Willingness to Pay for Multi-peril Hazard Insurance

Craig E. Landry, Sarah Anderson, Elena Krasovskaia, Dylan Turner

Land Economics, Volume 97, Number 4, November 2021, pp. 797-818 (Article)

Published by University of Wisconsin Press

Willingness to Pay for Multi-peril Hazard Insurance

Craig E. Landry *Professor, Department of Agricultural and Applied Economics, University of Georgia, Athens; clandry@uga.edu*
Sarah Anderson *M.S. student, Department of Agricultural and Applied Economics, University of Georgia, Athens; saraha94@uga.edu*
Elena Krasovskaia *Ph.D. student, Dyson School of Applied Economics and Management, Cornell University, Ithica, New York; ek558@cornell.edu*
Dylan Turner *Economist, Economic Research Service, U.S. Department of Agriculture, Washington, DC; dylan.turner2@usda.gov*

ABSTRACT *Increasing the number of insured assets in high-risk areas can help reduce the need for federal disaster aid and help communities rebuild quicker following a disaster event. Offering a bundled multi-peril homeowners' insurance product may be one way to do this. Using individual-level survey data, we assess demand for a hypothetical multi-peril insurance product and estimate a mean annual willingness to pay of $4,397. Both quantitative and qualitative analysis point to cost being the primary concern for adoption, however, reducing cognitive burden and uncertainty in the claims filing process appear to be important factors that appeal to homeowners.* (JEL Q54, G22)

1. Introduction

In addition to property destruction, human carnage, and societal upheaval, a natural catastrophe brings evidence of a growing insurance gap. Globally, natural catastrophe losses have been trending upward for decades, and the majority are uninsured losses (Swiss Re Institute 2019). Figure 1 shows magnitudes of global insured and uninsured losses from natural catastrophes since 1970; uninsured losses dominate insured losses. Figure 2 shows the ratio of insured to uninsured losses by year, indicating only one year since 1970 when insured losses were greater. Among developed countries, insurance rates tend to be higher, but a large share of exposed property is still uninsured. In the United States, total natural disaster losses in 2018 were estimated at $81.9 billion, of which $29.6 billion (36%) were uninsured (Insurance Information Institute 2019). Increases in market penetration for catastrophe insurance could reduce the need for disaster assistance payments (Kousky and Shabman 2016; Landry, Turner, and Petrolia 2021), reduce uncertainty over recovery in the wake of disasters (King 2012, 2013), improve risk pooling for insurance providers (OECD 2016), convey risk information that can guide more efficient development and investment decisions (Krutilla 1966; Bin, Kruse, and Landry 2008), and improve community and societal resilience in the face of climate change (OECD 2016).

A potential contributing factor for such large gaps in insurance coverage is the fractured nature of insurance against natural catastrophes. In the United States, typical homeowners' insurance policies specifically exclude damages caused by flooding, earthquakes, and landslides. Not coincidentally, these are also some of the costliest natural hazards. Annualized earthquake costs in the United States are estimated to be roughly $6.1 billion, with the majority (61%) of costs being realized in California (Jaiswal et al. 2017). Although substantial, these losses pale in comparison to flood-related damages. Between 1980 and 2020, the United States has been afflicted with 256 major climate- and weather-related natural catastrophes (National Oceanic and Atmospheric Administration 2020a).[1] Combined, these events have cost

Land Economics • November 2021 • 97 (4): 797–818
doi:10.3368/le.97.4.072820-0115R1
ISSN 0023-7639; E-ISSN 1543-8325

[1] "Major" is defined as events that have had total costs exceeding $1 billion (Consumer Price Index adjusted to 2020).

Appendix materials are freely available at http://le.uwpress.org and via the links in the electronic version of this article.

Figure 1

Global Natural Catastrophes: Insured versus Uninsured Losses (US$ 2019)

Source: Swiss Re Institute (2019)

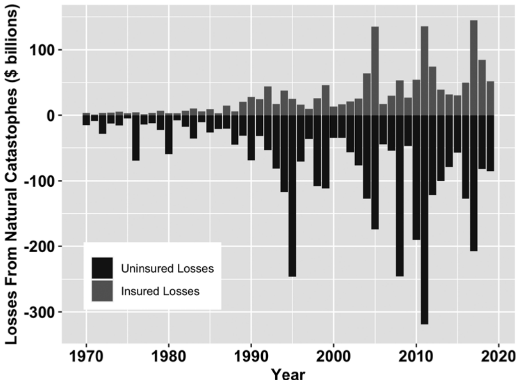
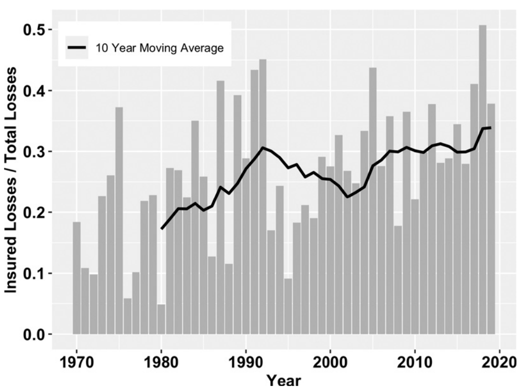


Figure 2

Global Natural Catastrophes: Insured Losses as Percentage of Total

Source: Swiss Re Institute (2019)



the nation $1.8 trillion, of which $1.1 trillion (62%) is attributable to tropical cyclones and other flood events.[2] Given the magnitude of these risks, insurers have been reluctant to include them in standard policies, but natural catastrophes induce other problems as well.

From an underwriter's perspective, natural catastrophes can be difficult to indemnify, since claims tend to be correlated with singular events that affect many homeowners simultaneously (thus, spatially clustered), and the loss distribution has fat tails (meaning that the magnitude of loss declines slowly relative to the probability, as probabilities get small). Diversifying risk across space is one way to deal with correlated losses; it is unlikely that a natural catastrophe will affect distant locations simultaneously. Fat tails typically require large capital reserves or placement of reinsurance to cover excess losses at the time of disaster events (Kousky 2019). For example, after the Northridge earthquake in California in January 1994, the total amount of paid insurance claims exceeded the aggregate premiums collected over the previous 30 years (Insurance Information Institute 2020).

From a consumer's perspective, there is clearly confusion over what hazards are covered by a standard homeowners' policy. The Insurance Information Institute's (2017) Consumer Insurance Survey revealed that 43% of homeowners mistakenly believed major rain-induced flooding was covered under their standard homeowners' policy. Similarly, roughly 30% incorrectly believed hurricane storm surge and earthquakes to be covered events. Even if they understand provisions of coverage, many consumers may have limited information about their personal risk or may have skewed subjective perceptions of likelihood or consequences of risk. U.S. flood maps are often outdated and do not accurately reflect risks; FEMA flood maps indicate that 13 million U.S. households face a 1% annual risk of flooding, while estimates from other researchers put that number at closer to 41 million households (Wing et al. 2018). Some consumers harbor unrealistic (overly optimistic) assessments of risk (Eichenberger and Oberholzer-Gee 1998; Kunreuther, Novemsky, and Kahneman 2001) that may lead them to make suboptimal decisions, such as forgoing insurance coverage (Kunreuther 1996; Chivers and Flores 2002), and there is some evidence that expectations of disaster assistance can reduce incentives for insurance and mitigation (Raschky and Weck-Hannemann 2007; Botzen, Aerts, and van den Bergh 2009; Raschky et al. 2013; Landry, Turner, and Petrolia 2021). Finally, the hassle of obtaining multiple quotes for multiple lines of coverage may be enough to dissuade marginal homeowners from obtaining adequate coverage.

Indemnifying all natural hazards in a single insurance policy is a potential way to address some of these problems. This idea is often

[2] See https://www.ncdc.noaa.gov/billions/summary-stats.

referred to as "all-hazards" or "multi-peril" insurance, and it has the potential to be advantageous to both homeowners and insurers. For insurers, multi-peril policies can lower costs by reducing administrative and marketing costs and can reduce risk by diversifying across hazards (Kunreuther 2018). On the homeowner's side (our focus in this article), multi-peril insurance could be a way to overcome some of the behavioral biases that cause some consumers to avoid insuring. Kunreuther and Pauly (2004) argue that uncertain events with a likelihood below a particular threshold will be ignored by some consumers. Cognitive burden and search costs associated with assessing hazards and their management may be viewed as too high given the low probability associated with the negative event. Bundling coverage for multiple hazards may simplify the cognitive process and increase the likelihood that a homeowner will experience a natural hazards loss that is covered by the policy. These factors may be sufficient to increase saliency, which may cross the threshold level of concern and justify the cognitive effort and search for an insurance policy (Kunreuther 2018). Finally, multi-peril policies significantly reduce the possibility of legal disputes over the source of damage (e.g., wind versus water) and should simplify the claims process, which reduces uncertainty over settlement and should generally improve timing of payments.

Multi-peril homeowners' insurance has been implemented in other parts of the world, particularly in European countries. Belgium, France, Spain, the United Kingdom, Switzerland, and France, as well as New Zealand and Bermuda, have some degree of multi-peril homeowners' coverage available. Risk-based premiums are still rare among existing multi-peril insurance schemes (McAneney et al. 2015; Kunreuther 2018), and adverse selection remains a notable concern (often requiring mandated coverage or public funds to shore up actuarially unsound programs; McAneney et al. 2015). In the United States (and Southeast Asia), multi-peril coverage must contend with the difficulties associated with insuring tropical cyclone catastrophes (Kousky 2011; Bakkensen and Mendelsohn 2016). Although multi-peril hazard coverage has not manifested in the United States, multi-peril crop insurance is widely available through the Federal Crop Insurance Program. A multitude of complicating factors, however, have been identified that challenge a sustainable multi-peril crop insurance market. Both adverse selection and extensive moral hazard have been shown to be significant issues (Just, Calvin, and Quiggin 1999; Wu, Goodwin, and Coble 2020). In addition, farming tends to be regionally concentrated, leading to high spatial correlation in risks, which make it difficult for an actuarially sound private crop insurance market to emerge (Miranda and Glauber 1997).

