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Models of Location Choice and Willingness to Pay to Avoid Hurricane Risks for Hurricane Katrina Evacuees

W. Douglass Shaw
Texas A&M University

Justin Baker
Duke University

We report on subjects' perceptions of the risks of hurricanes and relocation decisions. Our sample contains individuals displaced by Hurricane Katrina or Rita in Gulf-coast areas, as well as a comparison group of people, not much affected by the hurricanes. Results are presented for two choice experiments, conducted immediately after the hurricane and again roughly one year later, in which we evaluate the trade-offs between given levels of risks and income, while controlling for amenities and other location characteristics. We find that perceptions of risk and damages fade, and willingness to pay to obtain protection falls over time.

Keywords: Hurricane Katrina; risk perceptions; stated choice modeling

Introduction

Studies have shown that people's risk perceptions fall as time from the incidence of a risky event passes (e.g. Baker et al. 2009b; Brody, Highfield and Peacock 2004; also see the review in Lindell and Perry, 2000). A related question is: does maximum willingness to pay to reduce risk fall as time from an event passes? This paper explores this question in the context of hurricane risks. In the fall of 2005 two major hurricanes (Katrina and Rita) hit the Gulf Coast region, resulting in devastating impacts, particularly for residents of New Orleans. As is well known, the majority of residents of New Orleans were forced to evacuate, moving to many locations across the U.S. As of late October, 2007 most of the people who evacuated New Orleans still had not moved back to live there. Furthermore, many of these evacuees do not plan on moving back to the Gulf Coast (Wilson, 2006; Baker et al 2009a). For some evacuees, the intention to move back or not depends on the economic costs of relocating and not being willing to sacrifice current employment opportunities, whereas others fear a recurrence of a hurricane similar to Katrina or Rita, and wish to avoid traumatic evacuation experiences following the storm

(Personal interviews with evacuees, 2006 and 2007). Location and relocation decisions after natural disasters are in fact more complicated than one may think, involving income, ability to pay, and geographical conditions (see Kahn, 2005).

Baker et al. (2009b) asked people to judge the probability that a hurricane would hit New Orleans and regressed each individual's stated probabilities on his or her characteristics and the experiences the subjects had during the hurricane to evaluate how perceptions of risk are affected by these factors. Many other researchers have considered several measures of risk that might explain an individual's behavior (e.g., McDaniels, Kamlet and Fisher 1992). Objective or so-called "expert opinion" measures can be used, such as a fire department's rating of home parcels for wildfire risks (e.g., Donovan, Champ and Butry 2007), but most researchers try to uncover perceived risks, as the thought is that decisions such as home locations and purchases relate best to perceived, and not science-based, or objective risks. The formulation of risk attitudes or preferences, or opinions of subjective or perceived risks is complicated, depending on factors such as media coverage of hazards (see McCluskey and Rausser 2001). One number, or even one equation to explain the number, may not be enough: as will be discussed below, Lindell and Hwang (2008) go further than consideration of a single explanatory equation to estimate perceived risks.

Despite the potential complications, the results from Baker et al. (2009b) indicated that uncertainty about the true probability leads the evacuees who were interviewed after the hurricane to increase their "best guess" as to the probability of a hurricane. Results for that group were consistent with much of the ambiguity literature which finds that people facing situations of ambiguity (uncertainty about the probability or risk) will tend to act as if the probability of the undesirable event is at the high end of the plausible range (e.g., Ellsberg 1961; Gilboa and Schmeidler, 1989; Riddel and Shaw 2006).

Though there are few survey-based empirical studies, several researchers have explored ambiguity in laboratory experiments. For example, in another study of subjective hazard risks, Ewing, Kruse and Thompson (2008) asked subjects to predict the wind speed at which modular homes fail, and tested the hypothesis of overconfidence connected to lotteries related to the answers. Their test is for whether certainty equivalents for bets exceed expected payoffs that would be based on the accuracy of their predicted wind speeds.

Baker et al. (2009b) also found that subjects who were interviewed later 6 to 8 months after evacuating) provided lower subjective probabilities on average than those who were interviewed in the first round, supporting the hypothesis that risk perceptions fade over time. For more details on the subjective risk estimates, see Baker et al. (2009b).

We focus in this manuscript on the results of a location choice experiment in which subjects are asked to choose between multiple relocation, or labeled destinations. We evaluate the trade-offs between given categorical levels of risk and income presented to the subject, controlling for amenities and other characteristics of the hypothetical locations provided. We find that risks, though introduced differently than in the above subjective risk model, play a significant role in choosing particular locations. In the remainder of the paper we present the structure of the choice models, followed by results. Conclusions based on the choice modeling are presented in the final section.

Background Literature on Perceived Risks and Choice Modeling

In this section we briefly consider some relevant literature, first on perceived risk elicitation and modeling applied in the hazards area of research, and second, focused on stated choice modeling.

Aversion to hurricane damage can be instrumental in forming economic decisions. Kruse, Simmons and Smith (2002) argue that although citizens cannot decrease the probability that a hurricane will hit, they still seek to mitigate hurricane damage by fortifying their homes (adopting storm protection measures), or at least they arrange to be compensated for incurred damages by purchasing insurance. Behavioral effects are not singular to individuals, as public risk perception affects public planning for natural hazards. Brody et al. (2004) find that location is the most important factor affecting individual perceptions of hurricane risk relative to other factors.

Lindell and Perry (2004) develop a *Protective Action Decision Model* (PADM) that links hazard proximity, experience, perceived risk and expected continued residence, or "tenure" in the residence, attempting to establish causality between these variables. Lindell and Hwang (2008) extend that approach to examination of multiple hazards in Harris County, Texas, including floods, hurricanes, and toxic chemical release. They review several theoretical perspectives on formation of risk perceptions and behavior, most of which fall more into the domain of psychology than economics. Their rich data set allows them to explore the relationship between experiences with distinct types of hazards (i.e. flood versus toxic chemical releases), and perceived risks for those hazards.

