create a somewhat artificial type of ambiguity, one without any counterpart in most of the real-world decision-making under uncertainty.

Another distinguishing feature of this survey is its sample, which consists of 266 business owners and managers. The Appendix describes the sample in greater detail. Many experiments dealing with decision making under ambiguity use relatively small samples of students. Prominent exceptions are Einhorn and Hogarth's (1986) study of the responses of executives of life insurance companies and Hogarth and Kunreuther's (1985) analysis of insurance underwriters. The coastal business sample, in contrast, focuses on the other side of insurance markets–the potential buyers of insurance. Another distinctive feature of this survey is that it focuses on business, rather than personal, decisions made under ambiguity.

The survey contained three risk assessment scenarios consisting of two tasks per scenario. Panel A of Table 1 presents a sample of a risk assessment scenario. The first task for the subject was to choose between two areas in which to locate his or her business. In Area 1, two experts gave varying estimates of the risk of major storm damage, while in Area 2 the two experts agreed on the risk. The 'certain' risk in Area 2 was always the mean of the two risk estimates given for Area 1. The second task for the subject was to provide a risk level of indifference which he or she equated to the risk pair. Panel B of Table 1 presents an example of this second task.

Thus, the survey established ambiguity by providing conflicting risk estimates of storm damage. While the mean estimate is the same for each area, the estimates for Area 1 suggest a higher amount of uncertainty about the risk. In this survey, the subjects have at least some information about the outcome probabilities for each area. The

Table 1. Presentation of basic survey scenario[14]

Panel A: Task 1

In BEACH AREA ONE:	In BEACH AREA TWO:
The chance of heavy storm damage (per decade) is:	the chance of heavy storm damage (per decade) is:
Expert A says 20% Expert B says 40%	Both experts say 30%

If you had to locate your business in one of these areas, which one would you choose?
1. BEACH AREA ONE
2. BEACH AREA TWO

Panel B: Task 2

Now we will compare BEACH AREA ONE with a different area, BEACH AREA THREE

In BEACH AREA ONE:	In BEACH AREA THREE:
The chance of heavy storm damage (per decade) is:	the chance of heavy storm damage (per decade) is:
Expert A says 20% Expert B says 40%	Both experts say ????

Notice that there is no number given for BEACH AREA THREE. We want you to choose the risk for BEACH AREA THREE that would make you like each area about the same.

In other words, we want you to choose the exact chance of storm damage for AREA THREE so that AREA ONE and AREA THREE seem about the same to you.

At this point, the subjects chose from a checklist of numbers ranging from 20% to 40%.

risk for Area 2, however, is less ambiguous than the risk for Area 1, as the agreement between the experts suggests more confidence in the risk estimate for Area 2. For simplicity, we refer to Area

2 as the 'nonambiguous choice' since a scientific consensus was provided to the subjects. The mean probability for this nonambiguous choice presented in the survey ranged from 0.05 to 0.95, and the discrepancy between the two risk estimates in the ambiguous choice ranged from 0.08 to 0.50. The survey's wide range of probabilities allows for an examination of how perceptions of ambiguous risks vary across mean risk levels. The mean risk level did indeed affect the subjects' attitudes toward ambiguity. We discuss this effect below.

3. MODELING PERCEPTIONS WITH THE CROSSOVER POINT

3.1. *The learning model*

The main task for the survey subjects was to provide a risk level of indifference, which would equate a single risk with the risk range presented to them. This risk level of indifference therefore depends on the two risks as well as the subject's attitudes toward the ambiguity arising from these two risks. Extending the model of Viscusi and Magat (1992), let U(Y) be the utility if no loss is suffered and V(Y–L) be the utility arising if a loss does occur. In this case L represents the monetary loss to the business owner, which can be thought of as uninsured losses due to the storm or revenue losses in the storm's aftermath. We assume that U(Y) > V(Y), as the business owner is worse off after the storm even if the business is completely insured.[15] The subject provides a risk level of indifference, s, which he or she equates to the risk pair (r_1, r_2). We assume that the subject processes the risk pair (r_1, r_2) according to some risk belief function $p(r_1, r_2)$, where prior risk beliefs and personal characteristics may affect the shape of this relation. An expected utility-maximizing subject's risk level of indifference, s, satisfies

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

Solving for *s* yields

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

Equation 2 simply states that the subject's risk level of indifference s is equal to the subject's perceived risk of the two risk estimates, given by the function $p(r_1, r_2)$. The utility function terms do not influence the ultimate choice process, as the survey equality reduces to equating two probabilities.