It is not clear if the same issues that have afflicted existing multi-peril insurance schemes would prove to be similarly prevalent for multi-peril homeowners' insurance in the United States. The empirical literature for bundled homeowners' insurance, particularly in the domain of natural hazards, is extremely sparse. If multi-peril insurance products are to be seriously considered as a viable method for increasing the number of insured assets, more analysis is needed. It is not clear if there is sufficient homeowner demand to support such a product and if this type of insurance could be offered at a price that is attractive to consumers yet financially viable for underwriting agencies. Ahmadiani and Landry (2017) address bundled insurance using household-level survey data coupled with National Flood Insurance Program (NFIP) data on policies in force. They find positive willingness to pay (WTP) for bundled erosion and flood insurance for coastal homeowners, but potential for adverse selection because WTP is much higher for oceanfront homeowners (who face the greatest erosion risk). Laury, McInnes, and Swarthout (2008) test the effect of bundling insurance in a laboratory experiment; they find increasing levels of insurance purchasing as bundling increases the probability of loss. Their results suggest, however, that sensitivity to the loss probability depends on the way the loss is framed and whether incentives are real or hypothetical.[3] Wang et al. (2012) present results of a nationwide survey

[3] Laury, McInnes, and Swarthout (2008) suggest shifting the research focus to other explanations for the insurance

in China that assesses stated demand for an all-hazards homeowners' insurance; they find that roughly 73% of respondents expressed an interest in purchasing this kind of coverage.

We contribute to the literature by providing empirical estimates of the demand for a hypothetical multi-peril insurance product. Our empirical analysis is focused on Glynn County, Georgia, a part of the U.S. East Coast that, based on recent historical landfall data, has generally been perceived as lower risk for hurricanes relative to other parts of the U.S. Southeast (Needham 2016). The area, however, was adversely affected by major hurricanes in 2016 (Matthew) and 2017 (Irma). Thus, we expect coastal storm risks to be particularly salient among homeowners, although they may perceive coastal Georgia as lower risk relative to other areas in the region. Thus, the setting provides a unique situation to assess multi-peril hazard insurance, since the risk is perceived as somewhat lower (which could dampen demand) but is still (arguably) salient. Using household-level survey data, we estimate coastal homeowners' WTP for multi-peril insurance. We also investigate determinants of adoption through quantitative and qualitative methods (the latter making use of free-form survey responses). We estimate a mean WTP per annum of $4,396. Our qualitative analysis reveals that the reduction of cognitive burden and decreasing uncertainty are underlying perceptions that induce willingness to adopt multi-peril coverage.

2. Disaster Insurance in the United States

Insuring homes against natural disaster loss is a surprisingly recent phenomenon. As recently as the early 1900s, U.S. homeowners did not have the option to insure against natural disasters, leaving them completely responsible for covering any financial damages (Kunreuther 1968). The Red Cross was the first to set up a mutual insurance pool to ease the financial burden of natural disasters in 1905; the pool was funded entirely by private donations (2 Red Cross Act 1, 36 U.S.C. 1, 1962). The federal government became involved in flood management after the great Mississippi River floods in 1927, in which 120 levees along the Mississippi River failed, leaving approximately 600,000 people homeless. In response to this tragedy, the Flood Control Act of 1928 tasked the Army Corp of Engineers with responsibility for flood risk management. This led to a proliferation of flood control infrastructure in the United States (reservoirs, levees, redirected waterways) in an attempt to mitigate future flooding. At this time, people thought that flood insurance would never be available due to the uncertainty of the risk and the severity of the damages (Kunreuther 1968).

Before 1938, homeowners had the option to purchase fire insurance, but coverage against other forms of disaster was only available by specifically adding it to the policy via special riders. In 1938, Extended Coverage (EC) became an add-on option for those holding a fire insurance policy. EC initially covered perils such as wind, hail, explosions, riots, terrorism, civil commotion, aircraft wreckage, and smoke. Initially, EC was primarily adopted in the Midwest, where tornado damage was common, but in the 1940s severe storms and hurricanes in other parts of the country prompted legislation to make EC a requirement for a mortgage. The provisions of EC did not cover water damage, despite wind and water damage being highly correlated. Although EC would indemnify water damage if the walls were first breached by wind (Moore 1964), discerning which source of damage occurred first can be extremely difficult. This is known as the attribution problem, and it was a major issue for claimants and adjusters after Hurricanes Katrina and Rita in 2005.

The NFIP was created in 1968 as a unified flood management strategy, with the goals of reducing flood losses and decreasing public spending for disaster aid. The NFIP is the largest federal program covering riverine and storm-induced flooding. The Federal Emergency Management Agency (FEMA) holds primary responsibility for creating Flood Insurance Rate Maps (FIRMs) that are used to identify flood risk and set homeowners' premium rates; updating FIRMs to reflect

gap, such as moral hazards and high loading factors in insurance premiums.

changes in land use, rainfall, and storm water patterns; providing basic regulatory provisions for development in floodplains; and informing the general public of potential flood hazards (King 2013).

Since its inception, participation in the NFIP has been low, which has continually been a threat to the program's financial stability. Nationwide, only about 30% of homeowners in high-risk flood zones (defined by at least a 1% chance of flooding per year) have flood insurance policies (Kousky et al. 2018). In 2018, Congress relieved the NFIP of $16 billion of its debt, reducing it to $20.525 billion (FIMA 2018). Reasons for insolvency include inaccurate pricing of risk, disproportionate revenue sharing with insurance agents that sell and service NFIP policies (but bear no risk), and low levels of market penetration. With regard to the latter concern, FEMA created several amendments to the NFIP to try to increase participation. The Flood Disaster Protection Act of 1973 required flood insurance in the Special Flood Hazard Area (SFHA) for structures with mortgages from a federally backed financial institution.

Nonetheless, severe flooding in the Midwest in 1993 revealed that the mandatory purchase requirement was poorly enforced, as many homeowners were out of compliance. That flood provided the impetus for strengthening lender compliance through the mandatory purchase provisions in the National Flood Insurance Reform Act of 1994 (King 2013). Despite this reform, uptake rates of flood insurance are still low, even for those subject to the mandatory purchase requirement (Kriesel and Landry 2004; Dixon et al. 2006; Kousky 2010; Landry and Jahan-Parvar 2011; Ahmadiani, Ferreira, and Landry 2019).

Although the NFIP is a federal program, individual states have regulatory authority for catastrophe insurance in their jurisdictions, and some states have created their own programs to manage disaster risks. Many private insurers have dropped provision of wind coverage following disastrous storms, and a number of states on the East and Gulf Coasts have implemented state-run wind insurance programs. These programs offer coverage for tropical windstorm damage for residents in coastal counties but vary in their funding sources, operation, pricing, and risk management strategies (Dixon, MacDonald, and Zissimopoulos 2007; Kousky 2011; Insurance Information Institute 2013).

According to the U.S. Geological Survey's report, nearly half of all Americans face some level of earthquake risk (Jaiswal and Fitzpatrick 2015). Although infrequent in occurrence, earthquakes are rarely insured against. Of the $81.9 billion in U.S. losses posted in 2018, only $500 million were attributed to earthquakes, and $400 million of those losses were uninsured (Insurance Information Institute 2019).[4] Earthquake damage, like flood damage, is not covered under a standard homeowner's policy. Unlike flood insurance, earthquake coverage can be obtained through private insurers for most regions in the United States. For most of the United States, risks are relatively low, making private coverage affordable and feasible to underwrite. One notable exception is California, which faces substantially more earthquake risk due to the San Andreas Fault running through the state. The California Earthquake Authority (CEA) was established in response to the 1994 Northridge earthquake, which caused an unprecedented level of damage and associated insurance payouts (Insurance Information Institute 2020). In an attempt to limit exposure, private insurers began writing fewer homeowner's policies, leaving many exposed homes without coverage (Marshall 2018). The CEA was established as a privately funded but publicly managed insurance provider to address the mounting earthquake insurance crisis. The CEA is by far the largest provider of earthquake insurance in the United States, but coverage is only available to California residents. Kentucky also has a regulatory preference for earthquake coverage, requiring insurers to provide optional coverage as part of a homeowner's policy (Marshall 2018).

Despite provisions for earthquake coverage, market penetration tends to be low. Pothon et al. (2019) conclude that there are

[4] Tropical cyclones, on the other hand, are by far the costliest natural disasters. Of the top 10 costliest catastrophes ever recorded, 8 were due to tropical cyclones, many of which saw uninsured losses accounting for up to half of total losses (Insurance Information Institute 2019).

only two extreme situations that would lead most homeowners to purchase earthquake insurance: (1) a widespread belief that a devastating earthquake is imminent, or (2) a massive decrease in the average annual premium amount by a factor exceeding six (from US$980 to $160 (2015 dollars)). Considering the low likelihood of each situation, they conclude that new insurance solutions are necessary to fill this gap.

Today, a typical homeowners' insurance policy covers the home, garage, and other structures on the property, as well as personal contents on the property. These policies provide coverage for a wide range of named perils, such as fire, smoke, explosions, lightning, hailstorms, theft, vandalism, and nonflood-related water damage. The most common exclusions are for floods and earthquakes (Insurance Information Institute 2017). Although damage from wind storms is cited as one of the perils covered in the most basic policies, coastal homeowners may not automatically have wind coverage and would have to purchase it separately (Insurance Information Institute 2017). This is because of the high risk of wind damage from tropical storms or hurricanes in these areas.

