A close-up of a logo

Description automatically generatedA close-up of a logo

Description automatically generated

Erasmus School of Economics

MS Policy Economics

Rising tides:

Exploring determinants of household-level disaster preparedness

Philip Mueller: 634720

# Abstract

This proposal outlines a study to explore the effect of flood experience on preparedness in the United States. While existing literature addresses various determinants of flood disaster preparedness, the role of personal flood experiences remains unclear.

The study will utilize the latest data from FEMA’s (Federal Emergency Management Agency) National Household Survey, which captures adaptation measures like insurance take up, and community engagement as well as binary reporters on flood experience and socioeconomic covariates.

Besides addressing a gap in the literature, the findings can guide policymakers in designing more targeted interventions in an effort to increase societal resilience to climate change-induced coastal floodings.

Table of Contents

[Abstract 2](#_Toc197002957)

[List of Tables 3](#_Toc197002958)

[List of Figures 3](#_Toc197002959)

[1. Introduction 4](#_Toc197002960)

[2. A simple adaptation decision model 5](#_Toc197002961)

[3. Climate Change Induced Flood Adaptation 5](#_Toc197002962)

[3.1. Relevant Terms 5](#_Toc197002963)

[3.2. Types of Adaptation 6](#_Toc197002964)

[3.3. Determinants of adaptation 8](#_Toc197002965)

[3.4. Behavioral Adaptation Theories 9](#_Toc197002966)

[4. Research Questions 9](#_Toc197002967)

[5. Data 10](#_Toc197002968)

[5.1. Data Cleaning 12](#_Toc197002969)

[5.2. Data Exploration 12](#_Toc197002970)

[6. Analysis 13](#_Toc197002971)

[6.1. The effect of flood risk, perception, experience, and awareness 14](#_Toc197002972)

[6.1.1. Univariate models 15](#_Toc197002973)

[6.1.2. Predicting risk perception 19](#_Toc197002974)

[6.1.3. A multivariate model 20](#_Toc197002975)

[6.1.4. Robustness Checks 21](#_Toc197002976)

[6.2. Hypotheses from the literature 22](#_Toc197002977)

[6.2.1. The effect of insurance on adaptation 22](#_Toc197002978)

[6.2.2. The effect of efficacy on adaptation 22](#_Toc197002979)

[6.2.3. The effect of socioeconomic determinants on adaptation 23](#_Toc197002980)

[6.3. Next analysis 25](#_Toc197002981)

[Bibliography 26](#_Toc197002982)

[Appendix 29](#_Toc197002983)

[Appendix 3 29](#_Toc197002984)

[Appendix 5.2 31](#_Toc197002985)

[Appendix 6 35](#_Toc197002986)

**Alternative Table of Contents:**

1. Introduction
2. A simple Model
3. Determinant 1
   1. The literature
   2. Study results
4. Determinant 2
   1. The literature
   2. Study results

…

# List of Tables

[Table 1: Adaptation measures and corresponding survey variables 11](#_Toc194329526)

[Table 2: Determinants of preparedness. Selected variables from Koerth et al. (2017) 7](#_Toc194329527)

[Table 3: Selected Variables in "disaster preparedness dataset" 21](#_Toc194329528)

# List of Figures

[Figure 1: Effect of risk perception on adaptation; selected results from probit estimation 14](#_Toc195623939)

[Figure 2: Effect of experience on adaptation; selected results from probit estimation 15](#_Toc195623940)

[Figure 3:distribution of adaptation measures for large clean dataset 23](#_Toc195623941)

[Figure 4:distribution of adaptation measures for small clean dataset 23](#_Toc195623942)

[Figure 5: Distribution of adaptations per region for large clean dataset 23](#_Toc195623943)

[Figure 6: Distribution of adaptations per region for small clean dataset 24](#_Toc195623944)

[Figure 7: share of missing observations per variable 24](#_Toc195623945)

[Figure 8: Spatial distribution of observations 25](#_Toc195623946)

[Figure 9: Spearman Rank correlation of determinants 25](#_Toc195623947)

[Figure 10: Spearman rank correlation of socioeconomic determinants 26](#_Toc195623948)

# Introduction

<shift from mitigation to adaptation>

Global climate change is systematically driving scale and frequency of natural disasters (Coronese et al., 2019). Coastal regions around the world are bracing for a new wave of storm surges (Sauerborn & Ebi, 2012). With rising sea levels, efforts to mitigate floodings are proving evermore challenging (Haggag et al., 2021). Going forward, pure flood prevention strategies through large-scale infrastructure projects will not suffice. The global change community is shifting focus from mitigation to adaptation (Botzen & Van den Bergh, 2009; Wilby & Keenan, 2012). In wake of a systemic uptick in flood risk, societies will have to learn to prepare for rising tides.

<household level adaptation>

With a shift from mitigation to adaptation comes a shift from the state to the individual. When a flood disaster hits and mitigation fails, households will experience the adverse effects – and burden at least some of the damage. Hence, individual disaster preparedness is key. Future climate adaption policy hinges on our understanding of individual preparedness and its determinants.

<determinants of preparedness>

Multiple determinants are possible: Firstly, we expect flood experience to heighten individual flood risk perception and awareness, leading to an uptick in household-level adaptation (Pasquier et al., 2020). Secondly, we expect psychological mechanisms like adaptation fatigue and learned helplessness to have an offsetting effect on household-level adaptation (Harries & Penning-Rowsell, 2011). Thirdly, we expect community-level spillovers to affect household-level decision making. A household should be more likely to opt for a certain adaptation measure if that measure is widespread in the household’s neighborhood. Vice versa, adaptation measures should be less likely in neighborhoods with low initial adaptation levels (Wilby & Keenan, 2012). Finally, we expect financial constraints and socioeconomic realities to play a role in adaptation outcomes (Storbjörk, 2007).

<Research Gap>

Various determinants of household-level flood adaptation exist. Their effect direction and size seem to be dependent on regionality and other case-specific, non-individual factors. Interdependencies between determinants are possible. The literature on these determinants is still sparse. We recognize that personal experience of past floodings as a determinant for flood adaptation has not been studied yet – neither in the US nor elsewhere. We thus derive the following research question:

**What is the effect of flood experience on household-level flood adaptation?**

# A simple adaptation decision model

To explore the determinants of disaster preparedness, we hypothesize a simple adaptation model. A rational agent will prepare for disaster if he perceives the benefits of adaptation to outweigh the cost of disaster. Adaptation cost is known to the agent upfront. Flood damage to property such as house and car can be assumed very large. Hence, the agent can gauge the cost factors reasonably well. He will conclude that in the case of disaster the benefits of adaptation outweigh the cost of adaptation. In the case of no disaster, however, adaptation costs will outweigh the benefits. His decision to adapt thus largely hinges on his perceived probability of disaster. We model his adaptation decision in Equation 1.

Eq1:

Here, denotes probability of the agent deciding to prepare for a flood. denotes his subjective flood risk perception. and denote the cost of flood damage and the cost of adaptation, respectively. The probability to adapt is thus driven by risk perception, expected damage and preparation cost. As argued, a rational agent will assume . To predict household-level adaptation decisions, we thus want to understand the determinants of subjective risk perception. For now, we assume that risk perception is a function of real underlying flood risk, agents’ prior flood experience, and their awareness of the risks, as shown in Equation 2.

Eq2:

Here, denotes the unknown real probability of a flood disaster hitting the household. captures whether the household has been hit by a flood before, and whether the agent has been consuming information on flood risk and adaptation techniques. Note that by including prior experience and risk awareness, we are relaxing the rational agent assumption.

The cost of adaptation depends on the adaptation measure. Their scope and effectiveness differ too. The type of adaptation plays a role in the adaptation decision. To understand the determinants of adaptation, we thus first have to understand the types of adaptation that a household can choose from. In section three we will define relevant terms, discern between adaptation types, review the literature on determinants to adaptation and briefly touch on selected decision frameworks that have been put forward.

# Climate Change Induced Flood Adaptation

<mitigation v adaptation>

The climate change literature is discerning between adaptation and mitigation strategies (Fankhauser et al., 1999). Climate mitigation refers to actions that reduce greenhouse gas emissions or enhance their removal from the atmosphere (Finlayson & D’Cruz, 2008). Climate change adaptation is the “process of adjustment to actual or expected climate and its effects, in order to moderate harm or exploit beneficial opportunities” (Verschuuren, 2022, p.1). In natural systems, it involves making adjustments to the actual climate whereas in human systems it involves managing risk and vulnerability (Verschuuren, 2022). This thesis will focus exclusively on climate adaptation strategies, specifically flood adaptation.

