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Risk Preference Stability In The Aftermath of Natural and Human-Influenced Catastrophes: A Meta-Analysis

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RISK PREFERENCE STABILITY IN THE AFTERMATH OF NATURAL AND HUMAN-INFLUENCED CATASTROPHES: A META-ANALYSIS

by

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Abstract

We estimate the impact of natural and human-influenced catastrophes on individual risk preferences. Using the meta-analysis process with random-effects models, we examine the significance of the effect of different catastrophes on individual risk preferences. As natural and human-influenced catastrophes have become more frequent a number of studies have evaluated their effects on risk attitudes. In this thesis a meta-analysis is performed from the results in these recent studies, allowing for comparisons across catastrophes and against results from laboratory experiments. In evaluating the change in risk-taking behavior amongst affected populations it may better inform relief efforts and policy decisions. Overall, subjects from developed nations exhibit increased risk loving behavior on average in contrast to the shift to risk aversion in subjects from developing nations.

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1. Introduction

With the emergence of the COVID-19 pandemic people have been faced with increased uncertainty and a wider array of risky decisions than before. There is more risk associated with business investment, daily household activities, and unusually volatile capital markets. Climate change has also been a significant threat to individual livelihoods and global economic activities. The 21st century is likely to be one fraught with natural disaster; navigating through these uncertain times will no doubt come with heavy costs, not just to economic growth, but also to the decisions made by households, businesses, and governments. Developing countries in particular, with limited infrastructure and building regulations, are disproportionately susceptible to damage from natural disasters such as tsunamis, floods, earthquakes, hurricanes, and fires (Kahn, 2005).

Between 2001 and 2010 natural disasters killed over 100,000 people, affected over 232 million people, and caused more than $100 billion in damages worldwide (Guha-Sapir et al., 2013). Many of those deaths resulted from the Indian Ocean Tsunami in 2004. There is also evidence that natural catastrophes have caused over 8 million deaths and more than $7 trillion in damages since 1900 (Karlsruhe Institute of Technology, 2016). A proportionate amount of natural disasters affects developed nations, yet residents of low-income countries are 12 times more likely to die as a result of natural disasters and are disproportionately prone to the adverse economic consequences (Strömberg, 2007). The frequency and severity of natural disasters has been increasing over the past several decades due in part to global climate change, including tropical cyclones, droughts, and floods (Botzen and Van Den Bergh, 2009). According to Bates et al. (2008) climate change is likely to amplify the frequency and severity of natural disasters over the next century. Additionally, the devastation of these events has been exacerbated by the lack of natural buffering barriers such as vegetation on steep cliffs, intact coastal wetlands, and coral reefs (Ibarraran et al., 2009). Natural catastrophes occur at nearly the same rate across the globe, yet due to limited infrastructure, fewer early meteorological warning systems, and a lack of centralized catastrophe response, the aftermath of natural disasters in developing countries can be expected to be more severe than in developed countries. In fact, 98% of those affected by a natural disaster live in developing countries (Zorn, 2018). Considering the impacts disasters have on individual well-being, two natural questions regard whether risk preferences differ across catastrophe types and whether risk preferences over catastrophes differ between developed and developing nations. This thesis seeks to address both questions.

Individuals displaying risk averse behavior have preferences such that when faced with a risky gamble they have an expected utility of the payoff that is lower than the utility of the expected payoff (Atanasov, 2015). Thus, a risk averse individual always prefers receiving the expected return of a lottery with certainty over the lottery itself. That is, it is a preference for lower variance at the cost of lower expected returns. Alternatively, risk loving individuals derive a higher expected utility from the gamble than the utility of the expected payoff. And individuals are risk neutral if the expected utility of a gamble is equal to the utility of the expected payoff of the gamble. These behaviors, and how they change, are important because they influence important economic decision making such as investment and savings, fertility choices, and investment in human capital.

