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Second-Order Ambiguity in Very Low Probability Risks: Food Safety Valuation

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Food consumption involves inherently risky decisions with uncertain probabilities. This study examines how second-order ambiguity, or uncertainty over probabilities, affects food safety decisions. We conduct a food safety survey wherein subjects face both unambiguous and ambiguous situations, each with the same expected value. Respondents show a preference for unambiguous situations and state a willingness to pay to avoid ambiguity.

Key Words: ambiguity, ambiguity avoidance, expected utility theory, food safety, low probability events, risk, second-order probabilities, uncertainty

Introduction

Every time a person eats, there is a chance he or she may become ill as a result of food-borne pathogens such as *E. coli*, *Salmonella*, or *Trichinella*. By definition, eating requires making choices that involve risk. In the United States and other industrialized countries, an estimated one in four people annually suffer mild to severe symptoms from food-borne pathogens—1 in 1,000 are hospitalized, and 1 in 60,000 die—imposing a projected annual cost in the billions of dollars (Mead et al., 1999). Savage's (1954) subjective expected utility (SEU) model serves as a classic framework for understanding choices under risk given a range of possible outcomes with known probabilities, including how people value reductions in risk posed by food-borne disease (e.g., Hayes et al., 1995). Under this model, the subjective probabilities associated with decision-making outcomes are quantifiable, even while the outcomes of decisions are uncertain. The SEU model has also served as the framework for understanding how people value reductions in the risks posed by food-borne illness (e.g., Hayes et al., 1995).

Most health risks are ambiguous; food-borne illness is no exception. In theory, ambiguity arises when a person is uncertain of (*a*) the exact probabilities faced in a risky situation, and (*b*) the weight of evidence defining those probabilities (Camerer and Weber, 1992). This distinction can be traced as far back as Knight (1921), who characterized uncertainty as distinct from risk, because risk may be measurable but uncertainty is inherently unmeasurable. Few people are aware of the odds of becoming ill from food-borne pathogens. Most individuals have ill-formed and loosely defined beliefs about their chances of getting sick or dying from pathogens or other sources of health risk (Viscusi and Chesson, 1999).

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The "reduction of compound lotteries" (RCL) axiom assumes that a person is indifferent between any two lotteries with the same expected probabilities and payoffs. In the SEU model, a person's choices given unambiguous and ambiguous situations should therefore be the same. However, multiple studies have established that people will go out of their way to avoid ambiguous risks (e.g., Ellsburg, 1961; Hogarth and Kunreuther, 1989; Curley and Yates, 1989; Eisenberger and Weber, 1995). People would rather have the realized outcome of their choices depend on events defined by probabilities with which they are confident (Siniscalchi, 2008); i.e., they are ambiguity averse. Even if indifference is an option, people tend to prefer lotteries with known risk and will pay a price premium to avoid ambiguity (Camerer and Weber, 1992; Ahn et al., 2009). Ambiguity avoidance shows that uncertainty can bring individuals as much pain as the very risks they are uncertain about (Gilbert, 2009).

Many modern economic theories of decision making in the presence of ambiguity focus on "multiple probabilities."[1] The idea is that a person has a "second-order belief" about the risky event—a probability measure of probability measures (see Gilboa and Schmeidler, 1989; Siniscalchi, 2008). An individual considering a risky bet constructs a two-stage lottery defined by a likelihood of likelihoods. These models focus on preference rankings for second-order belief bets and reject the classic RCL assumption. We can model the decisions of a person who reacts to ambiguity using ambiguous and unambiguous lotteries with equivalent expected probabilities if we assume the person does not consider them equivalent (Klibanoff, Marinacci, and Mukerji, 2005). A person may reject RCL if, for example, collapsing a two-stage bet into a one-stage bet is computationally costly (see, e.g., Schelling, 1984; Segal and Spivak, 1990).

We use this theory of second-order beliefs to frame a person's choices and valuation given ambiguous food safety risks. Using the multiple probability definition of ambiguity, we define ambiguity as a range of possible probabilities with the median serving as the unambiguous case. We introduce ambiguity by offering conflicting expert estimates of risk incorporated using Bayesian updating; this is similar to the approach of Viscusi and Chesson (1999) on ambiguous risks of storm damages and Viscusi and Magat (1992) on ambiguous health risks. Other researchers have argued that ambiguity aversion cannot be fully captured by second-order beliefs and preferences regarding ambiguous bets. These researchers contend that ambiguity aversion should also reflect preferences over all other acts or noneconomic psychological factors such as avoiding negative feelings like regret, blame, or responsibility (e.g., Seo, 2009; Yates and Zukowski, 1976; Hogarth and Kunreuther, 1989; Heath and Tversky, 1991; Winkler 1991; Dow and Werlang, 1992; Sarin and Winkler, 1992). However, if ambiguity-averse people predominantly behave as though second-order beliefs are dominant, then this approach remains a useful model, and studying ambiguity with probabilities still can be a powerful tool. As Hogarth (1987) notes, "Uncertainty is best communicated through the medium of probability theory … [because] the quantitative form is precise and readily interpretable" (p. 191).

We consider how ambiguity affects food safety valuation by examining whether or not second-order belief ambiguity matters in two contexts. First, we evaluate choices and valuations over a range of very low probability events, reflecting the typical risks to one's health

[1] In an early effort, Becker and Brownson (1964) introduce ambiguity through the length of the range between the highest and lowest possible probabilities. Ellsberg (1961) characterizes risk using different colored balls in an urn to reflect different possible outcomes. Extending this idea, Hey (1997) notes that the most obvious way to operationalize uncertain probabilities would be a randomizing device that pre-selects the color of balls placed in such an urn. It is then natural to consider an urn a second-order probability distribution.

and safety (e.g., 1 in 100,000 to 1 in 10 million). Second, we examine choices and valuations framed as a health lottery—in our case, ambiguous probabilities of becoming ill from food-borne pathogens. We elicit choices and valuations for two scenarios: food safety at a restaurant based on the probabilities calculated in Hayes et al. (1995), and (following Ellsberg, 1961) monetary urns, which act as a comparative benchmark. Urns are a basic randomizing scheme. Think of a winning lottery ball picked from a tumbling urn containing a large number of balls. We ask respondents to choose and value very low ambiguous probabilities of loss typical of health and environmental contexts (e.g., van Ravenswaay and Wohl, 1995) (see the appendix for our survey). Our main finding is that ambiguity is a significant factor when making food safety choices. However, a scoping effect exists; i.e., people are insensitive to the probability of illness. Most people avoid ambiguous food safety scenarios. Avoidance behavior was similar for low (1 in 10) and very low (1 in 10 million) probabilities of loss. In addition, while the average person would pay more to avoid ambiguous risks, a bimodal response pattern emerged—people bid either \$0 or more than the expected loss. This pattern of willingness to pay (WTP) varied little, and the ambiguity premium varied modestly as the probability of the risky event varied.

