Homeowner Preferences for Post-storm Coastal Adaptation: An Application of Choice Experiments

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Abstract
Choice experiments are used to assess tradeoffs among rebuilding, mitigating, and relocating post-storm along the Gulf Coast. Residents have a strong preference to rebuild post-storm and exhibit considerable negative housing (relocation) utility associated with buyouts (particularly if the land were to be redeveloped rather than turned into a nature preserve). Utility is negative and concave in risk of housing loss, and stated marginal WTP to upgrade mitigation features to reduce risk ranges from $1,404 to $9,659 per year. Total WTP to upgrade property to reduce risk is around $134,000 (57% of pre-storm structure value). Social pressure to accept a buyout (as evidenced by neighborhoods opting for the buyout) decrease the buyout utilities considerably but has no effect on utility of rebuilding.

Key words: coastal; storm; mitigation; retreat; WTP; WTA

JEL codes: D60; D81; D91 ; Q54

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Introduction

Recent hurricanes have revealed the vulnerability of urban development along the Gulf and Atlantic coasts of the United States and its territories. Three of the 2017 storms, Harvey ($132 billion in damages), Maria ($97 billion in damages), and Irma ($82 billion in damages), rank in the top five of the estimated costliest Atlantic Hurricanes, alongside Katrina (2005, $168 billion) and Sandy (2012, $78 billion) (all figures converted to 2019 US dollars using the CPI) (US National Hurricane Center 2018). Coastal vulnerability is accentuated by increasing density of development in risky areas and effects of climate change leading to heightened intensity (and possibly frequency) of North Atlantic tropical cyclones (USGCRP 2017; NOAA 2020b; IPCC 2021). Tropical hurricanes can deliver copious precipitation, violent winds, and devastating storm surge that can threaten life and livelihoods of coastal residents and wreak havoc on coastal buildings and infrastructure, but this threat is intensifying with coastal erosion and sea level rise (SLR) (Gaiha, et al. 2015; NOAA 2020a). Neumann, et al. (2011) estimate mid-SLR scenario (IPCC A1B, 66.9 cm by 2100) would result in *optimal*[1] abandonment of 8,878 km^2 of previously habitable land across the US coastlines (with a low estimate of 6,171km^2 (baseline SLR) and a high estimate of 12,550km^2 (high SLR)). Zachry, et al. (2015) estimate that 22 million people along the US Gulf and East coasts are vulnerable to storm surge flooding (not taking tides or SLR into account).[2]

Policy options for managing coastal vulnerability include structural fortification measures (like dikes, seawalls, and riprap), passive measures to accommodate natural changes (like beach replenishment, shallow sediment deposition, and living shorelines), and organized adaptation (like shoreline retreat [or "transformative adaptation" (Dundon and Abkowitz 2021)], natural system reclamation, and ecological restoration) (Bukic, Smith, and Zhang 2015; Gopalakrishnan, et al. 2016; Roebeling, et al. 2018). While defensive approaches like structural fortification have been widely utilized over the last

[1] "Optimality" conditions are based loosely on Yohe (1995) and are stylized and approximate, at best.
[2] They note, "Florida is the most vulnerable state with 40% of its population at risk" from storm surge.

half-century, there is an increasing recognition that some parts of the coastline are more tenable than others, depending upon a range of factors, like development density, real estate values, and natural forces (Neumann, et al. 2011). Adaptation measures are becoming increasingly policy relevant in many coastal areas.

There is an extensive and growing literature on beach replenishment and other passive erosion-risk and storm-risk management options (Smith, et al. 2009; Landry 2011; McNamara, Murray and Smith 2011; Lazarus, et al. 2011; McNamara and Keeler 2013; Jin, Ashton, and Hoagland 2013; Gopalakrishnan, et al. 2016, 2017; Gopalakrishnan, Landry, and Smith 2020; Jin, Hoagland, and Ashton 2021). Dundon and Abkowitz (2021) provide a recent review of the literature on managed retreat from the perspective of civil engineering. Analysis of shoreline retreat policy, however, has primarily been the focus of local public finance, planning, and legal scholars (Abbot 2013; Siders 2013; Koslov 2016; Binder and Greer 2016; Mach, et al. 2019; BenDor, et al. 2020; Peterson, et al. 2020; Atoba, et al. 2021; Nelson, et al. 2021), with less input from economists (recent exceptions being Robinson, et al. (2018); Frimpong, et al. (2019); Frimpong, Howard, and Kruse (2019); Qing and Davlasheridze (2020)). Our objective in this paper is to contribute to the small but growing literature on coastal residents' willingness to adapt to coastal hazards through hazard mitigation on private property or retreat from hazards through relocation to less vulnerable areas.

After devastating storms strike low-lying coastal areas, there is an opportunity to either upgrade coastal development for improved resilience to coastal risks or to relocate people from threatened shorelines (Kousky 2014). The potential for rebuilding to greater standards of resilience is limited by policy provisions that restrict how insurance claims and other funds can be spent (e.g., flood insurance only funds restoring to previous condition). The ability to move households out of the most vulnerable locations (so-called "buyouts" or other provisions for relocation) raises efficiency problems related to moral hazard (encouraging over-development under expectations of a bail out), can create or exacerbate equity issues, and can suffer from coordination problems (Kick, et al. 2011; de Vries and Fraser 2012; Mach and Siders 2019; Mach, et al. 2019; Dundon and Abkowitz 2021). In this paper, we make use of a stated preference analysis designed to assess coastal residents WTP for post-storm mitigation to their home and their WTA compensation for buyouts that would permit them to move elsewhere.

Our study sites are Mobile and Pensacola Bays in Alabama and Florida, respectively. In addition to eliciting information on subjective risk perceptions (likelihood of hurricane strikes, conditional damage estimates, likelihood of future storm damage), we evaluate tradeoffs associated with building "as was", upgrading structure to be more flood and storm resilient, accepting a buyout from a nature preserve, or accepting a buyout from a developer. We vary out-of-pocket expenses for rebuilding (as a proportion of structure value) and buyout payment (as a proportion of total value [land and structure]), while also permitting variation in the level of risk associated with future location (whether rebuilding or moving). An additional design feature offers random assignment of social pressure, where the survey indicates that the majority of neighbors have elected for one of the four options. This permits some exploration of coordination problems and social influence.

We find that Gulf Coast residents have a strong preference to rebuild post-storm and exhibit considerable negative housing (relocation) utility associated with buyouts (particularly if the land were to be redeveloped rather than turned into a nature preserve). Utility is negative and concave in risk of housing loss over a 50-year time horizon, and stated marginal WTP to upgrade mitigation features to reduce risk ranges from $1,404 to $9,659 per year. Total WTP to upgrade property to reduce risk is around $134,000 (57% of pre-storm structure value). Social pressure to accept a buyout (as evidenced by neighborhoods opting for the buyout) decrease the buyout utilities considerably but has no effect on utility of rebuilding.

Previous Literature

While wave climate, tidal prism, and sediment characteristics largely determine short- and medium-term changes in patterns of shoreline erosion and accretion (Roebeling, et al. 2018), sea level rise (SLR) and periodic coastal storms are the major drivers of long-term dynamics. Taking these forces into account and using simplified heuristics to assess protection measures and abandonment decisions, Neumann et al. (2011) estimate abandonment to result in the loss of between 6,171 km^2 (baseline SLR scenario) and 12,550 km^2 (high SLR scenario) of coastal land through 2100, with total costs (including capital abandonment, land loss, armoring, and beach replenishment) ranging between $49 and $75 billion (presumably 2011 US dollars, discounted at 3%). Gopalakrishnan, et al. (2016) review the geo-economic dynamic optimization models that can provide a framework for assessing adaptation and mitigation decisions when management interventions induce dynamical effects; they note the need for research on benefits and costs of adaptation measures, and they highlight some of the difficulties associated with assessing timing and conditions associated with efficient transition to shoreline retreat (which Mach and Siders (2021) refer to as "transformational adaptation").