The underlying assumption that we use as the point of departure in this formulation is that individuals act in a way that might be termed naive Bayesians. We also assume that risk beliefs can be characterized using a beta distribution, which can assume a wide variety of skewed and symmetric shapes. Each of the two sources of information represents independent draws from a Bernoulli urn. The survey provides no information to distinguish the opinions of the experts regarding the risk of the loss. As a result, suppose that expert 1's opinion has information content ψ_1 and expert 2's opinion has informational content ψ_1 as well. The individual attaches a mean risk probability r_1 to expert 1's views, or the person acts as if expert 1's opinion consisted of ψ_1 draws from a Bernoulli urn, a fraction r_1 of which indicate a risk of storm damage. For expert 2, the person acts as if a fraction of the ψ_1 draws indicating the storm damage risk is r_2. Suppose also that the prior risk assessment is r_0 with informational content ψ_0. Then the posterior assessed risk value is

$$p(r_1, r_2) = \frac{\psi_0 r_0 + \psi_1 r_1 + \psi_1 r_2}{\psi_0 + 2\psi_1}. \tag{3}$$

If we let $a = \psi_0/(\psi_0 + 2\psi_1)$ and $b = \psi_1(\psi_0 + 2\psi_1)$, then the perceived probability that there will be a loss in the Bayesian ambiguous information case is

$$p(r_1, r_2) = ar_0 + br_1 + br_2, \tag{4}$$

where ar_0 is some constant c that is independent of the values of r_1 and r_2. If the informational content of the survey information relative to the prior beliefs is sufficiently great (i.e., as $(\psi_1/\psi_0) \to \infty$), then the perceived probability for the ambiguous case is

$$p(r_1, r_2) = 0.5(r_1 + r_2). \tag{5}$$

Respondents simply average the two risk assessments. In the case of the information provided by the two experts who agree, the simplest

assumption is to view respondents as treating this information as fully informative and equal to a precise risk value s. If that is the case, the empirical reference point that would hold for Bayesian learners is that

$$s = p(r_1, r_2) = c + b(r_1 + r_2). \tag{6}$$

The value of c is 0 (and b is 0.5) if the information swamps any influence of the prior beliefs.

If risk ambiguity has a role in a manner that is not consistent with Bayesian learning, then $p(r_1, r_2)$ may include some kind of ambiguity aversion or ambiguity seeking term $A(r_1, r_2)$, so that Equation 6 becomes

$$s = p(r_1, r_2) = c + b(r_1 + r_2) + A(r_1, r_2). \tag{7}$$

In the absence of ambiguity effects there will be no A term in Equation 7. If prior beliefs are dominated by the risk information, then the value of $b = 0.5$.

An alternative formulation is that respondents do not treat the concurring risk judgments s as fully informative but rather view the information in the same manner as the ambiguous information except for the absence of an ambiguity term. Thus, we have

$$s = c + 2bs. \tag{8}$$

Equating this term to the value of $p(r_1, r_2)$ in the risk-risk tradeoff yields

$$c + 2bs = c + b(r_1 + r_2) + A(r_1 + r_2), \tag{9}$$

or

$$s = 0.5(r_1, r_2) + A(r_1, r_2)/2b. \tag{10}$$

Since A can include a constant term in the formulation, from the standpoint of empirical estimation the partial information reference point Equation 10 is almost functionally identical to the full information expert reference point in Equation 7. The key to any ambiguity test is whether there is some additional ambiguity term A that affects perceptions in the ambiguous risk case. For concreteness, we will

keep the discussion below in terms of the fully informative case in which the experts agree, which is captured in Equation 7, recognizing that the analysis can be modified quite directly. The role of risk ambiguity may include a constant, though such a term could arise in the Bayesian learning case as well. As a result, let us focus on the components of the ambiguity term other than a constant effect. In addition, although the model presented here focuses on the case in which there is an interaction of the ambiguity effect with the risk mean, the empirical analysis will explore other formulations as well.

The analogous survey structure considers risks of a loss. In view of evidence that subjects are less ambiguity-averse for higher probabilities, we hypothesize that $A(r_1, r_2)$ decreases as the mean risk value becomes larger. For sufficiently low mean risk values, we hypothesize that there is a 'fear' effect with $A(r_1, r_2) > 0$ below some crossover point α. People act as if small but ambiguous risks are larger than their mean value. We hypothesize that for probabilities above the crossover point α that the value of $A(r_1, r_2)$ becomes negative, or the 'hope' effect becomes dominant.

Figure 1 illustrates the changing influence of the effect of risk ambiguity as the mean risk changes.[16] For the low mean risk values of lotteries, which are shown on the horizontal axis, subjects have an equilibrating probability that lies above the 45° line. The 'fear' effect is dominant, as the equilibrating risk exceeds the mean risk. For sufficiently large mean risks above the crossover point α, risk ambiguity is desirable. 'Hope' effects make the equilibrating probability for the ambiguous lottery smaller than a precisely understood equivalent mean risk.

