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How a changing climate is changing behavior: household adaptation to floods

Brayton Louis Noll

How a changing climate is changing behavior: household adaptation to floods

Dissertation

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by

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[W]e could have had such a damned good time together [...] Yes, I said. Isn't it pretty to think so?

E. Hemingway. The Sun Also Rises

Contents

Summary

Floods appear in many of the world's oldest stories (i.e. Noah and the Arc in the Abrahamic religions, Manu in Hinduism, and the Gun-Yu myth in Chinese mythology). When observed historically, they often have an element of mysticism about them, symbolizing eradication and rebirth. In the present, however, there is little that is mystical about the devastation brought on by floods as they cause more destruction annually than any other hazard. With much of the modern development taking place along the coast or near riverways, assets and livelihoods are increasingly concentrated in exposed areas. By-products of climate change such as sea level rise and extreme precipitation events increasingly devastate these regions; with the projection that the risk of floods will continue to increase in the future.

Top-down, government-led adaptation to floods on its own cannot contend with growing risk; rendering household participation essential. Governments, risk modelers, scientists, and other interest groups (i.e. NGOs) need a solid understanding of household behavior in order to formulate strategies and engage stakeholders across scales to address climate-induced risks. This dissertation devotes its attention to better understanding households' perceptions, intentions, and behavioral drivers and their dynamics, concerning floods in various social, geographical, cultural, and environmental contexts. More concretely, the principal research objective of this dissertation is:

To progress toward an understanding of how households perceive, are affected by, and adapt to floods in various contexts over time.

Following a comprehensive review and analysis of prior empirical research on household flood adaptation, this dissertation presents the analysis of a panel survey carried out between 2020-2021 aimed at collecting data to tackle the aforementioned objective. Focusing on large urban centers in the United States, China, Indonesia, and the Netherlands I use various statistical techniques and methods to analyze the survey data and study a range of aspects from household perceptions as they concern floods and climate change, to reported adaptation behavior. The survey solicits information on 18 adaptation measures that range from inexpensive, actions that do not require considerable effort (i.e. having an emergency preparedness kit, emergency coordination with one's neighbor, etc.), to costly measures that require a substantial time investment (i.e. elevating one's home, waterproofing one's windows, etc.)

In analyzing how household adaptation decisions are influenced, depending on the *type* of measure and the context in which the household resides, this dissertation offers insight into which socio-behavioral drivers and barriers of household adaptation are generic and those which may vary depending on the institutional and environmental conditions. A household's perceived ability to cope, and the emotion, "worry," plays a substantial role in driving household adaptation intention. In contrast, the financially calculated risk-based drivers: the perceived probability of a flood happening and the perceived damage should a flood occur, generally have a more subdued effect on household adaptation intentions.

This is related to the fact that not all households have sufficient capacity or awareness to subjectively assess the probability and damage of a potential flood. Individual risk-uncertainty - a trait more frequently found in populations historically more vulnerable to floods (i.e. women and lower educated) has a large detrimental effect on households' intention to pursue flood adaptation measures.

While internal perceptions are critical to consider, external factors can have an equally potent role in affecting household adaptation behavior. I examine the effect of context at multiple scales in this dissertation, assessing the role of social expectations, perceptions of government measures, and national culture on household adaptation decisions. Households use their observations of what others (i.e. their social network, the government) are doing with respect to flood adaptation, to inform their decisions. The degree to which both external and internal factors influence household adaptation decisions can differ based on the cultural and geographical context. Various factors have a weaker or stronger influence and at times even the opposite effect on adaptation behavior, depending on where the household resides.

While internal and external perceptions are requisite considerations in understanding household behavior, it is likewise crucial to account for experiences and the co-benefits of various household adaptive actions. The effects of prior flood experiences and the benefits of taking adaptations together are additional key considerations when studying household flood adaptation, due to the economic benefits that can arise from undertaking measures together. Furthermore, prior experience with floods can motivate adaptation behavior, but substantial financial damage from a flood impedes a household's adaptation intention; as their focus is on recovery, not adapting.