Kousky (2014) outlines policy steps that can proactively manage shoreline retreat. She notes that the occurrence of disasters offers on opportunity to implement managed retreat, as destruction of capital creates opportunities for redesign of coastal development and relocation of buildings and critical infrastructure. Key issues in managed retreat include incentivizing homeowners to relocate, coordinating relocation to prevent checker-boarding of development in high hazard areas, addressing loss in property tax revenues, and assuaging moral hazard problems related to over-development to reap returns from buyouts (Kousky, 2014). Analyzing data from eight coastal states, de Koning, et al. (2019) find that households' stated willingness to embrace retreat is motivated by fear of flooding (i.e. affect), but that the occurrence of hazard events can create a catalyst that triggers retreat.

Robinson, et al. (2018) use stated preference methods to analyze factors affecting households' willingness to accept buyouts. They find that the probability of accepting an acquisition offer is greater for those located within a floodplain, with a shorter expected tenure in the home, that have more experience with past hurricanes, and that have lower locus of control. The analysis did not include an offer price, so the results do not include estimates of Willingness to Accept (WTA) compensation for buyout. Further, Robinson, et al. (2018) review the relatively scant literature on buyout acceptance up to 2018; notable findings indicate that the likelihood of accepting an acquisition offer include the importance of place attachment, household costs associated with buyout, household income, whether the respondent believes others would accept the buyout, and perceived environmental benefits. (We direct the reader to their paper for review of older studies and focus our discussion on more recent research.)

Frimpong, et al. (2019) utilize panel data to estimate likelihood of accepting hypothetical buyout offers in eastern North Carolina. They record WTA using an offer price (expressed in percentage terms) menu and gauge WTA before and after a hypothetical storm has "seriously damaged" a respondent's home. They find the average homeowners is WTA 113% of market value before storm damage, but this figure reduces to slightly more than 100% after storm damage. Price elasticity is also lower, post-hurricane. The probability of accepting a given offer price is lower for those further from the shoreline, those with a larger lot size, those with longer tenure in their home, and for non-white homeowners. They also find lower likelihood of accepting a given buyout for homeowners in a floodplain (presumably reflecting amenities (e.g. scenic view and water access) that are correlated with risk).

Frimpong, Howard, and Kruse (2019) utilize a discrete choice experiment to assess coastal homeowners' preferences for retrofitting homes through elevation and accepting buyouts to relocate (relative to a status quo that entails increasing flood insurance premiums). Similar to Frimpong, et al. (2019), they present choices for both before and after experiencing flood damage. They find that the average respondent needs a subsidy of 40% to prefer elevation before damage occurs, but they do not require a subsidy after damage occurred (as long as future flood insurance payments decrease with elevation). Further, they find the average respondent is WTA 118% of home value for a buyout before storm damage, but only 95% after storm damage. Homeowners are more likely to choose elevation when associated costs are lower, when elevation subsidies are greater, and when increases in flood insurance are lower (due to increasing elevation). Likelihood of accepting a buyout is increasing in the offer price and time allowed to vacate the property and decreasing in the time before elapsed before buyout payment is received.

Using county-level federal data, Qing and Davlasheridze (2020) find that buyouts are positively correlated with recent flooding events and heavy rainfall. Moreover, their results suggest that cumulative large-scale flooding augments policy-driven buyouts and autonomous relocation from risky areas. Counties with greater property tax revenues invest more money in buyout programs, all else being equal, while counties that rely more heavily on property tax for local financing invest less money in buyouts. Flood insurance market penetration is negatively correlated with buyouts, as are structural flood protection measures, suggesting that these provisions serve as substitutes for floodplain relocation. Coastal counties exhibit lower levels of buyouts, while counties with greater population densities exhibit greater levels.

Other research indicates that household willingness to relocate away from climate risk is multidimensional, reflecting perceptions of future physical harm and distress, attachment to place, and trust in officials to implement effective and fair retreat policies (Kick, et al. 2011). Studies on implementation of buyouts under FEMA's Hazard Mitigation Grant Program (HMGP) indicate little evidence of policy learning as additional locations experiment with buyouts with little guidance on targeting and implementation from authorities (Binder and Greer 2016; Greer and Binder 2017), a lack of focus on ecological and aesthetic values in designing buyout program objectives (Atoba, et al. 2021), and the existence of participation barriers for middle- and low-income households (Nelson, et al. 2021). Mach and Siders (2021) recommend rebranding coastal retreat as a proactive transformation of vulnerable areas to adapt to climate change; further, strategic retreat should embrace a diversity of policy approaches and seek to integrate across relevant scientific disciplines and address incongruities across various levels of government through development of a holistic vision. Remaining research questions include where those that accept buyouts will move to (Siders 2019), the impacts of climate migration on receiving communities (Dundon and Abkowitz 2021), the potential negative effects of buyouts on local public finance, social and psychological factors that augment or impede adaptation measures (Dundon and Abkowitz 2021), and the role of place attachment as a barrier to strategic retreat (Hanna, White, and Glavovic 2020).

Data

Our study is focused on two estuarine systems in the northern Gulf of Mexico: Mobile Bay, Alabama and Pensacola Bay, Florida. (See Figure 1.) The region is prone to hurricanes and tropical storms, with a long history of landfalls causing significant damage. Our sampling frame focuses on homes within 0.5 miles of each of the bays, as these parcels face significant erosion, flooding, and storm surge risk, and they would be under consideration for strategic buyout initiatives that target high risk areas. A random sample was generated from Google Earth Pro and the county tax assessor websites in 2013 (excluding homes that had sold in the previous 12 months). Postcards inviting participation were dispersed to households; the primary mode was internet survey (website URL included on postcard [with unique login ID]), but paper surveys were subsequently mailed in a follow-up (in addition to those households that requested paper copy), with three addition follow-up postcard reminders as well. The online survey was hosted and administered using Qualtrics Research Suite, which also served as the database for mail-returned surveys. The adjusted response rate was 21% (n=583), with a mean completion rate of 83% and mean completion time of 20 minutes (for the online version).

Descriptive Statistics

Table 1 presents descriptive statistics for the sample. The sample is roughly split in half among Mobile Bay, Alabama and Pensacola Bay, Florida. Each bay is surrounded by two counties, with the following distribution of sample returns: 29% from Baldwin County, Alabama; 27% from Escambia County, Florida; 23% from Santa Rosa County, Florida, and 20% from Mobile County, Alabama. The majority of the sample identifies as white, but there are substantial portions of African American (5%), Asian (2%), and Latino (2%) respondents. Only 1% of respondents identify as Native American. Thirty-three percent of respondents report some college or other professional training, while 26% (28%) indicate college degree (graduate degree) as highest level of educational attainment (leaving 13% with high school diploma or less education). The average respondent is 52 years old with a household income of $90,000 and household size of 2.58. Just under half (46%) of respondents are male, and 43% have children under 16 years of age in their household.

Ninety percent of respondents are homeowners, and they have been living at their current residence for an average of almost 12 years. Seventy-eight percent of parcels are single-family homes. We measure perceived property and structure value using open-ended questions (item response n=505); the average market value of property was $386,597, with an average structure value of $261,540 (2013 US Dollars). Thirty-one percent of parcels are waterfront and the majority of those (21% overall) have some sort of armoring along their shoreline. Regarding future plans and place attachment, 74% of respondents indicated that they plan to “reside in [their] community for years to come”, and 67% indicate that friendships with neighbors in the area are an important part of place attachment associated with local "sense of place".

We next consider personal experience with storms and individual perceptions of risk. Almost 80% of respondents have experienced at least one coastal storm and associated flooding and property damages. Perceived likelihood of future storm damage is measured using a novel survey question designed to assess relative frequency over a long time horizon (while avoiding direct elicitation of probability):

> *"Consider 100 homes in YOUR COUNTY very similar to yours in terms of value, location, and physical risk factors (flood zone, proximity to water, erosion rate, and elevation). How many of these homes do you think could suffer significant damage due to wind, flooding, and erosion over the next 50 years?"*

Recoding of this response (B) as "baseline risk" R = B/100 provides a proxy for expected risk of storm damage over a time horizon that corresponds (roughly) with future coastal habitation.[3] The mean probability is 47%, with a median of 50%. Figure 2 depicts a histogram of baseline risk perceptions derived from this instrument. Note, there is significant weight at the upper limit (certainty of severe damage) and a non-negligible proportion at the lower limit (no chance of severe damage). Perceived consequences of severe hurricane (Category 3 or greater) strike measures expected property damage (expressed as a percentage of structure value). Scaling by perceived structure value provides an estimate of expected damage, which exhibits a mean of just over $151,000 and a median of $80,000.