Classic economic models maintain that risk preferences are stable, insofar as an individual's risk preferences stay the same throughout their life (Stigler and Becker, 1977). This assumption allows more malleable use of models; however, it does not take into account changes over one's lifetime or the effects of exogenous shocks. Recent experiments from behavioral economics and psychology on decision making under risk offer some evidence that individuals become more risk-averse as they age, or rather that younger cohorts have a higher proportion of individuals that exhibit risk loving behavior relative to older cohorts (Levin et al., 2007). Age is an exogenous factor that can influence risk preferences. As age increases people may take on more responsibilities, increasing the level of background risk, affecting their proclivity to take independent risks.

A literature review by Chuang and Schechter (2015) about the effect of natural catastrophes on risk preferences finds the degree of risk aversion may not be affected. However, the researchers concluded there was no significant effect of natural catastrophes on risk preferences. The lack of conclusive evidence in the literature was also noted in a review by Schildberg-Hörisch (2018). And now, with the growth in the literature on risk preferences and natural and human-influenced catastrophes, there is enough data to conduct a meta-analysis, the goal of this thesis. In this thesis we perform a meta-analysis from the results in the literature, allowing for comparisons across catastrophes, between developed and developing nations, and against results from laboratory experiments.

The literature on natural and human-influenced catastrophes and their effects on risk preferences has employed a wide array of risk attitude elicitation methods. The most frequent among these methods are measures of sample proportions of risky choices from repeated discrete lottery choice experiments, correlation coefficients between catastrophic events and risk aversion, and differences in the number of risky choices made between groups affected and unaffected by the event. Other studies have used structural econometric methods to estimate risk preferences, such as the constant relative risk aversion (CRRA) parameter, which then allows for direct comparison of estimates of the parameter obtained from laboratory experiments.

The immediate effects of natural catastrophes may be exacerbated by their effects on risk attitudes, time discounting, or prosocial behavior, each of which may affect how individuals and communities recover from natural disasters. We study risk preferences following different types of catastrophes in different areas of the world, including floods, tsunamis, cyclones, earthquakes, and human-influenced catastrophes such as wildfires and armed conflicts. Random-effects linear regression is used to model alternative measures of risk preferences as a function of catastrophe type and country development status.

From the many measurement approaches used in the literature we focus on two: estimates of the constant relative risk aversion (CRRA) parameter and sample proportions of risky choices. We use CRRA due to it being the most widely used utility specification for parametric estimation of risk preferences, and there is a wide availability of laboratory studies to compare the results against. As relatively few of the catastrophe studies have estimated CRRA coefficients, we also evaluate sample proportions of risk attitudes from repeated discrete choice experiments. The next section consists of a review summarizing the literature on risk preferences after catastrophes, with many of the papers being included in the analysis. The third section discusses the datasets that were constructed, specifies the models that will be estimated, and presents and discusses the estimation results. The thesis concludes with a discussion of the implications of the study for future research.

2. Literature Review

The literature review is divided into two sections. The first reviews the research on the effects of natural disasters on risk preferences. The second reviews the research on the effects of human-influenced catastrophes on risk preferences including armed conflicts and wildfires. The review will focus mainly on the recorded change in risk preferences and the risk measurement methods used in each study.

2.1 Natural Catastrophes

Researchers have evaluated the effects of floods, tsunamis, earthquakes, and tropical cyclones on risk attitudes. Page et al. (2014) investigated behavioral changes following an unexpected urban flood that hit Queensland, Australia, affecting 78% of the state and causing an estimated $5 billion in property damages. The authors used this natural experiment to evaluate differences in the risky choices made by those experiencing property damage and those who were unaffected. Their risk attitude elicitation method was through a choice between $10 (Australian Dollars) and a scratch card lottery that had a chance of winning $500,000. They found that those directly affected by flooding, through home property damages, had an increased likelihood to take risky gambles of around 50% compared to those unaffected. A potential reason for this effect is that after individuals lost home equity (on average $70,000 in home damage) the prospect of recouping their losses was tempting enough to choose the riskier lottery choice. The additional background risk from the catastrophe may have been offset by the statistical improbability of a future flood and the availability of the Australian government's emergency resources (food, prop-up shelters, and financial assistance). However, a gambler's fallacy may also play a role (Tversky and Kahneman, 1974) where individuals believe that due to the recency of an event its future probability is lowered, inducing them to take a larger bet as if the wagers were not independent events.[1]