3. Conceptual Model

Analysis of individual decision making under risk and uncertainty has been an area of active research for centuries (Cramer 1728; Bernoulli 1738; Von Neumann and Morgenstern 1944). Assessing natural disasters is a more recent phenomenon. Similar to how other types of risks are characterized, researchers and practitioners in risk management often describe natural hazards as consisting of two primary elements: the likelihood of occurrence and the magnitude of consequences (Du and Lin 2012). The likelihood of a natural disaster occurring is primarily determined by environmental forces, though human interventions can have some effects on probability and consequences. For example, public infrastructure projects can affect the likelihood of flooding, and changes in the built environment can exacerbate or ameliorate the effects of flooding. The consequences of natural disasters are also influenced by human behavior and cultural factors that determine where people are located and how they live (Du and Lin 2012). Last, improvements in technology have provided for better understanding of underlying natural processes and more accurate forecasting of disaster events.

Recent publications in the literature on individual responses to natural disasters has recognized the potential role of ambiguity, subjective likelihoods, perceived consequences, and expectations of environmental change and policy responses (Hogarth and Kunreuther 1985; Wachtendorf and Sheng 2002; Okuyama 2003; Martin and Martin 2017; Landry, Turner, and Petrolia 2021; Turner and Landry 2020). "Ambiguity" refers to situations where at-risk individuals have difficulty judging the probability of a bad outcome (Okuyama 2003). Ambiguity of natural disasters may arise from infrequency of occurrence and difficulties in predictability. At the same time, natural hazards often entail serious consequences that can result in significant risk of death, displacement, emotional distress, and property loss. Moreover, some natural disasters can be influenced by climate change, and risk management provisions may induce moral hazard, prompting people to ignore risks if they expect disaster assistance. These characteristics render natural disasters distinct from other socioeconomic risks, introducing many difficulties for standard economic analysis, which often assumes perfect information or common knowledge of risk probabilities. Decisions regarding natural hazard insurance are likely to be among some of the most difficult that consumers face, because they require homeowners to make individualized, subjective predictions about the likelihood and magnitude of rare and unfamiliar future events (Schwarcz 2010).

Expected utility theory (EUT) represents the conventional neoclassical economic approach to assess risky decisions (Von Neumann and Morgenstern 1944; Moscati 2016). The EUT framework has seen empirical application in analysis of insurance decisions, measurement of risk tolerance, and estimation of WTP to avoid risks (Ehrlich and Becker 1972; Schoemaker and Kunreuther 1979; Nyman 2001). Alternatives to EUT have proliferated in research about decision making under risk and uncertainty, but most formulations use constructions that build on likelihood and consequence (Landry, Colson, and Ahmadiani 2019). We make no claim to use or test any particular formulation; instead, we estimate a simple model that incorporates relevant elements of risky decisions available in our data set.

We assume that individuals strive to maximize some generalized version of subjective expected utility, but without presuming any structural form for the decision model. However, we build our reduced-form model on standard covariates suggested by EUT and posit utility as an increasing function of wealth, $U(W_j)$, where W_j is the final wealth associated with event j. The expected utility of an uncertain prospect is obtained by weighting the utility of each possible outcome by the corresponding probability. Under axioms of EUT, a rational utility maximizer will prefer the prospect with the highest expected utility (Botzen and van den Bergh 2009). Expected Utility of a prospect can be represented by the general formula:

$$EU = \sum_{j=1}^{n} P(E_j)U(W_j),$$

where E_j denotes exhaustive and mutually exclusive events of dimension n; W_j the corresponding wealth outcomes; P is the probability of event E_j, and U is the utility of receiving outcome W_j. Although many formulations focus on income or wealth, other consequences, such as death, morbidity, or unpleasant experiences (e.g., homelessness), can be included in the utility function. In the context of insurance, a EU maximizer would compare EU with and without insurance and select the prospect with the greatest EU. To make such a comparison, an individual should assess their subjective probabilities of disaster events, know the insurance premium and deductible, and assess expected damages caused by a disaster.

In accordance with EU theory, estimates of risk tolerance (also known as risk preference) are determined by the curvature of the utility function, $U(W_j)$. If the function is concave, the EU maximizer is considered risk-averse, and their WTP for insurance will be increasing with their level of risk aversion. The degree of risk aversion can be assessed by the Arrow-Pratt measure of relative risk aversion, which is given by

$$\gamma = -W\left(\frac{U''(W)}{U'(W)}\right),$$

with larger values of γ indicating greater risk aversion. The constant relative risk aversion (CRRA) utility function is a common formulation in empirical analysis across a variety of domains (Wakker 2008), and is given by

$$U(W) = \frac{W^{1-\rho}}{(1-\rho)},$$

where ρ is the coefficient of relative risk aversion (RRA),[5] which could take any value $\rho > 0$ for risk-averse agents, while risk-loving individuals can be described by any $\rho < 0$. Risk-neutral preferences are indicated by $\rho = 0$. CRRA utility has the convenient property that the standard Arrow-Pratt measure reduces to $\gamma = \rho$ and implies a constant level of risk aversion with respect to wealth. The CRRA formulation is relevant for our project, as our data set includes experimental results that allow us to classify respondents according to their implied CRRA parameter value. This provides for a test of internal validity in our regression analysis.

Other potentially important determinants of WTP for multi-peril insurance include the subjective perceptions of the likelihood and consequences of natural disasters, physical risk measures (e.g., location relative to flood zones), individual experience with disasters, and household income. Our data set includes unique information regarding household expectations of disaster assistance and their degree of worry about losing their house to a natural disaster.

4. Survey Design and Data

The broader research project that supported the survey was focused on coupled human-natural systems and coastal adaptation to climate

[5] In the case of $\rho = 1$, the CRRA utility function takes the form $U(W) = ln(W)$.

change. To provide insight into expectations, motivations, and preferences of current housing market participants, the sampling frame was composed of recent home buyers. Thus, we sampled from the tax assessor database for Glynn County, Georgia, focusing on those that had purchased a home in the previous two years (2016 or 2017). Because our focus was on coastal hazards, the sample was refined to include recent purchases in proximity to the shoreline (within 10 miles, where the majority of development is located).

Two small-scale focus groups and a few cognitive interviews were conducted with residents in nearby Georgia coastal counties in early fall 2018. Following refinement of the instrument, the mail survey was launched at the beginning of October, with a reminder postcard sent one week later. Households were instructed to have completed surveys postmarked by October 31 if they wished to receive an incentive payment for participation. In total 1,914 surveys were fielded during October, 266 of which were returned, yielding a response rate of 13.9%. Appendix Figure A1 provides a map the study area. To incentivize participation, respondents were given $5 for a completed and returned survey, although participants had the option of wagering their incentive payment as part of a risk preference instrument included in the survey.

To assess homeowners' attitudes, expectations, and beliefs about coastal habitation and climate change, the survey included a number of qualitative and quantitative measures. The data set includes attitudes and opinions about the coast, insurance information (flood and wind), subjective probabilities of a Category 3 hurricane and conditional expectations of the accompanying damage, expectations of disaster assistance payments, levels of worry across various domains, experimentally derived measures of risk preference, and basic demographics. Most pertinent to our analysis is the survey's contingent valuation question about willingness to purchase a hypothetical multi-peril insurance product.[6]

Survey participants were asked to imagine that they had the opportunity to purchase homeowners' insurance that would cover any damage to their home or possessions caused by flooding, wind, erosion, earthquake, terrorism, or other natural or man-made factors. Participants were asked if they would purchase this insurance at a cost of $X per $100 of coverage per year; where X differed by survey version and took on values of $0.50, $0.75, $1.00, $1.20, $1.45, or $1.80. These bid levels were selected based on expected levels of costs and benefits derived from a multi-peril insurance product and from responses to focus group prompts. Participants could respond with "yes," "no," or "I don't know" and were also prompted to enter an additional free form response to explain the reasoning behind their decision.

To help participants calculate the total annual premium they would face for a multi-peril insurance policy, participants were shown premiums associated with a series of coverage levels starting at $50,000 and going up to $600,000 in $50,000 increments. Respondents were asked to select the coverage level that was closest to the value of their home and contents to get their hypothetical multi-peril premium, which was conditional on the cost per $100 of coverage displayed on each respondent's particular survey version. Appendix Figure A2 displays the WTP question as it appeared in the survey.

Risk Preference Measures

The survey included a risk preference instrument, based on Eckle and Grossman (2002), in which participants are asked to choose among keeping their $5 incentive payment or gambling it through a choice of one of four possible lotteries. To create transparency in the lottery process and mitigate distrust of the randomness of the lottery outcome, payoffs in the instrument were based on future weather outcomes in Glynn County, GA.

[6] While other stated preference approaches (e.g., choice experiments) could be used to assess the demand for multi-peril hazard insurance, we chose contingent valuation to minimize the amount of space necessary, given that the survey was already quite lengthy. Future research should explore the use of choice experiments to assess attributes of insurance products (e.g., limits on coverage, deductibles, and premiums).

This has the added benefit of framing risk in a domain that is relevant for natural hazards.

Survey participants were informed that the lotteries would be based on weather outcomes as reported by the Brunswick, Georgia, Malcom McKinnon Airport weather station occurring between 12:01 a.m. November 1 and 11:59 p.m. November 30, 2018. The survey listed four possible temperature and precipitation weather outcomes and displayed the associated probability of occurrence based on historical weather data. These lotteries randomize payment by conditioning on realized weather outcomes and account for risk preference by providing mean-variance trade-offs in weather payment. The least risky lottery had a 50-50 chance of paying a higher or lower amount of money than the initial incentive payment, and the riskiest lottery had a low probability of paying a large sum (with a high likelihood of $0 payout). Participants chose whether to keep their $5 incentive payment or select one of the four lotteries. Appendix Figure A3 shows the risk preference instrument as it was presented in the survey. Because incentive payments were based on yet to occur weather events in November, participants were informed that incentive payments would only be mailed out for returned surveys that were postmarked by October 31.