Choice Experiment

This paper focuses primarily on a choice experiment that allows us to evaluate tradeoffs associated with rebuilding versus accepting a buyout in the wake of a storm. The stated preference scenario asks respondents to consider a hurricane strike that has resulted in total loss of structure. They are faced with four options: (1) rebuilding "as was", (2) upgrading structure to be more flood and storm resilient, (3) accepting a buyout from a

[3] We also measure annual likelihood of hurricane strike using an expected count of hurricanes (Category 3 or greater) making landfall in near vicinity of the respondents' community over the next 50 years.

nature preserve, or (4) accepting a buyout from a developer. We vary out-of-pocket expenses for rebuilding (as a proportion of perceived structure value) and buyout payment (as a proportion of perceived total property value [land and structure]), while also permitting variation in the level of risk associated with future location (whether rebuilding or moving). Table 2 presents a schematic of the choice experiment design.

Risk associated with upgrading varies within the choice set by experimental design. The residual risk associated with upgrading the building pivots off the baseline perceived risk, taking the levels $0.5\times R$, $0.75\times R$, or $0.95\times R$. The costs of rebuilding (net of insurance payment and other assistance) are expressed as a percentage of current structure value, taking the levels of 0.01, 0.03, 0.05 and 0.07, for rebuilding "as was" and 0.075, 0.1, 0.125, and 0.25 for rebuilding with an "upgrade" that will reduce risk. Importantly, the rebuilding costs shown to the subjects were the total amount that would be personally responsible for, (proportion)×(structure value), using perceived structure value. Subjects were told that low-interest loans would be available to fund rebuilding. The proportion of costs for rebuilding and upgrading were chosen to encompass a likely range of out-of-pocket cost for households that are insured or likely to receive some form of disaster assistance.

For buy-out options, residual risk is determined by subsequent relocation choice, while buyout payment varies as a proportion of total property value, taking levels of 0.7, 0.85, 1.0, and 1.1. We take two approaches to analyzing buy-out choice. For the first, we set risk equal to zero, realizing that we cannot know precisely what level or risk the household would face without know the details of their relocation choice. The survey data, however, does include queries into moving intentions if each subject were to accept a buy-out. For the second approach to assessing residual risk, we can utilize this information (with additional assumptions). The relevant question is:

After accepting a buy-out, where will you mostly likely move to?

1. *A coastal waterfront property along the Gulf Coast*
2. *A coastal waterfront property elsewhere*
3. *An inland waterfront property (e.g., lake or river)*
4. *A coastal, but non-waterfront property along the Gulf coast (coastal counties).*
5. *A non-waterfront property elsewhere.*
6. *Other ___________________*

Figure 3 presents a histogram of stated intentions for relocation after accepting a buy-out (with numbers corresponding to the above question). The following convention was utilized for assessing residual risk (though this assumption is subsequently subjected to sensitivity analysis): relocation options (1) and (2) are assigned 95% of the baseline risk associated with building "as was"; option (3) was assigned 10% of the baseline risk; option (4) was assigned 20% of baseline risk; and options (5) and (6) were assigned 5% of baseline risk. The assumptions will be subjected to sensitivity analysis.

An additional design feature offers random assignment of peer effects, where the survey indicates that the majority of neighbors have elected for one of the options. The treatments were defined as:

- *Treatment 1: As you consider these options, consider the following: Imagine that the majority of your neighbors have indicated that they will rebuild their house, as it was, in their current location.*
- *Treatment 2: As you consider these options, consider the following: Imagine that the majority of your neighbors have indicated that they will rebuild their house in their current location, but they will upgrade their dwelling to lower risk.*
- *Treatment 3: As you consider these options, consider the following: Imagine that the majority of your neighbors have indicated that they will accept the buy-out and relocate their family.*

Treatments were randomly assigned to roughly one-quarter of the sample, with the remaining quarter serving as control This permits some exploration of coordination problems and peer influence.

The choice experiment was designed using a fractional factorial algorithm in SAS. While there are some existing estimates of preference parameters in the literature, we did not feel there was enough information available to employ Bayesian design methods. We utilized standard algorithm to design an efficient fractional factorial of size 48 and blocked the choice sets into 24 groups of 2.

Methods

We specify household utility as a function of location-specific housing services and consumption of a numeraire good. At the time of deciding to rebuild or accept a buyout, the household formulates expectations of the utility of housing consumption under different scenarios, assesses the level of risk, and evaluates the costs of rebuilding (c) and the buyout payments (p) as changes to expected net income $\left(\frac{Y-H}{r}\right)$ – a proxy for numeraire consumption/wealth over the time horizon of housing consumption (where H is property rental payment and r is the discount rate). Utility of housing is composed of a fixed effect, α_h, and risk of housing loss due to storms, flooding, and erosion (R). Consider two state-contingent utilities:

$$V_{rb} = \alpha_{rb} + \theta R + \theta_2 R^2 + \mu_{rb}\left(\frac{Y-H}{r} - c\right) \tag{1}$$

$$V_{bo} = \alpha_{bo} + \theta R + \theta_2 R^2 + \mu_{bo}\left(\frac{Y-H}{r} + p\right), \tag{2}$$

that vary over utility of housing consumption, risk, and the marginal utility of income, μ_h, for rebuild=*rb* and buyout=*bo* scenarios. The parameter α_{rb} represents fixed components of housing utility (whether rebuilding "as was" or upgrading to reduce risk); the parameter α_{bo} is the expected utility effect of accepting a buyout and relocating, net of psychic search and moving costs. Since the household had not previously chosen to move from their current location, we expect this parameter to be negative. The parameters $\theta < 0$ and $\theta_2 > 0$ define the marginal utility of risk (recognizing the lack of formal structure for risky decision making [i.e., expected utility; prospect theory] and where the sign conventions are expected [but not imposed]). The distinction between rebuilding and accepting a buyout involves non-marginal consumption changes, such that we expect the marginal utility of income will differ across scenarios (1) and (2). Further, note there are two options associated with utility (1) and two options associated with utility (2) in our choice sets.

The baseline risk associated with rebuilding "as was" is defined by subjective perceptions of storm damage to respondents' current home over a 50-year time horizon. As described in the previous section, changes to risk for the rebuilding scenario are defined by the choice experiment design, while risk associated with buy-out are inferred from subsequent location choices and are defined under a set of labile assumptions. Costs for rebuilding and payments for buy-outs are set by choice experiment design but are scaled according to assessed levels of structure (net of land) and property value (including both land and structure).

Econometric Model

The Random Utility Maximization (RUM) model provides the empirical basis for our discrete choice analysis (as is standard in the economics literature). As such, we append an error term on the utilities in (1) and (2) to specify an econometric model:

$$U_{nht} = V_{nht} + \varepsilon_{nht} \tag{3}$$

where V_{nht} is the deterministic portion of utility (depicted in (1) and (2)) that depends upon explanatory variables contained in the choice experiment for respondent (n) associated with choice (h) on occasion (t), and ε_{nht} is a random variable following a type I extreme value distribution (McFadden 1974). Since the random error is unobserved by the researcher, we specify the probability of a particular choice in the data as:

$$\begin{aligned} \Pr(choice = h) &= \Pr\,(V_{nht} + \varepsilon_{nht} > \ V_{nkt} + \varepsilon_{njk}) \text{ for } \forall\ k \ \neq h \\ \Pr(choice = h) &= \Pr\,(\varepsilon_{nkt} - \varepsilon_{nht} < \ V_{nht} - V_{nkt}) \text{ for } \forall\ k \ \neq h \end{aligned} \tag{4}$$

The difference in Type I extreme random variants is distributed logistic, so the logit model can be used to estimate these probabilities. Ignoring the panel dimension of the data (repeated choices by each respondent), we can recover representative parameters for the utilities in (1) and (2) by estimating the standard multinomial logit model (AKA "conditional logit" in the literature):

$$\Pr(choice = h) = \frac{\exp\,(x'_{nht}\beta_h)}{\exp \sum_{k\epsilon\mathbf{C}}(x'_{nkt}\beta_h)}, \tag{5}$$

where β_h represent marginal utilities of the rebuild/buyout options that are implicitly normalized by the scale of the error term in (3) (assumed equal to one in the basic multinomial logit model). Estimation of equation (5) permits exploration of basic parameters of choice for rebuilding and relocation decisions, but does not incorporate individual heterogeneity in preference or scale parameters, utility differences across options (e.g., buyout from a developer vis-à-vis a nature preserve), experimental design on peer effects, or potential endogeneity of risk perception (correlation with individual-specific unobservables) or cost/ payment levels (due to functional dependence on housing value). We use estimates from (5) as a baseline for further modeling decisions.