The findings in this dissertation are of use to scientists, modelers, risk specialists, and policymakers; whether they are designing models, a communication strategy, or a policy aimed at encouraging household action. With the effects of climate change increasingly affecting communities across the globe, households are having to contend with hazards that are more extreme and frequent than in the living memory of humanity. Unless immediate action is taken across scales, the harrowing effects of climate change are expected to increasingly threaten extensive populations globally. This dissertation provides insights into how households think, perceive, behave, and learn over time concerning one of the most deadly and damaging hazards: floods.

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1

Introduction

1

1.1 Background and Context

Human behavior has contributed to a shift in the earth's climate, and in turn, climate change has necessitated a shift in human behavior. The reciprocal relationship compounds across time in that past interactions and reactions influence present and future responses from both sides (Hallegatte, 2009; Hennessy, Lawrence, & Mackey, 2022; IPCC, 2022; Kirchmeier-Young, Gillett, Zwiers, Cannon, & Anslow, 2019; Lim, 2022; Magnan et al., 2022). How humans should best respond or *adapt* to climate change is prominently featured in countries' policies, strategies, and national security plans across the globe.

In 1990, the International Panel on Climate Change prepared the first comprehensive report on climate change. By this time, it was becoming increasingly apparent (and accepted) that humanity had a marked impact on climate change and how humans should respond was a prominent research topic by scholars and governments alike (Mendelsohn, 2000). Recent high-profile conferences such as the United Nations climate conference in Bonn and COP26 in Glasgow have strongly reaffirmed the necessity of taking immediate efforts to adapt to the adverse effects of climate change (Pringle, Thomas, & Strachan, 2021). Likewise, the most recent COP, 27, in Cairo, focuses on loss and damage due to climate-related hazards, and how to adapt to mitigate further damage moving forward. Hazards such as wildfires, heat waves, floods, and droughts are all made more likely by climate change. As the world becomes more interconnected and the impacts of these hazards pervade all levels of society, an increasing number of people each year are negatively affected by climate change. (Hennessy et al., 2022; IPCC, 2022; Trenberth, Fasullo, & Shepherd, 2015).

Floods

Of all climate-induced hazards, floods are one of the most costly and destructive - each year killing thousands and causing billions (USD) in damage (Merz et al., 2021). The year of 2022 has been a tragically emblematic year in terms of the impacts that flooding can have. The 2022 floods in Pakistan caused upwards of 14 billion USD. Far more appalling, however, is the fact that the flood likely pushed between 3.7-4% of the country's population into poverty; meaning an additional 8.9 - 9.1 million people are living in poverty as a direct consequence of a single flooding event (WorldBank, 2022). While Pakistan suffered the most devastating floods in 2022, there are numerous other horrific examples of flooding disasters that occurred this year (i.e. in Australia (Jackson & Jose, 2022), Miami, Florida (Holpuch, 2022)). The water often subsides in days, and the impacts and destruction that it leaves behind however can hinder development for years and frequently disproportionately devastate already vulnerable populations (Hennessy et al., 2022; Schipper & Pelling, 2006).

Floods can spawn from various sources (heavy rainfall, river swelling, coastal storms, etc.); all of which can bring terrific destruction. Due to historical agglomeration forces that have resulted in much of humanity settling on or near the coast, sea level rise, which increases at an accelerating rate, is extremely concerning. Even under the most optimistic low emissions scenario (IPCC, 2014, 2022), the mean sea level is projected to increase between 0.29-0.59 meters by 2100 (relative to 1986–2005) (Magnan et al., 2022). Meanwhile, the number of extreme precipitation events - which can additionally lead to severe flooding - has been steadily increasing ($>$ 7%) for the past 80 years (Aghakouchak et al., 2020). Irrespective of actions taken in the present, flood risk is projected to continue to rise through the end of the century (IPCC, 2022; Winsemius et al., 2015). The actions of our (recent) ancestors coupled with our own have committed our species to living with floods. Mitigation is critical in curtailing as much (future) damage as possible, however, adaptation is an immediate necessity for the coming decades.

