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Risk Preferences, Risk Perceptions, and Risky Food

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Risk Preferences, Risk Perceptions, and Risky Food

Abstract

This paper presents the results of a study that tests the hypothesis that the effect of risk preference on choice is a function of the specific risk-preference measure utilized. In addition, this study tests the hypothesis that the effect of risk preference on choice depends upon its interaction with risk perceptions. I elicit three distinct measures of risk preference: a standard real-money Holt and Laury measure, a hypothetical health-variant of the Holt and Laury measure, and a non-context-specific self-assessment measure. I also elicit information regarding risk perceptions. These data are combined with choice data focused on consumer preferences for raw oysters. Results indicate that, after controlling for key oyster attributes, perceived food safety risk is highly significant. Additionally, risk preference is significant, and the effect depends on whether respondents held informative or non-informative food safety perceptions. In a treatment that includes only named oyster varieties, I find that although respondents generally prefer named Atlantic coast oysters to named Gulf and Pacific coast oysters, those who hold informative food safety perceptions are significantly more likely to choose Gulf coast oysters as the magnitude of risk aversion increases. In another treatment that includes a generic "commodity" Gulf coast oyster, I find that although named Gulf coast oysters are preferred to the commodity Gulf coast oyster, respondents with noninformative food safety perceptions are significantly less likely to choose named Gulf coast oysters as the magnitude of risk aversion increases.

Risk Preferences, Risk Perceptions, and Risky Food

1. Introduction

The importance of accounting for both risk perceptions and risk preferences when analyzing risky choices has been established in the literature (Pennings, Wansink, and Meulenberg 2002; Lusk and Coble 2005; Bruner et al. 2011; Petrolia, Landry, and Coble 2013; Petrolia et al. 2015). However, there are a variety of ways in which to elicit risk preference information (also called risk "attitudes" or risk "tolerance"). Currently, the most popular is the approach of Holt and Laury (2002, 2005), which has subjects make a series of non-hypothetical (i.e., real money) choices over pairs of lotteries where one is the "safe" and the other the "risky" lottery. The relative riskiness of the risky choice increases with subsequent choices, and the point at which the respondent switches from risky to safe lotteries is used as an indicator of the individual's relative preference for risk. This approach is very closely related to that of Binswanger (1981) and Eckel and Grossman (2002), who have subjects make one choice over multiple lotteries. But there are a variety of alternative approaches for measuring risk preferences (see Charness, Gneezy, and Imas 2013 for a detailed review), including the approach of Andreoni and Harbaugh (2010), which has subjects trade-off magnitude of payoff with probability of payoff under budget constraint; eliciting certainty equivalents (Harrison 1986; Kachelmeier and Shehata 1992; Pennings and Garcia 2001); giving subjects money to invest and observing how they do so (Gneezy and Potters 1997); inflating and popping virtual balloons, known as the Balloon Analogue Risk Task (Lejuez et al. 2002); or via

simple (i.e., single-question, as in Shaik et al. 2008 and Szrek et al. 2012) or more elaborate (Weber, Blais, and Betz 2002; Szrek et al. 2012) self-assessment questions.

With the exception of popping virtual balloons and some of the self-assessment approaches, these approaches are set in a financial context; i.e., subjects are asked to make risky choices over (real or hypothetical) monetary gains or losses. But are risk preferences consistent over different contexts? In other words, are preferences over financial risks consistent with, say, preferences over health risks?¹ And are risk preferences measured in one context good predictors of behavior in other contexts? Dohmen et al. (2011) found that a standard lottery measure had little predictive power over employment, driving, and personal health choices, and Rustichini et al. (2012) found similar deficiencies in predicting credit scores, job persistence, car accidents, and smoking. Anderson and Mellor (2008) report mixed results, finding that the standard Holt and Laury risk-preference measure significantly explains obesity, cigarette smoking, heavy drinking, and seatbelt non-use, but does not explain driving over the speed limit. However, their analysis fails to account for risk perceptions, so it is questionable whether these findings would stand up in the face of these likely important but omitted variables. Szrek et al. (2012) test seven different measures of risk preference and also find mixed results: they find that neither the standard Holt and Laury measure nor the balloon-

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¹ It has already been shown that even among monetary risks, preferences may differ under low-stakes gambles relative to high-stakes (Holt and Laury 2002, 2005; Kachelmeier and Shehata 1992; Dickhaut et al. 2013).

popping measure significantly explain smoking, heavy drinking, seatbelt non-use, or risky sexual behavior. They find that a general (i.e., non-context-specific) self-assessment measure explains all four behaviors at various levels of significance, and also find that their health-domain-specific self-assessment measure significantly predicts three out of the four behaviors, whereas the other domain-specific measures perform poorly. However, they, too, fail to control for risk perceptions. Their failure to account for time preferences may also be a factor, given that the effects of smoking and heavy drinking may not be realized until many years later.² Instances where the cross-domain measure does appear to work include Lusk and Coble (2005) and Bruner et al. (2011), who, controlling for risk perceptions, use the Holt and Laury measure to explain consumer preferences for genetically-modified foods and post-harvest-treated raw oysters, respectively.³

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² See Khwaja, Silverman, and Sloan (2007) and Harrison, Lau, and Rutström (2010), who study the relationship between time preferences and smoking, but control for neither risk preferences nor perceived risk of illness from these behaviors.

³ Other papers that study consumer choice over risky foods that account for risk perceptions but not risk preferences include Lusk, Schroeder and Tonsor (2014), Goddard et al. (2012), Teisl and Roe (2010), Loureiro and Umberger (2007), Marette, Roe, and Teisl (2012), Han and Harrison (2007), Lusk, Roosen, and Fox (2003), Hayes et al.

I am aware of only two papers that implement health-context measures of risk preference, which are approximations of the certainty-equivalent approach of choosing between a risky and risk-free lottery (van der Pol and Ruggeri 2008; Attema, Brouwer, and l'Haridon 2013). For example, Van der Pol and Ruggeri have subjects choose between gambles involving a 50/50 chance of immediate death or living another 5 years versus living another 2.5 years for certain. Attema, Brouwer, and l'Haridon have subjects imagine living for 30 more years and then dying, then offering them the choice between two drugs, one that will extend their life for a certain number of years versus another with a 50/50 chance that it will increase their life for different numbers of years. These, too, have a time dimension that may confound identification of risk and time preferences. Furthermore, although these papers extend the experimental measure of risk preference to the health domain, these papers do not actually test whether these experimental measures are significant predictors of any behavior of interest.