Generalized Multinomial Logit Model

We introduce heterogeneity via the Generalized Multinomial Logit model, which permits both utility and scale parameter heterogeneity, while nesting several common forms of choice models (Fiebig, et al. 2010; Gu, Hole and Knox 2013). Introducing utility parameter heterogeneity, we can employ the Mixed Multinomial Logit (MMNL) model which provides a flexible specification for parameters for population moments as:

$$\beta_h = \bar{\beta}_h + \eta_{hn}, \tag{6}$$

where $\bar{\beta}_h$ represents the mean parameters for rebuild/buyout options, and η_{hn} represents random draws from a pre-determined distribution for each respondent *n*. When η_{hn} is either not specified or not statistically significant, one interprets marginal utility parameters as fixed. Alternatively, we can introduce scale heterogeneity by specifying population moments as:

$$\beta_h = \bar{\beta}_h \sigma_n, \tag{7}$$

where σ_n represents heterogeneous scale around a common mean preference parameter $\bar{\beta}_h$. This represents a Scale Heterogeneity Multinomial Logit (SHML) model.

The Generalized Multinomial Logit (GMNL) utilizes a mixture of these approaches to parameterizing heterogeneity:

$$U_{nht} = [\sigma_n \beta_h + \gamma \eta_n + (1-\gamma)\sigma_n \eta_{hn}] x_{nht} + \varepsilon_{nht} \tag{3'}$$

where $\gamma \in [0,1]$ is a weighting parameter that can be set equal to zero or one to specify a particular form of model or can be freely estimated (Fiebig, et al. 2010; Gu, Hole and Knox 2013). Summing over *N* subjects, simulated log-likelihood function (SLL) is the product of *T* choice occasions composed of *H* options, and is given by:

$$\text{SLL}= \sum_{i=1}^{N} \ln \{\tfrac{1}{R} \sum_{r=1}^{R} \prod_{t=1}^{T} \prod_{h=1}^{H} \Pr\,(choice = h|\beta_{ih}^{[r]})^{y_{iht}}\} \tag{8}$$

where:

$$\Pr(choice = h|\beta_{ih}^{[r]})^{y_{iht}}) = \frac{\exp\,(x'_{nht}\beta_{ih})}{\exp \sum_{k \epsilon \mathbf{C}} (x'_{nkt}\beta_{ih})},$$

$$\beta_{ih}^{[r]} = \sigma_i^{[r]}\beta_h + \{\gamma + \sigma_i^{[r]}(1-\gamma)\}\eta_i^{[r]},$$

$$\sigma_i^{[r]} = \exp\,(\bar{\sigma} + \theta z_i + \tau v^{[r]}).$$

$\eta_i^{[r]}$ are generated using Halton (1964) draws to simulate the distribution of β_{ih}, and $v^{[r]}$ are generated using pseudorandom draws from truncated Normal model ($\pm$ 2) to simulate the distribution of σ_i (Gu, . (Truncation of the Normal distribution avoids draws from the tails, which tend to result in underflows or overflows in exponentiation (Fiebig, et al. 2010).) The joint distribution of β_{ih} and σ_i is evaluated by averaging over the $[r]$ draws. The GMNL permits scale heterogeneity to condition on individual factors z_i. Rather than treat γ as a free parameter, which sometimes gives risk to convergence problems, we employ a one-dimensional grid search to evaluate the optimal value of γ.

Empirical Specifications

Explorations of the specifications in (1) and (2) suggest the alternative specific constants (rebuild, buyout-nature preserve, buyout-developer) should be treated as both randomly distributed and scale heterogeneous. This finding is at odds with recommendations of Fiebig, et al. (2010); they suggest that random utility parameters are often appropriate for alternative specific constants, but less so with scale heterogeneity. Introducing scale heterogeneity, however, can be very effective in capturing lexicographic preferences, when one or more attributes may be much less important in assessing utility. In our context, the alternative specific constants have potential to be lexicographic for some respondents. Thus, it's not surprising that this specification appears to fit the data. On the other hand, we find little evidence of coefficient or scale heterogeneity for risk, rebuilding cost, or buyout payments. We estimate both linear and exponential WTP/WTA Generalized Multinomial Logit choice models.

A priori, we are concerned about potential endogeneity in risk, rebuilding costs, and buyout payments. Risk perceptions are often difficult to measure, but latent constructs of risk perception are likely correlated with unobserved, agent-specific factors. Recent research (Lloyd-Smith, et al. 2018) has demonstrated that perceptions of risk in other domains can serve as instruments in empirical analysis. For rebuilding costs and buyout payments, attribute levels pivot off baseline structure and total property values. These baseline levels are likely endogenous, and it is not clear if the experimental design is sufficient to render the costs and payments exogenous in the empirical models. We explore Hausman-type instruments, in the form of price levels in neighboring counties at the time of purchase.

Economic Welfare Analysis and Treatment Effects

Once we have recovered econometric estimates, we can estimate marginal WTP for risk reduction, peer effects on rebuild/buyout choice, WTP for rebuilding "as was" or upgrading to reduce risk, and WTA a buyout from a nature preserve or a developer. Annual marginal WTP for risk reduction is given by:

$$MWTP_{Rh} = \frac{\theta + 2\theta_2 R}{\mu_h} \times r, \tag{9}$$

where $\theta + 2\theta_2 R$ is the first derivative of risk level, μ_h=μ_{rb} for rebuilding scenarios, μ_h=μ_{bo} for buyout scenarios, and *r* is the discount rate. (We utilize 2% and 4% in estimating MWTP.)

Given random assignment, treatments effects can be assessed as the change in the probability of choosing a particular option conditional on being treated. Thus, we estimate the impact of the peer effects treatments as:

Pr(choose option h|social pressure=1) - Pr(choose option h|social pressure=0)

$$\text{Social Pressure Effect} = \frac{\exp\,(\tilde{x}'_{nht}\beta_h)}{\exp \sum_{k \epsilon \mathbf{C}} (\tilde{x}'_{nkt}\beta_h)} - \frac{\exp\,(x'_{nht}\beta_h)}{\exp \sum_{k \epsilon \mathbf{C}} (x'_{nkt}\beta_h)} \tag{10}$$

where $\tilde{x}_{nht}$ represents the coefficient vector with "social pressure" turned "on" (treatment) and x_{nht} is the coefficient vector with "social pressure" turned "off" (control). Impacts on Willingness to Pay can be assessed by incorporating treatment effects into the following analysis on estimation of Total Willingness to Pay (TWTP).