Adaptation

Adaptation is defined by the International Panel on Climate Change as "The process of adjustment to actual or expected climate and its effects" (IPCC (2014), Annex p.118), and is considered essential for building resilient societies. While countries across the globe are exposed to some degree to the threat of flooding, coastal regions are particularly vulnerable. The concentration of built assets, lessened natural/ permeable surfaces and continued expansion - many times into flood-prone zones - all contribute to inflated flood risk. When considered jointly with the climate-exacerbated extreme weather/ precipitation, urban coastal regions ubiquitously need to contend with the threat of floods (Magnan et al., 2022).

To grapple with flooding, there are various strategies coastal regions can implement. Large-scale adaptation measures, such as dikes, levees, and dams, by definition, must be public, or government-led as they impact many households and require centralized government planning (i.e. dykes in the Netherlands). Public adaptation however does not necessarily entail large-scale engineering solutions; resettlement strategies that promote or mandate population re-settlements (i.e. Indonesia moving its capital from Jakarta) is another form of public adaptation. Top-down directives such as the aforementioned examples, however, are extremely costly, require substantial resources and time to implement, and cannot completely eliminate risk (Adger et al., 2009; Mechler et al., 2020).

Private adaptation or action taken at the household level must complement public action for robust protection against floods (Adger, Arnell, & Tompkins, 2005; Berrang-Ford et al., 2021). Effectively coordinating private, and household adaptation to complement public measures however is a challenge. While governments - from local to national - can form and self-implement their own directives, legislating and enforcing households to follow suit is difficult. There are exceptional examples of this in select instances (i.e. with insurance mandates), however, more frequently governments turn to policies, instruments, and messaging strategies to drive action at the household level according to a plan; as opposed to promoting haphazard action.

Household adaptation strategies cannot be considered or taken independently of the surrounding environment - both the built environment and the natural (Adger et al., 2009). As such, varying risk and resource distributions engender that adaptation strategies from one region cannot be blindly extrapolated to another (Olazabal, Chiabai, Foudi, & Neumann, 2018). Hence, it is absolutely critical to apprehend what factors drive and inhibit behavior and how these factors change across place and time in order to put into practice multi-scale strategies that collude effectively in reducing the risk of climate-exacerbated floods.

1.1.1 Exploring household adaptation to floods

Effective strategies to contend with future climate exasperated floods cannot be singular in their approach (Adger et al., 2005). While government-led adaptation can reduce the probability of a hazard, dissemination of household adoption has a strong influence in determining the total damage and the speed of recovery. Hence, for households to limit their own risk/ exposure/ vulnerability, autonomous action is increasingly recognized as playing a salient role, especially in regions where policy interventions are lacking and government resources are insufficient (Berrang-Ford et al., 2021).

Due to its increasingly recognized importance, household behavior has become a central topic of research in the climate and flood risk domain. To study household adaptation behavior, there are a variety of methods that range from surveys, experiments, and ethnographic fieldwork, to games (Adger et al., 2005). Each research method offers unique benefits and can provide a distinct perspective on the complex issue of household adaptation. Of all the methods, surveys are one the most common as they are easily scalable, can reach broad populations, and can be written to gather data for diverse research goals. At the time of writing this thesis, results from more than 75 independent surveys that study household flood adaptation behavior have been published (Bamberg, Masson, Brewitt, & Nemetschek, 2017; Noll, Filatova, & Need, 2020; van Valkengoed & Steg, 2019).