3.2. *Empirical formulation*

The absolute magnitude of the ambiguity effect is of interest as well. Let us hypothesize that the value of the function $A(r_1, r_2)$ increases with the risk range for low probabilities and decrease with the risk range for high probabilities. To account for these changes in attitudes toward ambiguity and degree of ambiguity across the probability levels, let $A(r_1, r_2)$ be of the form

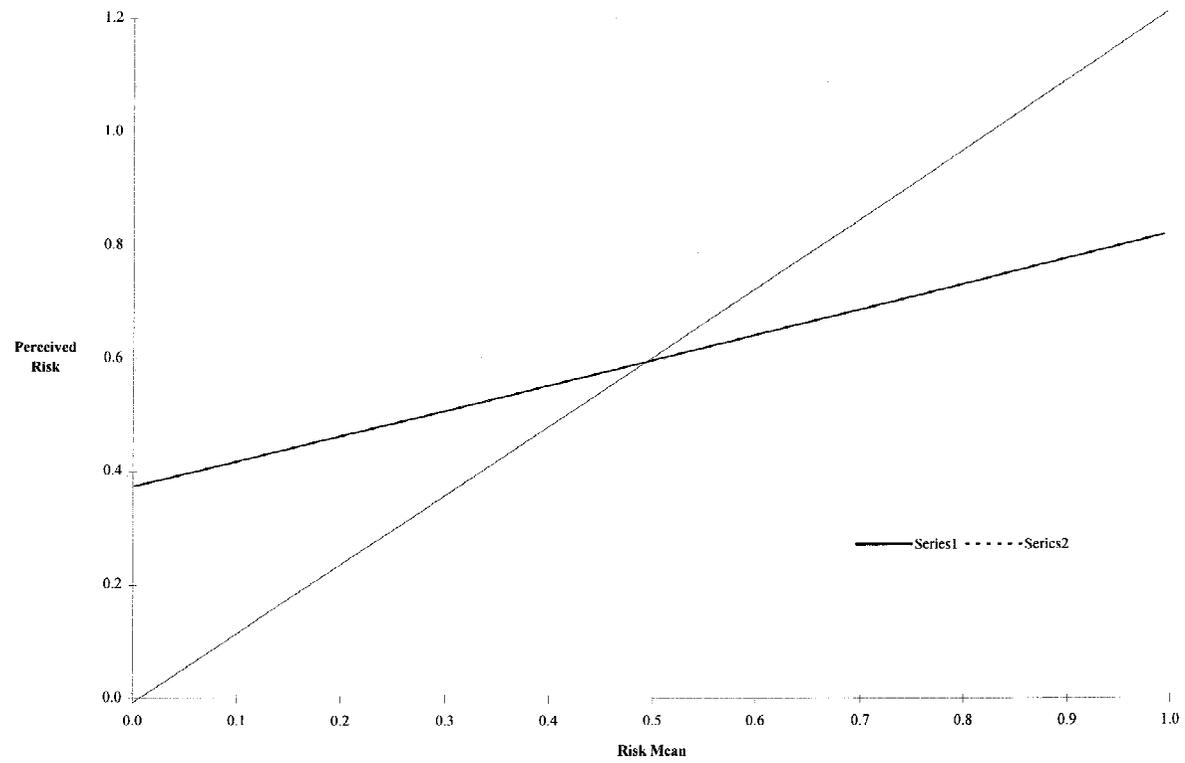$$A(r_1, r_2) = \left(\alpha - \frac{r_1 + r_2}{2} \right) \theta (r_2 - r_1), \tag{11}$$
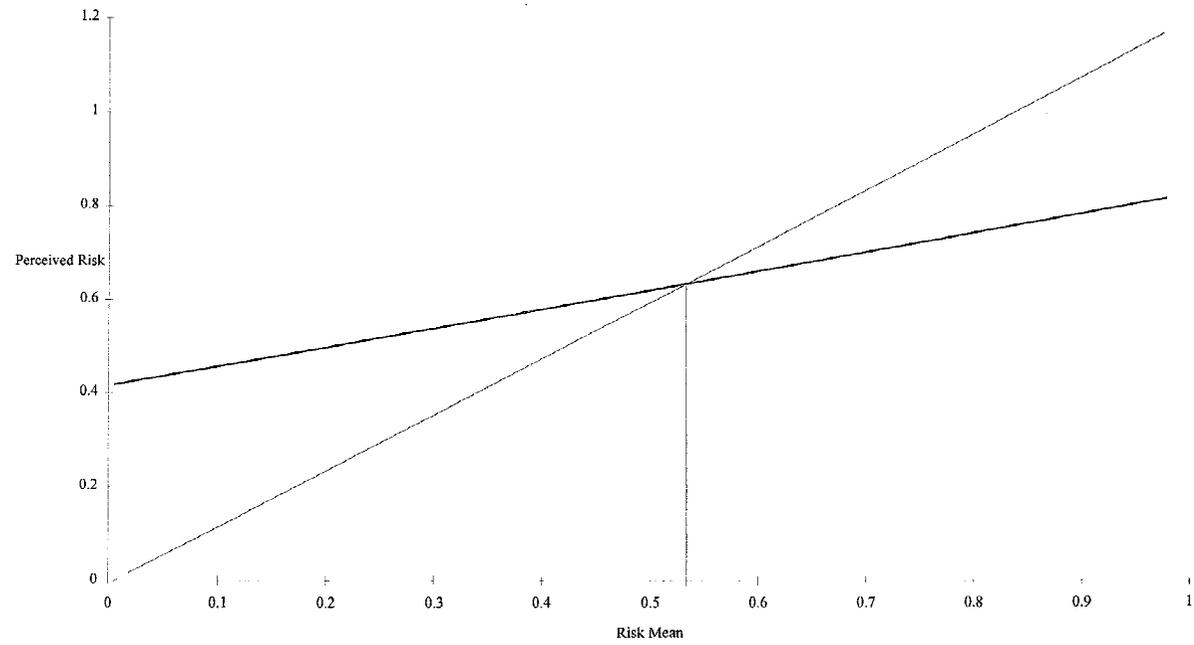
Figure 1. (Part one).