In this paper, I extend the literature, primarily, by doing exactly that: I construct and implement a health-domain variant of the Holt and Laury risk preference measure that uses days spent in the hospital as the risky "payoff", and use this measure to predict consumer choice over a risky food. I also implement a standard real-money Holt and Laury experiment such that the values and framing of the health and Holt and Laury experiments are as similar as is feasible, as well as a third measure, a simple single-

^{(1995),} and Morgan et al. (2013). Lundborg and Andersson (2008) do likewise in explaining smoking behavior.

question non-context-specific self-assessment measure. I then estimate models using each of the three alternative risk-preference measures and compare model performance and predictive ability to a naïve model that does not account for risk preferences as well as to each other. In these models, I also control for risk perceptions, in this case, perceived food safety.

Additionally, the effect of risk preferences on choice may be a function of the kind of risk perceptions held by the respondent.⁴ Here, I distinguish between those that hold *informative* risk perceptions regarding food safety of the individual oysters and those that hold *non-informative* risk perceptions. By *informative* risk perceptions, I mean those individuals that perceive differences in relative risks across alternatives, whereas those with *non-informative* risk perceptions are those who perceive no clear differences in risks across alternatives. So I extend the literature by not only controlling for both risk preferences and risk perceptions, but also by further distinguishing the effects of risk perceptions.⁵

⁴ This phenomenon may be related to the concept of background risk, which is the phenomenon that risk-taking behavior is affected by the presence or absence of other independent, uncorrelated risks experienced by the individual (see, for example, Lusk and Coble 2008).

⁵ To some extent, this is an application of Lusk and Coble (2005), who also model the interaction between risk preferences and risk perceptions. However, in the present paper,

This analysis is conducted in the context of a choice experiment administered to U.S. households that focused on consumer preferences for raw oysters on the half-shell produced along the three U.S. coasts. To test whether the effect of risk preferences and risk perceptions are sensitive to experimental design, I carry out four independent subdesigns along two dimensions: the first dimension is the presence or absence of a fixed "status-quo" alternative: in one sub-design there is a fixed, cheaper commodity (or, "generic") oyster to which higher-priced named oyster alternatives are compared; in the other sub-design, there is no fixed generic oyster: all alternatives are named oysters. The second dimension is the number of attributes: in one sub-design, there are only two attributes: oyster origin and price; in the other sub-design, three additional attributes describing the oyster alternatives are included: size, taste (saltiness), and production method (wild-caught or farm-raised). Under each sub-design it is possible that the effect of risk preferences and perceptions are mitigated (or accentuated) in the presence (or absence) of additional information about the alternatives (i.e., having additional

risk perception measures are elicited for each individual alternative in the choice sets, thus allowing for measures of relative differences in perceived risk across alternatives, and the question allowed for "don't know" responses, which we hypothesize to represent a distinct kind of risk perceptions, i.e., those with diffuse prior beliefs. The measure used in Lusk and Coble was of a more general nature (it was an aggregate measure across multiple questions regarding GM food risks) and may not have offered respondents a "don't know" option to identify those with diffuse prior beliefs.

attributes) or the nature of the alternatives presented (i.e., having a fixed "generic" alternative).

I find evidence that the context in which risk preferences are measured matters. Specifically, results indicate that the Holt and Laury measure of risk preference performs no better – and in some cases worse – than other measures of risk preferences.

Additionally, I find evidence that the effect of risk preferences on choice depends upon the interaction between risk preferences and risk perceptions. Specifically, I find that, in some cases, changes in risk preferences (i.e., increased risk aversion) significantly affects the probability of choosing a particular alternative, but that the effect differs depending on whether respondents hold informative or non-informative risk perceptions about the level of food safety associated with that alternative.

2. Conceptual Framework

Given the inherent food-borne health risks associated with consumption of raw oysters, I argue that choice of which oyster to consume is one of choice under risk. Thus, I propose that utility for raw oysters can be expressed as:

$$U_{ii} = U(\mathbf{x}_{ii}, \tilde{p}_{ii}, \tilde{r}_{i}) \tag{1}$$

where \mathbf{X}_{ij} is a vector of observable oyster-specific attributes for oyster alternative j offered to respondent i: price, size, saltiness, production method (wild vs. farm-raised), and origin (i.e., harvest location); \tilde{p}_{ij} represents the subjective food-safety rating of respondent i for the harvest location of oyster alternative j; and \tilde{r}_i represents the

subjective risk preference (i.e., risk aversion) of respondent *i*. Besides price, which I expect to affect utility inversely, I have no expectations regarding sign for the remaining oyster attributes: some consumers prefer smaller oysters, whereas other prefer larger; some prefer wild-caught whereas others may associate more uniform shapes and sizes of oysters with farm-raised oysters. As for origin, I have a weak expectation that oysters deriving from locations nearer to the respondent are preferred to those farther, *ceteris paribus*, but oyster labels, which usually conveys harvest location, may also signal other latent characteristics (real or perceived) to the respondent. Perceptions regarding food safety of the oyster and/or the waters of its harvest location are presumed to be one of these latent characteristics. For this reason, it is necessary to attempt to disentangle preferences associated with origin of a given oyster *per se* from perceptions of the food safety risks that are signaled by the origin. Econometrically, I attempt to do this by interacting the variable indicating each oyster alternative with the corresponding subjective food safety rating for that oyster's harvest location.

Additionally, it is possible that not all respondents will have informative food safety perceptions about each harvest location that would influence their choices. For example, in the present study, respondents were asked to provide a numerical rating for what they perceived to be the level of food safety for each oyster harvest location. Those that had non-informative perceptions, however, could instead respond "I don't know." Consequently, one should not assume that the effect on utility of those respondents with informative food safety perceptions (i.e., those that reported a numerical food-safety rating) would be the same as those with non-informative perceptions (i.e., those that

responded "I don't know"). Econometrically, I account for this possibility by excluding those with who responded "don't know" to the food-safety rating questions from the observations contributing specifically to the effect on utility of food-safety perceptions. Consistent with this argument, it may also be the case that risk preferences may affect choices differently for these two groups: a risk-averse individual who perceives relatively greater risk in consuming a given alternative is expected, all things equal, to be less likely to choose that alternative. And as that individual's level of risk aversion increases, the likelihood of choosing that alternative decreases further. But if that same individual perceives no differences in relative risk across alternatives, then increases in risk aversion should have no effect on choice, or more weakly put, should not affect utility in the same way it does an individual who does perceive differences in relative risk across alternatives. For this reason, I estimate separate coefficients on risk preference according to whether an individual informative or non-informative food-safety perceptions.