In the following section we will introduce relevant concepts, before discussing adaptation strategies and determinants of household-level adaptation in more detail.

## Relevant Concepts

<exposure and risk>

Brooks (2003) defines exposure as the presence of people, livelihoods or infrastructure that could be adversely affected by a disaster. By prohibiting construction in inundation areas, we thus adapt to climate changing by reducing exposure. Limited exposure reduces risk. Risk is commonly defined as a function of hazard exposure and the probability its occurrence (Brooks et al., 2005). Systematic changes in climate patterns mean that the flood risk function in coastal regions is currently changing, resulting in a systematic uptick in observed flood disasters.

<vulnerability and social vulnerability>

Increasing flood risk leaves coastal population vulnerable. Adger (2006) defines vulnerability as “susceptibility to harm from exposure to stresses… and from the absence of capacity to adapt” (p.1). This “vulnerability to environmental hazards means the potential for loss” (Cutter et al., 2003, p.1). Social vulnerability captures the observation that the potential for loss oftentimes differs systematically across socioeconomic groups through factors like poverty, inequality, and marginalization (Cutter et al., 2003).

<adaptive capacity, preparedness and adaptation>

Vulnerability is lower in systems with high adaptive capacity (Engle, 2011). Originating from ecology and since often used in the context of system dynamics and climate studies, adaptive capacity is describing a “system’s (culture’s) ability to adapt fast and easily to exogenous change (Denevan, 1983). The concept applies to environmental and social systems alike. Adaptation itself constitutes “manifestations of adaptive capacity” (Smit & Wandel, 2006, p.5). In disaster research – and in this thesis – the terms adaptation and preparedness are used interchangeably (Koerth et al., 2017).

Adaptation also constitutes a human response to risk. We often observe adaptation as a result of interaction between exogenous shocks such as flood events on one hand and human adaptive capacity and vulnerability on the other (Smit & Wandel, 2006). Whereas adaptive capacity describes the potential for adaptation, adaptation outcomes describe the consequences of adaptation. Specifically, adaptation outcomes describe the long-term effect of adaptation measures aimed at improving livelihood, for instance by reducing expected damage to assets (Donatti et al., 2020). While adaptation is often referring to single instances of agent-level observations, the concepts of adaptive capacity and adaptation outcomes usually refer to system-level (e.g., macro level) phenomena. As such, adaptation outcomes often emerge from individual adaptation.

<emergence>

Emergence denotes system‑level regularities that “arise from decentralized bilateral interactions” (source) among boundedly rational agents. Prominent examples are Schelling segregations, flocking swarms or boom-bust cycles that materialize on the aggregate level without agentic intention or coordination. Emergent behavior is best understood as an internal property of model structure rather than a consequence of external shocks.

In economics, emergence is epitomized by Hayek’s (source) notion of spontaneous order, wherein markets, price systems and legal norms form as unintended outcomes of agent-level transactions that exceed policy maker’s design capacity. Complexity economics formalizes this insight by treating the economy as a “nonequilibrium computational process” (source) whose agents adapt to – thereby simultaneously reshaping – the aggregate environment, so that “patterns emerge probabilistically, last for some time and dissipate” (source).

<bounded rationality>

Emergent adaptation is often assumed to be subject to bounded rationality (source). (Source) argues that a rational agent’s decision-making process is limited by limited information available, limited decision time, and limited computed to make the decision. The more limited either one of these three resources are in the decision-making process, the more the agent relies on heuristics and the less optimal the decision (source). Bounded rationality is key to understanding human adaptation behavior in disaster settings, as different types of adaptation are subject to more time constraint and heuristic decision making then others.

## Types of Adaptation

<autonomous v planned>

Carter et al. (1994) distinguish between planned and autonomous adaptation. Planned adaptation carries an element of analysis and is often implemented via top-down policy intervention. Autonomous adaptation, defined as “spontaneous adjustments in the face of a changing climate” (Carter et al., 1994, p.32), is typically emergent in nature and carries less certainty with regards to its exact manifestation and total associated cost. Note that planned adaptation often yields adaptation outcomes through central top-down planning, thus circumventing the uncertainties connected to emergent, autonomous adaptation.

The differentiation is intuitive in theory but blurred in practice. Holding fresh water supplies at home can be regarded as planned adaptation by the household and as autonomous adaptation from a government’s perspective. In this thesis, we will focus on agent-level adaptation that is spontaneous from a system-level perspective but planned from on agent-level perspective. By understanding its determinants, we hope to identify levers to incentivize or steer adaptation behavior and its emergent impact on coastal communities.

< reactive v anticipatory>

The distinction between planned and autonomous adaptation allows us to more clearly distinguish between the behavior of an individuals and the system as a whole. Another useful distinction runs along the time axis. Adaptation can occur as a response to exogenous events, e.g., “reactive”, or in anticipation of a change in environment, e.g., “anticipatory” (IPCC, 2001). However, like with the distinction between autonomous and planned adaptation, the lines between reactive and anticipatory adaptation are blurred as well. We will show that personal disaster experience has a positive impact on adaptation. Whether adaptation post disaster experience is reactive to that experience or anticipatory of an expected next disaster, is hard to discern.

<3 objectives of adaptation>

Flood adaptation in nature-human coupled systems is following three main objectives (Dronkers et al., 1990). Firstly, construction development in inundation areas is to be avoided. For that purpose, the Federal Emergency Management Agency (FEMA) is continuously mapping Special Flood Hazard Areas (SFHA) (*Flood Zones | FEMA.Gov*, 2020). In the face of changing climate patterns, inundation areas are subject to change as well. Secondly, the continued functioning of critical natural systems such as swamps and dunes is to be ensured in order to maintain the natural systems adaptive capacity. Thirdly, human life, property, and economic activity are to be protected against disaster. While this thesis will focus on the latter objective, it is important to understand any adaptation strategy in the context of all three objectives.

<protection, accommodation, retreat>

Dronkers et al. (1990) furthermore categorizes adaptation strategies into protection, retreat, and accommodation. Protection, defined as the “defense of vulnerable areas, especially population centers, economic activities, and natural resources” (p.417), cannot only be achieved without policy intervention and typically involves hard infrastructural measures such as dikes, levies, pump stations, and salt-water intrusion barriers but also soft structural measures such as nurturing mangroves, wetlands, and dunes. Note how the lines between objectives are blurred. Protecting human livelihoods and economic activity oftentimes goes hand in hand with protecting natural adaptive capacity.

Dronkers et al. (1990) defines retreat as the “abandonment of land and structures in vulnerable areas, and resettlement on inhabitants” (p.146). Policy such as prevention of development in hazard areas and withdrawal of subsidies are prominent examples (source: CRS and FEMA). In the absence of coordinated policy, retreat can also occur through emergent adaptation, albeit oftentimes post-disaster and thus at much higher cost to livelihoods.

Accommodation, the “continued occupancy and use of vulnerable areas” (p.147) is of particular interest in this thesis. This type of adaptation can be both the result of top-down intervention, for instance through changes in land use and building codes, or an agent-level response to changes in risk or policy. Changes in perceived vulnerability – either through changes in risk or through policy aiming at enhancing risk awareness – prompt households to make changes to their accommodation. Adaptation to people’s accommodation always requires an anticipatory element. These adaptations can be structural as well as non-structural.

<Structural v non-structural adaptation>

On the household-level adaptation is often categorized into structural and non-structural measures. Structural adaptation refers measures such as elevating the living area, usage of flood barriers, flood vents, and flood proof materials. Non-structural measures include measures such as keeping food supplies and battery powered radios, signing up for flood alerts, preparing personal communication and evacuation plans, participating in community planning and disaster drills, and taking up flood insurance.

Inspired by the aforementioned categories of reactive and anticipatory adaptation, Koerth et al. (2017) is making a distinction between short-term coping and long-term preparedness measures. Although this distinction is blurred as well, it lends itself better to the adaptation types discussed in this thesis. While structural adaptation usually enhances long-term preparedness, non-structural adaptations like keeping battery-powered radios are aimed at coping with disaster in the immediate aftermath. While measures within the same category might substitute each other, measures from opposite categories might rather complement each other.

Structural measures are often more costly and anticipating on longer time horizons.

The lines are blurred

* Non-structural measures can be more autonomous and anticipatory
* Non-structural measures can be more focused on short-term coping and are often cheaper
* Flood insurance is different in that it is short-term coping (income smoothing) but also costly and planned. Motivate why insurance is worth having a look at later?