Vietnam is subject to strong monsoon seasons and associated catastrophic flooding. Aubert and Reynaud (2014) use instances of recent catastrophic flooding as a natural experiment in order to measure differences in risk preferences between villages affected by the floods and those which were unaffected. Using repeated discrete choice experiments involving lotteries with numeric risk tolerance intervals and a prospect theory framework, they measure the proportion of individuals in each group that chose risky versus riskless alternatives. They find a significant increase in risk aversion for losses, but no significant effect for gains. This suggests that the impact of natural catastrophes may largely be emotional, as psychological literature has established that emotions are far more intensely involved in experiencing losses than gains. This is consistent with the risk-as-feeling hypothesis proposed by Loewenstein et al. (2001) and furthered by Eckel et al.'s (2009) study of the effect of emotion on risk preferences in the aftermath of Hurricane Katrina. Eckel et al. studied three waves of refugees from Louisiana to investigate their emotions after the storm, and the storm's effect on individual risk preferences. Eckel et al. used a sample proportion method, on three waves of refugees, and found the first wave to be significantly more risk loving. However, the two subsequent waves of refugees did not differ from the Houston control group.

In Japan following the historic 2011 earthquake, which destroyed over 130,000 homes and disrupted the power and water supply of millions of other households, Hanaoka et al. (2017) used a hypothetical lottery question about respondent willingness to pay for a 50 percent chance of winning 100,000 Japanese Yen (USD 1,000). Additional data collected from the questionnaire

[1] In China, Yin et al. (2016) find a long-term increase in purchases of flood insurance after a significant typhoon. However, after two or three typhons a decrease is actually documented that is most sizeable amongst males.

indicates that men affected by the earthquake engaged in more risk-seeking behavior including drinking, smoking, and gambling, which persisted over several years. However, women were found to display more risk averse behavior. The reason for the increase in risk-seeking behavior in men may be similar to that observed following the Brisbane flood, which Page et al. (2014) considered to be an attempt at recouping losses by engaging in risky gambling activity.

Research by Kahsay and Osberghaus (2018) was conducted in Germany following the effect of hail storms on risk preferences. Data was collected from a nationwide property owner panel from 2012 to 2014. A significant increase in risk seeking was found for those households that experienced property damage. The effect is measured from an 11-point Likert scale given to the participants as a risk preference elicitation method. The increase in risk loving behavior may be attributed to a windfall of compensation through storm insurance payouts leading to more risk seeking behavior or with the emotional state of the victims following the event. Noted in this study, and consistent with the findings of Eckel et al. (2009), risk-loving behavior of respondents increased in accordance with the risk-as-feeling hypothesis. This provides some support from prior research that psychological states of mind may modify risk preferences (Loewenstein et al., 2001).

In contrast to the findings of risk loving effects following natural catastrophes in some developed countries, the literature has documented that the perceived future disaster probability plays a larger role in developing nations. Background risk involves risk that cannot be avoided or diversified. Background risks may make individuals less willing to take independent risks such as participating in lottery games. Natural disasters are one such example of background risk (Gollier and Pratt, 1996). In developing countries with less infrastructure and fewer post-catastrophe guidelines, individuals may perceive background risk as being higher because of the additional disaster-induced risks associated with poverty, starvation, rebuilding costs, and the future likelihood of a natural catastrophe. After flooding in rural Indonesia, a marked shift to risk-aversion is observed from a higher frequency of affected individuals choosing the lowest risk lotteries. These individuals also reported higher subjective probabilities of a similar natural disaster occurring in the near future (Cameron and Shah, 2012). Those affected showed a 41% decrease in the probability of making a risky choice compared to those in unaffected rural areas. The earthquake may have caused a large increase in background risk, further affecting participants' behavior in the lottery games. Historical flooding in Vietnam has been found to increase risk aversion in the event of losses, while increasing trust in and the size of social networks, both of which have also been found to be positive correlates with risk aversion (Aubert and Reynaud, 2014). This effect is only present in the case of losses. According to Chinese Earthquake data, Li et al. (2011) also finds increases in risk aversion for losses, however a decrease in risk aversion for probable gains.