The occurrence of natural disasters provides a unique opportunity for economists to examine behavioral impacts of such events. Quite recently, Carbone, Hallstrom and Smith (2006) and in related work, Hallstrom and Smith (2005) measure the influence of a "near miss" hurricane as an information signal in the housing market for two Florida counties. Using a repeat-sales hedonic property valuation model, they find that the real-estate market was significantly affected by hurricane strikes in both counties, with the rate of increase in housing prices decreasing after the storm. This decrease was found to be significantly larger for the county that experienced the full effects of the hurricane. This unique behavioral impact implies that information signals regarding hurricane risk are more pronounced in counties that have previously been affected by a storm. Using the same hurricane event and similar data, Smith, Carbone, Pope, Hallstrom and Darden (2006) also demonstrate that household income (actually income for census blocks, which was the data the authors had access to), matters a great deal in determining home-location behavioral responses to hurricanes.

Whitehead (2005) also examines behavior related to hurricanes (focusing on evacuation intensions and behavior), using both revealed and stated preference responses. Like we do, he uses an indicator scale for risks. However, his indicator is specific to wind and floods, and he uses the individual's perceived risks (high, medium, low) directly, in his empirical modeling.

The Choice Models

In this section, we describe a stated choice model and experiment that includes the attributes of labeled locations. The model allows us to explore the role that hurricane risks play in choosing among locations. Because we include location-specific income and housing expenditures as attributes of the choices, we are able to recover an estimate of the sample willingness to pay to avoid the hurricane risks.

Stated-choice models and the experiments accompanying them are now standard in much marketing (Huber and Zwerina 1996; Kuhfeld, Tobias and Garratt 1994), transportation or commuting (e.g., Hensher 2006), environmental economics (see the collection of papers in Bennett and Blamey 2001), health economics (e.g., Viney, Savage and Louviere 2005), and other economics-related literature involving discrete choices (see Louviere, Hensher and Swait 2000). There are many variants, ranging from experiments that are similar to paired-choice conjoint experiments to ranking several alternatives or choices (A is my first preferred, B is my second, C is my third), or assigning ratings to alternatives using some numerical scale to indicate the strength of preference (e.g., On a scale of 1 to 10 (best), I rate A as an 8, B as a 6, and C as a 4).

In its simplest form, as is used here, a person is faced with the pair A and B, and asked to choose between them, then faced with the pair C and D, asked to choose between them, and so on. As will be seen below, we offer each person the opportunity to evaluate four choice pairs.

Of interest to hazard researchers is that we also attempt to incorporate risk into the description of an alternative. This, like any effort to communicate and get responses to risk, is difficult, and we know of few others who have attempted to introduce something about the risk describing an alternative in the choice experiment. An early study, and in fact one of few exceptions we can find in this regard, is the study of morbidity risk valuation by Magat, Viscusi and Huber (1988). There, the authors consider percentage reductions in the chance of getting injured from more safe products as the risk measure, and acknowledge that getting people to understand that kind of measure is difficult.

An emerging finding in choice modeling is that task complexity can influence the individual's choice (e.g. Swait and Adamowicz 2001), so the design has to balance the amount of information that could be collected with overwhelming complexity, with the amount that is much smaller, that can be collected without much complexity for the respondent. This is discussed more below, under the heading of choice-set design.

Following Lancaster's theory of utility (1966), stated-choice methods assume that utility is defined not only by the goods an individual consumes, but by a set of qualitative attributes that define a good. Thus, a consumer's consumption of a particular good or combination of goods provides access to attributes that are the source of the consumer's utility. Solution vectors to a constrained optimization problem typically involve a mapping of attributes, or consumption services, into objective function characteristics for the purposes of prediction and inference (Louviere, Hensher and Swait 2000). As it is typically applied to stated-preference choice modeling, the models are known as random utility models (RUMs).

In the usual RUM an individual's conditional utility (V) for choice i (V_i) is compared to the conditional utility after another choice is made (V_k), where k is not equal to i. As researchers we do not observe everything that the individual does, and are therefore left with the usual investigator error (ε_i), which generates randomness in the model. Since it is impossible to incorporate all arguments that influence an individual's utility into a given model, the utility function is composed of a deterministic component, V_i, and an unobservable (stochastic) component, ε_i (Grafton, et al. 2004):

$$U_i = V_i + \varepsilon_i . \tag{1}$$

Here, suppressing a subscript for the individual, V_i represents the indirect utility of alternative i, which can be specified as a direct function of the attributes which define alternatives (x_k), income (Y), the price of the alternative (P_i), and a vector of demographic variables (Z). The conditional indirect utility function is typically specified such that net income ($Y - P_i$) is the argument in the utility function involving money: once the choice is made the budget is adjusted to reflect the unit price drawdown (the price of the alternative that was chosen). Note that in the individual choice model, if components of Z do not vary across the alternatives (e.g. a person's gender doesn't change even though a person as alternatives they face change), they only influence choices if they enter the utility function in non-linear form, or when interacted with variables that do vary across alternatives.

With this formulation, the choice data are assumed to flow from a decision process in which the individual maximizes utility (assuming no uncertainty from their perspective) by choosing alternative i ($i \neq j$) when

$$V_i(Y - P_i, X_{ik}, Z) + \varepsilon_i > V_j(Y - P_j, X_{jk}, Z) + \varepsilon_j . \tag{2}$$

Or, alternatively, the probability that an individual will choose alternative *i* is expressed as:

$$\Pr\left[V_i(Y-P_i,X_i,Z)+\varepsilon_i-V_j(Y-P_j,X_j,Z)-\varepsilon_j>0\right] \tag{3}$$

When the errors are Type I extreme value (also known as Gumbel) distributed, the resulting econometric model is the conventional conditional binomial logit (or conditional multinomial logit if there are more than two alternatives). Greene (2003) provides a discussion of the conditional logit (p. 719-721).

Choice Set Design

There are many trade-offs between exact design approaches taken in the experiment (see Viney, Savage and Louviere 2005), and we keep ours as simple as possible, avoiding the use of too many attributes in favor of only a few key attributes that are used to describe a place to live. Choosing on the basis of few attributes is not necessarily inconsistent with rational behavior (Simon, 1995, notes that individuals may use devices to simplify their decisions and that this may be a rational way of making choices), and our design reflects awareness of the relatively different nature of the evacuee sample, as compared to a random sample of the general population.