<complements and substitutes>

* Discuss the expected cost and benefit of adaptation
* Discuss the interactions between adaptation cost and benefit

<what type of adaptation is this work focusing on?>

## Determinants of behavioral adaptation

Many determinants of adaptation have been proposed in the literature. In their literature review, (Koerth et al., 2017) have summarized determinants into cognitive, situational, socioeconomic, and geographic variables (see Table 2).

* We add insurance & rent mortgage
* A sentence on study location? Should some variables have different effect directions in different regions? Socioeconomic and situational?

|  |  |
| --- | --- |
| Determinant | Determinant type |
| **Age** | Socioeconomic variable |
| **Income** |
| Gender |
| **Education** |
| Family status |
| **House ownership** |
| Employment status |
| **Perceived risk** | Cognitive variables |
| Perceived severity |
| Perceived likelihood |
| Perceived damage |
| **Perceived efficacy** |
| Perceived responsibility |
| **Experience** |
| **Awareness** |
| Governmental assistance | Situational variables |
| Social norms |
| Style of occupation |
| Distance to water **(could calculate this)** | Geographic variables |
| **Living in a high-risk area** |

Table 1: Determinants of preparedness. Selected variables from Koerth et al. (2017)

The authors note that **age and income exhibit ambiguous effect directions**. Whereas perceived risk and damage are having a positive effect on disaster preparedness, their effect on the implementation of structural adaptation measures seems to be weak.

<findings syntehsized>

* Experience has a positive impact on preparedness
* Socioeconomic variables
  + Age (ambiguous)
  + Income (ambiguous)
  + Education (positive)
  + Homeownership (positive)
* Insurance has a positive impact on other adaptation measures
* Risk perception has a positive impact on adaptation
  + Particularly positive on signing up for alerts
  + Less positive on structural adaptation
* Perceived efficacy has a positive impact on adaptation
* Risk awareness has a positive effect on adaptation

## Behavioral Adaptation Theories

< adaptation decision models>

* Protective Action Decision Model (PADM)
* Theory of Reasoned Action (TRA)
* Model of Private Proactive Adaptation to Climate Change (MPPACC)
* Protection Motivation Theory (PMT)
* Look also into the Terpstra model (Koerth et al., 2017)

# Research Questions

* From these insights we derive our first round of hypotheses

<Research Gap>

* We will look at specific adaptations and see if there are differences between them
* We will see what the effect is in the US

<Hypotheses from the Model>

* H1: Risk perception has a positive effect on adaptation
  + Confirmed by the literature
  + Literature expects stronger effect size for alerts and weaker effect size for structural adaptation measures
* H2: Flood risk has a positive effect on adaptation
  + Not confirmed by the literature (but kinda obvious no?)
  + We cannot directly test this because we have no time series data to model underlying risk change.
  + We can gauge this by looking at the difference of adaptation outcomes in **flood zones and non-flood zones**
* H3: Flood experience has a positive effect on adaptation
  + Confirmed by the literature
* H4: Risk awareness has a positive effect on adaptation
  + Confirmed by the literature

<additional hypotheses from the literature>

* H5: Insurance has a positive effect on adaptation
  + Literature is finding positive impact
  + Economic rationals:
    - Moral hazard: **negative effect**
      * Insurance reduces the cost of flood damage, disincentivizing people from spending on other adaptation
      * In this case insurance is a substitute to other adaptations
      * We would expect insurance to negatively impact structural adaptations
      * However, some adaptations complement each other as well. Here we would expect no or even a positive effect
    - Income smoother and liquidity constraint:
      * Should have a **positive effect** on reactive adaptation
      * Should have a **negative effect** on precautionary adaptation
    - Risk signaling effect of insurance (2.0)**: positive effec**t
      * Should have a positive effect on awareness in this case
    - Adverse selection?
* H6: efficacy has a positive effect on adaptation
  + “Have you already implemented adaptation and do you feel confident to implement further adaptation?”
* H7: Socioeconomic variables had an effect on adaptation performance
  + Age ambiguous
  + Income ambiguous
  + Education positive
  + Homeownership positive

# Data

<data provider>

The Federal Emergency Agency publishes results from their annual survey on disaster preparedness in the National Household Survey (*National Household Survey | FEMA.Gov*, 2023). The data sets reach back to 2017 and capture most of the relevant variables for our purpose (see Table \_\_\_). Since the data is anonymized, we cannot trace respondents across time, ruling out time series analysis. Furthermore, the constructs changed in the latest data, since the survey instrument underwent an overhaul in 2023. Hence, repeated cross-sectional analysis is ruled out too.

<dataset>

The 2023 survey is split into different disaster surveys. We are working with the coastal flooding survey, which includes 509 respondents. There is a survey instrument on hurricanes as well, which we could not leverage to augment the analysis because respondents cannot be traced across survey instruments. After cleaning, 385 respondents remained, of which 180 are in Florida, 43 in New York, and 60 in Washington. To increase study power where possible, we ran a second cleaning procedure in which we dropped variables with most missing data before dropping rows. This second dataset contains 427 observations, of which 209 are in Florida, 59 in New York, and 75 in Washington. For a detailed breakdown of the cleaning procedure please consult section \_\_.

<variables>

The survey provides us with ten different adaptation measures. All ten variables are binary reporters, indicating whether the respective adaptation measure has been implemented. In the following, we will refer to the variables as per our own coding. For the original coding in the survey instrument, please consult the EDA script in appendix \_\_\_and on github.

<adaptation measures>

The only reported structural adaptation measure is “made\_safer”. The corresponding question asked the respondent whether she had “made my home safer” (source). Insurance refers to property flood insurance. “learned\_rountes” refers to “learned my evacuation routes”. “supplies” refers to “assembled or updated supplies”. “involved” refers to “got involved in my community”. “planned\_neighbors” refers to “planned with neighbors”. “made\_plan” refers to “made a plan”. “practiced\_drills” refers to “practiced emergency drills or habits”. “alerts” refers to “signed up for alerts and warnings”. “family\_communication” refers to “tested family communication plan”. “documents” refers to “safeguarded documents” (*2023 National Household Survey on Disaster Preparedness: Survey Instrument (English)*, 2023).

|  |  |  |
| --- | --- | --- |
| **Adaptation type** | **Adaptation measure** | **Variable** |
| Structural measures | House elevation | “made\_safer” |
| Valuables elevation |
| Flood barriers |
| Flood-proof materials |
| Non-structural measures | Flood insurance | **insurance**: “Documented and insured property” |
| Collecting information | **learned\_routes**: “learned my evacuation routes” |
| Storage | **supplies**: assembled or updated supplies”  **Documents:** Safeguarded documents |
| Participation and communication | **involved**: “got involved in the community”  **Planed\_neighbors**  **Alerts**  **Family\_communication** |
| *Other non-defined measures* | * **Made\_plan** * **Practiced\_drills** |

Table 2: Adaptation measures as categorized by Koerth et al. (2017) and corresponding survey variables

<determinants >

The following determinants are captured by the survey: age and income are binned, education is categorical, homeownership, perceived flood risk, perceived efficacy, flood experience, awareness, flood zone. Age and income and, education are categorical, the other determinants are binary. For perceived flood risk – coded as “perception” – the respondent was asked if “thinking about the area you live in, how likely would it be for coastal flooding to impact you?” (p.17). Perceived efficacy is computed from two survey questions, asking the respondent if she already implemented preparedness measures and if she feels confident to sufficiently prepare for a flood event. The corresponding variables “efficacy” is coded as 1 if the answer to both question was positive. Flood experience is coded as one if the household has experienced a flood event before and 0 otherwise. Awareness refers to whether the respondent has consumed any information on flood preparation in the last year (*2023 National Household Survey on Disaster Preparedness: Survey Instrument (English)*, 2023).

<further features>

* Shapefiles

## Data Cleaning

<cleaning>

Constructs with more than 5% missing values were dropped from the data. Flood zones were missing for more than 14% of responses. Roughly 8% of respondents did not report on efficacy and awareness, and roughly 7% of responses are missing on perception. All four variables were dropped from the data. The remaining rows with missing data were dropped afterwards (see Figure \_\_\_). To prevent skew, no techniques to fill missing data were deployed.