To estimate the economic value of rebuilding or accepting a buyout, we consider TWTP for each scenario. In our application, estimating TWTP is complicated by the differences in marginal utility of consumption across states (specifically, rebuild and buyout) and non-linearity in income introduced by the exponential WTP model. To estimate Willingness to Pay for rebuilding and Willingness to Accept a buyout, we build upon equations (1) and (2) and invoke Small and Rosen (1981) and Hanemann (1982) to define:

$$E(MaxU_n) = ln \left(\begin{array}{c} \sum_{h \in rb} \exp\left(x'_{nh}\beta_h + \mu_{rp}\left(\frac{Y-H}{r} - c\right)\right) \\ + \sum_{h \in bo} \exp\left(x'_{nh}\beta_h + \mu_{bo}\left(\frac{Y-H}{r} + p\right)\right) \end{array} \right) + C \quad (11)$$

where $E(MaxU_n)$ is the expected value of maximum utility associated with a given choice set, and C is the constant of integration. Since the marginal utility of income is not constant across choices, the $\mu_h$parameter is not easily eliminated from the TWTP calculation (nor is expected net consumption $\frac{Y-H}{r}$). For the utility function that linear in income, we define compensating variation (CV)/WTP for rebuilding/buyout option h implicitly as:

$$E(MaxU_n) = ln \sum_{j \neq h} e^{V_j} e^{\mu_j WTP_n}, \quad (12)$$

where V_j are the utilities given in (1) and (2), but summed over all options other than h (Hanemann 1982). Using the approximation $e^z \cong (1+z)$, we can show:

$$\sum_j e^{V_j} = \sum_{j \neq h}(1 + \mu_j WTP_n)e^{V_j}$$

yielding the approximation:

$$WTP_{hn} = (\sum_j e^{V_j} - \sum_{j \neq h} e^{V_j}) / \sum_{j \neq h} \mu_j e^{V_j} \quad (13)$$

which for the case of eliminating choice option h simplifies to:

$$WTP_{hn} = e^{V_h} / \sum_{j \neq h} \mu_j e^{V_j} \quad (13')$$

Note, each utility includes income effects (μ_h) and expected net consumption ($\frac{Y-H}{r}$), which is not typical in RUM models. This complication arises due to the long time horizon over which housing consumption is defined. The approximation in equation (13) is reasonably good in the range of $V_h \in [-1,1]$, but deviates from the true value increasingly as the range of fitted utilities moves away from the boundaries on this range. Other numerical approximations are available, which will be explored in future analyses.

Results

Table 3 presents conditional logit model results for the basic RUM models (equation (5)) presented in equations (1) and (2). Standard errors are clustered at the individual level. Rebuild "as was" is the excluded category; results indicate a positive housing consumption utility associated with upgrading the property to reduce risk and negative housing consumption utility associated with the buyout option. Further, we find a decreasing and concave effect or risk of housing loss on utility. The cost and Ln(cost) coefficients are negative (as expected), but not statistically significant. The payment and Ln(payment) coefficients are positive (as expected), but not statistically significant. We next consider the Generalized Multinomial Logit that takes account of the (quasi-) panel dimension, permits heterogeneity in choice parameters, and allows the scale of the error to vary with individual characteristics.

Table 4 presents mixed multinomial logit models results (equation (8)). Based on experimentation and model comparison, we specify housing utility parameters as random (differentiating between buyout utilities associated with nature preserve and developer), correlated, and having scale heterogeneity that varies with connection to place ("friendship" – a dummy variable indicating that friendships with neighbors in the area are an important part of place attachment associated with local "sense of place") and household income. We found little evidence in support of specifying risk or cost/payment as random coefficients or having variability in scale.

Similar to the basic RUM model results, we find positive utility associated with upgrading and negative utilities associated with buyouts. The relative magnitude of upgrade utility to buyout utility, however, is larger; whereas the mean of rebuild housing utilities are around 1.4 (2.9) in magnitude in the linear (exponential) WTP model, mean buyout utilities are around -1.7 to -2.8 (-23.9 to -25.2) for the linear (exponential) WTP model, with developer always being more negative (though differences are not statistically significant). Variance-covariance estimates for the housing utilities are presented in Table 5. There is significant variation in upgrade utilities, indicating that a portion of the distribution would fall in the negative region for both the linear and exponential WTP models. But, there are distinct differences in variability in buyout utilities across the models. (Figures 5 and 6 present the distribution of housing utilities for the Linear and Exponential WTP, respectively.) The variability in nature buyout utilities includes a much larger portion of negative values for the linear WTP relative to the exponential WTP model. Developer buyout utilities, however, are more tightly bound around negative values for both models. All housing utilities are positively correlated. Regarding scale heterogeneity, the variance of the error is increasing in both place attachment (as measured by “friendship” ties) and income. The relative value of the tau parameter indicates greater variability in the Linear WTP model relative to Exponential WTP.

Parameters for the experimental design component indicate that buyout utilities are ameliorated somewhat by social pressure, significantly increasing the negative buyout utilities. For the Linear WTP model, the treatment effect of 2.37 is large enough to change the sign of the negative nature buyout parameter and shift the distribution of developer buyout more into the positive range. The results are less pronounced in the Exponential WTP model. Social pressure treatment has no effect for rebuild “as was” or upgrade. Both risk measures exhibit negative and concave relationships in the utility function ($\theta < 0$ and $\theta_2 > 0$ in equations (1) and (2), as expected). Figure 7 depicts the marginal utilities for the two models. All marginal utility of net income/consumption estimates are statistically significant (at the 5% level for the Linear WTP model, 1% level for the Exponential WTP model). The marginal utilities differ by an order of magnitude for rebuilding relative to buyout: 0.02 (rebuild) compared to 0.004 (buyout) for the Linear WTP model, but 0.86 compared (rebuild) compared to 4.32 (buyout) for the Exponential WTP. The switch in relative magnitudes will have significant impacts on welfare analysis.

Table 6 presents average annual marginal WTP for one-unit reduction in risk of housing damage (from the mean annual subjective risk perception of 13.5%). Ninety-five percent confidence intervals are presented in parentheses. Across all models, WTP is greater for the buyout scenario relative to rebuilding. The Linear WTP estimates are less precise and significantly larger in magnitude, ranging from $4,214 to $45,547 (not plausible). The Exponential WTP estimates appear much more reasonable, ranging from $1,404 to $9,659. The latter estimates are significantly different from zero at the 10% level, but the 95% confidence intervals include a small number of negative values in the lower tail.

Turning to estimates of WTP to rebuild post-storm, we find average total WTP (net of insurance and/or assistance) of $17,629 to rebuild “as was” and $134,029 to upgrade to reduce risk by an average of 23.5 “points” (reducing baseline risk from 34.7% to 11.2%). These correspond to about 6.7% and 57% of average perceived structure value. We have yet to estimate WTA buyouts, nor have we been able to compute confidence intervals for Total WTP.

Discussion

Original theoretical and econometric formulations of Random Utility Maximization explored a wide array of qualitative consumption choices (McFadden 1974; Hanemann 1982; McFadden 1984). While most straightforward applications involve choice among ordinary consumer products, subsequent research has embraced extensions of the framework to assess labor choices (e.g., Kornstad and Thoresen 2007; Rao, et al. 2013), housing markets and location choice (Börsch-Supan and Pitkin 1988; Yates and Mackay 2005), and other goods with distinctive features that require modification to the standard approach. In our application, modeling rebuilding or selling of a home represent distinct choice options with long time horizons that are likely to violate the Independence of Irrelevant Alternatives (IIA) assumption, give rise to differences in the marginal utility of consumption across choices (particularly rebuild v. buyout), and create potential problems stemming from endogeneity of subjective risk perception of monetary payments for rebuilding or buyout that are based on property values.

We utilize the Generalized Multinomial Logit Model to permit preference and scale heterogeneity in our empirical choice model, which we find exclusively affects the housing utility fixed effects associated with rebuilding or buyout (nature preserve v. developer); empirical results support treating risk parameters and marginal utility of consumption as fixed. Realizing the complexity of multidimensional risk perceptions that reflect subjective assessment of physical harm, distress, displacement, and place attachment (Kick et al. 2011), we employ a survey instrument to measure subjective risk of housing loss, attachment to place, and other relevant factors. We further assess moving intentions (in the event of a buyout) to provide some information on residual risk after relocation (Greer and Binder 2017; Siders 2019). Given that our choice experiment is based on status quo risk perceptions and property/structure value, the design is similar to a pivot design (where attributes are expressed as changes from a baseline level that varies by respondent) but with a branding application that dictates risk (rebuild “as was” or upgrade) or residual use of abandoned coastal property (nature preserve or re-developed).

Overall, our stated preference results indicate that residents of Mobile and Pensacola Bays have a strong preference to rebuild post-storm, and we find considerable

WTP to upgrade mitigation features to reduce future risk. Considering the Exponential WTP model (which exhibited best fit), we find the distribution of the utility for upgrading is almost (but not entirely) in the positive domain, while the utilities for buyout from nature preserve and developer are entirely in the negative domain (see Figure 5); the variance of developer buyout is much smaller, putting the mass for this option more heavily in the negative domain. Buyout utilities are affected by the social pressure treatment, shifting the means significantly in the positive dimension, but rebuild utilities are not.