As stated above, choice set complexity can distort estimates from the models (DeShazo and Fermo 2002). Perhaps the key difficulty in choice-experiment design begins with the fact that one wants all possible combinations considered by people in an experiment, but the number of possible combinations of choice alternatives expands very quickly when more attributes of the alternative are added. The design ideally includes all relevant attributes, or a mis-specification issue in modeling arises, but by including too many, the choice experiment becomes intractable. A related issue is that the attributes must be bundled in such a way as to avoid correlation problems (see discussion in Louviere, Hensher and Swait 2000), leading to what are known as orthogonal designs.

Another trade-off involves how many alternatives the subject must simultaneously evaluate. On one end, the researcher desires presenting each subject with all possible alternatives simultaneously (i.e. instead of choosing between only A and B, the respondent chooses simultaneously between A, B, C, and D). However, ranking or choosing the alternatives becomes an increasingly difficult conceptual task as the number of alternatives increases (Bennett and Adamowicz 2001). If subjects are highly educated (e.g., college students) they might be comfortable with such complex mental tasks. If not, it may be better to find an easier type of experiment. A simpler choice alternative approach is to present each subject with a single pair of alternatives at a time (A and B), let them make a choice between A, B, or neither, then proceed to another pair of alternatives (C and D), etc. Given the relatively low educational attainment level of many of our subjects, we follow this pair-wise choice approach below.

The choice options used in the experiment in this study asked individuals to indicate whether they would prefer location A, location B, or whether "Neither of these choices sounds appealing." The locations were defined by three main characteristics that vary in the provided choice pairs: housing cost, monthly income, and risk of damage from a hurricane (Figure 1). A fourth attribute, which captures the host of other characteristics that define a city, was described to subjects by including text that said: "Weather, culture, dining, entertainment and recreation opportunities [that] are much like New Orleans [or Houston, or College Station.]"

Figure 1. Example Choice Scenario

Please indicate which of the following locations you would choose.

Location A has…	Location B has…
Monthly housing cost (not including phone service) of *$700*	Monthly housing cost (not including phone service) of *$1500*
Each month you and your family would earn, in total: *$5,000*	Each month you and your family would earn, in total: *$2,000*
The Risk of damage from a major hurricane is: *Medium*	The Risk of damage from a major hurricane is: *Medium*
Weather, culture, dining, entertainment, and recreation opportunities are much like: *New Orleans*	Weather, culture, dining, entertainment, and recreation opportunities are much like: *College Station/Bryan*
__ I would prefer to move to location A.	__ I would prefer to move to location B.

This "attribute" becomes a choice or alternative label, which simplifies the experimental design because it is used in lieu of many possible attributes that define each city. Choice models that use alternatives with labels can lead to different results than designs that have no labels (see Blamey, Bennett, Louviere, Morrison and Rolfe 2000), but because of the large number of attributes that might define a city, we felt it best to simplify the design and use a single label. We expected that at least two of these three cities would be familiar to all of the subjects in our sample group, particularly New Orleans, which they evacuated, and their host city of either Houston or College Station. A generic format would have used hypothetical locations that were comprised of all of the important attributes that define a city, and we would not have easily been able to discern whether displaced New Orleans residents would have chosen a “New Orleans” type of alternative, which we were quite interested in discerning.

Although we allowed individuals to opt out of making either choice in the pair offered to them (we feature the “I choose neither” option in addition to each pair offered), we confine our analysis here to the sub-sample who did not do so. Many choice modelers believe that choosing the “neither” alternative can be ambiguous because an individual might simply choose neither to avoid the mental effort required by the fully described alternatives (Swait and Adamowicz 2001). In addition, to fully comprehend the “neither” or opt out choice requires considerable devotion of text and space in the survey to describe exactly what neither is meant to represent (in our case it does not simply always mean the status quo, as some are able to discern the choice to mean).

Researchers who lengthen their survey to fully explain “neither” choices like this might lose subjects who will not spend the extra time to understand this alternative. Therefore, while we allow for non-participation in the two choices each person faces, we focus the empirical analysis on the two fully described alternatives and for these it is possible to estimate the relative weights given to the attributes.

Attributes and Econometric Specification

Each subject was given four choices to make, each involving a single pair of alternatives, and simply asked to choose between the pair given to them. Each pair of alternatives presented has attributes that can vary greatly; with a full factorial design each alternative can be described by the number of attributes and the levels of these. The location choice takes three levels (Bryan/College Station, Houston, or New Orleans). The risk attribute variable has four (none, low, medium and high risk—more is said on this below); income can take eight levels, and housing cost can take seven levels. There are thus 672 combinations of attributes for each location that can be faced in the experiment (3 X 4 X 8 X 7), but these must be squared because there are two location alternatives, so the collective number of combinations is in the thousands, which obviously is not tractable in design. Each person in the experiment faces combinations for their 4 choice/8 alternatives randomly drawn from the full factorial choice set. More efficient designs can be obtained using a variety of methods, each with advantages and disadvantages. These are discussed in Johnson et al. (2006), however, the gains in efficiency are more likely to be forthcoming with larger samples of individuals than we have available here.

The resulting model can be treated as a binomial logit model with two alternatives. If one assumes that errors are type I extreme value the probability of choosing the i^{th} alternative, Pr(i), can be written as:

$$(\Pr ob(i) = \frac{\exp(\beta' X_i)}{\sum_{k=1}^{J} \exp(\beta' X_k)}, \tag{4}$$

where β is a vector of parameters on the variables, X is a vector of variables that explain the individual's probability of choosing an offered alternative, and J is the total number of alternatives (J is the total, as summed over each k^{th} alternative) . In our case, (4) collapses to the simple binomial logit for two alternatives, i.e., J = 2. Note that each person in our sample receives four choice opportunities, or face a pair of alternatives to choose from, four separate times.

Some stated choice modeling researchers have adopted a "short panel" approach as an appropriate way to consider the data instead of using the simple binomial logit specification. The usual econometric panel approach pertains in cases where the data vary across both individuals (cross section) and the response data, akin to the presence of a "time" element t. For example, one might ask a household their income at ten points in time, say two to five years apart. A short panel might only ask them their income two times (t = 1, 2).

The underlying premise of a short panel approach as it is used in stated choice modeling is that there may be a relationship between the unobservables related to the responses that a single person makes when offered four opportunities to make a choice. Following this approach, the model in (4) can be modified to explicitly account for correlation of the error terms between the choice set responses.