Since efficacy, awareness, perception, and flood zone are being deployed in some of the subsequent regression analyses, a second dataset has been produced, keeping these variables. By searching for responses on flood zone from respondents in the same zip code we managed to reduce the share of missing flood zones down to roughly 7.5%. Note that this technique is not accurate as flood zones can run through zip codes, potentially skewing results. Again, rows with missing data were dropped. Including these variables decreased overall dataset size by 18.4%. In the following, this dataset is being deployed only if the respective analysis includes awareness, perception, efficacy, or flood zones.

## Data Exploration

<unimodal distributions>

<spatial distributions>

* Figure \_\_ shows the spatial distribution of survey responses. Most responses are clustered around the states of Florida, New York, and Washington. In Florida, observations are spread between Jacksonville and Miami on the east coast and along Sarasota on the west coast. Iin the state of New York, observations are clustered around New York City but also spread out into New Jersey, Atlantic City, and Orleans. In the state of Washington, the bulk of observation is clustered around Seattle.
* Responses per zip code vary between one and four – too little to investigate spatial interactions between respondents.

<correlations>

Figure \_\_\_ shows that the difference in the distribution of response variables between both cleaned datasets is only marginal. The same holds true for correlations between socioeconomic variables.

* Age is negatively correlated with cognitive and situational determinants. Rentmortgage is positively correlated
* Household-level preparedness is stronger in Florida across all individual adaptations. Particularly supply, insurance take up, evacuation routes, made\_plan, made\_safer, documents, and alerts are highly adopted (>20%). In relative terms, the difference between Florida and the other states is strongest in insurance take up and evacuation routes. On the other hand, comminuty involvement seems more pronounced in the state of New York, compared to the other states. Washington seems least prepared.
* When comparing the distribution between both datasets, the difference in responses across regions in alerts and family emergency communication plans becomes less pronounced. Otherwise, data cleaning has little impact on the spatial distribution of responses.

<multicollinearity>

* Include determinants / determinants of risk perception
  + Or directly include all determinant?
* Include socioeconomic determinants
* Also include correlation between socioeconomic determinants and determinants?

# Analysis

<probit v logit>

<r\_square>

To enhance interpretability of model fit, we chose to report McKelvay Zaviona R as pseudo R\_square, since this measure replicates the OLS R\_square more closely than the standard choice of McFadden’s R (Veall & Zimmermann, 1994). Although our choice of measure generally leads to higher R\_square scores, achieving a score above 0.2 is unlikely given the binary probit design (source).

Additionally, we report p-values to the McFadden’s log likelihood ratio test. It tests for the improvement of model fit including the predictors, compared to the baseline model of only the intercept. Unlike McFadden’s R-square which computes the ratio between both fits, the statistic plots the difference of both on a chi-square distribution. A significant p-value indicates that the included predictors are explaining a significant part of the outcome variable.

, y\_i\_hat = P(Y=1|X)

<BIC>

* BIC punishes model complexity through number of parameters and sample size.
* Low BIC is good

<explain marginal effect here once>

* Average marginal effect AME
* Marginal effect at the mean
* …

## The effect of flood risk, perception, experience, and awareness

* We hypothesized that real flood risk, individual risk perception, flood experience, and flood risk awareness are all predicting adaptation behavior (H1, H2, H3). If that is the case, a household should be more likely to implement an adaptation measure if they experienced a flood before, their reported risk perception is higher, they have read or consumed information on flood disasters and preparedness, or they reside in an area of higher real flood risk.
* We are measuring real flood risk through residency inside or outside designated flood zones. The Federal Emergency Managemen Agency (FEMA) is regularly auditing and updating flood risk in coastal areas. Areas in which FEMA computations predict a 1% or higher chance of flood induced inundation in any given year are classified as Special Flood Hazard Area (SFHA), colloquially referred to as flood zone. We use the binary data on flood zones as a proxy for the continuous underlying distribution of real flood risk. Note that changing weather patterns are continuously affecting the latent underlying risk distribution, rendering attempts to realistically gauge the underlying probability distribution quasi-impossible.
* Instead of asking, how “aware” respondents’ are of their exposure to flood risk, the survey instrument asks, whether the respondent has “read, seen, or heard any information about how to get better” (*2023 National Household Survey on Disaster Preparedness: Survey Instrument (English)*, 2023b, p.17). Awareness is thus measuring – perhaps self-induced – exposure to preparedness information campaigns.
* Risk perception is asking respondents, how likely they think to be impacted by coastal flooding. Possible answers ranged from unlikely to likely and very likely, including also “don’t know” (*2023 National Household Survey on Disaster Preparedness: Survey Instrument (English)*, 2023b, p.19).
* Experience is a binary reported and not just limited to experience in the past year but across all household members in their lifetimes.

<on our simple model>

* In our simple model, we hypothesize that likelihood of adaptation is a function of risk perception which itself is a function of real flood risk, awareness, and experience. If these equations hold true, we expect that risk perception has a stronger effect on adaptation than real flood risk, awareness, and experience. Furthermore, we would expect that real flood risk, awareness, and experience are predicting risk perception.

<following>

* In the following section (6.1.1.) we will report result from univariate models
* In section 6.1.2. we will test whether equation two from our simple models holds true by estimating risk perception through real flood risk, awareness, and experience.
* In section 6.1.3. we will report results from a multivariate model, in order to control for latent effects. It is reasonable to assume that one of the determinants can be explained away through another.
* Section 6.1.4. entails robustness checks

### Univariate models

<risk perception>

A table of numbers and text

AI-generated content may be incorrect.

Figure 1: Effect of risk perception on adaptation; selected results from probit estimation

The effect of risk perception is positive and statistically significant on all adaptation measures. scores are > 10% for all models, indicating that risk perception has a generally positive effect on adaptation behavior across the board. Especially **community involvement** ( = 0.297, marginal effect = 0.205), **insurance take up** ( = 0.239, marginal effect = 0.307), and **practicing drills** ( = 0.202, marginal effect = 0.145) are predicted well. Considering BIC, the decision to implement a family communication plan seems also reasonably well-explained by risk perception.

<experience>

A table with numbers and text

AI-generated content may be incorrect.

Figure 2: Effect of experience on adaptation; selected results from probit estimation

The effect of experience is positive and statistically significant on each adaptation measure as well. However, this set of models exhibits significantly lower explanatory power with regards to both, information criterion and explained variance. Experience best predicts **stocking up on supplies** ( = 0.145, marginal effect = 0.249), **community involvement** ( = 12.5, marginal effect = 0.125), and **learning evacuation routes** ( = 0.11, marginal effect = 0.222). Note that while on average effect sizes are smaller, the marginal effects on those adaptation measures that were predicted well are only slightly smaller, compared to effect sizes of the best-explained adaptation measures, explained by risk perception.

It is worth noting that experience seems to predict different adaptation measures, compared to risk perception, indicating that different underlying mechanisms are driving individual behavior. When comparing model fit for supplies, community involvement, and learning evacuation routes between experience and risk perception, however, risk perception predicts all three outcome variables better. To see whether risk experience picks up the latent effect of risk perception, we will run a multivariate model in section 6.1.3.

<awareness>

A table with numbers and text

AI-generated content may be incorrect.

Similar to the model results of risk experience, the effect of awareness is positive and significant on all adaptation measures, albeit at lower model fit, compared to risk perception. However, the difference in model fit between risk perception and awareness is much lower, compared to experience, indicating that risk awareness plays a role in household adaptation behavior. In four cases, the estimates of awareness outperformed those of risk perception with regards to BIC and R: **Learning evacuation routes** ( = 0.168, marginal effect = 0.26), **stockpiling supplies** ( = 0.193, marginal effect = 0.269), making an **emergency plan** ( = 0.142, marginal effect = 0.232), and making **family communication plans** ( = 0.129, marginal effect = 0.134). These four adaptation measures are typically recommended preparedness actions in information campaigns and flyers to the public (source).

Although we found awareness to have a particular effect on those adaptation measures that are being promoted awareness campaigns, we also observe that model fit and marginal effect sizes are in a comparably small range of each other across outcome variables. This finding is slightly contradicting the previous, since it indicates that the effect of awareness is not limited to particular adaptation practices. One conceivable explanation lies in the way that awareness is being measured. Note that respondents are being asked whether they have consumed information on disaster preparedness. It is reasonable to assume that respondents with high risk perception are more likely to proactively search out such information. We check for this reverse causality in section the following section. Furthermore, real flood risk and flood experience might confound awareness in that respondents who have prior experience or live in flood zones are more likely to seek out information on preparedness or be targeted by public information campaigns (see robustness checks in section 6.1.4.).