Figure 1. Risk ambiguity and the crossover point for hope-fear effects.

where α is the crossover point and θ is an ambiguity scale effect parameter. The first component term on the right side of Equation 11 permits the crossover point to reverse the sign of the ambiguity effect. In particular, this term is the difference between the crossover point α and the mean risk. For mean risks below the crossover point α, subjects are ambiguity-averse and for risks above the crossover point subjects are ambiguity-seeking. The term θ is a scaler ($\theta > 0$) that permits the level of the ambiguity effect to vary. The final term in Equation 11 arises because we hypothesize that for mean probabilities below the crossover point α the perceived risk increases with the risk range. For mean probabilities above α the perceived risk decreases with the risk range. Now the subject's risk level of indifference s can be written

$$
\begin{aligned}
s =& c + b(r_1 + r_2) + (\theta)(\alpha)(r_2 - r_1) \\
& - (\theta)\left(\frac{r_1 + r_2}{2}\right)(r_1 - r_1).
\end{aligned}
\tag{12}
$$

Put in verbal terms Equation 12 is

$$
s = c + 2b(\text{mean}) + (\theta)(\alpha)\text{range} - (\theta)(\text{mean})(\text{range}).
\tag{13}
$$

One of the models we estimate is the following equation for the crossover point and its associated effects on the perception of ambiguous risks:

$$
\begin{aligned}
s =& \beta_0 + \beta_1\left(\frac{r_1 + r_2}{2}\right) + \beta_2(r_2 - r_1) \\
& + \beta_3\left(\frac{r_1 + r_2}{2}\right)(r_2 - r_1) + \sum_{i=4}^{n}\beta_i\pi_{i-3} + \epsilon,
\end{aligned}
\tag{14}
$$

where the various β values are coefficients, ϵ is a random error term, and the π_i terms in Equation 14 and in some of the estimations below represent personal characteristics such as age and income. Differences in prior beliefs of the risk and the constant term component of $A(r_1, r_2)$, each could lead to such effects. In the case reflected in equation 14, we have the prediction that the risk mean is the initial anchor, and subjects make adjustments depending upon the parameters β_2 and β_3. Since $\beta_2 = (\alpha)(\theta)$, (the crossover point

times the positive scaler), it is expected that $\beta_2 > 0$. Equation 14 also suggests that $\beta_3 < 0$ since $\beta_3 = -\theta$. One can calculate the crossover point, α, from the estimated values of β_2 and β_3 according the equation

$$\alpha = -\frac{\beta_2}{\beta_3}. \tag{15}$$

In addition, we also estimate a person-specific fixed effects model since subjects responded to more than one equilibrating risk question. This formulation eliminates the influences of all fixed person-specific differences. For this model, the constant term β_0 varies across individuals, and the personal characteristic variables do not enter the equation, producing an equation to be estimated given by

$$s = \beta_{0i} + \beta_1 \left(\frac{r_1 + r_2}{2} \right) + \beta_2 (r_2 - r_1)$$
$$+ \beta_3 \left(\frac{r_1 + r_2}{2} \right) (r_2 - r_1) + \epsilon. \tag{16}$$

4.   RANGE EFFECTS AND PROBABILITY LEVELS

4.1. *Mean risk levels and attitudes toward ambiguity*

The subjects in this survey displayed a tendency toward ambiguity aversion for low probabilities and ambiguity-seeking behavior for high probabilities. For probabilities below 0.5, more subjects favored the ambiguity-averse choice, while for probabilities above 0.5 fewer responses favored the ambiguity-averse choice. Table 2 summarizes these results. These data understate the degree of switching from ambiguity-averse to ambiguity-seeking behavior since some subjects cross over from 'fear' to 'hope' within these risk ranges. The regression analysis affords a more complete test of the crossover effect.