The subscript t will refer to the number of the choice set scenario (1st, 2nd, 3rd, 4th) faced by the individual. Panel structures, even when small like this, are increasingly popular in discrete-choice analyses because they allow for the analysis of fixed and random effects of qualitative attributes, and they have been applied in choice modeling (e.g. Anderson, Das and Tyrrell 2006). Suppose the aforementioned conditional model were reformatted to include the subscript t, as well as constant term α_j. Then

$$\Pr\left(V_{jt} \middle| X_{jt}\right) = \frac{\exp(\alpha_j + \beta' X_{jt} + \varepsilon_{jt})}{\sum_{k=1}^{J} \exp(\alpha_k + \beta' X_{kt} + \varepsilon_{kt})}. \tag{5}$$

The assumption of fixed effects (some think it is better called "related" effects) implies that the term α_j is potentially correlated with some or all of the regressors X_{kt}. Thus, an estimation procedure is required that allows for the estimation of this model while eliminating α_j so that it does not have to be estimated for all k alternatives. Such an approach yields consistent estimates of the β parameters.

Alternatively, if one wants to evaluate whether individual-specific heterogeneity exists within the model but this is not correlated with the regressors, then the random-effects approach is appropriate. Let the subscript for the individual be *m*. Rearranging the investigator's error term ε_{it}, into two separate random terms we have:

$$\varepsilon_{it} = \eta_{it} + \gamma_m, \tag{6}$$

where γ_m is the unobserved source of individual-specific heterogeneity (Greene, 2003). Under the random-effects model, γ_m is not expected to be correlated with the alternative (*i*) specific characteristics X_{it} (under the fixed-effects model, γ_m and X_{it} can be related to one another). However, the random-effects model restricts the heterogeneity in the model to be normally distributed, so

$$\begin{aligned}
&\eta_{it} | X \sim N(0,1) \\
&\text{and} \\
&\gamma_{\mathrm{m}} | X \sim N(0,\sigma_\gamma^2). \\
&\text{Then} \\
&\varepsilon_{\mathrm{it}} | X \sim n(0, 1+\sigma_\gamma^2) \\
&\text{and} \\
&Corr[\varepsilon_{\mathrm{it}}, \varepsilon_{\mathrm{is}}] = \rho = \frac{\sigma_\gamma^2}{1+\sigma_\gamma^2},
\end{aligned} \tag{7}$$

where σ_γ is the standard deviation of the unobserved heterogeneity variable and ρ is the correlation coefficient between the error terms for different responses (i.e. different choice questions).

The log-likelihood function for this model is shown in Anderson, Das and Tyrell (2006) and a more detailed discussion of these properties is found in Greene (2003). Using this information, the random-effects model can be estimated using the Gauss-Hermite quadrature approach. The random-effects model differs from the fixed effects version as additional parameters are estimated (α_j, ρ, and σ_γ). A simple test of the appropriateness of the random-effects approach is to test the significance of the parameter σ_γ. Results of the fixed and random-effects models applied to our data are reported in Tables 6 and 7 and will be discussed further below.

Finally, one may question whether the relationship between a single individual's multiple responses is actually between the error terms for each response.[1] It could be argued instead that each time the person receives quite a different pair of alternatives to evaluate, they are in fact facing a different "good." If that is true, then the connection in responses is actually more likely to be in correlations across their tastes for the attribute, which relates to the parameter (the estimated coefficient) on the attribute, not to the error term.

Under this quite different assumption, a random effects model that otherwise assumes fixed parameters should be replaced with a random parameters logit (RPL), or mixed logit model (see Train 1998). In mixed logit or RPL models each estimated coefficient that is assumed random is estimated for each individual in the sample, a distribution for the coefficient is assumed and, thus, one looks for the significance of a standard deviation that is non-zero. A degenerate distribution may collapse to a single point, signifying that the best fitting model involves no distribution (i.e., no variance around the point) and in that case, one may as well use fixed parameters. We note here that we did estimate our choice model using a mixed logit form of the discrete choice econometric model, but were unable to obtain meaningful results in terms of coefficients and the significance of their standard deviations (also see discussion of mixed logit models in the final section, below).

Method

Focus Groups

Focus groups were used to initially test various questions to be used for the experiment, especially with regard to expressing and processing or understanding measures of hurricane risks. Data from focus group subjects are not included in our analysis here, as they received preliminary versions of the survey or only parts of it. Nonetheless, the focus group data were informative. The focus groups revealed that subjects from New Orleans were actually quite mixed in their desire for returning, with some reasons having very little to do with hurricane risk. In fact, some said that they had already been hoping to leave New Orleans for years, but just could not afford to do so. A prominent reason for wanting to leave New Orleans had to do with crime risks. However, others disliked the culture in Bryan-College Station as compared to their home and felt uncomfortable there.

It also became quickly clear from the focus groups that using quantitative measures of risk and related jargon, such as used by statisticians and academics, would be problematic. For example, the word "probability" was discarded from use in the survey instrument because of confusion about its meaning. This is consistent with others' work on risks. For example, Bassett and Lumsdaine (2001) find that 21 percent of their large sample of individuals who take the Health and Retirement Survey provide answers to probability questions that are inconsistent with the laws of probability. As others have done, we substituted the word "chance" in association with the probability of an outcome (e.g., Viney, et al. 2005). We also avoided a design with explicitly allowed complicated interactions between the attributes, though in some cases this may have been desirable.

Experimental Design

The final experimental protocol was designed and implemented using a computer-based survey text that individuals were given in person. Each subject was provided with a laptop computer to answer questions asked them in the survey and was assisted with the technology. A person to monitor the subject, as well as be available for questions about the survey questionnaire, was present during each of the survey interviews. Key questions are explained below.

In this manuscript, we report findings from a quasi-field choice experiment of a group of subjects, most of who were displaced by the 2005 hurricanes, Katrina and Rita. We also include a small group of 25 subjects for comparison purposes. These are people who lived well inland in the state of Texas and were not displaced by the hurricanes, and hereafter designated as the "comparison" group. The sampled group of evacuees is remarkable in that they all were deeply and personally affected by the hurricanes; they were evacuated from their homes and were still away well over a year after the hurricane. The homes of a majority of the evacuee sample were severely damaged and almost a third of them lost a family member in the hurricane. Our research evaluates their risk perceptions and location choices based on a series of options presented to each subject in a choice experiment.