Similar findings of increased risk aversion were documented after a tsunami in Thailand. Estimates of the CRRA parameter for the affected population were 20% higher than those of subjects in control villages (Cassar et al., 2017). The subjects were also found to show increases in trusting and impatient behaviors. Three channels were observed through which natural disasters change risk preferences: large income shocks, increased subjective probabilities of another disaster, and changes in emotional states. The last channel is inconsistent with the conclusions of Eckel et al. on the risk-as-feeling hypothesis, where the authors find an increase in risk loving behavior due to changes in emotional states, and Cassar et al. attribute increased risk aversion to the altered emotional state. Despite subjects' emotional states, an increase in perceived background risk may explain some of the variation in risk preferences in these populations.

Ahsan (2014) utilized a gambling game to evaluate risk preferences in Bangladesh following two cyclones in 2007 and 2009. The game allowed participants to invest an initial endowment of 200 taka (Bangladeshi currency) in 5 different amounts with the roll of a die deciding their payoff. This game is different from the lottery game used by Cassar et al. because of its use of a die. A roll of anything above a 3 had a positive return and anything below had a negative return (3 is break-even). Farmers affected by the storms showed statistically significant differences in risk-averse behavior when engaging in the games compared to those who were unaffected. Although an initial endowment is provided to experimental subjects, one may question whether the differences may be attributed to direct income/wealth shocks (Shaw, 1996). Farmers who recently experienced negative wealth effects may have a higher proclivity to keep freely given endowments rather than risk them in games that may be difficult to understand. This puts into question whether risk preferences are only affected by wealth/income effects as a result of natural disasters, or if natural catastrophes add unique background risk.

Although differences in risk preferences between individuals in developed and developing nations have been documented in several studies, in the aftermath of similar natural events, experimental evidence from Pakistan suggests behavior more consistent with that of developed nations (Said et al., 2015). Cameron and Shah (2012) found that individuals in villages experiencing more frequent floods displayed more risk averse behavior on average, however this may reflect longstanding village differences. Although Cameron and Shah used CRRA utility specifications to determine whether lottery choices revealed risk averse or risk loving behavior they did not report estimates of the CRRA parameter. Instead, they reported sample proportions of risky choices made, similar to Aubert and Reynaud (2014). The evidence from flood data in Pakistan indicates that individuals experiencing a more severe natural disaster increase risk-seeking behavior across income and wealth categories, which is similar to the findings of Page et al. (2014). However, individuals that experienced a higher frequency of flood events showed significant risk averse proclivities, indicating that repeated natural catastrophes have a risk aversion inducing effect while shorter more severe catastrophes induce risk loving behavior. This may offer insight into the difference between the Indonesian flood data and findings from developed countries.

Interestingly, an increase in risk aversion is documented in the United States by Schupp et al. (2017) after a tornado hit communities in Oklahoma. They used 10 lotteries where participants could pick either a risky option (A) or a safe option (B) in each of the lotteries. They altered the safe payout and expected payout for each lottery so that a risk neutral individual would pick A for lotteries 1 through 4 and B for 6 through 10. Risk averse individuals would pick more safe options and switch earlier. They found that those affected by the tornado chose the risky option more often and switched later than those unaffected. Not only do estimates of risk aversion increase, there is evidence of increased savings and willingness to invest in public infrastructure. Participants directly affected by the tornado are found to, on average, choose lotteries with the same expected payoffs and lower variances compared to the control group of participants who were unaffected.

2.2 Human-Influenced Catastrophes

In addition to research on risk preferences following natural disasters there has also been interest in how risk preferences change following human-influenced disasters, such as wildfires and armed conflicts. Wildfires occur naturally, but are increasingly human-influenced as campfires, cigarette butts, and even gender-reveal parties have caused massive forest fires in the western United States. Armed conflicts are also man-made; however, significant droughts as a result of climate change in Sub-Saharan Africa have been attributed to violent conflict and inflaming already delicate ethnic tensions over the past few decades (Von Uexhull, 2014).