Risk Perception Measures

Because they are the primary natural hazard risk in Glynn County, hurricanes constitute our main focus for risk perception. To assess the likelihood of a natural disaster, respondents were asked to report the expected number of Category 3 hurricanes to strike their community in the next 50 years. Their responses are used to create an annual likelihood of Category 3 hurricane landfall. To ascertain expected damages associated with a Category 3 hurricane, the survey instrument includes a question that elicits expected property damage as a percentage of structural value. Because we sampled from the Glynn County tax assessor's database, we have access to estimates of home structure value, and we use this in conjunction with the percentage measure to create a variable for expected damage.[7] In addition to perceptions of risk, we know whether the respondent has lived most of their life on the coast, whether they have experienced flood damage in the past, their level of worry about natural disasters, their FEMA flood zone, perceptions of erosion risk, expectations of disaster assistance, and basic demographic factors.

Summary Statistics

Variable definitions for the data used in our analysis are reported in Table 1, and summary measures are reported in Table 2.[8] The mean hypothetical annual premium that respondents faced for the multi-peril insurance product was $4,081 and ranges from $250 up to $10,800. Alternatively, this corresponds to a mean price per $100 of coverage of $1.17. Respondents reported income by selecting one of eight intervals ranging from "less than $35,000" up to "more than $250,000." We assign the midpoint of the interval as the level of household income; the bottom interval was coded at $30,000. About 16% of respondents selected the highest income level category. We follow Hout (2004) in addressing income estimation for the unbounded top income interval. This entails extrapolation based on a Pareto distribution using frequencies of the last and penultimate income intervals. Applying this method produces a top income interval estimate of $496,124. The mean and median income for the sample after all transformations was $171,670 and $125,000 respectively.

We now turn to measures of risk perception. The average respondent expects just under 10 Category 3 hurricanes over the next 50 years, which corresponds with a perceived

[7] By Georgia law, property tax assessments are to be based on fair-market value (FMV). Tax bills, however, are a based on a portion of FMV, with adjustments for homestead, exemptions, or other grandfathering provisions. Thus, counties are expected to undertake due diligence in estimating FMV. We believe tax-assessed values represent the best widely available data source for home structure values. We are not aware of any evidence that suggests this data would be inaccurate. To the extent that assessed values are deflated (due to political influence of residents), our damage measure could be biased downward.

[8] In addition, the exact text for each survey question used to construct covariates for our analysis is reported in Appendix Table A1.

Table 1
Variable Descriptions

Variable	Type	Description
Purchase	Binary	=1 if respondent indicated they would purchase the hypothetical multi-peril policy
Annual premium	Continuous	Hypothetical annual premium for multi-peril insurance product
Price per $100	Discrete	Hypothetical price for $100 of multi-peril coverage
Household income	Discrete	Annual household (interval responses—coded at midpoint)
Probability Category 3	Continuous	Expected number of Category 3 hurricanes over the next 50 years divided by 50 (with values over 1 replaced with 1)
Flood zone	Binary	=1 if reported living in SFHA zone
Flood damage	Binary	=1 if reported home had previously sustained flood damage
Erosion risk	Binary	=1 if expect erosion to worsen in the future
Expected damage ($1,000)	Continuous	Expected damage (in dollars) to home from a Category 3 hurricane
Life time	Binary	=1 if most of life has been spent on the coast
Expected individual assistance	Binary	=1 if expect federal individual assistance following natural disaster
Natural hazard worry	Binary	=1 if worries about loss of home from a natural disaster
CRRA	Discrete	elicited coefficient of relative risk aversion
Conservative	Binary	=1 if politically conservative
Brunswick	Binary	=1 if living in Brunswick
Higher education	Binary	=1 if received bachelor's degree or higher

Table 2
Descriptive Statistics

	Mean	Std. Dev.	Min	Max	Count
Purchase ("don't know"=0)	0.33	0.47	0.00	1.00	246
Purchase ("don't know" dropped)	0.47	0.50	0.00	1.00	171
Annual premium ($1,000)	4.08	2.45	0.25	10.80	254
Price per $100	1.17	0.40	0.50	1.80	266
Household income ($1,000)	171.67	149.36	30.00	496.12	253
Probability Category 3	0.19	0.24	0.00	1.00	238
Flood zone	0.42	0.49	0.00	1.00	238
Flood damage	0.15	0.36	0.00	1.00	261
Erosion risk	0.77	0.42	0.00	1.00	266
Expected damage ($1,000)	149.39	245.38	3.78	3075.00	254
Life time	0.36	0.48	0.00	1.00	261
Expected individual assistance	0.35	0.48	0.00	1.00	266
Natural hazard worry	0.46	0.50	0.00	1.00	266
CRRA	0.49	0.38	0.01	0.85	251
Conservative	0.49	0.50	0.00	1.00	266
Brunswick	0.55	0.50	0.00	1.00	266
Higher education	0.24	0.43	0.00	1.00	266

annual probability of 0.19. This statistic is skewed by a small number of respondents who indicated they expected a Category 3 hurricane every year (presumably misunderstanding the question). The median annual probability of a Category 3 storm was 0.10 (or five Category 3 storms over the next 50 years). Nonetheless, perceptions of future hurricane risk are much higher than what historical data would suggest, which could be construed as evidence of misperceptions of risk but may simply be a result of respondents believing major storms will be more frequent in the future relative to the past. According to NOAA, coastal Georgia has a major hurricane return period of 33 years, corresponding to an annualized probability of about 3%.[9] Forty-two

[9] We note that NOAA calculates return periods based on storms passing within 50 nautical miles, whereas our survey question was based on a 30-mile threshold.

percent of survey respondents reported living in the special flood hazard area (SFHA, 100-year flood zone),[10] and 15% reported previous experience with flood damage. Seventy-seven percent of respondents indicated that they expected coastal erosion to get worse in the future. For the consequences of a Category 3 storm, the average respondent reported 30% of structure value, which corresponds with a mean expected damage of approximately $150,000. The median was $107,117. Multiplying the annualized probability of a hurricane by expected damages provides a metric for each respondents annualized expected loss (in dollars) from a Category 3 storm. The average respondent expected annual losses of $15,656 with a median value of $6,784.

Thirty-six percent of our sample reported living most or all of their lives on the coast. Thirty-five percent of respondents indicated that it was likely that they would be eligible for federal or state grants for rebuilding personal property in the event of a major hurricane. Forty-six percent indicated that they worry about the loss of their home due to a natural disaster. Detailed results from our risk preference instrument are reported in Appendix Table A3. One-hundred twenty-three (46.24%) of the survey participants chose the safe $5 incentive payment with an implied CRRA coefficient of 0.85 or greater. Lottery 1 was chosen by 21 participants (7.95%) indicating a CRRA coefficient between 0.3 and 0.85; 27 (9.85%) chose lottery 2, indicating a CRRA coefficient between 0.09 and 0.3; lottery 3 was chosen by 32 participants (12.12%), implying a risk coefficient of between 0 and 0.09. Lottery 4 was chosen 49 times (18.56%), which indicates risk-loving preferences and a negative risk coefficient. Fifteen survey participants (5.64%) declined to answer the risk preference question. Approximately half of respondents considered themselves to be politically conservative. Fifty-five percent of our sample resided in Brunswick, the primary municipality of Glynn County, and 24% indicated they had a bachelor's degree or higher level of education attainment.

[10]Comparing reported SFHA status against actual SFHA status based on FEMA flood zone maps reveals that most respondents (71%) knew their SFHA status.

Appendix Figure A4 reports a summary of responses to the hypothetical multi-peril insurance question. Just over 15% of participants who were quoted a price of $1.80 per $100 of coverage indicated they would purchase, and around 65% would not purchase the coverage. The remaining minority of respondents that received the highest price stated "I don't know." Twenty-five percent indicated they would purchase at the $1.45 price, and almost 50% declined this price. The positive response to the $1.20 bid was also around 25%, and the no responses were lower for this price (about 45%). The $1.00 offer price garnered a positive acceptance rate of 34% and a negative rate of 25%. The two lowest prices of $0.75 and $0.50 price each had an affirmative rate close to 50%, with $.75 generating about 15% negative and $0.50 generating about 8% negative. The proportion of "I don't know" responses was generally decreasing in offer price.

5. Empirical Methods

To estimate demand for multi-peril insurance, we use a binary probit model with yes/no responses as the dependent variable and a selection of relevant covariates. Approximately one third of survey participants responded with "I don't know" when asked if they would purchase multi-peril insurance at their quoted price. To map our responses into a binary outcome, we code those who answered "yes" as 1 and those who answered "no" as 0 and drop observations that responded "don't know." As a robustness check, we estimate an additional model that codes both "no" and "don't know" as 0.

WTP for the bundled insurance product can be estimated using the results of the probit model and following a standard calculation, where $\overline{z'}$ is a vector of independent variables evaluated at their sample mean, $\hat{\delta}$ is a vector of coefficient estimates, and $\hat{\alpha}$ is the coefficient estimate for the variable capturing the amount of the bid:

$$E(WTP \mid \overline{z'}, \beta) = \overline{z'}\left[-\frac{\hat{\delta}}{\hat{\alpha}}\right].$$

The probit model can result in inconsistent WTP estimates if the distribution or functional form is misspecified (Haab and McConnell 2002). As an additional robustness check, we calculate WTP using a Turnbull estimator, which is nonparametric and thus does not rely on distributional assumptions. The Turnbull estimator calculates WTP using the ratios of "no" responses to the total number of responses for that bid price. This approach does not allow for inclusion of additional covariates. Thus, it provides no information on factors influencing WTP and cannot incorporate individual heterogeneity in the WTP estimates. Sample size was a limiting factor in the analysis. Several respondents (eight in total) indicated a preference for purchasing multi-peril insurance but did not supply a value of their home and contents, which is necessary for calculating their hypothetical annual insurance premium. Annual premiums for these observations were constructed using the most recent sale price of their home.