The hurricane evacuees were interviewed at two points in time: once about nine months after the hurricane (Spring 2006 – Round I), and then again, about one year from that initial interview (late Spring and early summer, 2007—Round II). Our hypothesis, as guided by psychological research on risk perceptions, is that perceived risks and willingness to pay (WTP) to reduce those risks fade as time from the hurricane incidents pass. The 25 (35% of 72 surveyed in Round II) members of the relatively unaffected comparison group were interviewed at roughly the same time as the second round of evacuee interviews.

The survey questions presented to respondents during each round of choice experiments is virtually identical, mainly differing in small ways in the survey text because of the dissimilar dates. In the survey respondents take, we first elicit the sample participants' uninformed perceptions of hurricane risk. Such subjective perceptions may be much more informative about behavior than expert or scientific assessments of risks (e.g., Slovic, 1987). During the interview the subjects are repeatedly asked about their assessments of the probability that a hurricane will hit New Orleans (or wherever they evacuated from) in the next hurricane season. Prior to the first in the series of these types of questions, no information is presented to the reader. As more information is provided later, respondents may update their prior assessment of risks if they wish to do so.

For the sample, subjects were recruited in the broader Houston, Texas region. This area includes Bryan/College Station, about 90 miles northwest of Houston. Many displaced residents of New Orleans evacuated to this area. The text of the radio and newspaper advertisements used to recruit subjects asked for people displaced by hurricanes Katrina or Rita to contact investigators at Texas A&M University. All subjects accepted into the study were told they would be paid $50 at each of two points in time for their completed participation in the experiment. The first interview took place in May and June of 2006, approximately seven months after the hurricanes, and following weeks of preliminary focus group analysis. After extensive attempts to advertise and recruit subjects, 78 subjects were recruited yielding 77 usable responses for Round I. A year later we attempted to contact all of the people interviewed in Round I, but as is common, we were only partially successful in retaining all subjects within this transient group. We obtained completed interviews from 47 evacuees in Spring/early summer of 2007, and while not all of these individuals were also in the Round I group, the new individuals were quite similar people to those who were in the original round, as seen below.

The Sample Profile and the Survey Questions

The first round of interviews began with subjects being asked demographic questions including age and income in 2004. Next, they were asked about their life prior to hurricane Katrina or Rita, how long they had lived on the Gulf Coast, under what conditions they left their home, and their losses. Tables 1 and 4 summarize results for the Round I subjects. This pool of subjects is certainly not representative of the average citizen of the United States, but is likely not at all atypical of those who evacuated New Orleans during Hurricane Katrina. Most Round I subjects are African-American/Black (86%); only eight are Caucasian. Most are 21 to 40 years old (55%), and most reported their gross income from all sources in 2004 was fairly low: 60 subjects reported earning $24,999 or less in 2004. Note also that 55 of the subjects did not have insurance against storm damage and that the majority are in fair or poor health (58%).

Subjects lived from less than a year to somewhere between 41 to 50 years on the Gulf Coast, with most having lived there between 5 and 40 years. Most of the subjects (61 of those reporting) did not own their own home when the hurricane hit; twelve subjects said they did own their home. Whether owned or not, the average time spent in the home before we interviewed them was about nine years, with a maximum of 53 years. Of those responding, 68 subjects said they still had relatives in New Orleans or wherever they were when the hurricanes hit the Gulf Coast; only nine said they did not. This indicates close personal ties to the area where they were, presuming the subjects liked their relatives.

Table 1. Demographic Summary: Round I (*n* = 77), Round II (*n* = 47) Comparison (*n* = 25)

Variable	Round I	Frequency Round II	Comparison
Age			
< 21	9	7	1
21 to 30	22	12	7
31 to 40	20	9	3
41 to 50	15	7	7
51 to 60	7	0	6
61 to 70	2	3	1
> 70	1	1	0
2004 Gross income			
< $5,000	16	14	4
$5 to $14,999	29	18	5
$15 to $24,999	15	8	7
$25 to $34,999	8	2	3
$35 to $44,999	3	1	0
$45 to $54,999	1	1	2
$70 to $84,999	1	1	0
> $100,000	2	0	2
Race			
African-American/Black	66	43	4
Caucasian/white	8	3	13
Hispanic	1	1	8
Education			
no high school	4	3	0
some high school	14	9	5
high school graduates	32	16	5
some college	14	12	9
College graduates	3	2	3
post-college	9	0	3
Insurance coverage at time of Katrina			
No	55	36	9
Yes	10	6	15
Health Status			
Excellent	4	13	6
Very Good	14	11	9
Good	10	11	5
Fair	18	6	3
Poor	27	2	0

Note: Some questions were left unanswered so the sum of the frequency may not equal the number of observations

As Tables 2 and 3 show, the Round II group is, on average, quite similar in most ways (racial composition, income, education) to the group in Round I, and in fact, 35 people are the same in each group. Table 2 reports *p* values for two-tailed *t* tests of differences in key variables for all three groups. Round I and Round II groups are quite similar in income, education, and insurance coverage, but not in their self-health rating. This supports the use of the Round II sample in lieu of a perfect match of respondents from Round I, with the exception of health, which may have changed over the time period. In Age, all three groups are not significantly different, but Round I and II members are significantly different from the Comparison group in income, insurance coverage, and health.

Table 2: Differences for Key Variables: Round I, Round II, and Comparison Samples

	Age	2004 Gross Income	Education	Insurance	Health
Round I to Round II	0.50	0.13	0.19	0.84	0.001
Round I to Comparison	0.16	0.07	0.32	0.03	<0.0001
Round II to Comparison	0.46	0.03	0.05	0.07	0.08

* *p* values for two-tailed *t*-tests

A key distinction evident from basic statistics in Table 3 and results in Table 5 is that the Round II group has a lower perceived risk than the Round I group interviewed just after the hurricanes, as we hypothesized might be true (see Baker et al., 2007). The Round II group may have slightly lower income: 32 (68%) of them reported 2004 income of $15,000 or less. It also appears that the Round II group is, on average, healthier, at least in their own or self-rating of health, which could be true as they have settled into their different living situation and recovered from the stress of the storm.