Utility is decreasing and concave in risk of housing loss (see Figure 7). Empirical estimates suggest annual marginal WTP for reduction risk by one-unit to range from $1,404 to $2,808 for the rebuilding scenario and $4,829 to $9,659 for the buyout scenario (Exponential WTP model using discount rates of 2% and 4%, respectively). Estimates of total WTP for rebuilding suggest significant economic value in upgrading to reduce risk: mean TWTP of $134,029 (or 57% of structure value) relative to $17,629 (or about 7% of structure value) to rebuild "as was". This comparison is associated with average risk reduction of 23.5 percentage points (reducing baseline risk from 34.7% to 11.2% chance of housing damage over 50 years). Given the difference in marginal utility of consumption parameters across rebuild and buyout, we haven't yet been able to estimate average WTA buyout. This remains an important area for future work.[4] In addition, we plan to explore the use of control functions to assess endogeneity of risk perceptions and cost/payment levels.

Conclusions

There is considerable inertia that promotes rebuilding in hazard-prone locations after a disaster (Greer and Binder 2017). Incentivizing risk mitigation and relocation in the face of climate change is an important social and policy consideration, particularly along vulnerable coastlines. To date, "managed retreat projects have been largely incremental, minor adjustments implemented using a handful of policy tools, guided by a limited set of

[4] The procedure for estimating TWTP is based on a linear approximation to the exponential distribution. This is one source of error/difficulty. In addition, because the marginal utility of consumption is not constant across options, expected net consumption (the covariate from or to which payments are made) does not cancel out of TWTP expressions. Future research will explore different ways to recover WTP and sensitivity to necessary assumptions.

social values, and small scale in their contributions to climate change adaptation" (Mach and Sliders 2021). We contribute to the literature by employing a choice experiment that is designed to assess tradeoffs among rebuilding, mitigating, and relocating. We find evidence that Gulf Coast residents have a strong preference to rebuild post-storm, exhibit considerable negative housing utility associated with buyouts (particularly if the land were to be redeveloped), have considerable stated WTP to upgrade mitigation features to reduce future risk, and exhibit negative and concave utility in risk of housing loss. Further, results of our experiment suggest that social pressure to accept a buyout (as evidenced by neighborhoods opting for the buyout) decrease the buyout utilities considerably. Important questions about coastal adaptation remain, nonetheless, including optimal timing and execution of buyouts (Nelson, et al. 2021), how property liquidations with "rent-backs" from state agents might facilitate retreat (Keeler, et al. 2022), the diverse roles of place attachment in decisions to move (Dundon and Abkowitz 2021), and how to remove participation barriers for low- and middle-income neighborhoods (Nelson, et al. 2012).

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Table 1: Descriptive Statistics – Mobile and Pensacola Bays

	n	Mean/Prop.	SD
State:			
Alabama	583	.49	
Florida	583	.51	
County:			
Mobile (Alabama)	583	.20	
Baldwin (Alabama)	583	.29	
Escambia (Florida)	583	.27	
Santarosa (Florida)	583	.23	
Race/ethnicity:			
white	583	.87	
black	583	.05	
native	583	.01	
asian	583	.02	
latino	583	.02	
Education:			
some_college	583	.33	
bachelor	583	.26	
graduate	583	.28	
Other:			
age	547	52.69	17.41
inc	502	90.15	73.24
male	578	.46	
hh_num	574	2.58	1.59
children	555	.43	.83
years_home	570	11.65	10.63
own_prop	583	.90	
sfh	583	.78	
house_value	505	$261,539.81	$438,433.02
prop_value	505	$386,597.49	$525,633.80
waterfront	583	.31	
shoreline_armor	583	.21	
plantoreside	583	.74	
friendship	583	.67	
storm_exp	583	.79	
prob_cat3	535	.15	
damage_cat3	536	41.84	25.08
prob_damage	484	.48	.31
like_assist	461	.37	.31

Table 2: Choice Experiment Design

Option	Location	Risk	Cost
Rebuild 'as-was'	Stay in current location	Baseline risk: likelihood of loss R = B/100 over the next 50 years	(0.01, 0.03, 0.05, 0.07)×(structure value)
Rebuild, but upgrade	Stay in current location	Lower risk: .5× R; .75× R; .95× R	(0.075, 0.1, 0.125, 0.25) × structure value)
Accept 'buy-out' from Nature Organization: surrounding land will be dedicated to nature preserve w/ public access	Move somewhere else	Risk determined by location choice	Household receives: (0.7, 0.85, 1.0, 1.1) × property value)
Accept 'buy-out' from Real Estate Developer: surrounding land will be redeveloped for residential housing	Move somewhere else	Risk determined by location choice	Household receives: (0.7, 0.85, 1.0, 1.1) × property value)

Table 3: Conditional Logit Models for Rebuilding/Relocation

	Linear WTP	Exponential WTP
upgrade	0.6891***	0.8126***
	(0.1347)	(0.1665)
buyout	-0.6118***	-1.2262**
	(0.2111)	(0.6224)
risk	-2.4951***	-2.5681***
	(0.9140)	(0.9146)
risk^2	2.0179**	2.0779**
	(0.8313)	(0.8314)
cost	-0.0015	
	(0.0029)	
pay	0.0002	
	(0.0003)	
Ln(cost)		-0.1141
		(0.0848)
Ln(pay)		0.0901
		(0.1195)
Observations	3512	3512
Standard errors in parentheses		
="* p<0.10	** p<0.05	*** p<0.01"

Table 4: Generalized Multinomial Logit Models for Rebuilding/Relocation

	Linear WTP	**Exponential WTP**
cost	-0.0217**	
	(0.0103)	
pay	0.0040**	
	(0.0018)	
risk	-5.8543*	-8.4152**
	(3.1917)	(4.1198)
$risk^2$	4.7245*	6.5194**
	(2.7065)	(3.3089)
aswas_sp	0.5660	0.6271
	(0.7116)	(0.7631)
upgrade_sp	0.1476	0.3096
	(0.7228)	(0.6792)
buyout_sp	2.3703*	4.3164***
	(1.4281)	(1.6117)
upgrade	1.4192**	2.9453***
	(0.5817)	(0.6532)
buyout_nature	-1.7146*	-23.7921***
	(0.9786)	(6.6882)
buyout_develop	-2.8944**	-25.2516***
	(1.1465)	(6.7402)
Ln(cost)		-0.8645***
		(0.2428)
Ln(pay)		4.3251***
		(1.1461)
Heterogeneity		
friendship	0.4050**	0.1273***
	(0.1932)	(0.0389)
income	0.0027*	0.0011***
	(0.0014)	(0.0003)
Tau		
Constant	0.3328*	-0.1271***
	(0.1990)	(0.0183)
SLnL	-841.66433	-820.2526
AIC	1721.329	1678.505
BIC	1836.34	1793.517
Observations	3144	3144

Standard errors in parentheses
="* p<0.10 ** p<0.05 *** p<0.01"

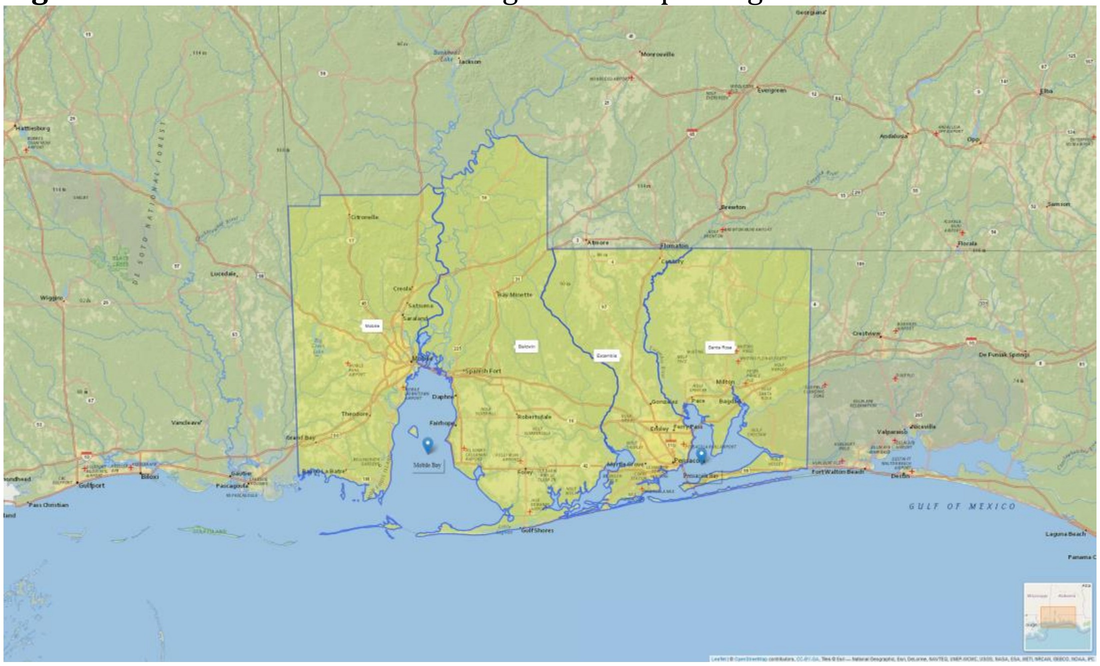
Table 5: Variance-covariance Estimates for Housing Location Utilities