6. Quantitative Results

Parameter estimates from the probit estimation of the decision to purchase multi-peril insurance are reported in Table 3 with average marginal effects reported in Table 4. We run two primary specifications of the probit model, dropping the "don't know" responses. The first model uses the total annual premium as the price variable (first column of Table 3), and the second uses the bid price per \$100 coverage as the price variable (second column of Table 3). The first price variable is perhaps more intuitive as an indicator of WTP but may suffer from endogeneity because it reflects the chosen level of (presumably full) coverage. The second price variable is purely random (within our bid design) and is thus strictly exogenous. We note, however, that the first model has the largest log-likelihood, and the two models produce similar estimates of price elasticity, −1.945 for the full premium model and −2.220 for the price per \$100 coverage model.

For the annual premium model, we find that the likelihood of electing to purchase multi-peril coverage is decreasing in price and lower for those respondents who consider themselves politically conservative. The likelihood of purchase is greater for those located in the SFHA, those with a larger CRRA coefficient, and for households that perceived greater magnitude of storm damage. Unlike perceived consequences, we find no evidence to support perceived likelihood of Category 3 storm affecting WTP for multi-peril insurance. Likelihood of purchase is increasing in income and greater in the city of Brunswick (relative to the other areas of Glynn County, the excluded category). We find no evidence that experience with flood damage or more time spent on the coast affects stated intentions to purchase multi-peril hazard. Similarly, perceptions of erosion risk, expectations of disaster assistance, measures of worry over natural disasters, and level of education have no effect on stated likelihood of purchase. Findings for the price per \$100 cover model are similar, though CRRA and log(household income) are not statistically significant.

Turning to average marginal effects in Table 4, we focus primary attention on the full premium model. The probit regression results indicate the following relationships: a \$1,000 increase in the annual premium reduces the likelihood of purchase by 15%. A \$1,000 increase in household income increases the likelihood of purchase by 0.11%. Residents who reported living in the SFHA flood zone were 38% more likely to opt for multi-peril insurance. The coefficient on self-identified politically conservative suggest a 24% decrease in insurance purchase for this group. This is consistent with previous literature, which has shown that Republicans tend to be less likely to invest in flood mitigation measures (Botzen et al. 2016). Last, we find that increasing the mean expected damage from a Category 3 storm by \$1,000 increases the likelihood of purchase by 0.127%.

Finally, we calculate WTP using the results from the probit model and the Turnbull estimator. The mean annual premium that homeowners were willing to pay was \$4,397 based on the probit model. The Turnbull estimator produced a (lower bound) estimate of \$3,394. To put these numbers in perspective, reported insurance premiums from our survey sample indicate that the average homeowner in our sample, who has flood insurance, wind insurance, and a standard homeowners' policy,

Table 3
Probit Estimation of Decision to Purchase Multi-peril Policy

	"Don't Know" Dropped		"Don't Know"=0	
Annual premium ($1,000)	–0.38***		–0.22***	
	(0.08)		(0.06)	
Price per $100		–1.73***		–0.86***
		(0.38)		(0.27)
Log(household income)	0.44*	0.13	0.56***	0.40**
	(0.23)	(0.22)	(0.18)	(0.17)
Probability Category 3	0.34	0.37	–0.12	–0.05
	(0.65)	(0.63)	(0.45)	(0.45)
Flood zone	0.94***	0.59*	0.48**	0.36
	(0.34)	(0.30)	(0.23)	(0.23)
Flood damage	0.43	0.52	0.31	0.35
	(0.50)	(0.48)	(0.35)	(0.34)
Erosion risk	0.01	–0.03	0.32	0.26
	(0.35)	(0.34)	(0.27)	(0.26)
Log(expected damage)	0.49**	0.30*	0.19	0.10
	(0.20)	(0.18)	(0.15)	(0.14)
Life time	–0.17	0.07	–0.22	–0.16
	(0.33)	(0.33)	(0.24)	(0.23)
Expected individual assistance	0.25	0.30	–0.09	–0.01
	(0.32)	(0.32)	(0.23)	(0.22)
Natural hazard worry	0.34	0.38	0.12	0.14
	(0.30)	(0.30)	(0.23)	(0.23)
CRRA	0.86**	0.46	0.20	0.09
	(0.39)	(0.37)	(0.28)	(0.28)
Conservative	–0.61**	–0.56*	–0.18	–0.18
	(0.30)	(0.30)	(0.23)	(0.23)
Brunswick	0.66*	0.89**	0.50*	0.70***
	(0.38)	(0.38)	(0.28)	(0.27)
Higher education	0.01	–0.05	0.26	0.20
	(0.32)	(0.31)	(0.25)	(0.24)
Constant	–3.88***	–1.01	–3.92***	–2.67**
	(1.43)	(1.38)	(1.08)	(1.08)
Observations	128	128	186	186
Log-likelihood	–58.572	–61.007	–98.198	–100.711
Income elasticity	0.424	0.126	0.665	0.470
Price elasticity	–1.945	–2.220	–1.140	–1.240
WTP	$4,396.93	$1.22	$1,781.19	$0.59
WTP (Turnbull)	$3,393.65	$1.00	$2,100.90	$0.60
WTP (Firth)	$4,355.65	$1.21	$1,816.90	$0.59

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

pays a combined total of $3,152 for all three types of coverage. Mean WTP per $100 of coverage was $1.22 using the probit model and approximately $1.00 according to the Turnbull estimates.

As a check on robustness and sensitivity, we reestimate our model assuming that all those that responded with "I don't know" would not purchase the multi-peril insurance; this is a common approach to assessing a conservative estimate that may be conceived as a lower bound. The last two columns of Table 3 report estimates from these specifications. The results are qualitatively equivalent to our main specification. Annual premium and price per $100 of coverage have negative coefficients and are highly significant although with lower measures of responsiveness (price elasticities of −1.14 and −1.24, respectively). Residing in a flood zone, residing in Brunswick, and household income are all significant and have the expected effect. Political affilia-

Table 4
Marginal Effects

	"Don't Know" Dropped		"Don't Know"=0	
Annual premium ($1,000)	–0.15***		–0.08***	
	(0.03)		(0.02)	
Price per $100		–0.69***		–0.30***
		(0.15)		(0.10)
Log(household income)	0.18*	0.05	0.20***	0.14**
	(0.09)	(0.09)	(0.06)	(0.06)
Probability Category 3	0.14	0.15	–0.04	–0.02
	(0.26)	(0.25)	(0.16)	(0.16)
Flood zone	0.38***	0.24*	0.17**	0.13
	(0.13)	(0.12)	(0.08)	(0.08)
Flood damage	0.17	0.21	0.11	0.12
	(0.20)	(0.19)	(0.12)	(0.12)
Erosion risk	0.00	–0.01	0.11	0.09
	(0.14)	(0.14)	(0.09)	(0.09)
Log(expected damage)	0.19**	0.12*	0.07	0.04
	(0.08)	(0.07)	(0.05)	(0.05)
Life time	–0.07	0.03	–0.08	–0.06
	(0.13)	(0.13)	(0.08)	(0.08)
Expected individual assistance	0.10	0.12	–0.03	–0.00
	(0.13)	(0.13)	(0.08)	(0.08)
Natural hazard worry	0.13	0.15	0.04	0.05
	(0.12)	(0.12)	(0.08)	(0.08)
CRRA	0.34**	0.18	0.07	0.03
	(0.16)	(0.15)	(0.10)	(0.10)
Conservative	–0.24**	–0.22*	–0.06	–0.06
	(0.12)	(0.12)	(0.08)	(0.08)
Brunswick	0.26*	0.35**	0.18*	0.25***
	(0.15)	(0.15)	(0.10)	(0.10)
Higher education	0.00	–0.02	0.09	0.07
	(0.13)	(0.12)	(0.09)	(0.09)
Observations	128	128	186	186

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

tion and expected damages are insignificant, whereas they were significant in our main specification. Other elasticity estimates are qualitatively consistent with our main specification. Annual WTP is estimated at $1,781 using the probit estimates and $2,101 based on the Turnbull estimator. WTP for $100 of coverage is estimated to be $0.59 for the probit model and $0.60 for the Turnbull estimator.

To mitigate concerns about small sample bias of the probit estimator, we conduct an additional robustness check that makes use of a logit model estimated via penalized maximum likelihood (PML). This method, proposed by Firth (1993), uses a modified likelihood (ML) function with an additive penalty term attached. The PML estimator has been shown to have lower bias and variance than the standard ML for logit model coefficients (Copas 1988; Firth 1993). More importantly, the PML estimator has been shown to have much better small sample properties than a standard ML estimator. Rainey and McCaskey (2021) use Monte Carlo simulations to show that PML estimated logit coefficients offer substantial improvements in terms of reduction of bias caused by small samples. In their worst-case scenario simulation (which is based on a model with nine parameters that are estimated on a scant 30 observations), the standard ML estimator had a bias of 69%, whereas the PML estimator only exhibited a 6% bias. Thus, we reestimate WTP for our multi-peril insurance product, this time deriving WTP based on coefficients obtained from estimating a logit model using PML. We report these

Table 5
Topic Frequency by Purchase Decision

Topic	Yes	No	I Don't Know	No Response	Total
Cheaper/better value	29	0	1	0	30
Too expensive	2	58	2	2	64
Self-insure	0	3	0	0	3
Need more info	1	1	3	0	5
Concerns about risks and damages	10	1	1	0	12
Concerns about payouts	9	3	0	0	12
Convenience	18	1	0	0	19
Deductible	6	1	3	0	10
Additional coverage not important/satisfied with current coverage	0	21	0	0	21
Total mentions	75	89	10	2	176*
Total unique comments	60	75	7	2	144*

*Total mentions differ from total unique comments because some comments mention multiple topics.