After the basic demographic questions, the subjects were asked several things about New Orleans or the city they left during the hurricanes, including whether they planned to move back to New Orleans or the Gulf Coast. Table 3 reports key parts of this information. It is striking that the large majority of subjects loved (68%) or liked (23%) the home they left. Yet, 52 (68%) of those surveyed indicated that they did not plan to move back. Following these and several specific risk questions, each subject was asked to choose between pairs of locations presented to them. In the next section, we present the key results. From the Round I sample, 21 individuals lost the life of a family member during the storm, and 19 indicated losing a friend. Approximately 2/3 of our Round I sample were forced to leave New Orleans because their home was flooded or destroyed, meaning they did not partake in the official evacuation prior to the storm.

Choice Model Specification and Results

Utility is assumed to be a linear function of net income (Y) less housing costs (C), an indicator level of risk (r) for each alternative (none, low, medium; high risk represents the base case scenario), and indicators for the city bundles or labels "like New Orleans," and "like Houston," respectively:

$$V_i = \beta(Y_i - C_i) + \sum_{k=1}^{K-1} \gamma_k r_{ik} + \alpha_1 NO + \alpha_2 HOU \ . \quad (8)$$

Table 3: Hurricane Losses, Evacuation Reasons and New Orleans Preferences: Round I (*n* = 77) and Round II (*n* = 47)

Variable	Round I Frequency*	Round II Frequency*
Losses Incurred		
Lost Life of family member	21	8
Lost a friend	19	22
Lost a pet	11	14
Lost Home	46	22
Most Important Loss		
Life of family member	23	10
Life of a friend lost	17	8
Pet Lost	9	5
Reason They Left		
Officially Evacuated	25	21
Home Destroyed	21	14
Home Flooded	29	14
Plan to Move Back?	Yes (23) No (52)	Yes (16) No (29)
If Yes, Why?		
To return to family	8	11
To return to job/school	8	5
Because it is home	15	11
How did you feel about the place you left?		
Loved it/didn't want to leave	50	30
Liked ok, didn't plan to move	17	8
Stuck there, didn't like it	6	7

Figure 1 depicts one of the choice scenarios that people face. They also face three others that are similar, but where the attribute levels may vary. For example, after choosing the alternative (A, B, or neither in Figure 1), the respondent then sees the next screen on the laptop, which has at least some attribute levels that differ from those shown in the previous screen.

The verbal risk indicator is somewhat similar to the color schemes for threats currently used at airports in the United States (yellow, orange, etc.) and our use of it might be controversial for some researchers, but in fact the measure of risk to use in hurricane studies is not a trivial matter. First, all quantitative and numerical measures of probability have problems—see the recent discussion of probability information and risk communication by Visschers et al. (2009). In addition, many define "risk" as not only being a probability, but the probability multiplied by the consequences (e.g., Larson,

Table 4: Choice Model Results: Round I Only

Variable	Conditional (Fixed Effects) Logit Model Specification I Coefficient	*t* ratio	Random Effects Logit Model Specification II Coefficient	*t* ratio
Risk Level:				
None	1.09	2.35	1.01	3.76
Low	0.976	2.53	0.940	3.52
Medium	0.696	1.83	0.655	2.55
Net Income (Y-C)	0.00011	3.23	0.0001	2.85
Constant	--	--	-1.09	-3.95
Houston label	-0.004	-2.51	-0.009	-0.04
New Orleans label	0.123	-1.75	0.114	0.54
σ_u	--	--	0.157	
ρ	--	--	0.007	
Maximum likelihood at convergence	-250.82		-341.275	

n = 72; 508 responses

Table 5. Choice Model Results: Round II Only

Variable	Conditional (Fixed Effects) Logit Model Specification I Coefficient	*t* ratio	Random Effects Logit Model Specification II Coefficient	*t* ratio
Risk Level:				
None	0.830	3.86	0.768	2.28
Low	0.945	3.63	0.939	2.58
Medium	0.659	2.68	0.553	1.64
Net Income (Y-C)	0.00017	2.85	0.00016	3.05
Constant	--	--	-0.792	-2.20
Houston label	-0.831	-0.02	-0.777	-2.40
New Orleans label	-0.489	0.58	0.475	-1.72
σ_u	--	--	0.157	
ρ	--	--	0.007	
Maximum likelihood at convergence	-143.79		-199.85	

n = 45; 206 responses

Table 6. Choice Model Results: Comparison Group Only

Variable	Conditional (Fixed Effects) Logit Model		Random Effects Logit Model	
	Specification I		Specification II	
	Coefficient	*t* ratio	Coefficient	*t* ratio
Risk Level:				
None	2.37	3.96	2.11	3.90
Low	1.48	2.04	1.27	2.53
Medium	1.22	2.04	0.95	0.53
Net Income (Y-C)	0.000145	1.60	0.00012	1.40
Constant	--	--	-1.13	-1.98
Houston label	-0.83	-1.84	-0.86	-1.97
New Orleans label	-0.61	-1.43	-0.58	-1.42
σ_u	--	--	0.157	
ρ	--	--	0.007	
Maximum likelihood at convergence	-99.64		-68.88	

n = 45; 206 responses

2009). Thus, with hurricanes, some might think that the ideal risk measure might be the expected damages one might incur with various hurricanes. However, this begs the question of whether and how to include the losses that many view as intangible.

Second, many researchers recommend the use of perceived risks, not science-based measures, but some researchers view perceived risks as being too difficult to obtain and model. As a way around this thorny issue for example, McCluskey and Rausser (2001) use media information on hazards as an instrumental variable that might serve as a proxy for perceived risks. Although not allowing an exact quantitative or numerical risk estimate to be incorporated as a weight for the expected utility function, the experiment was designed to keep the assessments of risk perceptions simple. Thus, although risk is not depicted as a ratio scaled number, the format we used allows for marginal utility difference measures between each categorical risk level.

Note that normally in RUMs, the linear specification of the utility function and the usual data would result in no variation in income across the alternatives an individual faces. As most modelers do, we assume a constant marginal utility of income in (7), however, we offer an income level for each choice, so in our case income does vary for alternative *i* versus *j*.