Finally, it is hypothesized that the context in which risk preference is measured affects the performance (i.e., explanatory power) of the risk-aversion measure in explaining choice. Econometrically, I estimate three separate models: one that utilizes a risk preference measure derived from the standard Holt and Laury experiment over money, one that utilizes a risk preference measure derived from a hypothetical health-risk adaptation of the Holt and Laury experiment, and one that utilizes a simple single-question self-assessment measure of risk preference. Collecting all of the aforementioned

issues discussed above, equation (1) may be specified empirically as a randomcoefficients logit model:

$$U_{ij} = \boldsymbol{\beta}_{j}' \mathbf{x}_{ij} + \boldsymbol{\sigma}_{ij}' \mathbf{x}_{ij} + \gamma_{j} (1 - DK) \tilde{p}_{ij} + [\delta_{j}^{R} (1 - DK) + \delta_{j}^{DK} (DK)] x_{ij}^{origin} \tilde{r}_{i}^{m}$$
(2)

where β_j is a vector of fixed coefficients associated with alternative-specific attributes \mathbf{x}_{ij} , including terms capturing differences due to information treatments; σ_{ij} is a random term capturing preference heterogeneity over the attributes, including random terms capturing differences in scale across information treatments; γ_j is a fixed coefficient associated with subjective food-safety rating \tilde{p}_{ij} and DK is a binary indicator which equals one if the respondent responded "don't know" (DK) to the food-safety rating question and zero otherwise; the superscripts on δ_j indicate the food-safety rating group, where "R" are those that reported a numerical rating and "DK" are those that responded "don't know". The scalar indicator x_{ij}^{origin} must be included to induce variation across the alternatives given that \tilde{r} is not alternative-specific. The superscript m on \tilde{r} indicates which specific measure of risk preference is being used in the model, which are described in detail in the next section.

3. Experimental Design and Data Collection

An experiment was designed to test consumer preferences over multiple oyster varieties, attributes, and prices. The overarching motivation for the experiment was to gain a better understanding of the market potential for named Gulf of Mexico oyster varieties, both

along the Gulf coast and in other U.S. markets. Raw oysters are generally marketed in two ways that tend to coincide with the geographic region in which they are being marketed. Along the east and west coasts of the U.S., oysters tend to be differentiated by brand, origin, etc., and consumers generally have a choice over multiple varieties when purchasing. Along the Gulf coast, however, oysters typically sell as a commodity, with almost no differentiation.

The experimental design was generated using NGene software, and all designs were optimized according to s-efficiency (ChoiceMetrics 2011).⁶ There were four separate designs that differed along two dimensions. The first dimension concerned whether a "generic" Gulf coast oyster was included as one of the alternatives. To account for differences in oyster marketing, I designed a treatment for each of these market arrangements: one, referred to as the "non-generic" treatment, which includes only "named", i.e., origin-specific oyster alternatives; and another, referred to as the "generic" treatment, which includes a generic Gulf coast oyster as the fixed third alternative in each choice set.⁷

⁶ To generate an S-efficient design, it is necessary to assume prior parameter estimates. The priors used in the present study were based on the results of a conditional logit regression model estimated over choice data collected during pre-testing of the survey.

⁷ For the generic Gulf coast oyster only, size was fixed at the level "sizes vary" and saltiness was fixed at the level "saltiness varies" to reflect the true variation in size and

The second dimension concerns the number of attributes included in the choice set. There is great variation in what information is provided to consumers when purchasing raw oysters. Some restaurants provide very detailed information whereas some provide only minimal information. To account for these differences, one treatment, referred to as the "High-Information" treatment includes all five attributes: oyster origin/name, price, size⁸, saltiness level, and production method (wild or cultivated). A second treatment, referred to as the "Low-Information" design included only two attributes: oyster brand/name and price. Thus, the design has four independent treatments: 1) non-generic, high-information; 2) non-generic low-information; 3) generic, high-information; and 4) generic, low-information. Table 1 summarizes the attributes and their levels used in the online survey.

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saltiness found in a typical order of generic Gulf coast oysters. All other oyster varieties took on one of the specific levels (i.e., "small", "medium", or "large"; "sweet", "mildly salty", "salty") with the following exceptions to reflect the true characteristics of particular oyster varieties: the production method of Point aux Pins was fixed at "Cultivated" and the saltiness level of Hood Canal oysters was constrained to be either "mildly salty" or "salty".

⁸ To provide guidance to respondents regarding the size levels, a visual was included to show what a typical "small", "medium", and "large" oyster look like.

Responses were elicited using the best-worst elicitation (BWE) format. BWE has emerged of late as an alternative to the format of having respondents indicate only their first-best choice (Flynn and Marley 2014; Flynn et al. 2007; Marley and Louviere 2005; Potoglou et al. 2011; Rigby, Burton, and Lusk 2015; Scarpa et al. 2011). The BWE format asks respondents to indicate the "best" alternative and then to indicate the "worst" alternative, and then, of the remaining alternatives, to indicate the "best" of those remaining, then the "worst", etc., until a full ranking is achieved. The argument is made that choosing "bests" and "worsts" is a relatively easy task for respondents, and yields more information per choice set than the standard question format. Thus, it represents a further extension of the discrete-choice experiment format with the potential to increase survey administration cost efficiency even further.

My particular BWE format is an application of "Case III" BWE (the multi-profile case; see Flynn and Marley 2014), and included a single question with three alternatives, and elicited the "best" and "worst" choice of the three alternatives, thus yielding a full ranking. This ranking was then decomposed following the method of rank-order explosion proposed by Chapman and Staelin (1982), which, in my case, yields two choice observations for each choice set evaluated: a three-alternative observation (first-best case) and a two-alternative observation (second-best case). In this particular context, respondents were asked to indicate which of the three alternatives they were "Most Likely to Buy" at the posted prices (i.e., "best"), and which of the three alternatives there were "Least Likely to Buy" at the posted prices (i.e., "worst"). See Figure 1 for example

choice sets. Example A in Figure 1 represents a non-generic, low-information choice set, and Example B, a generic, high-information choice set.