The literature on wildfires and risk preferences largely focuses on experts in the field of forest management instead of individuals or households. However, a recent paper by Harrison et al. (2020) studies risk aversion in both experts and non-experts in response to virtual reality simulated forest fires in Florida. An appeal of this method is that it has the natural stimuli of field settings and provides the control aspects of the laboratory. This paper used CRRA coefficients estimated from participants' choices of lottery games. Although both groups are found to be risk averse, the coefficient estimates are lower than what laboratory experiments have found of subjects in the same country.

There are also studies documenting changes in risk attitudes after violent conflicts between armed militant groups. Voors et al. (2012) focused on the civil war in Burundi (1993-2003) and its effect on individual risk preferences. Using repeated lottery choice experiments, they find that those affected display less risk aversion over gains with no significant effect over losses. Jakiela and Ozier (2016) find conflicting evidence with impacted populations displaying significantly more risk aversion following post-election violence in Kenya. Their risk measurement methods are more generalizable to laboratory methods and much of the natural catastrophe literature because they estimate intervals of the CRRA parameter with data from repeated lottery choices. Kijima and Guintai (2018) also estimate the CRRA parameter for individuals affected by armed violence in Northern Uganda. They find that both groups who were affected and unaffected displayed very risk averse behavior. Moya et al. (2018) finds that higher levels of severe violence induces higher levels of risk aversion in Colombian victims of armed conflict. The authors contrast these findings with those of Voors et al. (2012) and Callen et al. (2014), where subjects in

Afghanistan's regions experiencing at least one terrorist attack displayed more risk loving behavior. Moya et al. cites that both of the previous papers only measured areas with a history of violent conflict, with fewer than 35% of individuals in each sample actually directly exposed to said violence.

3. Data, Model Specifications, and Estimation Results

3.1 Data

The data used in the proceeding meta-analysis (MA) was collected from the peer reviewed field studies discussed above. In constructing the dataset, variables were identified that were expected to affect the stability of risk preferences after natural and human-influenced catastrophes. The two prevailing measures of risk preferences discussed above will serve as the dependent variables in the random-effects regression models. These include estimates of the CRRA parameter and sample proportions of risky choices from repeated discrete choice experiments.

The dataset constructed for the analysis that uses CRRA parameter estimates is comprised of all catastrophe studies based upon expected utility theory and which report estimates of the CRRA parameter. The control group of laboratory studies is restricted to those which are also based upon expected utility theory and which report estimates of the CRRA parameter. The laboratory studies include estimates from both developed and developing countries, similar to those of the selected field experiments.

As discussed in the literature review, the country of origin and type of disaster may affect the degree or direction of a change in risk aversion. Dummy variables for the type of natural or human-influenced disaster and developed nation status comprise the independent variables in the models.

To conduct the analysis involving the CRRA parameter, it is important to note the specification of the utility function is given by:

$$U(M) = \frac{M^{1-r}}{1-r} \tag{1}$$

where M is income and r is the risk aversion parameter to be estimated, where r = 0 indicates risk neutrality, r < 0 risk loving preferences, and r > 0 risk averse preferences.

Table 1 provides a list of the studies used in our analysis of CRRA estimates. Summary statistics on the CRRA estimates for the full sample and each catastrophe type are reported in Table 2. There are 26 observations in the dataset with approximately 50% of the observations coming from developed nations. The estimates of the CRRA parameter range from 0.39 to 1.93. There are 4 observations involving wildfires, with CRRA estimates ranging from 0.44 to 0.57. Observations from tsunamis made up approximately 25% of the data, with 6 observations ranging from 0.73 to 0.79. There were only two observations from armed conflicts, with estimates of the CRRA parameter ranging from 1.11 to 1.14. We also provide a summary of the 15 CRRA estimates from laboratory studies, which range from 0.39 to 1.93.