WTP values in the bottom of Table 3. Overall, we find that the WTP estimates obtained using PML are very close to our original WTP estimates. The largest difference was in the model reported in the third column of Table 3, where the PML estimated WTP is approximately 2% larger than the original value. All other models resulted in a PML estimated WTP that was within 1% of the original value. We interpret this as evidence of minimal small sample bias in our primary WTP estimates.[11]

7. Qualitative Results

The qualitative analysis provides additional insight into the primary motivations behind respondents' decision to purchase multi-peril insurance. Out of the 246 people who answered the multi-peril question, 144 provided a comment regarding their decision. Appendix Figure A5 shows the nine topics presented in the comments and their frequency as a percentage of total comments. Table 5 shows the distributions of topics based on the individual's purchase decision. Out of the people who left comments, 34 had current premiums (wind, flood, and homeowners) greater than the multi-peril premium, and 22 (64.7%) of them responded "yes." One hundred ten had current premiums less than the multi-peril premium, and 38 (34.5%) responded "yes" to purchase.

The majority of comments were left by respondents who indicated they would not purchase multi-peril insurance, followed by those who said they would. Only a few of the "I don't know" respondents left comments. The two respondents who did not answer the multi-peril question both commented "too expensive." Table 5 shows most of the comments from those who indicated they would not purchase the insurance were centered around the insurance being "too expensive" and Appendix Figure A5 shows that more generally most comments were focused on the cost of the insurance product. The next most frequent category of comments was focused on multi-peril insurance being unnecessary. Comments in this category generally mentioned that additional coverage was not important or that current coverage was sufficient. It is worth noting that comments related to multi-peril insurance being unnecessary frequently in-

[11] An anonymous reviewer raised the concern of anchoring WTP on current NFIP premium (which was recorded via open elicitation at an earlier point in the survey instrument). To alleviate concerns over bias introduced by anchoring, we run another robustness check. We construct a variable for each respondent that indicates their cost per $100 of flood structure coverage based on a default deductible, full coverage policy (this provides us with counterfactual flood insurance costs for those who did not report having a flood policy). We create an indicator for their flood insurance premium cost being greater than the bid price in the multi-peril question. We include this indicator in reduced-form regressions to identify if it has any bearing on reported willingness to purchase a multi-peril policy. This indicator is not significant in any of the reduced-form regressions and has minimal effects on overall WTP estimates (the largest disparity being a 3.5% reduction in WTP for one of the specifications).

cluded negative sentiments about the cost of the insurance.

Similarly, most comments from those who indicated they would adopt multi-peril coverage focused primarily on price. Most of the comments remarked that the multi-peril insurance was cheaper or a comparable price to their current policy. Several comments also stated that a modest increase in price was worth the additional coverage. Comments related to convenience were also common among those who were interested in purchasing and made reference to the simplicity of an all-hazards policy. A handful of comments mentioned concern for the risk of claims being denied or damages being uncovered. Comments of this type were primarily from those who indicated they would purchase multi-peril insurance. Several of these comments specifically brought up frustration with the seemingly subjective nature of claims payouts.

Responses of "yes," "no," and "I don't know" to the multi-peril insurance question were all represented in comments related to deductible. All but one of these comments expressed wanting a low deductible (or no deductible, in one case). A single person who did not want to purchase a multi-peril policy indicated a higher deductible was preferred to reduce the size of the annual premium. Preference for low deductibles could be attributed to people thinking of insurance as an investment, with a low deductible being a way to increase the chance of getting a return on that investment if a loss occurs (Kunreuther and Pauly 2005). Preference for a low deductible may also be a result of overestimating the likelihood of a loss and thus the value of the deductible (Schwarcz 2010). Over one-third of "I don't know" respondents who left a comment mentioned the deductible, suggesting that this is a major focal point for those who expressed uncertainty about the insurance product.

8. Discussion

To date, many studies have been published on single-peril flood insurance demand, but multi-peril or all hazards insurance has received relatively little attention despite offering some ways to address many issues plaguing insurance markets for natural hazards. Our income elasticity of 0.424 (based on annual premium) classifies multi-peril insurance as a normal good, which is consistent with previous evidence from the literature (Kriesel and Landry 2004; Hung 2009; Botzen and van den Bergh 2012; Ahmadiani, Ferreira, and Landry 2019). To further assess external validity, we compare our stated preference results to revealed preference flood insurance data for this same data set (Glynn County, GA); Landry and Turner (2020) estimate an income elasticity of 0.19 for actual take-up of flood insurance for these same households.[12] Given the expanded coverage offered by multi-peril insurance, our income elasticity estimate seems plausible and reasonable.

Estimated price elasticities from the full premium specification and the unit-coverage price model are around −2, suggesting that homeowners are relatively sensitive to changes in insurance price. Our alternative specification, in which "I don't know" responses are assumed to be "no" indicate lower sensitivity (close to −1) and are most similar to previous findings for the NFIP (e.g., −0.997, Browne and Hoyt 2000; −0.87, Landry and Jahan-Parvar 2011). Hung (2009) finds similar estimates for two Taiwanese cities (−0.84 to −0.94). Using a proxy variable for catastrophe insurance demand in Florida and New York, Grace, Klein, and Kleindorfer (2004) estimate price elasticities of −0.86 and −1.08.[13] Thus, we find evidence that our price elasticity estimates are similar or greater (in absolute value) than what is suggested by the existing literature.[14]

[12] The estimate of 0.19 is very similar to our multi-peril estimate from the unit-price model (0.126), though this estimate is not statistically significant.

[13] In their revealed preference analysis of flood insurance demand, Landry and Turner (2020) find an insignificant price effect (which they attribute to correlation in price and risk factors).

[14] Regarding other covariate effects, we find the following comparisons with Landry and Turner (2020) in their analysis of RP flood insurance demand for the same data set: they find that households in the SFHA are 23% more likely to hold flood insurance, whereas our estimates indicate an effect of 38% for multi-peril coverage. They find a positive marginal effect of 21% for CRRA, while we find a average marginal effect of 34% for CRRA. Given the extended coverage offered by multi-peril, it does not seem unreasonable

A complicating factor in analysis of NFIP is mandatory purchase requirements, which should depress econometric estimates of price responsiveness and create difficulties in isolation price from risk (Kousky 2010, 2011; Landry and Turner 2020). Neither difficulty applies to our contingent valuation estimates, however. Evidence of greater price responsiveness could be a result of the voluntary nature of purchase combined with our stated preference bid design that exposes households to a wider array of insurance prices. In addition, homeowners may place less value on the additional coverage for hazards they perceive to be unlikely in their locale (i.e., East Coast coastal homeowners may be unwilling to pay much extra for earthquake coverage).

An important caveat for our estimates is that they are based on a hypothetical insurance product, which is not a binding commitment; thus, our WTP estimates are subject to the standard perils associated with responses to essentially hypothetical questions. Hypothetical bias typically exaggerates WTP estimates (Loomis 2011), sometimes by a factor of two to three (List and Gallet 2001), but the severity of hypothetical bias typically varies based on the elicitation methodology, nature of the good being valued, and other factors. We note affirmative findings related to internal validity—positive income effects and the significant influence of the CRRA parameter and subjective risk perceptions. Moreover, our qualitative results indicate that price was a significant motivating factor in both "yes" and "no" responses, suggesting that respondents took the offer price seriously in their consideration of response. However, no unequivocal solution exists for potential hypothetical bias.

Notably, hypothetical bias is generally lower for WTP elicited for private goods, suggesting the prevalence of hypothetical bias in our analysis may be less severe than in other cases (Penn and Hu 2018). Although some have suggested that ex post calibration of WTP estimates can reduce potential hypothetical bias, others have noted that calibration factors vary by the type of good and context of valuation (among other factors) (e.g., List, Margolis, and Shogren 1998; Murphy et al. 2005). Nonetheless, we explore potential for hypothetical bias by applying a fitted calibration factor following Penn and Hu (2018). Using their regression results for a trimmed data set (removing bottom and top 2.5% of observations with extreme calibration factors), we obtain a calibration factor of 1.81 (for WTP for private good collected in the field from nonstudent subjects). Applying this to our empirical estimates suggests that coastal households in Glynn County are WTP $2,429 for multi-peril insurance or $0.67 per $100 of coverage. In any event, we consider our estimates useful initial indicators of the value and determinants of multi-peril insurance, and we welcome additional research that can address potential shortcomings.

An additional concern for the feasibility of a multi-peril insurance market is the degree to which adverse selection would persist. Our results indicate that residing in a flood zone significantly increases the probability of adopting multi-peril insurance, suggesting that adverse selection may manifest if such a product was introduced. Multi-peril insurance by design, however, mitigates the impact of adverse selection compared with insurance for singular hazards. Even if adverse selection exists in each class of hazards, an efficient market is still possible if the hazards are sufficiently uncorrelated spatially. For example, our sample consists of people who face comparably greater storm and flood risks but lower earthquake risks relative to other parts of the country. Many California residents face higher earthquake risk but lower storm and flood risk. If both groups of residents are combined in a multi-peril insurance market, each group may exhibit adverse selection with respect to their hazard of primary concern (although this depends on pricing). Combining multiple hazards implies that each hazard would still have a mix of high- and low-risk individuals participating for each hazard type (which would allow for some degree of cross-subsidization).

that covariate effects would be somewhat larger. Quite the contrary, we construe this as potential evidence of internal validity (though it is also possible that hazard exposure and risk tolerance feed into a strategic bias). Last, Landry and Turner (2020) find that the subjective perception of storm damage increases flood insurance demand by 32%, but we find a very small effect of 0.12% (perhaps not surprising given that multi-peril covers more than storm damage).

Potential heterogeneity in WTP with respect to objective risk remains an important area of focus for future research. Our limited sample size prevents us from estimating reliable WTP estimates across flood zone status. Appendix Table A4 reports frequency of responses to our hypothetical multi-peril insurance questions separated by flood zone status. In general, higher proportions of flood zone residents indicate that they would be willing to purchase multiperil insurance at each quoted price, which is consistent with these residents having higher WTP values.