This finding, that ambiguity aversion decreases as the probability of a loss increases, suggests there might be some probability at which attitudes toward ambiguous risks change. This threshold probability, which we term the 'crossover point' between fear and

Table 2 Overall distribution of subjects' attitudes toward ambiguity for low and high probabilities

For low mean probability ($p < 0.5$)		For high mean probability ($p > 0.5$)	
% ambiguity-averse	% ambiguity-seeking	% ambiguity-averse	% ambiguity-seeking
58.4	41.6	43.0	57.0
N = 269		N = 316	

The ambiguity-averse value is statistically different from the percent ambiguity-seeking value at 0.001 significance level (two-tailed test).

hope effects, is the probability at which subjects begin to prefer the ambiguous choice. We will estimate the value of this crossover point. Subjects who prefer the ambiguous choice presumably might prefer higher degrees of ambiguity than the subjects who prefer the nonambiguous choice. If this is true, then a subject's attitudes toward the degree of ambiguity would change at the crossover point, the point at which the subject's attitude toward ambiguity changes.

The survey provides scenarios with varying risk ranges which allow the examination of the crossover point and its associated change in the subjects' attitudes toward the degree of ambiguity. The risk range (the discrepancy between the expert estimates of the risk) varied from 0.08 to 0.50. We used larger ranges when such ranges were possible, given the constraint that any probability estimate cannot be lower than zero or higher than one. Thus, there was a tradeoff between the size of the risk range and the absolute difference between the mean probability and 0.5. That is, a mean risk of 0.5 offers the potential for a large symmetric risk range around the mean, while a mean risk of 0.95 or 0.05 does not. Two particular mean probability levels, 0.3 and 0.7, offer room for varying the size of the risk range while remaining somewhat distinguishable as low and high probability means. The following section discusses range effects for these two probability levels.

4.2. *The crossover point and attitudes toward the degree of ambiguity*

There were three different risk ranges used for the mean risks of 0.3 and 0.7. The risk pairs for the mean risk 0.3 were (0.25, 0.35), (0.20,

0.40), and (0.10, 0.50), while the risk pairs for the mean risk 0.70 were (0.65, 0.75), (0.60, 0.80), and (0.50, 0.90).

Low probability scenario.   For the low mean risk (0.30), the risk pairs (0.25, 0.35) and (0.20, 0.40) are grouped together in the low range category, while the high range category contains the risk pair (0.10, 0.50).[17] For the low probability (0.30), 43.5% of the subjects were ambiguity-averse when presented with a high risk range, while only 23.7% were ambiguity-averse when facing a low risk range. That is, subjects facing the high range pair of estimates (0.10, 0.50) were more likely to be ambiguity-averse than the subjects facing the low range risk pairs (0.25, 0.35) and (0.20, 0.40). This difference is significant at the 0.10 level. This significance, however, depends in part on the grouping of the two lower risk ranges into one low range category. Due to the small size of the subsample, ambiguity aversion in the higher risk range (0.10, 0.50) is not quite significantly different from the medium range (0.20, 0.40), although it is significantly different from the low range (0.25, 0.35) at the 0.05 level. Table 3 summarizes these findings.

High probability scenario.   For the high probability cases ($p = 0.70$), 35.1% of the subjects were ambiguity-averse for the low risk ranges while only 15.8% were ambiguity averse when facing a high risk range. That is, subjects facing the high range pair (0.50, 0.90) were less likely to be ambiguity averse than the subjects facing the low range risk pairs (0.65, 0.75) and (0.60, 0.80). This difference is significant at the 0.05 level.[18] The percentage of subjects who are ambiguity-seeking is fairly constant for the two range levels, however.

5. EMPIRICAL ESTIMATES OF THE CROSSOVER POINT EQUATION

These data make it possible to estimate the crossover point in the perception of ambiguous risks. First, ambiguity aversion decreases significantly as the mean probability of a loss increases. Second, the results in Table 3 suggest that subjects prefer low risk ranges when the probability of a loss is 0.3 and prefer high risk ranges when

Table 3 The effect of the risk range and probability on attitudes toward ambiguity

For low mean probability ($p = 0.30$)			
	% ambiguity-averse	% ambiguity-neutral	% ambiguity-seeking
low risk range (N = 38)	23.7	52.6	23.7
high risk range (N=23)	43.5[a]	34.8[a]	21.7

For high mean probability ($p = 0.70$)			
	% ambiguity-averse	% ambiguity-neutral	% ambiguity-seeking
low risk range (N=37)	35.1	29.7	35.1
high risk range (N=38)	15.8[b]	47.4[b]	36.8

[a] Percentage in low risk range is significantly different from the percentage in the high risk range at the 0.10 significance level (one-tailed test).
[b] Percentage in low risk range is significantly different from the percentage in the high risk range at the 0.05 significance level (one-tailed test).

the probability of a loss is 0.7. This reversal is consistent with the hypothesis that there is some intervening probability at which attitudes toward the degree of ambiguity change. Table 3, however, only reports results for a small subsample so that it is not as instructive as the full sample in estimating the probability effect on attitudes toward ambiguity.