Most respondents cooperated fully and provided a complete set of item responses. Many respondents were asked to choose between options with the same city label (for example, both A and B are "like New Orleans") but different attribute levels (i.e., risks or income or costs varied). This is plausible, given that any location will have uncertain income and housing cost opportunities in coming years. Most respondents chose locations with less than "high" risk, but some were willing to choose high-risk locations and we can shed light on why they do so using the logit model that controls for all the attributes.

The choice model results for the short-panel logit specifications are presented for each round of interviews in Tables 4, 5, and 6, with the first column containing the fixed effects, and the second, the random-effects model. The first two sets of results (Tables 4 and 5) correspond to our evacuee sample only, while Table 6 provides parameter estimates for the comparison group.

In both panel estimation approaches, the estimated parameters are usually significant and most have expected signs. Higher net income increases the probability of choosing a location. Net income can be thought of as ability to pay, as it factors in potential earnings in the location setting, less the costs of housing. Thus, our results using the stated choice framework are consistent with other studies that find that ability to pay matters in location decisions (e.g. Smith et al. 2006).

All of the indicator variables for risk, which are compared to the default case (i.e., the reference category) of high risk, also have expected signs and significance. This is consistent with our hypothesis that respondents may be willing to sacrifice potential income and cultural amenities for decreased levels of hurricane risk. Moreover, although subjects were sensitive to the hurricane risk level "high," they may have been indifferent when given the choice between low and medium hurricane risk. The fixed effects estimator incorporates some simple algebra to eliminate the constant term, but the random effects model and estimator does not. The negative sign on the constant term in the random-effects model can be interpreted as capturing the effect of the base case of "high" hurricane risk, which is negatively correlated with the probability that one will choose a particular location. The estimated parameter σ_γ in the random-effects model is significant, indicating that the assumption of correlation in the unobservables for the different questions or responses each person makes is valid. Based on this result and the reported log-likelihood values at convergence, the random-effects model is preferred to the fixed-effects model.

In the model for the Round I participants only, the city labels are not significant (note here that Bryan/College Station is the reference category), while in the Round II sample, both the Houston and New Orleans labels are at least weakly significant, and negative. As the Round I participants were interviewed sooner after the hurricane than the Round II participants, the labels might not matter Round I participants' attention was on the other attributes presented in the choices. By contrast, the negative coefficients on the labels in Round II may reflect an adjustment over time to living in Houston and not liking it, living in College Station and liking it, or a weak desire to avoid a New Orleans type of city.

Individuals in both rounds have a significantly higher probability of choosing a location when hurricane risks are none, low, or medium. These results might seem to conflict with Lindell and Hwang (2008), whose more complete investigation of multiple hazards found that expected residence tenure is not significantly correlated to perceived personal risks. However, we are not using perceived risks in the choice model, as we do not have all the needed elicited risks for each location. The estimated parameters suggest that Round II participants are slightly less sensitive to the risk levels in making their choice than Round I participants, though the differences are not all statistically significant. This is consistent with the hypothesis a psychologist would make, and consistent with the aforementioned results that subjective risk perceptions fade over time.

Finally, we also estimated the models for the comparison group, which consists of people who were interviewed at the same time as the Round II participants, were never displaced by the hurricanes, and which on average, have higher actual income. Results for this group are displayed in Table 6. Note that there is the same pattern of relationships for this comparison group as the other two, however, it is interesting to note that the "no risk" coefficient in both the random- and fixed-effects models is about the twice that of the coefficient for either the Round I or Round II sample groups. This indicates a much stronger relationship between having no risks at all, and location choice for these subjects who were never displaced, and who have mostly lived in Bryan/College Station for a long time.

Compensating Variation/Marginal Willingness to Pay

The choice-model coefficients yield the willingness to pay because we include monthly income and housing expenditures as attributes of the alternatives. The decision involves where to live between two given alternatives as a function of net monthly income (income less housing expenditures), risk levels, and the type of city amenities one receives—as indicated by city labels. This is a one-time decision relating to a change in the state of the world (one gets one life in location A versus a life in location B). Assuming no income effects (a constant marginal utility of income, β), the compensating-variation measure of consumer's surplus is equal to the equivalent variation, or the Marshallian consumer's surplus. It can be interpreted as a maximum willingness to pay to bring about an improvement (reduced risk), assuming risk is a "bad." It can be estimated using the log-sum formula:

$$CV = \frac{1}{\beta}\{\ln(\sum e^{V_{ij}^{0}}) - \ln(\sum e^{V_{ij}^{1}})\}. \tag{9}$$

While one could calculate a modified CV with income effects for a state change (see Morey and Rossmann 2007), we report a special case of the marginal WTP for the attribute, which is its coefficient converted to dollars by dividing by the marginal utility of income (using the coefficient on income). In the case of a discrete variable as our risk indicator, the change in risk is equal to one level. Thus, although this is not strictly a marginal change for a continuous variable, it is common practice to report a "marginal" WTP of this nature. In fact, Morey and Rossmann (2007) show that the CV, when there is a state change in the attribute (below designated as q) with no income effects and no price changes, is:

$$CV = \frac{\alpha (q^1 - q^0)}{\beta}, \tag{10}$$

where α is the coefficient on the attribute being considered in the scenario and β is the coefficient on the net income variable. If the change from q^0 (before the change) to q^1 (after the change in state) is equal to one, as is true when dummy variables are involved, then CV is the ratio of coefficient α to coefficient β.

Table 7 reports this marginal WTP for reductions in risk conditions for the Round I, Round II, and Comparison groups. All estimates indicate that, on average, the sample members are willing to pay thousands of dollars to avoid all hurricane risks. The willingness to pay for the Round I sample is roughly double that of the Round II sample, as might be expected if concerns about risks have diminished. Because the net income coefficient is not much different for each round, the difference is driven by the smaller coefficient on the no risk dummy variable for the Round II group.

Table 7: Average Marginal WTP for Risk Scenarios, by Sample*

	Round I Only	Round II Only	Comparison Group
High risk to None	$10,100	$4800	$17,583
High risk to low risk	$9400	$5869	$10,583
High risk to medium	$6550	$3456	$7917
Difference between High to None and High to low	$700	$-1068	$7000
Difference between High to None and High to medium	$3550	$1344	$9667
Difference between High to Low and High to Medium	$2850	$2412	$2667

* With no income effects, the marginal WTP = the compensating variation = the equivalent variation (EV); the maximum willingness to pay for a risk reduction is essentially Marshallian consumer's surplus.