Perceived food safety was elicited using the question "Please rate what you perceive to be the overall level of food safety of seafood in general from the following places, where a 1 is Poor and a 10 is Excellent." Respondents were asked to rate each location corresponding to the origin of each oyster alternative used in the experimental design. To mitigate the potential issue of non-comparability across individuals (who may have different interpretations of the qualitative labels attached to the numbers on the scale), I convert the raw ratings to relative ratings by subtracting the reported rating for each origin from that of the same individual's "base" oyster alternative in each model. 9

For the non-generic models, the Chesapeake Bay oyster was set as the omitted base oyster, so that the food safety rating variable reflects the difference in rating of each oyster alternative relative to the Chesapeake Bay oyster. For the generic models, the generic Gulf coast oyster served as the base.

Risk preference measures were elicited using three different methods. For ease of discussion, these measures are referred to as *HL*, *Health*, and *Self-Assessed*, respectively. The *HL* risk-preference measure used a real-money Holt and Laury (2002) experiment.

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⁹ See Andersen et al. (2014) for a discussion of how the recovery of subjective probabilities must either consists of elicitation mechanisms that control for risk aversion or that undertake "calibration adjustments" to elicited reports.

Respondents were asked to make five choices each between low-variance and high-variance risks of monetary loss. ¹⁰ The experiment was framed as follows:

In the following section, we are interested in how you make decisions about possible losses of money.

You will be asked to make 5 choices, but only one choice will be randomly selected to determine your actual earnings, but you will not know in advance which one will be used.

Respondents were then presented with the five risk-choice questions. An example is given below:

Which risk of <u>loss of money</u> do you prefer to face?

- A 1-out-of-10 chance of losing \$5 and a 9-out-of-10 chance of losing \$4
- A 1-out-of-10 chance of losing \$10 and a 9-out-of-10 chance of losing \$1

Probabilities were set at 0.1/0.9, 0.3/0.7, 0.5/0.5, 0.7/0.3, and 0.9/0.1 respectively, and the dollar amount was fixed as in the example above. Respondents were told that one of their choices would be selected randomly for an actual payoff so that incentive compatibility was ensured. Respondents received a \$10 endowment to participate.

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¹⁰ The original Holt and Laury method utilized ten such questions. To manage the length of the survey while including the health-risk questions, I opted to use only five such questions. Thus, I acknowledge some loss of accuracy in our measure relative to using ten questions.

The *Health* risk-preference measure used a hypothetical health-risk experiment design to mimic the Holt and Laury experiment.¹¹ Respondents were asked to make five choices each between low-variance and high-variance risks of days spent in the hospital due to illness. The experiment was framed as follows:

In the following section, we are interested in how you make decisions about possible risks to your personal health and safety.

For example, you might think about risks to your personal health and safety when deciding travel plans, which job to take, what to eat or drink, or where to live.

Suppose you were faced with a situation where you had <u>no choice but to face</u> some risk to your personal health and safety.

You will be asked FIVE questions. For each one, you are asked to choose between two different risks of spending some number of days in the hospital.

Respondents were then presented with the five risk-choice questions. An example is given below:

Which risk of days spent in the hospital would you prefer to face?

I acknowledge that the risk tasks are essentially very different. The Holt and Laury task is over money, and is non-hypothetical, whereas the health task is over health risk and is (necessarily) hypothetical. But that is precisely the point: the real-money Holt and Laury task is used ubiquitously throughout the literature in a variety of contexts, both financial and otherwise. I hypothesize, however, that measuring risk preference in the context of health may be more appropriate when attempting to use the risk preference measure to predict choice in a health-risk context. Thus, the study allows for the comparison of two very different risk tasks to predict the same choice under risk.

- A 3-out-of-10 chance of spending 5 days in the hospital and a 7-out-of-10 chance of spending 4 days in the hospital.
- A 3-out-of-10 chance of spending 10 days in the hospital and a 7-out-of-10 chance of spending 1 day in the hospital.

Probabilities were set at 0.1/0.9, 0.3/0.7, 0.5/0.5, 0.7/0.3, and 0.9/0.1, respectively, and number of days were fixed as in the example above. I use the total number of low-variance choices as measures of increasing risk aversion for both the *HL* and *Health* measures.¹²

The *Self-Assessed* risk-preference measure was based on the response to the question:

Using the scale below, please tell us how much you agree or disagree with the following statement about your work and life: I tend not to take many risks in everyday life.

Response choices were *Strongly Agree*, *Somewhat Agree*, *Neither Agree nor Disagree*, *Somewhat Disagree*, and *Strongly Disagree*. Responses were coded to reflect increasing risk aversion, i.e., Strongly Disagree was coded as a 1, Somewhat Disagree as a 2, etc.

¹² Although it is fairly common in the literature to use the total number of low-variance choices as measure of risk aversion, there is a growing literature on the importance of estimating structural econometric models and how different stochastic error specifications can have profound effects on estimates of risk preferences (Hey 2005; Loomes 2005; Wilcox 2011; Drichoutis and Lusk 2014). I acknowledge that the choice to use the more common and straightforward metric of total number of low-variance choices may suffer from imprecision.

GfK Custom Research administered the survey using sample from their KnowledgePanel®, and consisted of two sample waves (first half fielded in April 2013 and second half fielded in November 2013). Select U.S. metro areas were identified as being key markets for raw oyster consumption. The target population consists of general-population adults age 18+ who were English language survey takers in one of the pre-identified markets. To sample the population, GfK selected respondents based on an initial screening for those who consume raw oysters on the half-shell at least once per year. Table 2 reports the specific metro areas that were included in the sample and the number of respondents in each treatment. The non-generic treatments are a stratified random sample across the selected markets across the U.S. Given the nature of the marketing arrangements by region, the generic treatments are limited to respondents in or near the Gulf coast.

4. Results

4.1 Comparison of Risk Preference Measures

Figure 2 contains a comparison of the proportion of respondents choosing the "safe" lottery under the *HL* and *Health* experiments, against what a risk-neutral agent is expected to choose. The horizontal axis reports the progression through the five lottery decisions. The variance of the "risky" lottery increases as the experiment progresses, so that during the first decision the respondent chooses between the "safe" lottery and the lowest-variance "risky" lottery. During the first and second decisions, a risk-neutral agent is expected to choose the "risky" lottery. During the fifth decision, it is a choice

between the "safe" lottery and the highest-variance "risky" lottery. During the third, fourth, and fifth decisions, a risk-neutral agent is expected to choose the "safe" lottery. As a group, the probabilities over the sequence of lotteries are fairly consistent, indicating that both question types lead to similar choices. There are some subtle differences worth noting, however. For the initial lotteries, where a risk-neutral agent would never choose the "safe" lottery, there is a slightly higher proportion of "safe" choices in the *Health* experiment, whereas for the latter lotteries, where the risk-neutral agent would never choose the "risky" lottery, there is a slightly lower proportion of "safe" choices in the *Health* experiment. In other words, choices over the *HL* experiment tend toward risk-neutrality slightly more than that of the *Health* experiment.