In order to test for the crossover point, with its associated changes in perceptions of ambiguity and levels of ambiguity, we will utilize the information provided in the responses of all the subjects. Due to the wide variety of probabilities and ranges employed by the survey, a regression analysis of the responses is more meaningful than separate analyses of the relatively small number of responses to a specific mean risk or risk range.

Table 4 reports the OLS estimates for the model specified in Equation 14. Column 1 of Table 4 reports the results when the mean-range interaction is included, while column 2 does not include the interaction.[19] The equations pool the multiple responses by individuals in a single regression so that there are 613 observations.[20] The predictions that $\beta_1 = 1$ (in the special Bayesian case), $\beta_2 > 0$, and $\beta_3 < 0$, are borne out for the first equation in Table 4. Note that β_1, the coefficient for the mean risk variable, is not significantly

Table 4 Regression estimates equilibrating risk equation

Independent variable	Coefficients (standard errors)	
	(1)	(2)
Intercept	-0.022 (0.022)	0.128 (0.020)
Mean risk	1.018 (0.017)***	0.957 (0.008)***
Risk range	0.163 (0.048)***	−0.012 (0.023)
Mean × Range	−0.333 (0.080)***	
Age	$−3.1 \times 10^{-4}$ (2.2×10^{-4})	2.3×10^{-4} (2.2×10^{-4})
Income	$−1.5 \times 10^{-7}$ (1.5×10^{-7})	1.4×10^{-7} (1.5×10^{-7})
Income missing	0.011 (0.010)	0.012 (0.010)
Education	3.4×10^{-4} (9.7×10^{-4})	5.5×10^{-5} (9.8×10^{-4})
Current smoker	0.010 (0.006)	0.010 (0.006)
Wears seatbelt	0.008 (0.009)	0.010 (0.009)
R^2	0.961	0.960
N	613	613

***denotes significance at 0.01 level, ** = 0.5 level, and * = 0.10 level, two-tailed test.

different than 1. This result suggests that the mean risk is indeed the starting point of the risk estimate. Further, $\beta_2 > 0$ and $\beta_3 < 0$, and both of these estimates are statistically significant at the 0.01 level. The ambiguity adjustment process depends on the risk range and the risk mean interaction. These estimates of β_2 and β_3 place the point estimate of the crossover point α at 0.49 (using column 1 estimates).

Note the significance of including the mean-risk interaction. Column 2 of Table 4 reports the results when the interaction is omitted from the specification. Without including the interaction, there appears to be no significant effect of the risk range on the risk perceptions. The null hypothesis, that the interaction adds no explanatory power to the model, can be rejected at the 0.01 level.

5.1. *Correcting for subject-specific effects*

Since there were multiple responses per subject, this feature of the survey makes it possible to eliminate the influence of any subject-specific effects. This approach involves the estimation of Equation 16. The dependent variable is the subject's risk level of indifference for each of the different treatments. The independent variables only include the different measures of the risk structure because

Table 5 Regression estimates of equilibrating risk using a fixed effects model

| Independent | Coefficients (standard errors) | |
variable	(1)	(2)
Intercept	−0.038 (0.035)	−0.062 (0.035)*
Mean risk	0.973 (0.018)***	0.932 (0.012)***
Risk range	0.089 (0.041)**	−0.015 (0.023)
Mean × Range	−0.222 (0.073)***	
R^2	0.988	0.988
n	619	619

***denotes significance at 0.01 level, ** = 0.5 level, and * = 0.10 level, two-tailed tests.

all person-specific differences are captured through the fixed effect terms. Thus, the demographic variables no longer enter. Table 5 reports these results.[21]

The results are similar to the estimates for the pooled data including the personal characteristic variables. The hypotheses that $\beta_2 > 0$ and $\beta_3 < 0$ still hold, and these estimates are significant for the specification which included the risk-mean interaction (columns (1)). The prediction that $\beta_1 = 1$ is borne out for column (1), as β_1 is not significantly different than 1 using a two-tailed test (0.05 significance level).