<real flood risk>

A screenshot of a table

AI-generated content may be incorrect.

Figure 3: Effect of residency inside a flood zone on adaptation; selected results from probit estimation

We proxy flood risk through residency in a flood zone. The effect of real flood risk is positive and statistically significant on all adaptation measures again. Real flood risk does not describe adaptation behavior as well as perceived flood risk, lending further support to our simple model. Flood risk is best explaining the decision to **sign up for** **alerts** ( = 0.137, marginal effect = 0.218), **practice emergency drills** ( = 0.123, marginal effect = 0.116), **get involved in the community** ( = 0.1, marginal effect = 0.118). Note, however, that estimates from flood risk perception are more robust for all three outcome variables with regards to both BIC and explained variance. As with experience, the results are raising the question, whether real flood risk is a reliable determinant of adaptation behavior, rather than just picking up the latent effect of risk perception in a univariate model setup.

<conclude>

The results support our simple model thus far: Risk perception is the best predictor of adaptation behavior. Based on these preliminary results, cannot be rejected. We find support for and as well, albeit to lesser extent. The results hint to model misspecification. The effect of prior flood experience, and real flood risk might be explained away by the unobserved effect of risk perception. To design targeted policy, we would ideally want to find a determinant that can be observed naturally, e.g., through available data, rather than gathered survey data. Therefore, experience and real flood risk are particularly interesting to us, since spatial data flood zones and areas with flood damage are publicly available (source).

Awareness as a predictor of adaptation behavior is outperforming risk perception with regards to family communication plans, learning evacuation routes, making emergency plans and stockpiling supplies. On these preliminary results, we fail to reject . As aforementioned, reverse causalities are possible: Are respondents who report awareness being made aware of risks through information campaigns or do they perceive flood risk as high a priori and thus actively seek out information to prepare? Given the way that awareness is being surveyed, we have reason to believe that our hypothesized direction of causality is in fact false.

In order to further investigate and , we test a multivariate model setup in the following section. We will furthermore try to predict risk perception through awareness, experience, and real flood risk. If our simple model holds true, we will be able to predict risk perception and the multivariate estimation of adaptation behavior will show similar or better model fit, especially with regards to BIC.

### Advancing our simple model

By regressing on all three determinants of flood risk together, we can find out which determinant contributes to what preparedness measure more precisely by controlling for latent effects between predictors. We will compare model fit against each other to identify models that are describing the data systematically better.

Figure 4:BIC in multivariate v univariate model

The Bayesian information criterion is a measure of fitness that trades off goodness-of-fit against model complexity. We thus expect the multivariate model to show higher BIC-values at equal goodness-of-fit compared to the univariate models. Interestingly however, **perception outperforms the multivariate model** on this metric across all outcome variables, except for making an emergency plan (BIC=409 v BIC=406). Recall that the multivariate model is using all three assumed determinants of perception: awareness, experience, flood risk. However, only experience as a stand-alone predictor achieves notably less model fit across outcome variables, compared to the multivariate model. **Experience is scoring almost consistently worst, while perception is scoring almost consistently best with respect to BIC**. Next, we will evaluate goodness-of-fit with regards to how well the model explains the variance in the data.

Figure 5: R\_2 in univariate v multivariate models

Since does not punish model complexity, the results are less comprehensive. Nevertheless, perception scores best across all univariate models and significantly outperforms the multivariate model in predicting insurance take up ( v ) and community involvement ( v ). Experience and real flood risk fail to meaningfully describe the variance in the data. However, awareness achieves decent model fit.

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **dependent** | **independent** | **beta** | **p** | **R2** | **LLPr** | **BIC** | **T** | **VIF** | **dy/dx** | **Pr(>|z|)** |
| **awareness** | **Intercept** | -0.478 | 0 | 0.242 | 0 | 482 | 0.758 | 1.319 |  |  |
| **experience** | 0.541 | 0.001 | 0 | 482 | 0.186 | 0 |
| **floodzone** | 0.893 | 0 | 0 | 482 | 0.307 | 0 |
| **experience** | **Intercept** | -1.166 | 0 | 0.257 | 0 | 415 | 0.743 | 1.346 |  |  |
| **awareness** | 0.534 | 0 | 0 | 415 | 0.155 | 0 |
| **floodzone** | 0.926 | 0 | 0 | 415 | 0.269 | 0 |
| **floodzone** | **Intercept** | -1.252 | 0 | 0.322 | 0 | 407 | 0.678 | 1.475 |  |  |
| **awareness** | 0.864 | 0 | 0 | 407 | 0.246 | 0 |
| **experience** | 0.924 | 0 | 0 | 407 | 0.263 | 0 |

Table 3: Robustness Check for the regression of adaptation behavior on awareness, experience, and floodzone.

To check for robustness, we iteratively regressed predictors on each other (see Figure\_\_\_). The Variance Inflation Factor is between 1 and 3, not indicating multi collinearity. The T-value () is sufficient given the amount of variables deployed (Veall & Zimmermann, 1994). Recalling section \_\_\_EDA, correlation between the variables deployed is relatively high, however, ranging from 0.27 between awareness and perception to 0.55 between real flood risk and perception. Overall, model results seem to not be biased by multi collinearity among regressors.

Perception appears to be the best determinant of adaptation behavior thus far. The multivariate model that is using all three hypothesized determinants of risk perception to predict adaptation behavior is not explaining the data significantly better. Interestingly, risk awareness seems to explain adaptation behavior better than the other determinants of risk perception. The question arises, whether our assumption that risk perception is a function of awareness is correct. To check for this assumption, we next regress risk perception on risk awareness, real flood risk and flood experience.

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **dependent** | **independent** | **effect** | **p** | **R\_2** | **LLPr** | **BIC** | **dy/dx** | **Pr(>|z|)** |
| **perception** | **Intercept** | -0.516 | 0 | 0.561 | 0 | 387 |  |  |
| **awareness** | 0.103 | 0.525 | 0 | 0.027 | 0.524 |
| **experience** | 0.896 | 0 | 0 | 0.238 | 0 |
| **floodzone** | 1.876 | 0 | 0 | 0.499 | 0 |

Table 4: Predicting flood risk perception through awareness, experience, and flood zone

Awareness is not predicting risk perception (p = 0.525). The finding is in line with the low correlation of 0.27 between awareness and perception *(see section EDA*). However, the regression of awareness on perception is statistically significant, further indicating reverse causalities between the two variables.

In light these results, we can slightly revise our simple model. Perception seems to predict awareness but not vice versa. Both, prediction and awareness proved reliable determinants of adaptation behavior. Real flood risk and flood experience seem to play only an indirect role in household-level adaptation decisions. We thus revise Equation 2 in our simple model to the following (see also Figure\_\_\_).

Eq1:

Eq2: , where



Figure 6: Direction of causality based on the results

<conclude>

Households that perceive their individual risk of coastal flooding as high, are model likely to read up preparation information. Note that consuming information on how to prepare for flooding has been defined as awareness in our dataset. We cannot measure the spatial distribution of risk perception on a large scale without conducting costly surveys. Instead, we can extrapolate flood experience from satellite data and real flood risk from readily available flood risk data. Our results indicate that there is a more accurate predictor of adaptation behavior that we can measure at large scale and low cost. For instance, google searches on how to prepare for coastal flooding can predict adaptation behavior globally, granted position data is provided alongside. We identify this as a further avenue of research, for instance, whether our results hold true outside of the data set and outside id the United States.

## The effect of insurance on adaptation behavior

Since data is available at least for the US-based NFIP program, flood insurance take up is posing another interesting determinant for adaptation behavior. The literature is postulating a positive effect of flood insurance on other adaptation behavior (see H5 in section\_\_\_). The economic rationale behind this finding, however, is not straight-forward.

Insurance has a smoothing effect on household income (source). The smoothing out of damage-related cost across periods in time, as well as a general decline in monthly disposable income post insurance premiums should disincentivize households to spend more on substitutes like other anticipatory adaptation that also invests into long-term preparedness. For instance, households might decide against costly structural adaptation such as elevating the property if that property is already insured.

On the other hand, the NFIP program offers premium reductions in certain cases if policy holders implement said structural adaptation, rather suggesting a positive relationship (source: NFIP CRS system). Moreover, investments into short-term coping capacity should not be impacted by insurance take up and its effect on income. Firstly, some such adaptation measures like taking part in drills and signing up for flood alerts are neglectably cheap. Secondly, while property insurance relieves financial burden and thus increases long-term preparedness, it has no effect on the ability to cope with danger to lives and adverse effects on livelihoods in the immediate aftermath of a flood disaster.