Another comparison across risk-preference measures can be made using correlation coefficients, which provides an indication of the strength of the linear relationship between each pair of risk-preference measures. This also allows for some comparison that includes the self-assessment measure. The correlation coefficient between the *HL* measure and the *Health* measure is 0.34, indicating a moderate positive linear relationship between these two. Between the *HL* measure and the *Self-Assessed* measure (where an increase in value indicates an increase in stated risk-aversion), the correlation coefficient is 0.14, indicating a weak, but positive relationship. Finally, between the *Health* measure and the *Self-Assessed* measure, the correlation coefficient is 0.05, indicating almost no linear relationship between these two. Although these measures are reported simply to give some idea about the consistency across the three measures, they do provide evidence that these measures are different, and could imply a

difference in the strength and direction of the explanatory power of these measures to explain behaviors of interest.

4.2 Regression Results

Although twelve individual oyster varieties were specified in the experimental design, preliminary testing indicated no significant differences in marginal utility for varieties with the same regional origin. Thus, I constrain the coefficients on all Gulf coast varieties to be equal, those of all East coast varieties to be equal, and those of all West coast varieties to be equal. Preliminary testing also indicated that it was feasible to pool high-information and low-information treatments as long as differences in scale were allowed for, which in our particular model, was accomplished by including binary indicators for these treatments interacted with the oyster alternatives and then randomizing these parameters.

4.3 Non-generic Treatment

Table 3 reports the names and descriptions of the variables used in the regression models. Table 4 contains the results of the four random-parameter logit regression models for the non-generic treatment. Note that the sample for the non-generic treatment is dominated by Atlantic-coast households (refer back to Table 2 for details), which implies an expectation of preferences away from Gulf and Pacific coast oysters. Each model differs in terms of which risk-preference measure is used (and are so-named). Comparing first at the overall model level, I report the results of likelihood-ratio tests which test the null

hypothesis that the interaction of risk preferences and risk preferences are jointly not significant (i.e., that risk preference effects do not differ between those with informative and those with non-informative risk perceptions). The test statistic is distributed χ^2 with two degrees of freedom (one restriction each for Gulf and Pacific coast oysters), and are reported in the bottom row of the table. The null hypothesis is rejected for all three models, indicating a significant reduction in the likelihood value due to the constraints on the risk-preference / risk perception interaction terms. In other words, the tests indicate that each model is significantly and negatively affected by failing to account for the interaction effects between risk preferences and risk perceptions.¹³

Next, I compare models based on which risk preference measure is used. Because models are non-nested, the likelihood-ratio test is not appropriate. However, Akaike and Bayesian Information Criteria (AIC and BIC) can be used for this purpose. Both AIC and BIC values indicate that the model relying on the self-assessed measure of risk preferences outperforms all others (i.e., has the lowest AIC and BIC values), followed by the *HL* model, then the *Health* model.

Turning to the individual parameter results, results are fairly consistent across all four models: the coefficient on price is significant and of the expected sign and

¹³ Note that I also tested each model against a naïve model that does not account for risk preference effects at all, i.e., constrains all risk preference parameters to be equal to zero, and the null hypothesis is rejected in all cases, indicating that a failure to account for risk preferences significantly and negatively affects model performance.

magnitude.¹⁴ Results indicate disutility associated with small oysters (relative to medium-sized), with salty oysters (relative to mildly salty), and with Gulf and Pacific coast oysters (relative to Atlantic coast oysters), but, as indicated by significance of the standard deviation of these parameters, heterogeneity over such preferences. Results indicate positive utility associated with wild-caught oysters (relative to farm-raised), also with significant preference heterogeneity. No significant utility differences are detected for large oysters or for sweet oysters, although significant preference heterogeneity is found for both.

Results indicate limited effects of the information treatment on preferences. Only for the *Self-assessed* risk-preference model is the interaction term on Pacific oyster and high information significant, indicating a higher tendency for Pacific oysters to be preferred relative to those same oysters in the low-information treatment. Significant preference heterogeneity is detected, however, in many cases, on these interaction terms. Regarding food-safety perceptions, results are highly-significant and have the expected negative sign (i.e., the lower a particular oyster is rated for food safety relative to the Chesapeake Bay oyster, the less utility associated with that oyster).

¹⁴ Note that I implement Carson and Czajkowski's (2013) reparameterization of the coefficient on (the negative of) price to enforce a theoretically correct positive coefficient. The coefficient on (the negative of) price can be recovered by exponentiating the parameter value reported in the tables.

Turning now to the individual risk-preference parameters, note that results are reported according to how risk preferences are interacted with risk perceptions. The interaction is obtained via the "DK" variable, which is a binary indicator for respondents that gave an "I don't know" response to the food-safety rating question for a particular oyster harvest location (i.e., respondents that have non-informative risk perceptions). Note also that the risk preference variables are coded such that they reflect increased risk aversion; thus higher values are associated with more risk-averse respondents. Results indicate a significant positive effect of risk preferences on preferences for Gulf coast oysters in the HL and Health models. In other words, as a respondent's level of risk aversion – as measured by either the HL or the Health risk-preference experiments – increases, the probability of choosing a Gulf coast oyster increases, but only among those respondents holding informative food-safety perceptions. In other words, increased risk aversion had no effect on the choices of those respondents who had non-informative food-safety perceptions; but among those that did, they were more likely to choose Gulf coast oysters relative to Atlantic coast oysters. Results from the *Health* model also indicate marginally significant disutility for Pacific coast oysters among respondents with non-informative food-safety perceptions. Post-estimation Wald tests of parameter equivalence confirm these results, and indicate highly-significant differences in risk preference effects between those with informative and those with non-informative risk perceptions over Gulf Coast oysters, but not Pacific Coast oysters (significance of these results are indicated by the † in the tables.)