	Linear WTP	Exponential WTP
$\sigma^2_{upgrade}$	3.2315***	4.0323***
	(0.6127)	(0.6625)
$\sigma_{upgrade,nature}$	2.0235	4.6566***
	(1.5017)	(0.7903)
$\sigma_{upgrade,developer}$	2.4530*	5.1263***
	(1.4132)	(1.0244)
σ^2_{nature}	5.4967***	10.9224***
	(1.4298)	(2.7763)
$\sigma_{nature,developer}$	6.1631***	11.4382***
	(1.5724)	(2.7878)
$\sigma^2_{developer}$	1.4522***	1.5746***
	(0.3681)	(0.4484)

Table 6. Annual Marginal WTP for Risk Reduction

	Linear WTP	**Exponential WTP**
2% discount rate; rebuild	\$4,214 (-\$1,494 - \$9,922)	\$1,404 (-\$68 - \$2,877)
2% discount rate; buyout	\$22,773 (-\$10,010 - \$55,557)	\$4,829 (-\$96 - \$9,755)
4% discount rate; rebuild	\$8,428 (-\$2,988 - \$19,845)	\$2,808 (-\$137 - \$5,754)
4% discount rate; buyout	\$45,547 (-\$20,021 - \$111,115)	\$9,659 (-\$192 - \$19,511)
Average annual marginal WTP for one-unit reduction in risk of housing damage; 95% confidence intervals (in parentheses calculated via Delta Method)		

Figure 1. Northern Gulf of Mexico region encompassing Mobile and Pensacola Bays



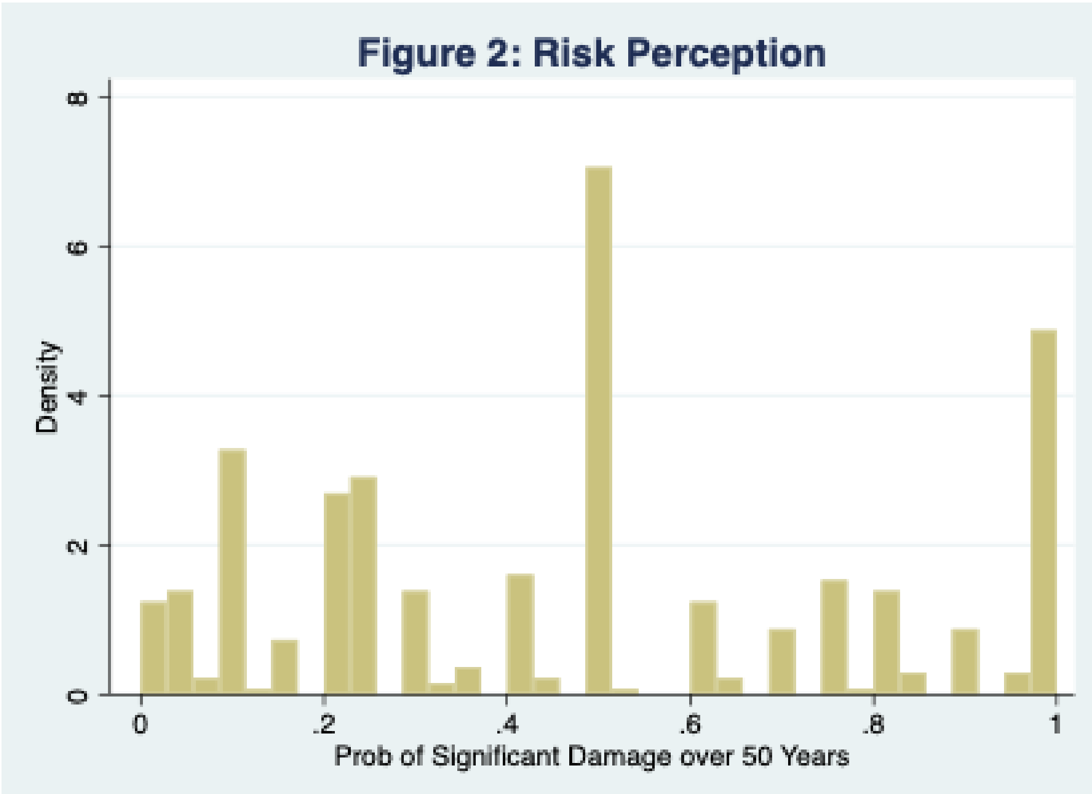


Figure 2: Risk Perception
Density
0
2
4
6
8
0
.2
.4
.6
.8
1
Prob of Significant Damage over 50 Years

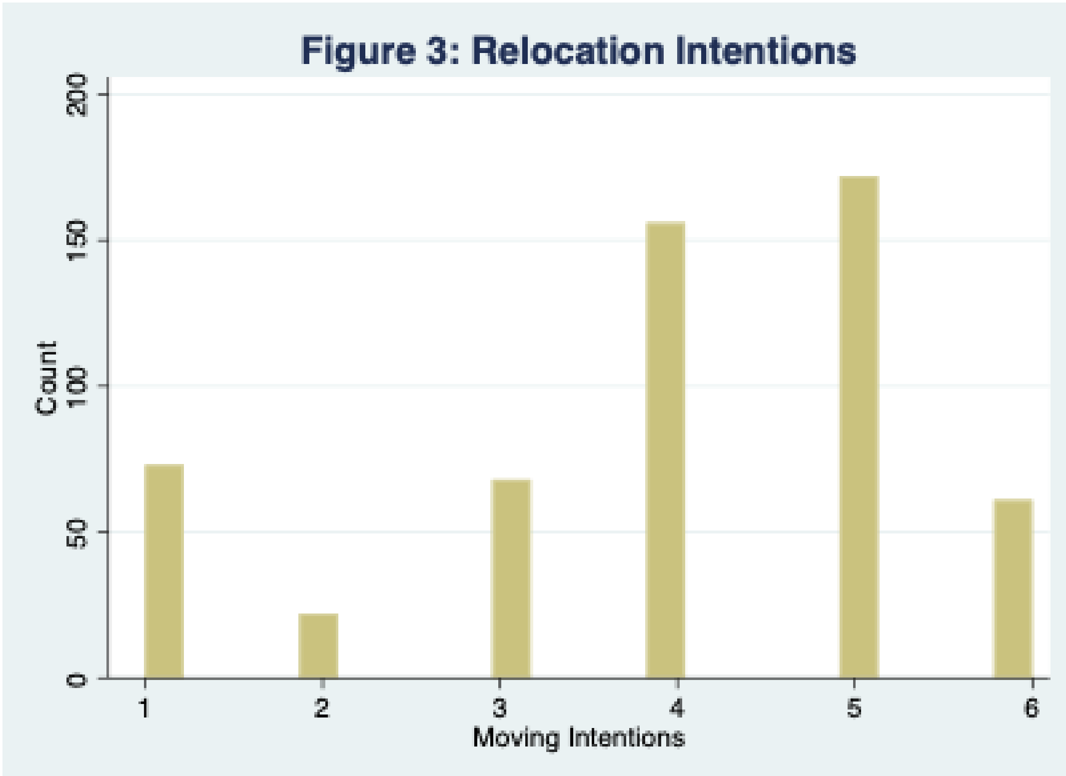


Figure 3: Relocation Intentions
Count
0
50
100
150
200
1
2
3
4
5
6
Moving Intentions