<psychological theory>

Risk signaling effect of insurance (2.0)**: positive effec**t

* + - * Should have a positive effect on awareness in this case

<economic reational>

,

1. we will investigate another promising determinant that has been identified in the literature but is not the hypotheses identified in the literature that are not captured by our simple model.

* H5
* outside of our model
* the literature is reporting a positive effect of insurance on adaptation
* economic rational?

A table with numbers and letters

AI-generated content may be incorrect.

Figure 7: Effect of insurance on adaptation

* The effect of insurance is large and significant across all adaptation measures
  + learned routes (33%)
  + documents (27%)
  + alerts (26%)
  + supplies (25%)

### The effect of efficacy on adaptation

* H6
* Outside of our model but reported in the literature

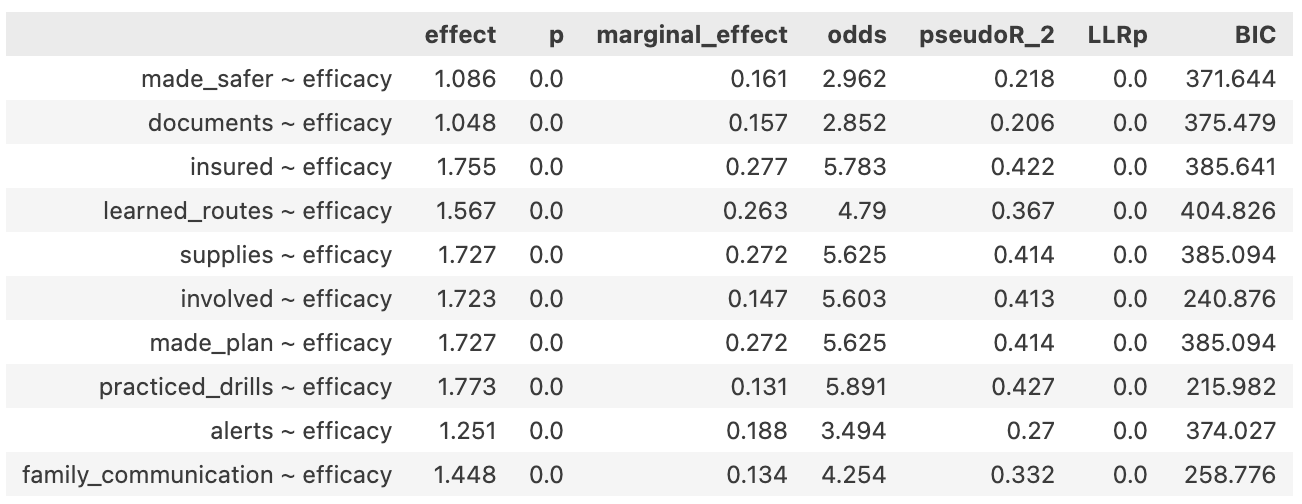


Figure 8: Effect of efficacy on adaptation

* The effect of efficacy on adaptation is positive and significant across all adaptation measures
  + Insured (28%)
  + Supplies (27%)
  + Made plan (27%)
  + Learned routes (26%)

## The effect of socioeconomic determinants on adaptation

* H7
* Outside of our model but reported in the literature
* Repeat here what has been found in the literature (which determinants? Which effect directions?)
* Age is significantly affecting
  + Insurance: -0.2% marginal effect
  + Supplies: -0.3% marginal effect
  + Practiced\_drills: -0.2% marginal effect
  + family communication: -0.2% marginal effect
  + When regressing only age (preparedness ~ age) supplies become significant too (-0.3% marginal effect)
  + All effects are small
  + All effects are slightly negative, contradicting findings in the literature (hypothesizing an ambiguous effect)
* Homeownership is significantly affecting
  + Made Safer: 9.9% marginal effect
  + Insurance: 12% marginal effect
  + Community involvement: -6% marginal effect
    - Find out in the literature if anyone has observed this
  + When regressing only homeownership, the made\_safer highly insignificant (p=0.26)
    - insurance: 9.5%, involvement -6.2%
  + This finding finding is slightly contradicting the literature since homeownership is rather ambiguous than always positive
* Income and education have no significant effect, also not in the robustness checks, contradicting the literature
* The effect of income, albeit highly insignificant, is also ambiguous, further contradicting the literature

<did any effects change when we include rentmortgage?>

* income is now also significantly affecting made\_safer. The AME effect is 0% however.
* No changes in age
* No changes in homeownership
* Rentmortgage is significant in practiced\_drills, and family\_communication. However, both AME are 0%

<robustness check>

* Based on R2, the multivariate model has much higher explanatory power
* Results are okay for:
  + Involved
  + Racticed\_drills
  + Family\_communication
  + Insured
  + Supplies
* The rest is kinda questionable …
* BIC is okay across all models for
  + Practiced\_drills
  + Family communication
  + Involved
* Socioeconomic determinants reasonably predict the likelihood of households implementing a family communication plan, getting involved in the community and practicing drills. The results indicate that socioeconomic indicators predict people’s tendency to get involved in their immediate social environment.
* Education, income and gender have an effect neither on people’s decision to participate in adaptation planning in their immediate environment, nor on any other adaptation strategies such as insurance take up, stocking up on supplies or any structural adaptation measures.
* While income turns out not to predict the decision to implement structural adaptation, rent and mortgage payments do.
* The multivariate model produces the most reliable results, especially regarding adaptation involvement in the immediate social environment. Younger people are more likely to get involved but the discovered effect sizes stay in the 0.1% to 0.3% area. Note that the lowest reported age in the survey is 25 years. As shown in the section on Exploratory analysis, the age distribution in the sample is flat.

Figure 9: R\_2 for selected socioeconomic models

Figure 10: BIC for selected socioeconomic models

## Next analysis

* + Differences between flood zones -> real flood risk a
  + Differences between hurricane regions?
  + Group adaptations into high-cost low-effect and low-cost high-effect
  + Interactions between insurance

# Bibliography

*2023 National Household Survey on Disaster Preparedness: Survey Instrument (English)*. (2023).

Adger, W. N. (2006). Vulnerability. *Global Environmental Change*, *16*(3), 268–281. https://doi.org/10.1016/j.gloenvcha.2006.02.006

Botzen, W. J. W., & Van den Bergh, J. C. J. M. (2009). Managing natural disaster risks in a changing climate. *Environmental Hazards*, *8*(3), 209–225. https://doi.org/10.3763/ehaz.2009.0023

Brooks, N. (2003). *Vulnerability, risk and adaptation: A conceptual framework*.

Brooks, N., Neil Adger, W., & Mick Kelly, P. (2005). The determinants of vulnerability and adaptive capacity at the national level and the implications for adaptation. *Global Environmental Change*, *15*(2), 151–163. https://doi.org/10.1016/j.gloenvcha.2004.12.006

Carter, T. R., Parry, M. L., Harasawa, N., S., & Nishioka, S. (1994). *IPCC Technical Guidelines for Assessing Climate Change Impacts and Adaptations—IPCC*. Department of Gography, University College London. https://www.ipcc.ch/report/ipcc-technical-guidelines-for-assessing-climate-change-impacts-and-adaptations-2/

Coronese, M., Lamperti, F., Keller, K., Chiaromonte, F., & Roventini, A. (2019). Evidence for sharp increase in the economic damages of extreme natural disasters. *Proceedings of the National Academy of Sciences*, *116*(43), 21450–21455. https://doi.org/10.1073/pnas.1907826116

Cutter, S. L., Boruff, B. J., & Shirley, W. L. (2003). Social Vulnerability to Environmental Hazards\*. *Social Science Quarterly*, *84*(2), 242–261. https://doi.org/10.1111/1540-6237.8402002

Denevan, W. M. (1983). Adaptation, Variation, and Cultural Geography∗. *The Professional Geographer*, *35*(4), 399–407. https://doi.org/10.1111/j.0033-0124.1983.00399.x

Donatti, C. I., Harvey, C. A., Hole, D., Panfil, S. N., & Schurman, H. (2020). Indicators to measure the climate change adaptation outcomes of ecosystem-based adaptation. *Climatic Change*, *158*(3–4), 413–433. https://doi.org/10.1007/s10584-019-02565-9

Dronkers, J., Gilbert, J. T. E., Butler, L. W., Carey, J. J., Campbell, J., James, E., McKenzie, C., Misdorp, R., Quin, N., Ries, K. L., Schroder, P. C., Spradley, J. R., Titus, J. G., Vallianos, L., & von Dadelszen, J. (1990). Coastal Management. In *Strategies for Adaptation to Sea Level Rise*. Intergovernmental Panel on Climate Change.