Table 3 lists the studies used in the analysis of sample proportions of risk averse behavior. Summary statistics of sample proportions of risky choices for the full sample and each catastrophe type are reported in Table 4. Of the 11 observations in the dataset, 7 come from developed nations with a range of 0.20 to 0.80. There are 3 earthquake observations with 1 from Hanaoka et al. (2015) and 2 from Cameron and Shah (2012) that range from 0.80 to 0.89. There are 2 hurricane observations from Eckel et al. (2009) that range from 0.65 to 0.75. Lastly, there are 9 observations for floods that range from 0.20 to 0.89. The number of observations for each independent variable is greater than the 11 total observations because the observations from Cameron and Shah is included for the flood category and earthquake category because there are instances of both in their study.

3.2 Model Specifications

As both datasets include studies that report multiple estimates of the CRRA parameter or sample proportions of risky choices, random-effects model specifications are used for estimation.[2] Two versions of the model with the CRRA parameter as the dependent variable are estimated. In the first the catastrophe is disaggregated by type and is specified:

$$r_{ij} = \beta_0 + \beta_1 Developed_{ij} + \beta_2 Wildire_{ij} + \beta_3 Tsunami_{ij} + \beta_4 Armed\ Conflict_{ij} + u_i + \varepsilon_{ij} \quad (2)$$

where r_{ij} is estimate j of the CRRA parameter from study i, the β's are parameters to be estimated, u_i is the study specific error term, ε_{ij} is a mean zero error term, and each independent variable is a dummy variable. The base case references the results from laboratory experiments in developing nations. That is, $E(r) = \beta_0$ when $Developed = Wildfire = Tsunami = Armed\ Conflict = 0$. β_1 then identifies the difference in $E(r)$ between laboratory results from developing and developed nations. β_2, β_3, and β_4 can be interpreted in a similar manner with respect to differences in $E(r)$ between each catastrophe type and the laboratory results in developing and developed nations. Both models are also estimated with the dependent variable expressed in natural logarithms. In the second specification of the model all catastrophes are aggregated into a single independent variable, which is interacted with *Developed* in order to test whether the effect of catastrophes on risk preferences differs between country type:

$$r_{ij} = \beta_0 + \beta_1 Catastrophe_{ij} + \beta_2 Developed_{ij} + \beta_3 \left(Developed_{ij}\ x\ Catastrophe_{ij}\right) + u_i + \varepsilon_{ij} \quad (3)$$

[2] Estimation of models with study specific fixed effects would be feasible if the dataset contained multiple studies that evaluated multiple catastrophe types.

In this model, β_0 represents *E(r)* when *Catastrophe* = *Developed* = 0, which corresponds to laboratory results in developing nations. If *Catastrophe* = 1 and *Developed* = 0, then $E(r) = \beta_0 + \beta_1$; if *Catastrophe* = 0 and *Developed* = 1, then $E(r) = \beta_0 + \beta_2$; and if Catastrophe = 1 and Developed = 1 then $E(r) = \beta_0 + \beta_1 + \beta_2 + \beta_3$.

The model with sample proportions (*Prop*) as the dependent variable is specified:

$$Prop_{ij} = \beta_0 + \beta_1 Developed_{ij} + \beta_2 Earthquake_{ij} + \beta_3 Flood_{ij} + \beta_4 Hurricane_{ij} + u_i + \varepsilon_{ij} \quad (4)$$

In contrast to the models with the CRRA parameter as the dependent variable (4) excludes tsunamis, wildfire, and violent conflicts but includes earthquakes, floods, and hurricanes due to the nature of the catastrophes that each class of studies investigated. Additionally, due to the absence of laboratory results reporting sample proportions, estimation of a model with *Developed* interacted with a catastrophe categorical variable (similar to (3)) is not possible. Like with the CRRA analysis, the model is also estimated with the dependent variable expressed in logarithms.