Because the comparison group's no-risk coefficient is twice as large as that for the other groups, they have a higher marginal WTP than the other two groups. The comparison group has a higher average actual income than the other groups, which might be captured in the econometric model indirectly, in several ways. There may also be a premium this group places on being in a safe location.

We have no expectations for how the middle-level risk changes would be ordered in our model. If the framework we used exactly adhered to the strict assumptions that correspond with the expected-utility (EU) model and, in conjunction with that, were we able to quantify risks numerically, then the EU model requires that the WTP for an equivalent risk change be constant throughout the range of risk. The EU model would predict that if reducing risk from high to medium is the same change as from medium to low, then the WTP would be constant. Because we cannot strictly map the risk indicators to quantifiable and numerical estimates of probability, and because we believe subjective risks may be important here, we do not adopt the rigid EU framework.

For the Round II sample, the marginal WTP to reduce risks from high to low is actually larger than what should be a logical higher marginal risk reduction (from high to none). The difference between these WTPs is thus negative. In all other cases the differences are positive, as one would expect, but this one result remains puzzling. Note that the difference between the marginal WTPs going from high to low and high to medium are about the same for all sample groups. Interestingly, however, the comparison group's WTP to move from medium to no risk is nearly three times that of the Round I participants and seven times the WTP for Round II participants. Obviously given our small sample sizes, the statistical significance of these comparisons is weak and the puzzling result may be due to sampling issues, but the results do suggest interesting patterns in WTP for risk reductions that merit further consideration.

Non-EU models (e.g. Riddel and Shaw 2006) may lead to non-constant WTPs, and our results are consistent with that. Note that a frequently observed outcome in laboratory experiments is that WTP may be larger at extremes such as removing all risks, and for the sample groups here, there may be indications that removing all risks get special consideration.

Summary, Further Discussion, and Suggestions for Future Research

The analysis in this paper is based on a sample of people, most of whom were displaced by Hurricane Katrina or Rita in the fall of 2005. We report results from implementation of a stated-choice model involving possible locations that have hurricane risks as their attributes. One might view these location decisions as quite similar to the "tenure expectations" that several researchers have explored (see Lindell and Hwang 2008, who cite others who do this also]. The panel logit models of location choice pairs indicate that a high level of risk significantly and negatively affect the likelihood that a location will be chosen, whereas net income (income less housing expenditures) positively influences choice probabilities. A possible limitation of this choice modeling procedure is that we use verbal indicators of risk, and were not able to closely tie these to perceived risks in numerical terms (see Baker et al. 2009b).

Our categorical hurricane risk levels of none, low, medium, and high remain consistent in these first and second round samples, and the difference in the risk coefficients for the first and second group can be explained by the interpretation that these levels lead to different risk preferences for our subjects at the different points in time. This supports the "closing window of opportunity" notion that, as time passes after a disaster, memories of damage fades, and willingness to pay to obtain protection from that risk decreases.

What is of most interest is that we consider the risks in relation to the implied maximum willingness to pay to reduce that risk. When a sample of evacuees is interviewed almost a year after the first sample, the implied marginal willingness to pay to obtain no hurricane risks falls by about 50% as compared to the first group interview. Our results may be consistent with Lindell and Perry's (2004) protective action decision model (PADM), which suggests that information is combined with experience, stimulating actions, though the choice model used here involves only a small subset of features of the PADM.

To our knowledge, no previous studies have examined the change in WTP related to risk reductions, as time has passed from the risky event. We do not force the restrictive nature of the EU framework within our model, and our WTP results may be consistent with non-EU models, in that they are not constant across risk changes.

We add several caveats and make some suggestions for future work. First, much recent work in stated choice modeling has demonstrated that the results can be quite sensitive to the choice set design (Scarpa and Rose, 2008) With large research budgets, researchers can develop two or more designs, testing the effect of these on key results, but we had no such luxury. For example, one can actually design an initial choice set combination of attributes, their levels, and so on, next estimate efficiency statistics, and then redesign the choice set combinations to achieve higher efficiency. Our orthogonal design was extremely simple, and future similar designs could be easily superior to ours in terms of much greater efficiency in estimating the parameters (see for example, Patil et al. 2009). In addition, some recent investigations into choice set design recommend that the researcher scrutinize the choice set combinations for "implausible" combinations, and discard those which fit this description (Breffle, 2009). We did not do this, largely because of the additional time and effort that would have been needed to investigate what was plausible or implausible, perhaps by doing extensive focus group work with a sub-sample of participants.

We also add a reminder here pertaining to the possibility that a model with multiple responses from the same individual is best approached using a mixed logit (Train, 1998), rather than random effects logit. We tried this approach with no great success, but that approach should be explored in future research involving stated choice modeling. While mixed logit estimation is becoming more common because of the emergence of computer software routines offered in "canned" packages such as *Limdep* and *Stata*, it is still relatively difficult, particularly when one has no intuition about the most appropriate probability distribution that should underlie any particular coefficient or parameter.

Second, many more moderate mitigation efforts or averting behaviors (some call these "hazard adjustments") might be undertaken by people who face hurricane risks, as opposed to the extreme measure of changing residential locations in response to these risks (Burton, Kates and White 1993), so further exploration of the magnitude of risk that triggers an actual move away from a location would be fruitful research. Related to this, a limitation of the study here is that there was not enough time in conducting the survey to explore links between an individual's risk perception and what they would think "low" versus "medium" or "high" risk was. Ideally, one would want to use perceived risk in the state choice model, adjusting econometrically for the fact that perceived risk is very likely an endogenous variable. However, doing so requires a first-step of estimating the variation in perceived risks across people, which is not a trivial task in itself (see for example, Nguyen et al. 2009).

As a last caveat, again we note that using our approach, we cannot, as Lindell and Hwang (2008) do, carefully analyze the full spectrum of possible causal relationships between perceived risk, behavior, and experience. However, our results do also suggest consistency with the possibility that the role of a distinct past experience (being evacuated in the hurricanes) may diminish over time, it will help diminish perceived risks, and finally, reduce the individual's willingness to pay to avoid these risks.

Notes

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