Engle, N. L. (2011). Adaptive capacity and its assessment. *Global Environmental Change*, *21*(2), 647–656. https://doi.org/10.1016/j.gloenvcha.2011.01.019

Fankhauser, S., Smith, J. B., & Tol, R. S. J. (1999). Weathering climate change: Some simple rules to guide adaptation decisions. *Ecological Economics*, *30*(1), 67–78. https://doi.org/10.1016/S0921-8009(98)00117-7

Finlayson, M. C., & D’Cruz, R. (2008). *Climate Change Mitigation*. OECD. https://www.oecd.org/en/publications/climate-change-mitigation\_9789264059610-en.html

*Flood Zones | FEMA.gov*. (2020, July 8). https://www.fema.gov/about/glossary/flood-zones

Haggag, M., Siam, A. S., El-Dakhakhni, W., Coulibaly, P., & Hassini, E. (2021). A deep learning model for predicting climate-induced disasters. *Natural Hazards*, *107*(1), 1009–1034. https://doi.org/10.1007/s11069-021-04620-0

Harries, T., & Penning-Rowsell, E. (2011). Victim pressure, institutional inertia and climate change adaptation: The case of flood risk. *Global Environmental Change*, *21*(1), 188–197. https://doi.org/10.1016/j.gloenvcha.2010.09.002

IPCC (Ed.). (2001). *Impacts, adaptation, and vulnerability*. Cambridge Univ. Press.

Koerth, J., Vafeidis, A. T., & Hinkel, J. (2017). Household‐Level Coastal Adaptation and Its Drivers: A Systematic Case Study Review. *Risk Analysis*, *37*(4), 629–646. https://doi.org/10.1111/risa.12663

*National Household Survey | FEMA.gov*. (2023, December 22). https://www.fema.gov/about/openfema/data-sets/national-household-survey

Pasquier, U., Few, R., Goulden, M. C., Hooton, S., He, Y., & Hiscock, K. M. (2020). “We can’t do it on our own!”—Integrating stakeholder and scientific knowledge of future flood risk to inform climate change adaptation planning in a coastal region. *Environmental Science & Policy*, *103*, 50–57. https://doi.org/10.1016/j.envsci.2019.10.016

Sauerborn, R., & Ebi, K. (2012). Climate change and natural disasters – integrating science and practice to protect health. *Global Health Action*, *5*(1), 19295. https://doi.org/10.3402/gha.v5i0.19295

Smit, B., & Wandel, J. (2006). Adaptation, adaptive capacity and vulnerability. *Global Environmental Change*, *16*(3), 282–292. https://doi.org/10.1016/j.gloenvcha.2006.03.008

Storbjörk, S. (2007). Governing Climate Adaptation in the Local Arena: Challenges of Risk Management and Planning in Sweden. *Local Environment*, *12*(5), 457–469. https://doi.org/10.1080/13549830701656960

Veall, M. R., & Zimmermann, K. F. (1994). Evaluating Pseudo-R2’s for binary probit models. *Quality & Quantity*, *28*(2), 151–164. https://doi.org/10.1007/BF01102759

Verschuuren, J. (2022). In *Research Handbook on Climate Change Adaptation Law, Chapter 1: Introduction to Climate Change Adaptation*.

Wilby, R. L., & Keenan, R. (2012). Adapting to flood risk under climate change. *Progress in Physical Geography: Earth and Environment*, *36*(3), 348–378. https://doi.org/10.1177/0309133312438908

# Appendix

## Appendix 3

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Predictor** | **Adaptation outcome** | **exp(beta)** | **Signifi** | **Marginal effect** | **Pseudo R\_squar** | **LLR p** |
| Experience  Dataset:  clean\_n | Made\_safer | 2.25 | P=0.001 | 11.9% | 2.3% | 0.001 |
| Insured | 2.79 | P=0.000 | 16.5% | 3.8% | 0.000 |
| Learned\_routes | 3.80 | P=0.000 | 21.6% | 6.5% | 0.000 |
| Supplies | 4.80 | P=0.000 | 24.2% | 8.9% | 0.000 |
| Involved | 5.23 | P=0.000 | 12.6% | 8.7% | 0.000 |
| Made\_plan | 2.82 | P=0.000 | 16.9% | 3.9% | 0.000 |
| Practiced\_drills | 3.35 | P=0.000 | 8.7% | 4.6% | 0.000 |
| Alerts | 2.28 | P=0.001 | 12.3% | 2.4% | 0.001 |
| Family\_  communication | 2.54 | P=0.003 | 8.3% | 2.8% | 0.004 |
| Insurance  Dataset:  Clean\_n | Made\_safer | 5.16 | P=0.000 | 22.3% | 8.8% | 0.000 |
| Learned\_routes | 8.86 | P=0.000 | 31.1% | 15.4% | 0.000 |
| Supplies | 4.51 | P=0.000 | 23.6% | 7.4% | 0.000 |
| Involved | 6.11 | P=0.000 | 13.6% | 10.1% | 0.000 |
| Made\_plan | 3.41 | P=0.000 | 19.7% | 4.8% | 0.000 |
| Practiced\_drills | 7.00 | P=0.000 | 13.3% | 11.5% | 0.000 |
| Alerts | 6.82 | P=0.000 | 25.4% | 12.1% | 0.000 |
| Family\_  communication | 7.46 | P=0.000 | 16.5% | 12.7% | 0.000 |
| Risk perception  Dataset:  Clean\_k | Made\_safer | 3.47 | P=0.000 | 18.4% | 5.1% | 0.000 |
| Insured | 7.59 | P=0.000 | 32.5% | 12.1% | 0.000 |
| Learned\_routes | 4.40 | P=0.000 | 25.7% | 7.5% | 0.000 |
| Supplies | 5.50 | P=0.000 | 27.9% | 9.2% | 0.000 |
| Involved | 17.1 | P=0.000 | 24.1% | 12.9% | 0.000 |
| Made\_plan | 3.89 | P=0.000 | 22.9% | 6.3% | 0.000 |
| Practiced\_drills | 8.82 | P=0.000 | 16.3% | 9.2% | 0.000 |
| Alerts | 4.99 | P=0.000 | 23.8% | 7.9% | 0.000 |
| Family\_  communication | 4.42 | P=0.001 | 13.9% | 5.8% | 0.000 |
| Efficacy  Dataset:  Clean\_k | Made\_safer | 2.96 | P=0.000 | 16.1% | 4.5% | 0.000 |
| Insured | 5.78 | P=0.000 | 27.7% | 11.7% | 0.000 |
| Learned\_routes | 4.79 | P=0.000 | 26.3% | 9.6% | 0.000 |
| Supplies | 5.63 | P=0.000 | 27.2% | 11.4% | 0.000 |
| Involved | 5.60 | P=0.000 | 14.7% | 9.3% | 0.000 |
| Made\_plan | 5.63 | P=0.000 | 27.2% | 11.4 | 0.000 |
| Practiced\_drills | 5.89 | P=0.000 | 12.1% | 9.4% | 0.000 |
| Alerts | 3.49 | P=0.000 | 18.8% | 6.0% | 0.000 |
| Family\_  communication | 4.25 | P=0.000 | 13.4% | 7.0% | 0.000 |
| Awareness  Dataset:  Clean\_k | Made\_safer | 3.1 | P=0.000 | 16.9% | 4.8% | 0.000 |
| Insured | 3.66 | P=0.000 | 22.0% | 6.4% | 0.000 |
| Learned\_routes | 4.71 | P=0.000 | 26.4% | 9.0% | 0.000 |
| Supplies | 5.53 | P=0.000 | 27.5% | 10.4% | 0.000 |
| Involved | 4.78 | P=0.000 | 13.6% | 7.0% | 0.000 |
| Made\_plan | 4.11 | P=0.000 | 23.5% | 7.5% | 0.000 |
| Practiced\_drills | 4.5 | P=0.000 | 11.3% | 6.3% | 0.000 |
| Alerts | 4.29 | P=0.000 | 21.6% | 7.5% | 0.000 |
| Family\_  communication | 4.55 | P=0.000 | 14.1% | 6.8% | 0.000s |

Table 2023 National Household Survey on Disaster Preparedness: Survey Instrument (English). (2023).