Figure 4: Rebuild/Relocation Choice

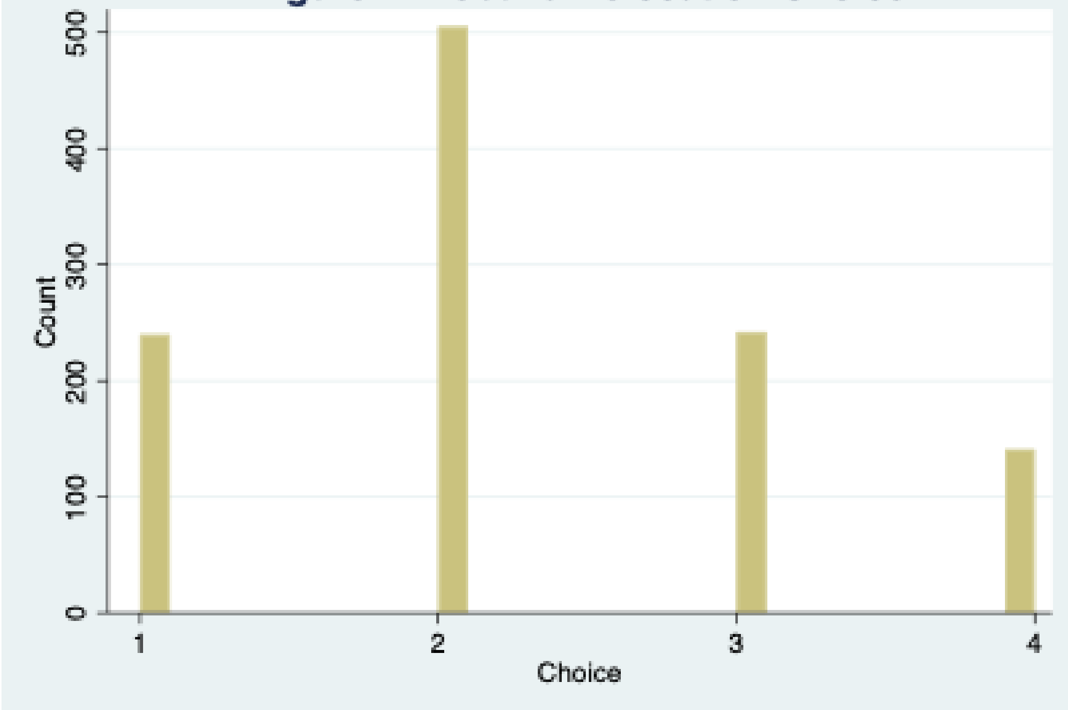


Figure 5. Distribution of Utilities for Linear WTP Model

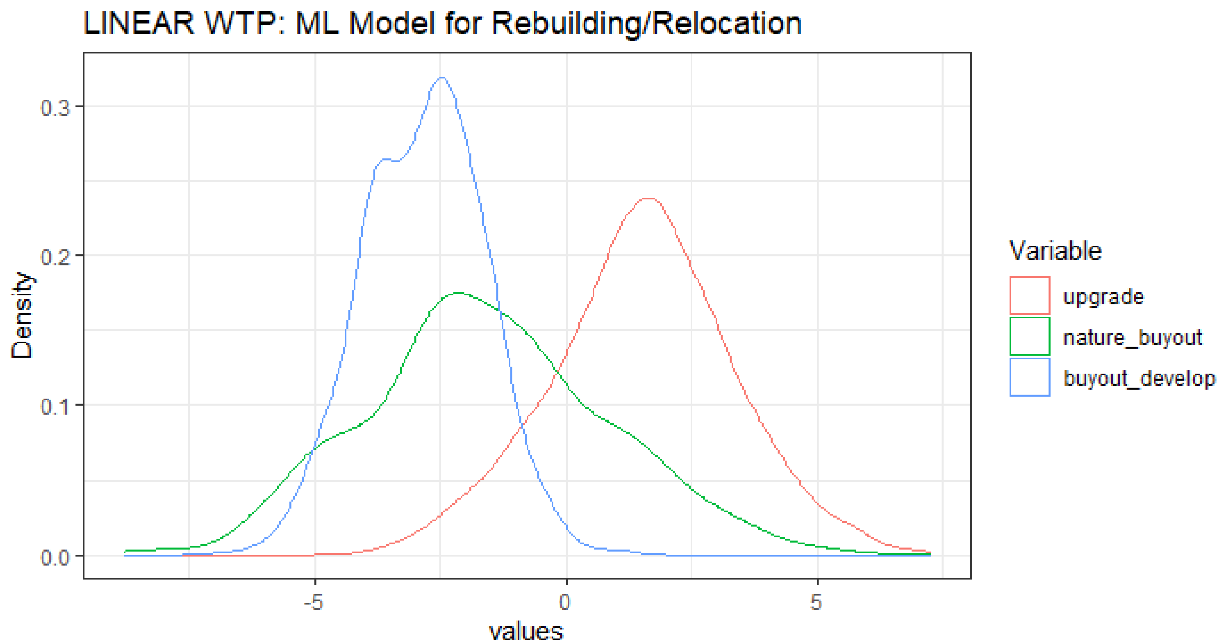


Figure 6. Distribution of Utilities for Exponential WTP Model

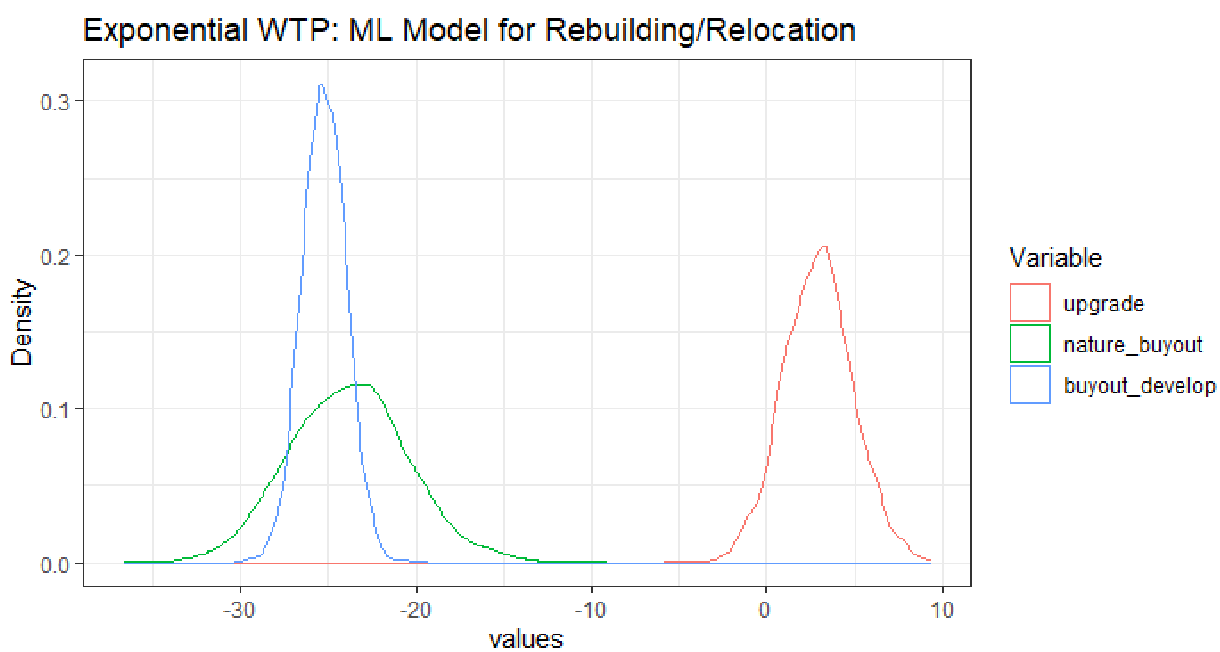


Figure 7. Mean Utilities of Risk