To date, many of the surveys examining household adaption to floods have taken place in Europe and North America (Hopkins, 2015). Due in large part to the financial and organizational resources required to implement a survey, most of the past surveys examining household adaptation to floods have had sample sizes in the hundreds, and been cross-sectional or provide a snapshot. There are notable exceptions to this paradigm; surveys that go beyond a single wave (i.e. Osberghaus and Fugger (2022)), or a single country (i.e. Mondino, Scolobig, Borga, and Baldassarre (2021)), but in general, they are scarce. The limitations inherent in the standard application of surveys are discussed further in Section 1.2.

1.1.2 Household flood adaptation measures

Different household adaptations are more appropriate or effective in various contexts; hence the measures that are studied often vary from study to study. There are almost as many methods of grouping as there are measures studied and as there are several recent meta-analyses (Bamberg et al., 2017; van Valkengoed & Steg, 2019). While I do not provide a comprehensive overview here, below I present a non-exhaustive list of the types of adaptations that are often studied:

- Actions that could prevent flood damage that involves physical modifications to one home (i.e. raising the ground floor, water-proofing wall, instilling anti-backflow on pipes, etc.) (Botzen, Kunreuther, Czajkowski, & de Moel, 2019; Brody, Lee, & Highfield, 2017; Maidl, Bresch, & Buchecker, 2020)

- Actions that could prevent flood damage but are temporary and do not require physical modifications to one's home (i.e. acquiring sandbags, purchasing/ installing flood barriers, etc.) (Koerth, Vafeidis, Hinkel, & Sterr, 2013; Poussin, Botzen, & Aerts, 2014)

- Actions that can aid in reducing physical damage once a flood has occurred and water has entered the home (i.e. purchase of a pump, "wet-proofing" one's home, etc.) (Brody et al., 2017; Richert, Erdlenbruch, & Figuières, 2017)

- Actions that better prepare the household in the event there is a flood (i.e. having an emergency supplies kit, storing important documents in a safe, accessible location, etc.) (Bubeck, Botzen, Suu, & Aerts, 2012; T. Wang et al., 2022)

- Actions that better inform the household as to what to do in the event of a flood (i.e. coordinating measures with neighbors or what to do if one is not home, informing oneself about evacuation plans, attending community meetings, etc.) (Koerth et al., 2013; Miceli, Sotgiu, & Settanni, 2008)

- Actions that can protect the health and safety of the household members in the event of a flood (i.e. attending a first aid course, installing an escape door in the roof of one's home, etc.) (Miceli et al., 2008; Poussin et al., 2014)

- The purchase of insurance (Bubeck, Botzen, Kreibich, & Aerts, 2013; Hudson, Botzen, Czajkowski, & Kreibich, 2017)

- Moving or migrating away from the flood zone (Bell, Calvo-Hernandez, & Oppenheimer, 2019; T. Wang et al., 2022)

While the exact benefits of a given adaptation measure are difficult to precisely quantify, what is broadly understood is that investment in adaptation before a flood can pay back up to five times compared to post-flood investment (Mechler et al., 2014). Particularly in contexts where governments (at any level) lack the adequate resources to implement comprehensive adaptation plans to curtail the risk of floods, action at the household level is paramount. A robust and coherent understanding of what drives household behavior is critical for scientists and policymakers to study and effectively steer societies in a direction of a resilient future.

1.1.3 Drivers and barriers of Household Adaptation

Under what circumstances people and households are driven to adapt to floods is as complex as it is critical to apprehend. When decisions are probabilistic, uncertain, or risky, how people decide if and how to act is a complex decision based on incomplete information. People rely on a variety of mechanisms of behavioral drivers ranging from self-perceptions, heuristics, and social norms (Groot & Thurik, 2018; Mata, Frey, Richter, Schupp, & Hertwig, 2018; Rogers, 1975; Slovic, Finucane, Peters, & MacGregor, 2004). Uncovering the main decision drivers (and barriers) in a heterogeneous population can be challenging as there are a plethora of behavioral theories that outline various cognitive pathways a person navigates to arrive at a decision.