Analytical Framework and Hypotheses

Analytical Framework

Following Viscusi and Chesson (1999), we employ a state-dependent Bayesian framework to capture the decisions made by a person faced with ambiguous food safety risks. We assume each individual knows his or her subjective prior beliefs (r_0) about probabilities of food safety risks and that each person receives two expert opinions (r_x and r_y) about the probability of contracting a food-borne illness. In the unambiguous case, the expert opinions are in agreement at the benchmark probability, $\bar{r}$ ($r_x = r_y = \bar{r}$); in the ambiguous case, the expert opinions are equal percentages above and below the benchmark probability (ε, $r_x = \bar{r} - \varepsilon$ and $r_y = \bar{r} + \varepsilon$, where $\varepsilon = 0.5\bar{r}$). Given no information about prior beliefs regarding each expert's reliability, we assume equal weighting of expert information to establish an average probability as a benchmark, $\bar{r}$ ($\bar{r} = 0.5r_x + 0.5r_y$). Specifically, the ambiguous lottery is a mean-preserving spread of the unambiguous case. Given this information, each person estimates a subjective probability of contracting a food-borne illness in the unambiguous case (p^u) and in the ambiguous case (p^a).

The state-dependent expected utility (EU) for unambiguous probabilities is written as:

$$EU^u = p^u(r_0, \bar{r})V(Y-L) + \left(1 - p^u(r_0, \bar{r})\right)U(Y), \tag{1}$$

and the state-dependent EU for ambiguous probabilities is denoted by:

$$EU^a = p^a(r_0, \bar{r}, \bar{r} + \varepsilon\bar{r}, \bar{r} - \varepsilon\bar{r})V(Y-L) + \left(1 - p^a(r_0, \bar{r}, \bar{r} + \varepsilon\bar{r}, \bar{r} - \varepsilon\bar{r})\right)U(Y), \tag{2}$$

where $\varepsilon = 0.5\bar{r}$, Y represents income, and L represents monetary losses associated with contracting a food-borne illness, which we treat as exogenous. Since food-borne illnesses create both morbidity and mortality risks, U is the utility in the state without food-borne illness and V is the utility with food-borne illness, such that $U(Y) > V(Y)$ for all Y. Equation (2) allows for ambiguity avoidance from many sources, including processing costs. People who find the range of odds challenging will express a preference for the unambiguous scenario; i.e., they will put greater emphasis on the ambiguous threat by heavily weighting the high end of the odds range.

To determine a person's ex ante WTP for complete removal of the risk of food-borne illness ($p^u = 0$ and $p^a = 0$), we estimate that

$$(3) \qquad U(Y - WTP^u) = EU^u = p^u(r_0, \bar{r})V(Y - L) + \left(1 - p^u(r_0, \bar{r})\right)U(Y)$$

in the unambiguous case and

$$(4) \qquad U(Y - WTP^a) = EU^a = p^a(r_0, \bar{r}, \bar{r} + \varepsilon\bar{r}, \bar{r} - \varepsilon\bar{r})V(Y - L) + \left(1 - p^a(r_0, \bar{r}, \bar{r} + \varepsilon\bar{r}, \bar{r} - \varepsilon\bar{r})\right)U(Y)$$

in the ambiguous case. If we normalize utility [$V(Y - L) = 0$ and $U(Y) = 1$], then equation (3) can be rewritten as $U(Y - WTP^u) = 1 - p^u(r_0, \bar{r})$ and equation (4) as $U(Y - WTP^a) = 1 - p^a(r_0, \bar{r}, \bar{r} + \varepsilon\bar{r}, \bar{r} - \varepsilon\bar{r})$.

Each person assigns a weight to each available probability estimate. In the unambiguous case, α_0^u represents the weight assigned to subjective prior beliefs r_0, and $\beta^u = (1 - \alpha_0^u)$ represents the weight assigned to the benchmark expert opinion $\bar{r}$, assuming $0 \le \alpha_0^u, \beta^u \le 1$. In the ambiguous case, α_0^a represents the weight on prior beliefs, α_x^a and α_y^a represent the weight assigned to each expert's opinion (r_x and r_y), and β^a ($= 1 - \alpha_x - \alpha_y - \alpha_0$) represents the weight given to the benchmark probability $\bar{r}$. Again, we assume $0 \le \alpha_0^a, \alpha_x^a, \alpha_y^a, \beta^a \le 1$. By combining and rearranging terms, the estimated probability of illness for the unambiguous case is $p^u = \bar{r} + \alpha_0^u(r_0 - \bar{r})$ and for the ambiguous case is $p^a = \bar{r} + \alpha_0^a(r_0 - \bar{r}) + (\alpha_x^a - \alpha_y^a)\varepsilon\bar{r}$.

Willingness-to-pay in the ambiguous (WTP^a) and the unambiguous case (WTP^u) can differ for two reasons. First, they can differ if an individual weights his or her prior beliefs differently in the presence of ambiguity; i.e., $\alpha_0^u \ne \alpha_0^a$. However, no evidence exists that causes us to expect the weight on prior beliefs will differ, since this information is independent of the option presented. We therefore assume $\alpha_0^u = \alpha_0^a$. Second, and more likely, WTP differences can arise from different weights being placed on expert opinions; i.e., $\alpha_x^a \ne \alpha_y^a$. Assuming equally weighted prior beliefs, we can solve $p^u = p^a - (\alpha_x^a - \alpha_y^a)\varepsilon\bar{r}$ and rewrite WTP^u as $U(Y - WTP^u) = 1 - p^a(r_0, \bar{r}, \bar{r} + \varepsilon\bar{r}, \bar{r} - \varepsilon\bar{r}) + (\alpha_x^a - \alpha_y^a)\varepsilon\bar{r}$. This allows us to directly compare the two measures of ex ante WTP, such that the difference in utility is based on the differences in weights assigned to the experts, $\{U(Y - WTP^u) - U(Y - WTP^a)\} = (\alpha_x^a - \alpha_y^a)\varepsilon\bar{r}$.