Results for the Self-Assessed model are different in terms of which risk preference parameters are significant, though consistent in terms of signs with the aforementioned results. In this model, the risk-preference parameter that is significant in the above models is not significant, but the other three risk-preference parameters are. In other words, respondents that had non-informative food-safety perceptions were less likely to choose both Gulf coast oysters and Pacific coast oysters relative to Atlantic coast oysters; additionally, those respondents with informative food-safety perceptions were less likely to choose Pacific coast oysters. Thus, the three different risk-preference measures yield qualitatively similar results, although they diverge in terms of where statistical significance is found. These results thus support the hypothesis that the effect of risk preferences depends upon both how risk preferences are measured as well as on the nature of risk *perceptions* held by respondents. Consistent with the previous two models, post-estimation Wald tests indicate highly-significant differences in risk-preference effects between those with informative and those with non-informative risk perceptions for Gulf Coast oysters here as well, but no significant differences for Pacific Coast oysters.

4.4 Generic Treatment

Table 5 contains the results of the four random-parameter logit regression models for the generic treatment. Note that, given the nature of the actual market for raw oysters, the sample for the generic treatment is limited to Gulf coast and surrounding households (refer back to Table 2 for details). Comparing first at the overall model level, I report the

results of likelihood-ratio tests which test the null hypothesis that the interaction of risk preferences and risk preferences are jointly not significant. The test statistic is distributed χ^2 with three degrees of freedom (one restriction each for Gulf, Pacific, and Atlantic coast oysters), and are reported in the bottom row of the table. The null hypothesis is rejected for all three models, indicating a significant reduction in the likelihood value due to the constraints on the risk-preference / risk perception interaction terms. In other words, the tests indicate that each model is significantly and negatively affected by failing to account for the interaction effects between risk preferences and risk perceptions. ¹⁵ The AIC and BIC values indicate the best model fit is for the model relying on the *Health* measure, followed by the *Self-Assessed* model, and lastly, the *HL* model.

In terms of individual parameters, the parameter on price is significant and of the expected sign and magnitude. The parameter on Small is significant in only two of the four models, although magnitude is similar across models. Significant preference heterogeneity is detected as well. The parameter on Wild is significant and positive, indicating positive utility associated with wild-caught oysters, with significant preference heterogeneity. The parameter on Gulf coast is significant in only two of the four models,

¹⁵ Note that I also tested each model against a naïve model that does not account for risk preference effects at all, i.e., constrains all risk preference parameters to be equal to zero. The null hypothesis is rejected in the case of the *Health* and *Self-Assessed* models, but not for the *HL* model, indicating that a failure to account for risk preferences significantly and negatively affects model performance in the first 2, but not the third.

although it is positive in all cases, with significant preference heterogeneity. The remaining parameters are not statistically different from zero, although there is significant preference heterogeneity associated with the attributes sweet, salty, Pacific oysters, and Atlantic oysters.

Food safety rating effects are highly significant and negative, as expected, and consistent across all models. Significant risk-preference effects are detected for respondents with non-informative food-safety perceptions; specifically, such respondents are less likely to choose named Gulf coast oysters relative to the base generic Gulf coast oyster. In the *Self-Assessed* model, respondents with non-informative food-safety perceptions were also less likely to choose Atlantic coast oysters relative to the base generic Gulf coast oyster. Post-estimation Wald tests indicate no significant differences in risk-preference effects between those with informative and those with non-informative risk perceptions. So although the likelihood-ratio test discussed earlier indicates that jointly constraining all such interaction effects significantly affects overall model performance, the individual Wald tests indicate no significant differences at the individual parameter level.

5. Conclusions

This study provides evidence that the effect of risk preferences on choice depends upon the context in which risk preferences are measured. Additionally, building upon the findings of Lusk and Coble (2005), this study provides further evidence that the effect of

risk preferences on choice depends upon the nature of respondents' risk perceptions, i.e., depends upon the interaction of risk preferences and perceptions.

Specifically, I find that each measure of risk preference yields a different level of model performance and results. For the non-generic treatment, results indicate that the simple *Self-Assessed* measure outperforms all other measures, with the *HL* and *Health* models performing similarly with similar results on the individual parameters. For the generic treatment, however, results indicate that the *Health* model outperforms all others, followed by the *Self-Assessed* model, then the *HL* model. These findings come as a bit of a surprise, given the popularity and incentive-compatibility of the Holt and Laury approach. But at least in the present application, the Holt and Laury measure does no better, and in some cases, worse – in terms of model performance measures – than the alternative measures. Thus, there is evidence here that risk preferences over money may not necessarily carry over well to explaining decisions in other contexts. As noted in the introduction, the literature is very thin on direct comparisons of explanatory power of alternative risk-preference measures, particularly measures over contexts other than money.

Furthermore, I find that either the sign, magnitude, significance, or all of the above associated with risk preference can differ based on whether respondents hold informative or non-informative risk perceptions. In other words, if respondents do not have any informative beliefs about the relative probability of illness (as indicated by food-safety ratings) across alternatives, then the effect of risk preferences may differ from that associated with respondents who do have informative beliefs. In my

application, I find this to be the case particularly with Gulf coast oysters, under both the non-generic and generic treatments. These findings indicate that researchers may need to control not only for risk perceptions and risk preferences, but to then test for more subtle interactive or differential effects between the two.

These findings also raise the question of how such beliefs should be elicited. In the survey instrument, I classified those who responded "I don't know" to the food safety rating questions as those with non-informative risk perceptions. Sometimes a "don't know" or other sort of opt-out response is not available for respondents to choose, or in other cases such responses may be assigned an arbitrary rating by the researcher *ex post* (e.g., the average). Whether those who responded "don't know" truly hold non-informative perceptions, or were just lazy in responding, my results indicate that, for whatever reason, such responses signal something different from those that did provide numerical ratings to the food-safety questions. This work should provide fodder for future research focused on understanding the role of risk preferences and risk perceptions on consumer choice under risk.

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Table 1. Attributes and their levels used in the experiment design. The low-information treatment included only the oyster variety and price per half-dozen.