Finally, we note that our sample is drawn from a population of coastal homeowners whose primary natural hazard threats are flooding and tropical cyclones. We feel the Georgia coast is an interesting study site, since it has historically been perceived as less risky, while recent hurricane landfalls have exposed some vulnerabilities. In assessing demand for hazard insurance, such a situation may provide a useful case study because the lower (perceived) baseline level of risk could provide a lower bound on economic value, while the recent exposure can make the risks salient. Thus, our results may not generalize to the broader population of homeowners on the East Coast who face hurricane risk or to other households that are primarily concerned with other natural hazards (e.g., wildfire, earthquake, tornado). Estimating WTP for multi-peril insurance among populations that face other natural hazards remains as an important avenue of future research that will be necessary for well-informed policy discussion related to multi-peril homeowners' insurance.

9. Conclusions

Multi-peril hazard insurance has recently been touted for its potential benefits to homeowners and insurers (Kunreuther 2018). On the homeowners' side, a multi-peril policy is simpler, reduces search costs associated with evaluating multiple types of policies, simplifies claim filing, and may help overcome cognitive biases that discourage the purchase of insurance. For insurers, the primary benefit is diversification of risk across a greater number of disaster types, which could make aggregate annual claims more predictable. Multi-peril insurance also eliminates the possibility of costly legal disputes over the source of damage, which is ultimately beneficial for homeowners and insurers.

Despite the many potential benefits, empirical evidence assessing the demand for multi-peril insurance is extremely limited. It is clear that multi-peril insurance could solve many public policy issues related to natural disaster insurance, but the ultimate success of a policy is conditional on including coverage relevant to homeowners and delivering it at a price that promotes widespread adoption while generating sufficient revenues for successful risk management.

Using a unique data set of individual-level survey responses, we assess the demand for a multi-peril or all-hazards insurance product that would insure homes against all natural hazards taking the place of a standard homeowners' policy, a federal flood insurance policy, and state-run wind insurance. We estimate WTP for multi-peril insurance and assess determinants of adoption by estimating a series of discrete choice models. In addition, we make use of free-form text responses that provide insight into the issues most important to homeowners considering a multi-peril policy.

We estimate mean WTP per annum of \$4,396 and mean WTP per \$100 of coverage of \$1.22. Use of a Turnbull estimator suggests lower bounds on the estimates of \$3,393 and \$1, respectively. For our preferred specification (the full premium model reported in the first column of Table 3), we find that risk aversion, income, and risk perception (magnitude of expected damage) increase likelihood of purchase, whereas WTP was lower for self-identified conservatives. Results from regression models along with insight gained from free-form responses suggest that cost is the primary concern for consumers thinking about adopting multi-peril insurance. This bodes well for the validity of our contingent valuation exercise, because it doesn't suggest that responses were motivated by hypothetical or strategic considerations. In addition to cost, survey respondents who indicated they would be willing to purchase multi-peril insurance left comments that suggested convenience and alleviation of concerns about payouts were important factors in their decision. The results presented here contribute to the understanding of demand for multi-peril hazard insurance, but our results are primarily based on homeowners who are concerned with damage from hurricanes, namely, wind and flood damage. Future work should assess demand for multi-peril insurance in locations that face different natural hazards.

Acknowledgments

This research was supported by the National Science Foundation's Coupled Natural-Human Systems Award 1715638. The views expressed here are those of the authors and cannot be attributed to ERS or the U.S. Department of Agriculture.

References

Ahmadiani, M., S. Ferreira, and C. E. Landry. 2019. "Flood Insurance and Risk Reduction: Market Penetration, Coverage, and Mitigation in Coastal North Carolina." *Southern Economic Journal* 85: 1058–82.

Ahmadiani, M., and C. Landry. 2017. "Economic Value of Multi-peril Coastal Hazard Insurance." Working Paper. University of Georgia.

Bakkensen, L. A., and R. O. Mendelsohn. 2016. "Risk and Adaptation: Evidence from Global Hurricane Damages and Fatalities." *Journal of the Association of Environmental and Resource Economists* 3: 555–87.

Bernoulli, D. 1738. "Specimen Theoriae Novae de Mensura Sortis: Commentarii Academiae Scientarum Imperialis Petropolitane." *Petropolitanae* 5: 175–92. Translated by L. Sommer (1954) "Exposition of a New Theory on the Measurement of Risk." *Econometrica* 22(1): 23–36.

Bin, O., J. B. Kruse, and C. E. Landry. 2008. "Flood Hazards, Insurance Rates, and Amenities: Evidence from the Coastal Housing Market." *Journal of Risk & Insurance* 75 (1): 63–82.

Botzen, W. J., J. C. Aerts, and J. C. van den Bergh. 2009. "Willingness of Homeowners to Mitigate Climate Risk through Insurance." *Ecological Economics* 68 (8): 2265–77.

Botzen, W. W., E. Michel-Kerjan, H. Kunreuther, H. de Moel, and J. C. Aerts. 2016. "Political Affiliation Affects Adaptation to Climate Risks: Evidence from New York City." *Climatic Change* 138: 353–60.

Botzen, W. J. W., and J. C. van den Bergh. 2009. "Bounded Rationality, Climate Risks, and Insurance: Is There a Market for Natural Disasters?" *Land Economics* 85 (2): 265.

———. 2012. "Risk Attitudes to Low-Probability Climate Change Risks: WTP for Flood Insurance." *Journal of Economic Behavior & Organization* 82 (1): 151–66. https://doi.org/10.1016/j.jebo.2012.01.005.

Browne, M. J., and R. E. Hoyt. 2000. "The Demand for Flood Insurance: Empirical Evidence." *Journal of Risk and Uncertainty* 20 (3): 291–306.

Chivers, J., and N. E. Flores. 2002. "Market Failure in Information: The National Flood Insurance program." *Land Economics* 78 (4): 515–21.

Copas, J. B. 1988. "Binary Regression Models for Contaminated Data." *Journal of the Royal Statistical Society B* 50 (2): 225–65.

Cramer, G. 1728. "Letter to N. Bernoulli" In D. Bernoulli, *Specimen Theoriae Novae de Mensura Sortis*. Commentarii Academiae Scientarum Imperialis Petropolitane, 175–92. Translated by L. Sommer (1954) "Exposition of a New Theory on the Measurement of Risk." *Econometrica* 22(1): 23–36.

Dixon, L., N. Clancy, S. A. Seabury, and A. Overton. 2006. "The National Flood Insurance Program's Market Penetration Rate: Estimates and Policy Implications." Working Paper. Santa Monica, CA: RAND Corporation.

Dixon, L., J. W. Macdonald, and J. Zissimopoulos. 2007. "Commercial Wind Insurance in the Gulf States: Developments since Hurricane Katrina and Challenges Moving Forward." Occasional Paper, Gulf States Policy Institute. Santa Monica, CA: Rand Corporation.

Du, X., and X. Lin. 2012. "Conceptual Model on Regional Natural Disaster Risk Assessment." *Procedia Engineering* 45: 96–100.

Eckle, C. J., and P. J. Grossman. 2002. "Sex Differences and Statistical Stereotyping in Attitudes toward Financial Risk." *Evolution and Human Behavior* 23: 281–95.

Ehrlich, I., and G. S. Becker. 1972. "Market Insurance, Self-Insurance, and Self-Protection." *Journal of Political Economy* 80 (4): 623–48.

Eichenberger, R., and F. Oberholzer-Gee, F. 1998. "Rational Moralists: The Role of Fairness in Democratic Economic Politics." *Public Choice* 94 (1–2): 191–210.

FIMA (Federal Insurance and Mitigation Administration). 2018. "The Watermark (Fiscal Year 2018, First Quarter Volume 1)." Available at https://www.fema.gov/media-library-data/1522167351921-a5e457454262dd100e2f15a7210d21c5/Watermark_FY18_Q1_v6_508.pdf.

Firth, D. 1993. "Bias Reduction of Maximum Likelihood Estimates." *Biometrika* 80 (1): 27–38.

Grace, M. F., R. W. Klein, and P. R. Kleindorfer. 2004. "Homeowners Insurance with Bundled Catastrophe Coverage." *Journal of Risk and Insurance* 71 (3): 351–79.

Haab, T. C., and K. E. McConnell. 2002. *Valuing Environmental and Natural Resources*. Northampton, MA: Elgar.

Hogarth, R., and H. Kunreuther. 1985. "Ambiguity and Insurance Decisions." *American Economic Review* 75 (2): 386–90.

Hout, M. (2004). "Getting the Most Out of the GSS Income Measures." GSS Methodological Report 101. Available at http://gss.norc.org/Documents/reports/methodologicalreports/MR101GettingtheMostOutoftheGSSIncomeMeasures.pdf.

Hung, H. 2009. "The Attitude towards Flood Insurance Purchase When Respondents' Preferences Are Uncertain: A Fuzzy Approach." *Journal of Risk Research* 12 (2): 239–58.

Insurance Information Institute. 2013. "Residual Markets." New York: Insurance Information Institute. Available at http://www.iii.org/issues_updates/residual-markets.html (accessed September 10, 2020).

———. 2017. "Homeowners Insurance: Understanding, Attitudes and Shopping Practices." New York: Insurance Information Institute. Available at https://www.iii.org/sites/default/files/docs/pdf/pulse-wp-020217-final.pdf.

———. 2019. "Facts + Statistics: U.S. Catastrophes." New York: Insurance Information Institute. Available at https://www.iii.org/fact-statistic/facts-statistics-us-catastrophes (accessed September 10, 2020).

———. 2020. "Background On: Earthquake Insurance and Risk." New York: Insurance Information Institute. Available at https://www.iii.org/ article/background-on-earthquake-insurance-and-risk (accessed September 10, 2020).

Jaiswal, K., D. Bausch, J. Rozelle, J. Holub, and S. McGowan. 2017. "Hazus Estimated Annualized Earthquake Losses for the United States." No. FEMA P-366. Washington, DC: Federal Emergency Management Agency.

Jaiswal, K., and J. Fitzpatrick. 2015. "Nearly Half of Americans Exposed to Potentially Damaging Earthquakes." Washington, DC: U.S. Geological Survey. Available at https://www.usgs.gov/news/nearly-half-americans-exposed-potentially-damaging-earthquakes.