If an individual faced with an ambiguous probability weights each expert equally $[(\alpha_y^a - \alpha_x^a)\varepsilon = 0]$, then the probability of illness is identical in both the ambiguous and unambiguous cases ($p^a = p^u$), and his or her WTP will be identical in each case ($WTP^a = WTP^u$). In this case, an ambiguity premium, which we define as the difference between the WTP in each case, does not exist: $AP = [WTP^a - WTP^u] = 0$. This implies a person pays more to reduce an ambiguous probability if and only if he or she assigns more weight to the negative information ($\alpha_y^a > \alpha_x^a > 0$), which leads to $p^a > p^u$, and thus $WTP^a > WTP^u$. In general, the literature offers support for the notion that people weigh negative information more heavily than positive (see Verbeke, Ward, and Viaene, 2000; Fox, Hayes, and Shogren, 2002).

A change in benchmark probability $(\bar{r})$ affects WTP for unambiguous probability as

$$(5) \qquad \frac{dWTP^u}{d\bar{r}} = \frac{(1 - \alpha_0^u)[U(Y) - V(Y - L)]}{U'} > 0 \quad \text{and} \quad \frac{d^2WTP^u}{d\bar{r}^2} = 0.$$

If the person attaches some weight to $\bar{r}$ ($\alpha_0^u < 1$), the first derivative is positive, since $U(Y) - V(Y - L) > 0$, $(1-\alpha_0^u) > 0$, and the marginal utility of wealth (U') is greater than zero. As $\bar{r}$ does not appear in the first derivative, the second derivative is zero. Specifically, we find WTP rises at a constant rate as the benchmark probability rises. Similarly, for ambiguous probability,

$$\text{(6)} \qquad \frac{dWTP^a}{d\bar{r}} = \frac{(1-\alpha_0^a)[U(Y)-V(Y-L)]}{U'} > 0 \quad \text{and} \quad \frac{d^2WTP^a}{d\bar{r}^2} = 0.$$

Equation (6) is positive if the person attaches some weight to $\bar{r}$ $[(\alpha_0^a + \alpha_0^x + \alpha_0^y) < 1]$. If

$$\frac{dWTP^j}{d\bar{r}} > 0 \quad \text{and} \quad \frac{d^2WTP^j}{d\bar{r}^2} < 0 \quad \text{for } j = \text{unambiguous, ambiguous,}$$

then WTP increases proportionally with probability level. This is the basis for the risk valuation hypothesis.

If modeling ambiguity through second-order uncertainty can generate results consistent with the literature on ambiguity avoidance, then second-order risk aversion may be a large part of people's reactions to ambiguity. As a first check of this new model, we designed a simple test using hypothetical questions.[2]

Hypotheses

We test for ambiguity avoidance in two ways. First, we consider three choice hypotheses. Given an unambiguous and ambiguous choice and holding expected values constant, the null hypothesis for urn choice and food safety choice says there is no difference between the number of unambiguous and ambiguous choices. The alternative hypothesis states that the unambiguous choice will be more frequent: H_o: $C_i^u = C_i^a$; H_a: $C_i^u > C_i^a$, for i = urn and food safety, where $C^{a,u}$ is the number of ambiguous choices (a) or unambiguous choices (u) made. The risk choice hypothesis tests whether the percentage of unambiguous choices ($\%C^u$) is independent of the probability level (using t-tests): H_o: $\%C^{u1} = \%C^{u2} = \%C^{un}$, for all probability levels 1 to n; H_a: $\%C^{um} \neq \%C^{un}$, for one or more probability level pairs. Table 1 summarizes our hypotheses. Table 2 shows the $n = 7$ probability levels differing by an order of magnitude, ranging from 1/10 to 1/10 million.

Second, we consider three valuation hypotheses. The urn valuation and food safety valuation hypotheses test whether people will pay more to avoid an ambiguous lottery than an unambiguous one with equal expected value. We test these using an ambiguity premium (H_o: $AP_i = 0$; H_a: $AP_i > 0$ for i = urn, food safety). We expect to reject the null hypothesis, consistent with previous results (e.g., Camerer and Weber, 1992). The risk valuation hypothesis tests whether WTP and AP increase directly with risk level (the null risk valuation-WTP hypothesis is written as: $WTP^{a1} = WTP^{a2} = WTP^{an}$) for all risk levels (1 to n). The alternative risk valuation-WTP hypothesis is expressed as: $WTP^{am} > WTP^{an}$, where $m > n$ by

[2] Hypothetical bias is real and important. We compare scenarios across different risks and ambiguity, holding hypothetical imposition constant. The real question is whether the difference across risks and ambiguity would be different under more real-world circumstances, but this question is beyond the scope of our paper. Responses to hypothetical data can be useful: Balisteri et al. (2001) find that while answers obtained from hypothetical dichotomous choice questions significantly exceed actual contributions, responses to hypothetical open-ended questions do not significantly differ from real-world responses.