Adger, W. N. (2006). Vulnerability. Global Environmental Change, 16(3), 268–281. https://doi.org/10.1016/j.gloenvcha.2006.02.006

Botzen, W. J. W., & Van den Bergh, J. C. J. M. (2009). Managing natural disaster risks in a changing climate. Environmental Hazards, 8(3), 209–225. https://doi.org/10.3763/ehaz.2009.0023

Brooks, N. (2003). Vulnerability, risk and adaptation: A conceptual framework.

Brooks, N., Neil Adger, W., & Mick Kelly, P. (2005). The determinants of vulnerability and adaptive capacity at the national level and the implications for adaptation. Global Environmental Change, 15(2), 151–163. https://doi.org/10.1016/j.gloenvcha.2004.12.006

Coronese, M., Lamperti, F., Keller, K., Chiaromonte, F., & Roventini, A. (2019). Evidence for sharp increase in the economic damages of extreme natural disasters. Proceedings of the National Academy of Sciences, 116(43), 21450–21455. https://doi.org/10.1073/pnas.1907826116

Cutter, S. L., Boruff, B. J., & Shirley, W. L. (2003). Social Vulnerability to Environmental Hazards\*. Social Science Quarterly, 84(2), 242–261. https://doi.org/10.1111/1540-6237.8402002

Denevan, W. M. (1983). Adaptation, Variation, and Cultural Geography∗. The Professional Geographer, 35(4), 399–407. https://doi.org/10.1111/j.0033-0124.1983.00399.x

Donatti, C. I., Harvey, C. A., Hole, D., Panfil, S. N., & Schurman, H. (2020). Indicators to measure the climate change adaptation outcomes of ecosystem-based adaptation. Climatic Change, 158(3–4), 413–433. https://doi.org/10.1007/s10584-019-02565-9

Dronkers, J., Gilbert, J. T. E., Butler, L. W., Carey, J. J., Campbell, J., James, E., McKenzie, C., Misdorp, R., Quin, N., Ries, K. L., Schroder, P. C., Spradley, J. R., Titus, J. G., Vallianos, L., & von Dadelszen, J. (1990). Coastal Management. In Strategies for Adaptation to Sea Level Rise. Intergovernmental Panel on Climate Change.

Engle, N. L. (2011). Adaptive capacity and its assessment. Global Environmental Change, 21(2), 647–656. https://doi.org/10.1016/j.gloenvcha.2011.01.019

Fankhauser, S., Smith, J. B., & Tol, R. S. J. (1999). Weathering climate change: Some simple rules to guide adaptation decisions. Ecological Economics, 30(1), 67–78. https://doi.org/10.1016/S0921-8009(98)00117-7

Finlayson, M. C., & D’Cruz, R. (2008). Climate Change Mitigation. OECD. https://www.oecd.org/en/publications/climate-change-mitigation\_9789264059610-en.html

Haggag, M., Siam, A. S., El-Dakhakhni, W., Coulibaly, P., & Hassini, E. (2021). A deep learning model for predicting climate-induced disasters. Natural Hazards, 107(1), 1009–1034. https://doi.org/10.1007/s11069-021-04620-0

Harries, T., & Penning-Rowsell, E. (2011). Victim pressure, institutional inertia and climate change adaptation: The case of flood risk. Global Environmental Change, 21(1), 188–197. https://doi.org/10.1016/j.gloenvcha.2010.09.002

Koerth, J., Vafeidis, A. T., & Hinkel, J. (2017). Household‐Level Coastal Adaptation and Its Drivers: A Systematic Case Study Review. Risk Analysis, 37(4), 629–646. https://doi.org/10.1111/risa.12663

National Household Survey | FEMA.gov. (2023, December 22). https://www.fema.gov/about/openfema/data-sets/national-household-survey

Pasquier, U., Few, R., Goulden, M. C., Hooton, S., He, Y., & Hiscock, K. M. (2020). “We can’t do it on our own!”—Integrating stakeholder and scientific knowledge of future flood risk to inform climate change adaptation planning in a coastal region. Environmental Science & Policy, 103, 50–57. https://doi.org/10.1016/j.envsci.2019.10.016

Sauerborn, R., & Ebi, K. (2012). Climate change and natural disasters – integrating science and practice to protect health. Global Health Action, 5(1), 19295. https://doi.org/10.3402/gha.v5i0.19295

Smit, B., & Wandel, J. (2006). Adaptation, adaptive capacity and vulnerability. Global Environmental Change, 16(3), 282–292. https://doi.org/10.1016/j.gloenvcha.2006.03.008

Storbjörk, S. (2007). Governing Climate Adaptation in the Local Arena: Challenges of Risk Management and Planning in Sweden. Local Environment, 12(5), 457–469. https://doi.org/10.1080/13549830701656960

Veall, M. R., & Zimmermann, K. F. (1994). Evaluating Pseudo-R2’s for binary probit models. Quality & Quantity, 28(2), 151–164. https://doi.org/10.1007/BF01102759

Verschuuren, J. (2022). In Research Handbook on Climate Change Adaptation Law, Chapter 1: Introduction to Climate Change Adaptation.

Wilby, R. L., & Keenan, R. (2012). Adapting to flood risk under climate change. Progress in Physical Geography: Earth and Environment, 36(3), 348–378. https://doi.org/10.1177/0309133312438908

: Logit results for cognitive determinants

|  |  |
| --- | --- |
| **Variable** | **Description** |
| Cfld\_prepactions\_a | Assembled or updated supplies |
| Cfld\_prepactions\_b | Documented and insured property |
| Cfld\_prepactions\_c | Got involved in the community |
| Cfld\_prepactions\_d | Learned my evacuation routes |
| Cfld\_prepactions\_e | Made a plan |
| Cfld\_prepactions\_f | Made my home safer |
| Cfld\_prepactions\_g | Planned with neighbors |
| Cfld\_prepactions\_h | Practiced emergency drills or habits |
| Cfld\_prepactions\_i | Safeguarded documents |
| Cfld\_prepactions\_j | Saved  for a rainy day |
| Cfld\_prepactions\_k | Signed up for alerts and warnings |
| Cfld\_prepactions\_l | Tested family communication plan |
| Cfld\_prepactions\_m | None of the above (exclusive) |
| Cfld\_prepactions\_n | Don’t know (exclusive) |

Table 3: Variables of adaptation measures and their corresponding description in the survey

## Appendix 5.2

A graph of different numbers

AI-generated content may be incorrect.

Figure 11: Distribution of socioeconomic determinants

**A graph of different types of objects

AI-generated content may be incorrect.**

Figure 12:distribution of adaptation measures for large clean dataset

**A graph of different types of objects

AI-generated content may be incorrect.**

Figure 13:distribution of adaptation measures for small clean dataset

A graph of different colored bars

AI-generated content may be incorrect.

Figure 14: Distribution of adaptations per region for large clean dataset

A graph of different colored bars

AI-generated content may be incorrect.

Figure 15: Distribution of adaptations per region for small clean dataset

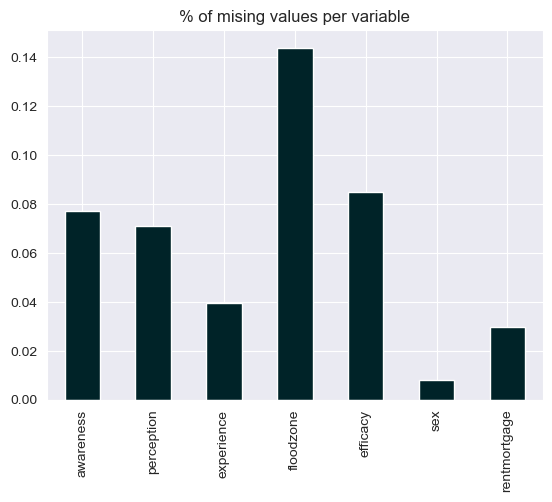


Figure 16: share of missing observations per variable



Figure 17: Spatial distribution of observations

<EDA\_n or EDA\_k?I think we can report both here>

A screenshot of a graph

AI-generated content may be incorrect.

Figure 18: Spearman Rank correlation of determinants

A screenshot of a graph

AI-generated content may be incorrect.

Figure 19: Spearman rank correlation of socioeconomic determinants

## Appendix 6

<univariate models BIC>

Figure 20: BIC for selected univariate models

<univariate models R2>

Figure 21: R\_2 for selected univariate models

Figure 22:Marginal effects for selected univariate models