Just, R. E., L. Calvin., and J. Quiggin. 1999. "Adverse Selection in Crop Insurance: Actuarial and Asymmetric Information Incentives." *American Journal of Agricultural Economics* 81: 834–49.

King, R. O. 2012. "CRS Report to Congress: National Flood Insurance Program: Background, Challenges, and Financial Status." Report 40650. Washington, DC: Congressional Research Service.

———. 2013. "CRS Report to Congress: The National Flood Insurance Program: Status and Remaining Issues for Congress." Report 42850. Washington, DC: Congressional Research Service.

Kousky, C. 2010. "Learning from Extreme Events: Risk Perceptions after the Flood." *Land Economics* 86 (3): 395–422.

———. 2011. "Managing Natural Catastrophe Risk: State Insurance Programs in the United States." *Review of Environmental Economics and Policy* 5 (1): 153–71.

———. 2019. "The Role of Natural Disaster Insurance in Recovery and Risk Reduction." *Annual Review of Resource Economics* 11: 399–418.

Kousky, C., H. C. Kunreuther, B. Lingle, and L. Shabman. 2018. "The Emerging Private Residential Flood Insurance Market in the United States." Technical Report. Philadelphia: Wharton Risk Management and Decision Processes Center.

Kousky, C., and L. Shabman. 2016. "The Role of Insurance in Promoting Resilience." Brink. Available at https://www.brinknews.com/the-role-of-insurance-in-promoting-resilience.

Kriesel, W., and C. Landry. 2004. "Participation in the National Flood Insurance Program: An Empirical Analysis for Coastal Properties." *Journal of Risk and Insurance* 71 (3): 405–20.

Krutilla, J. V. 1966. "An Economic Approach to Coping with Flood Damage." *Water Resources Research* 2 (2): 183.

Kunreuther, H. 1968. "The Case for Comprehensive Disaster Insurance." *Journal of Law and Economics* 11 (1): 133–63.

———. 1996. "Mitigating Disaster Losses through Insurance." *Journal of Risk and Uncertainty* 12 (2): 171–87.

———. 2018. "All-Hazards Homeowners Insurance: Challenges and Opportunities." *Risk Management and Insurance Review* 21 (1): 141–55.

Kunreuther, H. C., N. Novemsky, and D. Kahneman. 2001. "Making Low Probabilities Useful." *Journal of Risk and Uncertainty* 23 (2): 103–20.

Kunreuther, H., and M. Pauly. 2004. "Neglecting Disaster: Why Don't People Insure against Large Losses?" *Journal of Risk and Uncertainty* 28 (1): 5–21.

———. 2005. "Terrorism Losses and All Perils Insurance." *Journal of Insurance Regulation* 23 (4): 3.

Landry, C. E., G. Colson, and M. Ahmadiani. 2019. "Structured Empirical Analysis of Decisions Under Natural Hazard Risk." In *The Future of Risk Management*, edited by Howard Kunreuther, Robert J. Meyer, and Erwann Michel-Kerjan, 66–77. Philadelphia: University of Pennsylvania Press.

Landry, C. E., and M. R. Jahan-Parvar. 2011. "Flood Insurance Coverage in the Coastal Zone." *Journal of Risk and Insurance* 78 (2): 361–88.

Landry, C. E., and D. Turner. 2020. "Risk Perceptions and Flood Insurance: Insights from Homeowners on the Georgia Coast." *Sustainability* 12 (24): 10372.

Landry, C. E., D. Turner, and D. Petrolia. 2021. "Flood Insurance Market Penetration and Expectations of Disaster Assistance." *Environmental and Resource Economics* 79: 357–86.

Laury, S., M. McInnes, and J. Swarthout. 2008. "Insurance Purchases for Low Probability Losses." Andrew Young School of Policy Studies Research Paper 08-05. Atlanta: Georgia State University.

List, J., and C. Gallet. 2001. "What Experimental Protocol Influence Disparities between Actual and Hypothetical Stated Values?" *Environmental and Resource Economics* 20 (3): 241–54.

List, J. A., A. Margolis, and J. F. Shogren. 1998. "Hypothetical-Actual Bid Calibration of a Multigood Auction." *Economics Letters* 60 (3): 263–68.

Loomis, J. 2011. "What's to Know about Hypothetical Bias in Stated Preference Valuation Studies?" *Journal of Economic Surveys* 25: 363–70.

Marshall, D. 2018. "An Overview of the California Earthquake Authority." *Risk Management and Insurance Review* 21 (1): 73–116.

Martin, I. M., and W. E. Martin. 2017. "Understanding the Risk Mitigation Decision: Homeowners and Environmental Risks." In *The Customer Is NOT Always Right? Marketing Orientations in a Dynamic Business World*, 402–5. Dordrecht: Springer.

McAneney, J., D. McAneney, R. Musulin, G. Walker, and R. Crompton. 2015. "Government Sponsored Natural Disaster Insurance Pools: A View from Down-Under." *International Journal of Disaster Risk Reduction* 15: 1–9.

Miranda, M., and J. Glauber. 1997. "Systemic Risk, Reinsurance, and the Failure of Crop Insurance Markets." *American Journal of Agricultural Economics* 79: 206–15.

Moore, H. 1964. *. . . And the Winds Blew*. Austin: Hogg Foundation for Mental Health.

Moscati, I. 2016. "Retrospectives: How Economists Came to Accept Expected Utility Theory: The Case of Samuelson and Savage." *Journal of Economic Perspectives* 30 (2): 219–36.

Murphy, J. J., P. G. Allen, T. H. Stevens, and D. Weatherhead. 2005. "A Meta-analysis of Hypothetical Bias in Stated Preference Valuation." *Environmental and Resource Economics* 30 (3): 313–25.

National Oceanic and Atmospheric Administration (NOAA). 2020a. "U.S. Billion-Dollar Weather and Climate Disasters." Washington, DC: National Centers for Environmental Information. Available at https://www.ncdc.noaa.gov/billions/summary-stats.

———. 2020b. "Tropical Cyclone Climatology." Silver Spring, MD: NOAA.

Needham, H. 2016. "Matthew Makes the 'Protected Coast' the Most Dangerous Place of All." Wxshift. Available at https://wxshift.com/news/blog/ matthew-makes-the-protected-coast-the-most-dangerous-place-of-all (accessed June 15, 2020).

Nyman, J. A. 2001. "The Demand for Insurance: Expected Utility Theory from a Gain Perspective." Minneapolis: Center for Economic Research, Department of Economics, University of Minnesota. Available at http://hdl.handle.net/11299/55880.

OECD (Organisation for Economic Co-operation and Development). 2016. *Financial Management of Flood Risk*. Paris: OECD. http://dx.doi.org/10.1787/ 9789264257689-en.

Okuyama, Y. 2003. "Economics of Natural Disasters: A Critical Review." Working Paper 131. Morgantown, WV: Regional Research Institute.

Penn, J. M., and W. Hu. 2018. "Understanding Hypothetical Bias: An Enhanced Meta Analysis." *American Journal of Agricultural Economics* 100 (4): 1186–206.

Pothon, A., P. Gueguen, S. Buisine, and P. Y. Bard. 2019. "California Earthquake Insurance Unpopularity: The Issue Is the Price, Not the Risk Perception." *Natural Hazards and Earth System Sciences* 19: 1909–24.

Rainey, C., and K. McCaskey. 2021. "Estimating Logit Models with Small Samples." *Political Science Research and Methods* 9 (3): 549–64.

Raschky, P. A., R. Schwarze, M. Schwindt, and F. Zahn. 2013. "Uncertainty of Governmental Relief and the Crowding Out of Flood Insurance." *Environmental and Resource Economics* 54 (2): 179–200.

Raschky, P. A., and H. Weck-Hannemann. 2007. "Charity Hazard: A Real Hazard to Natural Disaster Insurance?" *Environmental Hazards* 7 (4): 321–29.

Schoemaker, P. J. H., and H. C. Kunreuther. 1979. "An Experimental Study of Insurance Decisions." *Journal of Risk and Insurance* 46 (4): 603–18.

Schwarcz, D. 2010. "Insurance Demand Anomalies and Regulation." *Journal of Consumer Affairs* 44 (3): 557–77.

Swiss Re Institute. 2019. "Insured vs Uninsured Losses, 1970–2019 (USD Billion, 2019 Prices)." Available at https://www.swissre.com/dam/jcr:7bd5953a-6d41-4797-9fd3-94adcd7c1eb7/sigma-2-2020-figure-15.xlsx (accessed March 13, 2020).

Turner, D., and C. E. Landry. 2020. "Structural Estimation of Decision Making under Natural Hazard Risk." Working Paper. Athens, GA: Department of Agricultural and Applied Economics, University of Georgia.

Von Neumann, J., and O. Morgenstern. 1944. *Theory of Games and Economic Behavior*. Princeton, NJ: Princeton University Press.

Wachtendorf, T., and X. Sheng. 2002. "Influence of Social Demographic Characteristics and Past Earthquake Experience on Earthquake Risk Perception." Second Workshop for Comparative Study on Urban Earthquake Disaster Mitigation, Kobe, Japan, 121–33.

Wakker, P. P. 2008. "Explaining the Characteristics of the Power (CRRA) Utility Family." *Health Economics* 17 (12): 1329–44.

Wang, M., C. Liao, S. Yang, W. Zhao, M. Liu, and P. Shi. 2012. "Are People Willing to Buy Natural Disaster Insurance in China? Risk Awareness, Insurance Acceptance, and Willingness to Pay." *Risk Analysis* 23 (10): 1717–40.

Wing, O. E. J., P. D. Bates, A. M. Smith, C. Sampson, K. A. Johnson, J. Farione, and P. Morefield. 2018. "Estimates of Present and Future Flood Risk in the Coterminous United States." *Environmental Research Letters* 13: 034023.

Wu, S., B. K. Goodwin, and K. Coble. 2020. "Moral Hazard and Subsidized Crop Insurance." *Agricultural Economics* 51: 131–42.