Table 1. Summary of Hypotheses

Hypothesis	Null	Alternative
Urn Choice	H_o: $C^u = C^a$	H_a: $C^u > C^a$
Food Safety Choice	H_o: $C^u = C^a$	H_a: $C^u > C^a$
Risk Choice	H_o: $\%C^{u1} = \%C^{u2} = \%P^{un}$ for all probabilities 1 to *n*	H_a: $\%C^{um} \neq \%C^{un}$ for one or more probability pairs
Urn Valuation	H_o: $AP = 0$	H_a: $AP > 0$
Food Safety Valuation	H_o: $AP = 0$	H_a: $AP > 0$
Risk Valuation-WTP	H_o: $WTP^{a1} = WTP^{a2} = WTP^{an}$ for all probabilities 1 to *n*	H_a: $WTP^{am} > WTP^{an}$ where $m > n$ by an order of magnitude
Risk Valuation-AP	H_o: $AP^{a1} = AP^{a2} = AP^{an}$ for all probabilities 1 to *n*	H_a: $AP^{am} > AP^{an}$ where $m > n$ by an order of magnitude

Notes: Superscript *u* denotes unambiguous case, superscript *a* denotes ambiguous case, *C* represents the number of choices, *WTP* is willingness to pay to avoid a given risk, *AP* represents the ambiguity premium (WTP to avoid ambiguous risk minus WTP to avoid unambiguous risk), and *m* and *n* are risk levels where $m > n$ by an order of magnitude.

Table 2. Ambiguous Food Safety Probabilities

Average Probability if Each Expert Opinion Is Equally Likely	Downside Probability	Upside Probability
1 / 10	1 / 6.7	1 / 20
1 / 100	1 / 67	1 / 200
1 / 1,000	1 / 667	1 / 2,000
1 / 10,000	1 / 6,667	1 / 20,000
1 / 100,000	1 / 66,667	1 / 200,000
1 / 1,000,000	1 / 666,667	1 / 2,000,000
1 / 10,000,000	1 / 6,666,667	1 / 20,000,000

an order of magnitude; the null risk valuation-AP hypothesis is stated as: $AP^{a1} = AP^{a2} = AP^{an}$, for all risk levels 1 to *n*; and the alternative risk valuation-AP hypothesis is given by: $AP^{am} > AP^{an}$, where $m > n$ by an order of magnitude.

Survey Design

Choices and valuations were elicited for two scenarios: monetary urns and restaurant food safety. Given that we wanted to test a broad range of odds, we constructed seven scenarios for both urns and food safety by varying the odds by orders of magnitude from 1 in 10 to 1 in 10 million (see table 2)—several orders of magnitude above and below more typical odds. Following standard experimental procedures, we distributed the surveys to 465 students enrolled at the University of Wyoming. The survey took less than a half hour to complete.[3]

[3] The survey instrument is shown in the appendix (the complete set of survey data is available from the authors on request).

Table 3. Choice Data: Urns by Raw Frequency and by Percentage of Total Responses

Description	0.1	0.01	0.001	0.0001	0.00001	1 / 1M	1 / 10M	Sum
Unambiguous (*U*)	37 56.8%	34 54.8%	42 63.6%	39 59.1%	43 66.2%	37 56.1%	43 66.2%	275 60.3%
Ambiguous (*A*)	6 9.1%	11 17.7%	6 9.1%	11 16.7%	8 12.3%	10 15.2%	8 12.3%	60 13.2%
Indifferent (*I*)	23 34.8%	17 27.4%	18 29.8%	16 24.2%	14 21.5%	19 28.8%	14 21.5%	121 26.5%
Weak test *t*-statistic	6.82***	3.99***	7.86***	4.78***	6.74***	4.27***	6.74***	15.32***
Strict test *t*-statistic	0.992	0.766	2.30**	1.50	2.75***	0.992	2.75***	4.50***

Note: Single, double, and triple asterisks (*,**,***) denote statistical significance at the 10%, 5%, and 1% levels, respectively.

We used open-ended responses for two reasons. First, open-ended responses match up with earlier work conducted on food safety (e.g., Ready, Buzby, and Hu, 1996; Hayes et al., 1995) and ambiguity (e.g., Eisenberger and Weber, 1995; Fox and Tversky, 1995). Second, Ready, Buzby, and Hu (1996) find that open-ended WTP questions for food safety perform better than dichotomous choice questions, since respondents in the latter group consistently agree with values greater than their actual WTP. Further, as noted by Whitehead (2003), a strength of open-ended answers is that they yield a precise point estimate.

We adopted Hayes et al.'s (1995) description of mild and severe forms of food-borne *Salmonella* in our food safety scenario. This helped guarantee continuity in valuation exercises and provided information about potential consequences of exposure to the pathogen. Following Viscusi and Chesson (1999), we presented ambiguity in food safety risks as "conflicting expert estimates" (p. 158). Food safety inspectors, each of whom is presumed to be an expert, provided differing opinions on the likelihood of contracting a food-borne illness when dining at a particular restaurant. To reduce decision costs, we provided the mean odds of contraction if each expert opinion is equally believed. According to Mead et al. (1999), 76 million cases of food-borne illness occur annually as a result of 30 billion total U.S. meals. Thus, the actual chance of contracting a food-borne illness is approximately 1 in 400 meals.

Results and Discussion

Urns

Due to a small number of responses for each mean risk, we follow Viscusi and Chesson (1999) by pooling our responses for all mean risk levels. Both a weak and a strict test are considered. If we consider only people who express a distinct preference for either the ambiguous or unambiguous probability (weak test), we reject the null of the urn choice hypothesis for all probabilities (table 3) using one-tailed *t*-tests utilizing OLS (for a binomial distribution) at the 1% level. However, if we consider all subjects—including those who were indifferent to ambiguous and unambiguous probabilities—in a strict test, the results are less definitive. The null is rejected for four of seven urn pairs at the 5% level. At 0.1%, 60.3% of people are averse to ambiguity for urns, 26.5% are indifferent, and 13.2% prefer ambiguity.

The percentage of subjects choosing the unambiguous probabilities did not appear to depend on the probability level. We cannot reject the null of the risk choice hypothesis, which examines whether WTP differs at different probabilities, for any pair of probabilities for urns (see table 4).