3.3 Estimation Results

Results for the models estimated with the CRRA parameter as the dependent variable are reported in Table 5. Across model specifications *Developed* is the only variable that is consistently significantly related to the CRRA parameter. The estimated coefficient on the *Developed* variable is negative in each of the levels models ($p<0.05$). However, no coefficients were significant in either of the logarithmic models. All else constant, the results indicate that on average experimental subjects in the developing nations included in the sample are significantly more risk averse than the subjects in the developed nations. The point estimate of the CRRA parameter is about fifty percent greater for subjects in developing nations than those in developed nations. The only catastrophe that has a significant effect is *Tsunami* ($p<0.05$) with a negative coefficient. However, this is only the case in model (1). Considering models (3) and (4), the results indicate no significant interaction between natural catastrophes and development status. Catastrophes are also not found to be significant in the models, consistent with the results from models (1) and (2). The R^2 statistic ranges between 0.273 and 0.360 in models (1) and (3) and between 0.288 and 0.385 in models (4) and (2).

Results for the models estimated with sample proportions as the dependent variable are reported in Table 6. In both the levels and logarithmic model specifications *Developed* and *Flood* are statistically significant ($p<0.01$) and their estimated coefficients are negative. Consistent with the results reported in Table 5 there is a significant difference between experimental subjects in developed and developing nations. Subjects in developing nations are significantly more risk averse than subjects from developed nations. For comparison to the CRRA results, the point estimate of sample proportion of risky choices made by individuals in developing nations is approximately forty-five percentage points higher than individuals in developed nations. Unlike with the CRRA results, one natural catastrophe is found to have a significant effect on the proportion of risk choices made relative to other catastrophes. Neither hurricanes nor earthquakes were found to have a significant effect on the sample proportion of individuals displaying risk averse behavior when compared against the single laboratory study and the additional field studies. The R^2 statistics are 0.871 and 0.769 for the levels and logarithmic models, respectively. However, since there are only 11 observations, strong R^2 variables are more likely to be expected.

4. Conclusions

With ongoing natural and human-influenced catastrophes worldwide, a growing body of studies have evaluated their effects on risk preferences. Two natural questions that arise from reviewing this literature regard whether risk preferences differ between catastrophe types and between developed and developing countries. In this thesis we used random-effects modeling to evaluate the effects of different catastrophe types across developed and developing nations on two measures of risk preferences that have been evaluated in the literature.

Our results from the analysis of sample proportions of risky choices made by subjects in field experiments suggest an increase in the number of risky choices from floods but not from other catastrophe types, including earthquakes and hurricanes. In addition, experimental subjects in developing nations were found to be significantly more risk averse than subjects in developed nations. Similar results on differences in the degree of risk aversion between subjects in developed and developing nations was also found in the analysis using estimates of the CRRA parameter, but there were no notable differences found between catastrophe types. Moreover, the availability of estimates of the CRRA parameter from laboratory experiments allowed for direct comparison to those obtained from field experiments involving natural and human-influenced catastrophes.

Many aspects of the consequences of natural catastrophes in developed economies may offer explanations for the significant differences in the degree of risk aversion between developed and developing nations such as insurance markets that allow individuals to protect against catastrophic losses. The effect of natural catastrophes on risk aversion in developing countries comes from this analysis as well. The implication, from the literature review and results, is that individuals in developing nations participating in these repeated discrete choice experiments display more risk averse behavior than individuals participating in similar experiments in developed nations.

The first noticeable issue with conducting this research is that, despite the recent increase in data on the subject of natural catastrophes and risk preferences, many authors choose to use different risk measurement methods. Without a standard method of risk attitude elicitation, it is difficult to compare different experiments to each other and to controlled laboratory data. This meta-analysis is the first of its kind in this literature, but it is limited by the lack of comparability in risk measurement methods. As more data for each for each risk measurement method becomes available, further study should be applied to parametric and non-parametric risk measurements from developing nations as more papers are published on the subject. It is important to parse out effects on this specific topic to optimize relief efforts and economic policy following natural and human-influenced catastrophes. If individuals in developed countries do on average display more risk loving behavior following natural catastrophes then governments may want to curb this risk-proclivity and encourage the affected population to save more or not take part in risky behaviors that could negatively affect their health. As the number of studies rises in the future, more conclusive, meta-analyses can be performed on the effect of natural and human influenced catastrophes on individual risk preferences.