5.2. *The mean risk – risk range interaction*

Note again the results from omitting the interaction term, as shown in column (2) of Table 5. As with the pooled data in Table 4, there appears to be no range effect when the interaction term is not included in the model.[22] This lack of a measurable effect of risk range occurs because the effect of risk range changes across probabilities, and observations above the crossover point will reflect range effects opposite from range effects of observations below the crossover point. When the mean risk – risk range interaction is not included, the range effect is canceled out because of observations above and below the crossover point.

5.3. *Estimates for the crossover point*

The estimates presented in column (1) of Table 5 imply a value of the crossover point of 0.40, suggesting that subjects become ambiguity-seeking when the per-decade probability of storm damage exceeds 40%. We note, however, that because the storm risks occur over time, our estimated crossover point is not directly comparable to a 'one-shot' draw from an Ellsberg urn or similar situations of ambiguity. That is, the subjects may have converted the per-decade risk estimates into much lower annual risk estimates. The estimate in Table 4 of the crossover point using the pooled data was 0.49. As in the case of the mean result reported in Section IV, subjects prefer higher risk ranges for the mean per-decade probability of 0.7 and lower risk ranges for the mean probability of 0.3. The results in Table 3 indicate that there is a crossover point somewhere between 0.3 and 0.7. These earlier finding only implied that there was a crossover point between 0.3 and 0.7. They did not indicate its magnitude. Our estimated values for the crossover point α of 0.40 and 0.49 fall within this range.

5.4. *Controlling for inconsistent subjects*

Each subject performs two tasks per scenario, and the decisions for each task should be consistent. First, the subject chooses between Area 1 and Area 2. After choosing, the subject provides the risk for another area, Area 3, such that he or she is indifferent between Area 1 and Area 3. This two-task method provides a built-in test for the subject's comprehension of the question, as the risk level of indifference for Area 3 should be higher (lower) than the initial risk given for Area 2 when Area 2 (Area 1) is initially preferred.[23] The results are similar whether using the full sample or the consistent-only sample. The findings using the consistent sample, just as for the full sample, suggest a crossover point at which subjects change their attitudes toward ambiguous risks. The risk range – risk mean interaction is significant for the consistent sample as well.

6. CONCLUSION

The business respondents reacted to differing degrees of ambiguity

for varying mean risks of a loss from storm damage exhibited what might appear to be conflicting behavior. Both ambiguity-averse behavior and ambiguity-seeking behavior were evident. These seemingly inconsistent responses reflected the differing effect of risk ambiguity depending on the mean risk level. The general pattern was a switch from 'fear' effects of ambiguity aversion to 'hope' effects of ambiguity seeking behavior as the mean probability rises.

The direction of the departure from expected utility theory arising from ambiguity reverses at the crossover point. This crossover point is the threshold probability at which ambiguity shifts from being a negatively valued fear to a positively valued hope. The empirical model formulated the subject's perceptions of ambiguous risks as being dependent on this crossover point. Estimations of the model found a significant interaction between the risk mean and the risk range, adding further support for the existence of the crossover point. The estimations of the model further suggest that the mean crossover point is somewhere between 0.40 and 0.49 in the context of ambiguous risks per-decade of storm damage. This crossover point may, of course, differ for risks with a different time frame or risks of a different character.

Decisions made in the presence of ambiguous environmental risks depend not only on the mean risk level but also on the degree of the ambiguity involved and on the interaction of the mean risk level and the degree of ambiguity. Respondents preferred lower risk ranges for low probability losses, and higher risk ranges for high probability losses. Increasing the degree of ambiguity has the expected desirability or undesirability depending on how ambiguity affects preferences at that particular probability.

The degree of uncertainty associated with information about a risk will affect the public's perception of that risk, and this effect depends upon the magnitude of the risk itself. For low probability risks, higher degrees of ambiguity will lead to higher risk perceptions. For high probability risks, higher degrees of ambiguity will lead to lower risk perceptions. Thus, the degree of ambiguity involved with a risk is an important part of the risk perception process. This role of the degree of ambiguity suggests that providers of risk information should be cognizant of the degree of ambiguity presented to the public in their efforts to generate accurate perceptions of

risk in situations involving ambiguity. For example, suppose that providers of risk information have decided to present ambiguous risks in the form of the risk mean or the risk range. The findings presented in this paper suggest that the presentation of the risk as a mean will lead to more rational risk perceptions for both low and high probability risks that more closely accord with a rational Bayesian learning process. The presentation of a risk range leads to higher risk perceptions for low probabilities and lower risk perceptions for higher probabilities. Conveying only mean risks ignores the normative debate on how ambiguous risks should be presented (i.e., as a mean, as a range, or a mean with some uncertainty). Moreover, failure to indicate the presence of risk ambiguity may jeopardize the credibility of the information source when the risk message changes after the acquisition of new information in the future.