Table 4. Likelihood of Choosing the Unambiguous Lottery (95% confidence intervals)

Description	1/10	1/100	1/1K	1/10K	1/100K	1/1M	1/10M	Avg. Across Probabilities
Urns:								
Mean	0.861	0.756	0.875	0.780	0.843	0.787	0.843	0.821
C.I. Lower Bound	0.754	0.625	0.779	0.662	0.741	0.667	0.741	0.710
C.I. Upper Bound	0.967	0.886	0.971	0.898	0.945	0.907	0.945	0.931
Food Safety:								
Mean	0.758	0.745	0.900	0.708	0.714	0.745	0.702	0.753
C.I. Lower Bound	0.606	0.627	0.804	0.576	0.559	0.623	0.568	0.626
C.I. Upper Bound	0.909	0.863	0.996	0.840	0.869	0.868	0.836	0.883

Similar to Segal and Spivak (1990), we test for ambiguity aversion using ambiguity premiums.[4] We test to see if people would pay more to avoid ambiguous risks in two complementary ways. Following Viscusi and Chesson (1999), we pool data for all seven mean risk levels since we also test losses over a large number of probabilities. *T*-tests to determine if ambiguity premiums were different from zero were significant at the 1% level for urns when all responses were pooled together (table 5). AP was significantly positive at 1/10 odds (1%), 1/1,000 (5%), 1/100,000 (5%), 1/1,000,000 (10%), and 1/10,000,000 (5%).[5]

We also test for ambiguity aversion employing a tobit regression of WTP using dummy variables to control for the probabilities [*TEN* (1/10), *HUND* (1/100), *THOU* (1/1,000), *TENTHOU* (1/10K), *HUNDTHOU* (1/100K), *MIL* (1/1M)], using 1/10M as the base, and ambiguity (*AMBIG*), assuming homogeneity of parameters across probabilities (Baltagi, Griffin, and Xiong, 2000). *AMBIG* is significant at the 1% level for urns (table 6). We reject the null of the urn valuation hypothesis; on average, people paid more to avoid ambiguous scenarios, compared to unambiguous ones with the same expected value.

Table 6 also provides evidence for the risk valuation hypothesis, which examines whether WTP differs at different probabilities. As reported by Hayes et al. (1995), WTP responses changed little for food-borne illnesses, in that WTP decreased by much less than the probabilities (p. 854). Our findings are consistent with their results. Responses were relatively insensitive to probability level, which ranged from very low (1/10 million) to high (1/10). WTP was significantly different compared to the 1 in 10 million scenario only for the 1 in 10 scenario in urns (5% level). We find evidence of a bimodal response pattern: some people paid zero to avoid risks while others paid more than the expected loss. McClelland, Schulze, and Coursey (1993) observed a bimodal distribution of valuation responses for insurance when the probability was 1/100, with a large number of zero responses, and a spike at a value

[4] We also conducted *t*-tests to see if the unambiguous WTP was different than the ambiguous WTP (results are available from the authors upon request). The mean WTP in the ambiguous case was significantly higher (at the 1% level) than the unambiguous mean WTP for six of the seven odds for urns, yet only significant for 1 in 10 million odds in food safety (and only at the 10% level).

[5] We ran these regressions excluding 97 outliers out of 1,798 possible (5.4% of responses) for several reasons. Data that were inconsistent with "obvious logic" were not used (bidding more than \$100 to prevent an uncertain loss of \$100, 11 of 465 responses for the ambiguous urn case, and 9 of 461 responses for the unambiguous case). Also, bids of \$9,000 and greater in the food safety survey weren't used since (*a*) these came primarily from the 1/1 million and 1/10 million cases, whereas the maximum bid for more likely odds was \$2,000 (seven in each case), and (*b*) these answers raised doubts about whether respondents considered their ability to pay in giving their responses. Including these responses increased the range of the mean data by several orders of magnitude. Refusals to play, non-numerical responses, and undefined comparisons were also not used. (Results with outliers are available from the authors upon request.)

Table 5. Ambiguity Premiums by Probability: Urns, with *t*-Test Results

Urns	1 / 10	1 / 100	1 / 1K	1 / 10K	1 / 100K	1 / 1M	1 / 10M	All
Ambiguity Premium – Mean	$14.31***	$2.05	$7.60**	−$5.37	$10.96**	$4.08*	$28.27**	$8.80***
Standard Error	33.11	28.86	35.50	116.23	39.377	25.264	113.97	68.78
Z-Value	3.958	0.561	1.700	−0.3808	2.192	1.281	1.984	2.711
Sample Size	*N* = 68	*N* = 62	*N* = 63	*N* = 68	*N* = 62	*N* = 63	*N* = 64	*N* = 449

Note: Single, double, and triple asterisks (*,**,***) denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 6. Tobit Results: Determinants of Willingness to Pay

		Coefficient Estimates	
Explanatory Variable	Definition	Urns (*N* = 913)	Food Safety (*N* = 819)
Constant	Constant term	−15.153*** (4.91)	−63.635*** (19.98)
AMBIG	= 1 if ambiguous	15.019*** (3.27)	29.864** (13.10)
TEN	= 1 if odds are 1 / 10	13.571** (6.02)	98.264*** (26.18)
HUND	= 1 if odds are 1 / 100	7.226 (6.17)	38.981 (24.36)
THOU	= 1 if odds are 1 / 1,000	6.711 (6.24)	−12.313 (24.86)
TENTHOU	= 1 if odds are 1 / 10,000	8.414 (6.14)	44.331* (24.85)
HUNDTHOU	= 1 if odds are 1 / 100,000	2.576 (6.18)	61.333** (25.98)
MIL	= 1 if odds are 1 / 1,000,000	−8.536 (6.35)	−20.818 (25.794)

Note: Single, double, and triple asterisks (*,**,***) denote statistical significance at the 10%, 5%, and 1% levels, respectively.

exceeding the expected value of the loss; many people either overrespond to low probability losses or disregard them altogether. Our results also reveal a bimodal pattern. For urns, a bimodal pattern emerges for average probabilities from 1/10 down to 1/1,000, with spikes at $0 and $10. For 1/10,000 and 1/100,000 probabilities, the bimodal pattern shifts to spikes at $0 and $1. For 1 in 1 million odds, the number of zeros dwarfs all other responses. At 1 in 10 million average probability, however, the bimodal pattern with spikes at $0 and $10 reemerges. In every case, a cluster of responses emerges lower than the expected loss, and in all but the 1/10 case, a cluster emerges that is greater than the expected loss.