Oyster Variety	Gulf Coast: Apalachicola Bay (Florida), Bay St. Louis
	(Mississippi), Champagne Bay (Louisiana), Lonesome Reef
	(Galveston Bay, Texas), Point aux Pins (Grand Bay,
	Alabama), Portersville Bay (Alabama), "generic" Gulf of
	Mexico
	Atlantic Coast: Cape Cod (Massachusetts), Chesapeake Bay
	(Virginia), Moonstones (Point Judith Pond, Rhode Island)
	Pacific Coast: Hood Canal (Washington), Netarts Bay
	(Oregon), Willapa Bay (Washington)
Production Method	cultivated, wild
Size	small, medium, large, sizes vary*
Saltiness	sweet, mildly salty, salty, saltiness varies*
Price per half-dozen	\$7*, 8, 9*, 10, 11*, 12, 14, 16, 18

^{*} Applies to generic Gulf of Mexico oyster only

Table 2. Frequency of respondents by market area.

Tuele 2. Trequency errospondents by market	Non-	Generic	Ge	neric
Market Area	Freq.	Percent	Freq.	Percent
Atlanta-Sandy Springs-Marietta, GA	23	0.08	59	0.20
Baltimore-Towson, MD	13	0.04		
Baton Rouge, LA	2	0.01	12	0.04
Boston-Cambridge-Quincy, MA-NH	14	0.05		
Charleston-North Charleston, SC	12	0.04	6	0.02
Chicago-Naperville-Joliet, IL-IN-WI	24	0.08		
Houston-Baytown-Sugar Land, TX	11	0.04	61	0.20
Jacksonville, FL	5	0.02	19	0.06
Las Vegas-Paradise, NV	9	0.03		
Miami-Fort Lauderdale-Miami Beach, FL	11	0.04	60	0.20
Mobile, AL	1	0.003	2	0.01
New Orleans-Metairie-Kenner, LA	6	0.02	22	0.07
New York-Newark-Edison, NY-NJ-PA	62	0.21		
Portland-South Portland, ME	1	0.003		
St. Louis, MO-IL	15	0.05		
San Francisco-Oakland-Fremont, CA	23	0.08		
Seattle-Tacoma-Bellevue, WA	10	0.03		
Tallahassee, FL	1	0.003	7	0.02
Tampa-St. Petersburg-Clearwater, FL	20	0.07	50	0.17
Washington-Arlington-Alexandria, DC-VA	31	0.11		
Total	294		298	

Table 3. Variable names and descriptions for regression models.

Variable	Description
Neg. Price	Negative of the offered price per half-dozen.
Small	= 1 if oyster size attribute is "small", = 0 otherwise
Large	= 1 if oyster size attribute is "large", = 0 otherwise
Sweet	= 1 if oyster taste attribute is "sweet", = 0 otherwise
Salty	= 1 if oyster taste attribute is "salty", = 0 otherwise
Wild	= 1 if oyster cultivation attribute is "wild-caught", = 0 otherwise
Gulf	= 1 if oyster harvested from one of the Gulf of Mexico coast locations, = 0 otherwise
Pacific	= 1 if oyster harvested from one of the Pacific coast locations, = 0 otherwise
Atlantic	= 1 if oyster harvested from one of the Atlantic coast locations, = 0 otherwise
High Info	= 1 if choice set included all 5 oyster attributes, = 0 otherwise
Food Safety	Difference between food safety rating for the base oyster alternative's harvest location and that of the given alternative. In non-generic treatment, the base location is Chesapeake Bay; in generic treatment, the base location is the Gulf of Mexico
DK	= 1 if respondent indicated "Don't know" to the food safety rating question for a given harvest location, = 0 otherwise
Risk Preference	For <i>HL</i> and <i>Health</i> models: number of "safe" choices made during the risk-preference elicitation experiment; for <i>Self-Assessed</i> models: = 1 if indicated "Strongly Disagree" to the statement "I tend not to take many risks in everyday life.", = 2 if "Somewhat Disagree", = 3 if "Neither Agree nor Disagree", = 4 if "Somewhat Agree", = 5 if "Strongly Agree"

Table 4. Random-parameters Logit Regression results for the Non-generic treatment	models.	reatment	generic tr	Non-	the N	for	results	Regression	Logit R	parameters	Random-	Table 4.
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	Holt-Laury		Health	Self-Assessed		
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Ln(Neg. Price)	-1.94 ***	0.06	-1.95 ***	0.05	-1.91 ***	0.05
Small	-0.81 ***	0.19	-0.80 ***	0.19	-0.82 ***	0.19
Std. Dev. (Small)	1.35 ***	0.20	1.39 ***	0.20	1.40 ***	0.20
Large	0.02	0.17	-0.11	0.17	-0.11	0.17
Std. Dev. (Large)	1.13 ***	0.15	1.12 ***	0.16	1.14 ***	0.16
Sweet	0.09	0.20	0.12	0.21	0.13	0.21
Std. Dev. (Sweet)	1.51 ***	0.19	1.53 ***	0.20	1.55 ***	0.20
Salty	-0.71 ***	0.17	-0.71 ***	0.16	-0.70 ***	0.16
Std. Dev. (Salty)	1.21 ***	0.19	1.15 ***	0.18	1.18 ***	0.18
Wild	0.43 ***	0.16	0.52 ***	0.16	0.52 ***	0.16
Std. Dev. (Wild)	1.33 ***	0.16	1.32 ***	0.16	1.33 ***	0.16
Gulf	-0.41 ***	0.06	-0.41 ***	0.06	-0.38 ***	0.07
Std. Dev. (Gulf)	0.45 ***	0.07	0.40 ***	0.07	0.45 ***	0.07
Pacific	-0.40 ***	0.09	-0.37 ***	0.08	-0.33 ***	0.08
Std. Dev. (Pacific)	0.57 ***	0.09	0.51 ***	0.09	0.46 ***	0.09
Gulf x Food Safety x (1 - DK)	-0.26 ***	0.05	-0.27 ***	0.05	-0.25 ***	0.05
Pacific x Food Safety x (1 - DK)	-0.27 ***	0.06	-0.29 ***	0.06	-0.31 ***	0.07
Gulf x Risk Preference x (1 - DK)	0.11 ***, +++	0.04	0.13 ***, +++	0.04	0.06	0.04
Gulf x Risk Preference x DK	-0.03	0.04	-0.03	0.04	-0.09 **, +++	0.04
Pacific x Risk Preference x (1 - DK)	-0.01	0.04	-0.02	0.04	-0.10 **	0.04
Pacific x Risk Preference x DK	-0.08	0.05	-0.08 *	0.05	-0.13 ***	0.04
Gulf x High Info	-0.19	0.19	-0.13	0.19	-0.01	0.19
Std. Dev. (Gulf x High Info)	1.37 ***	0.20	1.36 ***	0.20	1.39 ***	0.21
Pacific x High Info	0.10	0.17	0.17	0.17	0.36 **	0.17
Std. Dev. (Pacific x High Info)	0.59 **	0.24	0.60 ***	0.22	0.70 ***	0.21
N =	3263		3263		3263	
LL =	-2587.7	-	-2588.2		-2585.7	
AIC =	5225.4		5226.4		5221.4	
BIC =	5377.7		5378.7		5373.6	
LR χ2 Statistic (2 d.f.)	8.79 **		10.09 ***		8.06 **	

^{***, **, *} indicates coefficient is statistically different from zero at the 0.01, 0.05, and 0.10 level, respectively.