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Table 1. Studies used in the CRRA Analysis

Study	Country	Observations	Disaster Type
Harrison et al. 2020	United States	4	Wildfire
Cassar et al. 2017	Thailand	6	Tsunami
Kijima and Guantai 2018	Uganda	2	Armed Conflict
Harrison and Ruström 2008	United States	3	Lab - Control
Gandelman and Hernandez-Murillo 2015	Japan, Australia, Vietnam, Uganda, United States, Malaysia, Russia, Laos	8	Lab - Control
Guiso and Paella 2008	Italy	1	Lab - Control
Harrison et al. 2007	United States	2	Lab - Control

Table 2. Summary Statistics of CRRA Estimates across Categories

CRRA Estimates by Type	Obs.	Mean	Std. Dev.	Median	Min	Max
Full Sample	26	0.78	0.37	0.69	0.39	1.93
Developed = 0	12	0.92	0.37	0.74	0.65	1.93
Developed = 1	14	0.65	0.24	0.57	0.39	1.17
Wildfire = 1	4	0.51	0.06	0.51	0.44	0.57
Tsunami = 1	6	0.72	0.04	0.73	0.65	0.79
Armed Conflict = 1	2	1.13	0.12	1.13	1.11	1.14
Control Group = 1	15	0.84	0.40	0.66	0.39	1.93

Table 3. Summary of Sample Proportions Dataset

Study	Country	Observations	Disaster Type
Cameron and Shah 2012	Indonesia	2	Earthquake/Flood
Page et al. 2014	Australia	2	Flood
Hanaoka et al. 2015	Japan	1	Earthquake
Aubert and Reynaud 2014	Vietnam	2	Flood
Eckel et al. 2009	United States	3	Hurricane
Dohmen et al. 2007	Germany	1	Lab - Control

Table 4. Summary Statistics of Sample Proportions across Categories

Sample Proportions by Type	Obs.	Mean	Std. Dev.	Median	Min	Max
Full Sample	11	0.72	0.41	0.80	0.20	0.89
Developed = 0	4	0.85	0.03	0.85	0.82	0.89
Developed = 1	7	0.64	0.21	0.75	0.20	0.80
Earthquake = 1	3	0.84	0.04	0.83	0.80	0.89
Flood = 1	6	0.69	0.25	0.83	0.20	0.89
Hurricane = 1	2	0.70	0.05	0.70	0.65	0.75

Table 5. Random Effects Estimation Results from the CRRA Models

Variable	(1)	(2)	(3)	(4)
Constant	1.100***	-0.035	1.100***	-0.034
	(0.145)	(0.193)	(0.151)	(0.167)
Developed	-0.367**	-0.361	-0.367**	-0.361
	(0.171)	(0.225)	(0.178)	(0.225)
Wildfire	-0.228	-0.296		
	(0.171)	(0.225)		
Tsunami	-0.376**	-0.289		
	(0.187)	(0.389)		
Armed Conflict	0.025	0.153		
	(0.251)	(0.360)		
Catastrophe			-0.276	-0.098
			(0.185)	(0.278)
Developed x Catastrophe			0.048	-0.198
			(0.257)	(0.358)
R^2	0.360	0.384	0.273	0.288

Note: The dependent variable in (1) and (3) is in levels, while the dependent variable in (2) and (4) is in natural logarithms. *** and ** represent significance at 1% and 5%, respectively.

Table 6. Random Effects Estimation Results from the Sample Proportions Models

Variable	(1)	(2)
Constant	1.284***	0.745**
	(0.115)	(0.330)
Developed	-0.496***	-0.983***
	(0.089)	(0.255)
Earthquake	-0.013	-0.016
	(0.073)	(0.208)
Flood	-0.438***	-0.914***
	(0.089)	(0.255)
Hurricane	-0.088	-0.121
	(0.089)	(0.255)
R^2	0.871	0.769

Note: The dependent variable in (1) is in levels, while the dependent variable in (2) is in natural logarithms. *** and ** represent significance at 1% and 5%, respectively.