To test the risk valuation hypothesis for the ambiguity premium, we regress (using tobit) AP against probabilities (see table 7).[6] Compared to responses in the 1 in 10 million odds scenario, we find evidence that respondents facing more likely scenarios provide different

[6] Since some respondents answered a second question for a particular type of lottery (75 people answered urn questions for two different levels of odds, and 60 people responded to questions on two different food safety pages), we introduce the dummy variable *SECOND* to see if the responses from a second sheet someone answered differ from the responses given by others. We determined that *SECOND* was not significant.

Table 7. Tobit Results: Determinants of Ambiguity Premium

		Coefficient Estimates	
Explanatory Variable	Definition	Urns ($N = 450$)	Food Safety ($N = 395$)
Constant	Constant term	28.272***	39.519**
		(8.572)	(15.883)
TEN	= 1 if odds are 1 / 10	−16.159	−28.219
		(13.313)	(26.534)
HUND	= 1 if odds are 1 / 100	−29.451**	−45.555**
		(14.982)	(23.021)
THOU	= 1 if odds are 1 / 1,000	−20.669*	−32.942
		(12.171)	(22.072)
TENTHOU	= 1 if odds are 1 / 10,000	−33.644***	−27.343
		(11.944)	(21.809)
HUNDTHOU	= 1 if odds are 1 / 100,000	−17.308	−12.244
		(12.221)	(23.284)
MIL	= 1 if odds are 1 / 1,000,000	−24.194**	−31.600
		(12.171)	(21.894)
SECOND	= 1 if second time asked	4.667	20.922
		(12.496)	(22.149)

Note: Single, double, and triple asterisks (*,**,***) denote statistical significance at the 10%, 5%, and 1% levels, respectively.

responses. In four of the six odds for urns, the ambiguity premium is significantly larger than the AP for the 1 in 10 million scenario.

Food Safety

If we consider only distinct preferences for either the ambiguous or unambiguous probability (weak test), we reject the null of the *food safety choice hypothesis* for all probabilities (table 8). In contrast, for the strict test, the null is rejected for just one of seven food safety pairs at the 10% level. People who stated a distinct preference clearly preferred the unambiguous probability. We cannot infer that all people prefer the unambiguous option, but we can infer that the unambiguous choice is preferred by those expressing a choice. The behavior observed here is comparable to findings reported by Einhorn and Hogarth (1986) for hypothetical insurance purchases. Their subjects revealed 75% ambiguity aversion, 20% indifference, and 5% ambiguity preference for a 0.1% probability of harm. In comparison, our results show 53.0% ambiguity-aversion for food safety at 0.1%, 28.6% indifference, and 18.4% ambiguity preference. In addition, while other studies found ambiguity aversion for probabilities between 1% and 50%, we found no such threshold—ambiguity aversion is similar over the entire range of probabilities. Between 19% and 29% of our subjects were indifferent to ambiguous and unambiguous lotteries at very low probabilities (1/100K to 1/10M).

T-tests to determine if ambiguity premiums were different from zero were significant at the 1% level for food safety when all responses were pooled together (table 9). AP was significantly positive at the 1% level for 1/1,000 odds, at the 5% level for 1/10,000 and 1/1,000,000 odds, and 10% for 1/100,000 and 1/10,000,000 odds.

Returning to table 6, we cannot reject the null of the risk choice hypothesis, which examines whether WTP differs at different probabilities, for any pair of probabilities for food

Table 8. Choice Data: Food Safety by Raw Frequency and by Percentage of Total Responses

Description	0.1	0.01	0.001	0.0001	0.00001	1 / 1M	1 / 10M	Sum
Unambiguous (*U*)	25 51.0%	41 56.2%	36 56.3%	34 51.5%	25 51.0%	38 60.3%	33 50.8%	222 53.0%
Ambiguous (*A*)	8 16.3%	14 19.2%	4 6.3%	14 21.2%	10 20.4%	13 20.6%	14 21.5%	77 18.4%
Indifferent (*I*)	16 32.7%	18 24.7%	24 37.5%	18 27.3%	14 28.6%	12 19.0%	18 27.7%	120 28.6%
Weak test *t*-statistic	3.45***	4.18***	8.43***	3.18***	2.81***	4.02***	3.03***	9.59***
Strict test *t*-statistic	0.143	1.060	1.010	0.246	0.143	1.670*	0.124	1.220

Note: Single, double, and triple asterisks (*,**,***) denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 9. Ambiguity Premiums by Probability: Food Safety, with *t*-Test Results

Food Safety	1 / 10	1 / 100	1 / 1K	1 / 10K	1 / 100K	1 / 1M	1 / 10M	All
Ambiguity Premium – Mean	$23.32	$2.24	$6.58***	$12.18**	$27.27*	$7.92**	$38.44*	$15.86***
Standard Error	144.22	134.54	15.09	55.43	131.63	36.30	189.12	16.48
Z-Value	1.1085	0.138	3.320	1.716	1.420	1.690	1.507	2.706
Sample Size	*N* = 47	*N* = 68	*N* = 58	*N* = 61	*N* = 47	*N* = 60	*N* = 55	*N* = 395

Note: Single, double, and triple asterisks (*,**,***) denote statistical significance at the 10%, 5%, and 1% levels, respectively.

safety. In contrast, Viscusi and Chesson (1999) found the degree of ambiguity aversion increases as the probability decreases from 95% to 5%. We find no evidence that ambiguity aversion differs over our range, 0.1 to 0.0000001, suggesting ambiguity aversion is ubiquitous and fairly constant for losses with very low probabilities.

We reject the null of the food safety valuation hypothesis. On average, people paid more to avoid the ambiguous scenarios, compared to unambiguous ones with the same expected value. *AMBIG* is significant at the 5% level for food safety (table 6). WTP is significantly different compared to the 1 in 10 million scenario for the 1 in 10 (1% level), 1 in 10,000 (10% level), and 1 in 100,000 (5% level) scenarios in food safety. For food safety, a bimodal pattern with spikes at $0 and $10 emerges for all scenarios, except the 1 in 10 average odds. In that case, people respond with a variety of nonzero responses, consistent with findings reported by McClelland, Schulze, and Coursey (1993) for probabilities of 1/5 or greater. Our responses corroborate previous results that show some people overvalue low probability losses (Smith and Desvousges, 1987), while others value such losses at essentially zero (Kunreuther et al., 1978). Our results support the bimodal response to very low probability risks. Insensitivity to scope for WTP exists in ambiguous/very low probability situations, which may indicate inconsistency with a rational choice model. However, the large number of $0 responses may also suggest there exists a threshold below which risks are viewed as not worth worrying about, consistent with the sort of very low probability risks commonplace in everyday life, such as the risk of driving to work. These $0 responses may represent a type of bounded rationality, if the expected marginal utility changes involved in moving from, say, a risk of 1 in 10,000,000 to a 1 in 1,000,000 risk, are not large enough to warrant the cognitive costs of estimating them.