^{†††} indicates *Risk Preference* x (1-DK) coefficient statistically different from *Risk Preference* x DK coefficient at the 0.01 level, based on Wald test.

Table 5. Random-parameters Logit Regression results for the Generic treatment models.

Table 5. Random-parameters Logit Reg	Random-parameters Logit Regression results for the Generic treatment models. Holt-Laury Health Self-Assessed					
		S.E.	Health	C F	•	
Lu(Nas Dries)	Coef. -1.66 ***		Coef. -1.66 ***	S.E.	Coef. -1.69 ***	S.E.
Ln(Neg. Price)		0.07		0.07		0.07
Small	-0.35	0.22	-0.35	0.22	-0.42 **	0.21
Std. Dev. (Small)	0.76 ***	0.27	0.75 ***	0.29	0.73 ***	0.27
Large	0.25	0.20	0.25	0.21	0.27	0.20
Std. Dev. (Large)	0.43	0.35	0.44	0.35	0.48	0.31
Sweet	-0.08	0.25	-0.09	0.25	-0.21	0.24
Std. Dev. (Sweet)	1.48 ***	0.24	1.51 ***	0.25	1.43 ***	0.24
Salty	0.06	0.22	0.09	0.23	-0.02	0.21
Std. Dev. (Salty)	0.92 ***	0.26	1.00 ***	0.25	0.96 ***	0.24
Wild	0.47 **	0.18	0.48 ***	0.18	0.50 ***	0.17
Std. Dev. (Wild)	0.94 ***	0.26	0.94 ***	0.26	1.08 ***	0.21
Gulf	0.53	0.38	0.83 **	0.35	0.54	0.53
Std. Dev. (Gulf)	2.10 ***	0.16	2.09 ***	0.16	2.08 ***	0.15
Pacific	-0.58	0.51	0.25	0.44	-0.32	0.66
Std. Dev. (Pacific)	1.95 ***	0.25	1.97 ***	0.25	1.95 ***	0.25
Atlantic	0.44	0.67	1.00	0.68	0.77	1.03
Std. Dev. (Atlantic)	3.27 ***	0.34	3.18 ***	0.33	3.17 ***	0.33
Gulf x Food Safety x (1 - DK)	-0.35 ***	0.05	-0.35 ***	0.05	-0.35 ***	0.05
Pacific x Food Safety x (1 - DK)	-0.71 ***	0.09	-0.71 ***	0.10	-0.72 ***	0.10
Atlantic x Food Safety x (1 - DK)	-0.74 ***	0.16	-0.76 ***	0.16	-0.71 ***	0.12
Gulf x Risk Preference x (1 - DK)	0.02	0.12	-0.09	0.11	0.01	0.15
Gulf x Risk Preference x DK	-0.16 ***	0.06	-0.16 ***	0.05	-0.14 **	0.06
Pacific x Risk Preference x (1 - DK)	0.13	0.17	-0.14	0.15	0.04	0.18
Pacific x Risk Preference x DK	-0.06	0.12	-0.14	0.12	-0.08	0.11
Atlantic x Risk Preference x (1 - DK)	0.01	0.23	-0.19	0.22	-0.05	0.29
Atlantic x Risk Preference x DK	-0.20	0.17	-0.24	0.15	-0.29 **	0.13
Gulf x High Info	-0.53	0.41	-0.48	0.41	-0.62 *	0.36
Std. Dev. (Gulf x High Info)	1.23 ***	0.44	1.13 ***	0.43	0.21	0.56
Pacific x High Info	-0.57	0.45	-0.50	0.45	-0.26	0.45
Std. Dev. (Pacific x High Info)	1.56 ***	0.55	1.39 **	0.56	1.26 *	0.67
Atlantic x High Info	-1.25 **	0.61	-1.16 *	0.60	-0.86	0.56
Std. Dev. (Atlantic x High Info)	1.09 **	0.49	1.16 **	0.49	0.36	0.54
N =	3408		3408		3408	
LL=	-2435.2		-2430.4		-2434.6	
AIC =	4934.4		4924.9		4933.2	
BIC =	5130.7		5121.1		5129.5	
LR χ2 Statistic (3 d.f.)	7.95 **		10.77 **		8.90 **	

Imagine you are at a restaurant that is known to serve high-quality raw oysters on the half-shell in, say, November, and that the following selection of oysters is on the menu at the following prices.

Suppose they sold only as a half-dozen (6 oysters) and you could only order one variety of oyster at a time. Based on the menu shown below, which oysters are you <u>most likely</u> to buy, and which oysters are you <u>least likely</u> to buy?

Example A: Non-Generic Low-Information Choice Set

Oysters on the half-shell	Price per half -dozen	Most likely to buy	Least likely to buy
Apalachicola Bay, Florida	\$12	0	0
Willapa Bay, Washington	\$18	0	0
Chesapeake Bay, Virginia	\$9	0	0

^[] I am not willing to buy any of these oysters at these prices

Example B: Generic High-Information Choice Set

Oysters on the half-shell	Price per half -dozen	Most likely to buy	Least likely to buy
Point aux Pins, Grand Bay, Alabama Cultivated oysters, medium sized, mildly salty	\$12	0	0
Cape Cod, Massachusetts Wild oysters, small size, sweet	\$18	0	0
Gulf of Mexico Wild oysters, sizes vary, saltiness varies	\$9	0	0

^[] I am not willing to buy any of these oysters at these prices

Figure 1. Example Choice Sets



Figure 2. Plot of the probabilities of choosing the "safe" lottery under the realmoney Holt and Laury (HL) and hypothetical Health risk-preference experiments, compared to the risk-neutral choice. Variance of the risky lottery increases from left (decision 1) to right (decision 5).