APPENDIX: SAMPLE DESCRIPTION

The sample for this study consisted of 266 business owners and managers of coastal North Carolina businesses. Of this group, 23 respondents were not the owners or principal managers but held some other title, such as assistant managers. The responses of this group closely parallel those of the broader sample.

The location of the sample group is ideally suited to analyzing the response of business officials to economic damage from storms arising from global climate change.

Many of the risk ambiguity questions dealt with uncertain risks arising from storms due to climate change. These risks are of real consequence to the business manager subjects in the survey location. The coastal site for the study is one of the high risk areas threatened by climate change so that the survey dealt with potential risks that were pertinent to the business manager respondents.

The research staff distributed surveys in person to 373 businesses in Carteret County, North Carolina, which is situated on the Atlantic coast. The surveyor asked that the owner, manager, or some other employee complete the survey and return it by mail in the provided envelope. Over 90% of the surveys returned were completed by the owner or manager. Overall, 266 businesses of the 373 firms responded, for a response rate of 71.3%.[24]

Table A1 Summary of sample characteristics

Variable	Mean (standard error)
Age	43.74 (12.91)
Annual income ($)	48,150 (22,667)
Income missing (dummy variable)	0.20 (0.40)
Male	0.51 (0.50)
Education (years)	15.26 (2.88)
Married	0.72 (0.45)
Current smoker	0.23 (0.42)
N	266

Table A1 summarizes the sample characteristics. Respondents had an average of 15 years of schooling and an annual income of $44,000. Respondents were evenly divided between men and women.

NOTES

1. See Ellsberg (1961) for discussion of this phenomenon. Camerer and Weber (1992) provide a review of decision making under ambiguous uncertainty.
2. This illustration is based on an example given by Gärdenfors and Sahlin (1982).
3. See Camerer and Weber (1992) for a review.
4. The closest predecessor is Kahn and Sarin (1987), who consider reversals based on a mean risk interaction with a win/loss variable. The structure of their lotteries and their model is, however, substantially different.
5. Numerous studies report ambiguity-aversion: Becker and Brownson (1964), Slovic and Tversky (1974), Einhorn and Hogarth (1986), and Viscusi and Magat (1992) are examples.
6. Ambiguity aversion increased with probability only when one of the options included a nonambiguous choice. This experiment might explain why Larson (1980) did not find any interactive effects of range and mean probability, as Larson did not offer a nonambiguous choice.
7. This finding supports that of several others, such as Einhorn and Hogarth (1986).
8. Kahn and Sarin (1988), for example, examined risk-dollar tradeoffs.
9. Kahn and Sarin (1988) focused on market-related choices, such as the decision to purchase a warranty for a stereo. Such choices involve a choice between a small but certain loss and a larger, less certain loss.

10. See Becker and Brownson (1964), Yates and Zukowski (1976).

11. See Kahn and Sarin (1988), Einhorn and Hogarth (1986).

12. See Viscusi and Magat (1992).

13. See Hogarth and Einhorn (1990), Kahn and Sarin (1988). For the purposes of this paper, high probabilities are assumed to be above 0.5. This break point is arbitrary, of course, as a 0.5 risk per decade can be thought of, in simple terms, as approximately an 0.05 risk per year.

14. Some presentations included time lags before the two areas had risks that became different. The role of time lags had no significant effect on the equilibrating risk values, which is consistent with economic theory.

15. This assumption is not necessary in developing the model. One could achieve the same results by assuming instead that the loss to the storm can be captured entirely by the loss term L, and that $V(Y) = U(Y)$, for any given level of income.

16. This curve is based on the modal responses to the lotteries analyzed below, excluding subjects who expressed indifference. The study did not include extreme mean risks near values such as zero and 1. The curve drawn spans the entire range [0,1] even though such situations of certainty cannot involve ambiguity.

17. These risk pairs are grouped together due to the small size of the subsample. This grouping will be further examined later in the paper.

18. Again, this statistical significance depends on the grouping of the two lowest risk ranges into one low range category.

19. Two dummy variables, one for gender and one for marital status, also were included in the regressions but are not included in the table.

20. This sample excludes respondents who had incomplete answers to the personal characteristic questions. Table 5 includes all respondents in a fixed effects model, leading to 619 observations in all.

21. The equations reported in Table 6 include the same independent variables as Table 5, although only the results for the mean, range, and mean-range interaction are reported.

22. As with the pooled data, the null hypothesis that there is no range-mean interaction can be rejected at the 0.01 level.

23. Actually, the risk level of indifference could be equal to the initial risk level given for Area 2 without being inconsistent, as indifference was not allowed as an option in the initial choice between areas.

24. The initial response rate was almost 50%. The first follow-up raised the response rate to 60% and the second (final) follow-up brought the response rate above 70%. These three waves of responses were quite similar overall, suggesting that non-response bias was not a significant issue with this survey. Extensive details about the survey are available from the authors upon request.

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