Compared to responses in the 1 in 10 million odds scenario, we find weak evidence that respondents facing more likely scenarios provide different responses. Only in the 1 in 100 scenario does the AP differ for food safety, with 5% significance (table 7). This may be due to the larger standard errors in the food safety case; however, this result may also indicate that ambiguity is less important with respect to health (Goldberg, Roosen, and Nayga, 2006).

Conclusions

We find that people prefer unambiguous food safety choices over ambiguous ones with the same expected value, consistent with previous studies. Hogarth and Kunreuther (1989), for instance, found consumers' pricing decisions for insurance were sensitive to ambiguity. Ambiguity premiums—how much more people are willing to pay to avoid an ambiguous situation than an equivalent unambiguous one—are positive for both food safety and urn scenarios, indicating people are, on average, ambiguity averse for these very low probability risks. Our results also suggest that expenditures to improve people's knowledge of food-borne risks could be worth undertaking even if no corresponding decrease in the level of illnesses contracted occurs. Private and public information policies designed to reduce ambiguity can increase the utility of ambiguity-averse people. An interesting extension of this study would be a comparison of second-order uncertainty to extreme ambiguity (ignorance of probabilities) in order to determine how much more ambiguity aversion (if any) people would exhibit.

We note three caveats to consider following this study. First, it is likely that subjects' prior perceptions of risk affected the food safety results more than the urn results, especially if they could not separate food-borne illness from other common ailments (e.g., the flu). These heterogeneous and unobserved prior beliefs likely explain some variation in risk valuation. Second, our subject pool used students, who might have less risk-averse behavior than, say, middle-aged adults with young children. Further research expanding an ambiguity survey to a more representative population would be worthwhile. Third, we use an open-ended valuation question, the pros and cons of which have been debated in the valuation literature (e.g., incentive incompatibility, zero values), and we have eliminated several responses appearing to be outliers. Future experiments involving real money should be used to replicate these results while addressing these caveats.

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References

Ahn, D., S. Choi, D. Gale, and S. Kariv. "Estimating Ambiguity Aversion in a Portfolio Choice Experiment." Dept. of Agr. and Resour. Econ., University of California, Berkeley, 2009.

Balisteri, E., G. McClelland, G. Poe, and W. Schulze. "Can Hypothetical Questions Reveal True Values? A Laboratory Comparison of Dichotomous Choice and Open-Ended Contingent Values with Auction Values." *Environ. and Resour. Econ.* 18(2001):275–292.

Baltagi, B., J. Griffin, and W. Xiong. "To Pool or Not to Pool: Homogeneous versus Heterogeneous Estimators Applied to Cigarette Demand." *Rev. Econ. and Statis.* 82(2000):117–126.

Becker, S., and F. Brownson. "What Price Ambiguity? On the Role of Ambiguity in Decision-making." *J. Polit. Econ.* 72(1964):65–73.

Camerer, C., and M. Weber. "Recent Developments in Modeling Preferences: Uncertainty and Ambiguity." *J. Risk and Uncert.* 5(1992):325–370.

Curley, S. P., and J. F. Yates. “An Empirical Evaluation of Descriptive Models of Ambiguity Reactions in Choice Situations.” *J. Math. Psych.* 33(1989):397–427.

Dow, J., and S. Werlang. “Uncertainty Aversion, Risk Aversion, and the Optimal Choice of Portfolio.” *Econometrica* 60(1992):197–204.

Einhorn, H., and R. Hogarth. “Decision Making Under Ambiguity.” *J. Business* 59(1986):s225–s250.

Eisenberger, R., and M. Weber. “Willingness-to-Pay and Willingness-to-Accept for Risky and Ambiguous Lotteries.” *J. Risk and Uncert.* 10(1995):223–233.

Ellsberg, D. “Risk, Ambiguity, and the Savage Axioms.” *Quart. J. Econ.* 75(1961):643–669.

Fox, C., and A. Tversky. “Ambiguity Aversion and Comparative Ignorance.” *Quart. J. Econ.* 99(1995):585–603.

Fox, J., D. Hayes, and J. Shogren. “Consumer Preferences for Food Irradiation: How Favorable and Unfavorable Descriptions Affect Preferences for Irradiated Pork in Experimental Auctions.” *J. Risk and Uncert.* 24(2002):75–95.

Gilbert, D. “What You Don’t Know Makes You Nervous.” *The New York Times* (21 May 2009).

Gilboa, I., and D. Schmeidler. “Maxmin Expected Utility with Non-unique Prior.” *J. Math. Econ.* 18(1989):141–153.

Goldberg, I., J. Roosen, and R. M. Nayga, Jr. “Parental Response to Health Risk Information: A Lab Experiment on Evaluating Willingness-to-Pay for Safer Infant Milk Formula.” Paper No. 25672, presented at annual meeting of International Association of Agricultural Economists, Queensland, Australia, 2006. Online. Available at http://purl.umn.edu/25672.

Hayes, D., J. Shogren, S. Shin, and J. Kliebenstein. “Valuing Food Safety in Experimental Auction Markets.” *Amer. J. Agr. Econ.* 77(1995):847–858.

Heath, C., and A. Tversky. “Preference and Belief: Ambiguity and Competence in Choice Under Uncertainty.” *J. Risk and Uncert.* 4(1991):5–28.

Hey, J. “Experiments and the Economics of Individual Decision Making Under Risk and Uncertainty.” In *Advances in Economics and Econometrics: Theory and Applications*, eds., D. Kreps and K. Wallis. Cambridge, UK: Cambridge University Press, 1997.

Hogarth, R. *Judgement and Choice*, 2nd edition. New York: John Wiley and Sons, 1987.

Hogarth, R., and H. Kunreuther. “Risk, Ambiguity, and Insurance.” *J. Risk and Uncert.* 2(1989):5–35.

Klibanoff, P., M. Marinacci, and S. Mukerji. “A Smooth Model of Decision-Making Under Ambiguity.” *Econometrica* 73(2005):1849–1892.

Knight, F. H. *Risk, Uncertainty, and Profit*. Boston: Houghton Mifflin, 1921.

Kunreuther, H., L. Ginsberg, L. Miller, P. Sagi, P. Slovic, B. Borkan, and N. Katz. *Disaster Insurance Protection: Public Policy Lessons*. New York: Wiley, 1978.

McClelland, G., W. Schulze, and D. Coursey. “Insurance for Low-Probability Hazards: A Bimodal Response to Unlikely Events.” *J. Risk and Uncert.* 7(1993):95–116.

Mead, P., L. Slutsker, V. Dietz, L. McCaig, J. Bresee, C. Shapiro, P. Griffin, and R. Tauxe. “Food-Related Illness and Death in the United States.” *Emerging Infectious Diseases* 5(1999):607–625. Online. Available at www.cdc.gov/ncidod/eid/vol5no5/pdf/mead.pdf.

Ready, R., J. Buzby, and D. Hu. “Differences Between Continuous and Discrete Contingent Value Estimates.” *Land Econ.* 72(1996):397–411.

Sarin, R., and R. Winkler. “Ambiguity and Decision Modeling: A Preference-Based Approach.” *J. Risk and Uncert.* 5(1992):389–407.

Savage, L. J. *The Foundations of Statistics*. New York: John Wiley and Sons, 1954.

Schelling, T. C. “Self-Command in Practice, in Policy, and in a Theory of Rational Choice.” *Amer. Econ. Rev.* 74(1984):1–11.

Segal, U., and A. Spivak. “First-Order versus Second-Order Risk Aversion.” *J. Econ. Theory* 51(1990):111–125.

Seo, K. “Ambiguity and Second-Order Belief.” *Econometrica* 77(2009):1575–1605.

Siniscalchi, M. “Ambiguity and Ambiguity Aversion.” In *The New Palgrave Dictionary of Economics*, 2nd ed. Hampshire, UK: Palgrave Macmillan, 2008.

Smith, V. K., and W. Desvousges. “An Empirical Analysis of the Economic Value of Risk Changes.” *J. Polit. Econ.* 95(1987):89–114.

van Ravenswaay, E., and J. Wohl. "Using Contingent Valuation Methods to Value the Health Risks from Pesticide Residues When Risks Are Ambiguous." In *Valuing Food Safety and Nutrition*, ed., J. Caswell, pp. 287–318. Boulder, CO: Westview Press, 1995.

Verbeke, W., R. Ward, and J. Viaene. "Probit Analysis of Fresh Meat Consumption in Belgium: Exploring BSE and Television Communication Impact." *Agribus.: An Internat. J.* 16(2000):215–234.

Viscusi, W. K., and H. Chesson. "Hopes and Fears: The Conflicting Effects of Risk Ambiguity." *Theory and Decision* 47(1999):153–178.

Viscusi, W. K., and W. A. Magat. "Bayesian Decisions with Ambiguous Belief Aversion." *J. Risk and Uncert.* 5(1992):371–387.

Whitehead, J. C. "A Practitioner's Primer on the Contingent Valuation Method." In *Handbook on the Contingent Valuation Method*, eds., A. Alberini and J. Kahn, pp. 66–91. Cheltenham, UK: Edward Elgar, 2003.

Winkler, R. "Ambiguity, Probability, Preference, and Decision." *J. Risk and Uncert.* 4(1991):285–297.

Yates, J. F., and L. G. Zukowski. "Characterization of Ambiguity in Decision Making." *Behavioural Sci.* 21(1976):19–25.

Appendix: Survey Scenarios

Monetary Urn Scenario

Imagine two large urns, each containing 100 balls. **Urn A** contains 100 balls numbered 1 to 100, with each number represented by exactly one ball. If the number 67 is drawn from the urn, you lose $100; otherwise, you lose nothing. **Urn B** also contains 100 balls, but each ball is randomly selected over the range of 1 to 100. In other words, it is possible for any number of balls to have the number 67 on it, including zero of them. Note that each of the 100 balls has a 1 in 100 chance of showing 67. Again, if the number 67 is drawn from this urn, you lose $100; otherwise, you lose nothing.

[1] In dollars and cents, how much would you be willing to pay to avoid playing lottery A?

[2] In dollars and cents, how much would you be willing to pay to avoid playing lottery B?

[3] Would you rather *avoid* lottery A, lottery B, or are you indifferent between them?

Food Safety Scenario

The following description of *Salmonella* will be useful to you in answering questions:

- Mild: 1–2 days of abdominal discomfort, possible nausea and diarrhea; similar to a mild case of the flu.
- Severe: 1–3 weeks of acute abdominal pains, vomiting, diarrhea; usually requires hospitalization; 1 in 1,000 people who get *Salmonella* die.

Imagine you would like to go out to eat at a restaurant. You have information regarding the food safety practices in various restaurants. In your town there are two restaurants of similar quality. There are also two local food safety inspectors.

- At **Restaurant A**, both food safety inspectors agree there is a 1 in 100 (1%) chance of contracting *Salmonella*, per meal.
- At **Restaurant B**, however, the inspectors disagree on the per meal odds of contracting *Salmonella*, with one inspector placing the odds at 1 in 67 (1.5%), and the other placing them at 1 in 200 (0.5%), averaging 1.0%, or 1 in 100).

[1] How much would you be willing to pay to eliminate the chance of *Salmonella* contraction at restaurant A?

[2] How much would you be willing to pay to eliminate the chance of *Salmonella* contraction at restaurant B?

[3] If these two restaurants were your only choices for a meal this evening, and their prices were identical, would you rather eat at restaurant A, restaurant B, or are you indifferent between them?