As floods are probabilistic events that vary in severity, most behavioral theories tested in the household flood adaption domain begin with an assessment of risk or threat (Bubeck, Botzen, Suu, & Aerts, 2012; Noll et al., 2020). Subsequently, depending on the theory being tested (or not) most research utilizes a household's coping ability, social norms, socio-economic characteristics, and various other attributes to explain household behavior (van Valkengoed & Steg, 2019).

1.1.4 Behavioral theories

Human behavior is not driven by rational means or estimations of outcomes and likelihoods (Kahneman & Tversky, 1984; Tversky & Kahneman, 1974). Past research has demonstrated that people do not assess outcomes in an accurate manner and therefore rely on other mechanisms to guide decision-making. While there are considerable theories that seek to explain the human decision-making process, in the flood risk domain, three theories are especially noteworthy in a discussion on analyzing empirical data on household adoption behavior and when operationalizing adaptation behavior in models: Prospect Theory (Kahneman, 1992; Kahneman & Tversky, 1984; Osberghaus, 2017; Tversky & Kahneman, 1992), The Theory of Planned Behavior (Ajzen, 1985, 1991; Zhang, Ruiz-Menjivar, Luo, Liang, & Swisher, 2020), and Protection Motivation Theory (Bamberg et al., 2017; Grothmann & Reusswig, 2006; Rogers, 1975; van Valkengoed & Steg, 2019).

Prospect Theory

Prospect Theory examines how people (or households) make decisions based on the two core components of risk: perceived likelihood and consequences relative to a reference point (Kahneman, 1992). The theory posits that people are more averse to (potential) loss than they are open to (potential) gains. While there has been some prior empirical work in the flood risk domain that tests Prospect Theory (Osberghaus & Hinrichs, 2021), determining a reference point for survey respondents when studying an event such as flooding is challenging, hence it is more often tested in controlled settings such as labs (Tversky & Kahneman, 1992).

Theory of Planned Behavior

The Theory of Planned Behavior (TPB), which is inclusive of the Theory of Reasoned Action, proposes a broader range of factors that influence behavior. These factors coalesce under three principle components: Attitude, Perceived Control, and Subjective Norms (Ajzen, 1991). In flood adaptation research, Attitude is where the household assesses the likelihood of various outcomes based on their own beliefs. Perceived Control, is the households' perceived ability to cope with floods meanwhile Subjective Norms are the household's perceptions of others' opinions on flooding and how to respond (Chen, 2016; Zhang et al., 2020). Models that test TPB are regularly extended to include households' socioeconomic characteristics and additional information such as prior experience (Zhang et al., 2020).

Protection Motivation Theory

Finally, the most commonly tested theory in the domain of climate change flood adaptation research is Protection Motivation Theory (PMT) (van Valkengoed & Steg, 2019). PMT is comprised of two principal categories: Threat Appraisal and Coping Appraisal - both typically measured with three distinct factors. Threat Appraisal is comprised of the households' perceived *likelihood* of a flood; the perceived *damage* should a flood occur. While the original PMT only included these two factors (Rogers, 1975), the vast majority of contemporary applications of PMT additionally include the amount of *worry* a household has about a flood (Grothmann & Reusswig, 2006; van Valkengoed & Steg, 2019). Coping Appraisal is the household's self-assessed capacity to cope with the flood. It is composed of *self efficacy*, the household's perception of their own ability to undertake measures to reduce their flood risk; *response efficacy* is how effective the household believes these measures will be in reducing their risk; and the final component is *perceived cost* or how affordable a household believes these measures to be.

While the aforementioned two categories, threat appraisal, and coping appraisal, comprise the core of PMT, in the majority of modern work the theory is extended to include other information (van Valkengoed & Steg, 2019). Beliefs, socio-economic characteristics, prior experience with (adapting to) floods, and social components are all commonly used to extend PMT (Bamberg et al., 2017). Figure 1.1 displays a conceptual diagram of many factors contributing to a household's making process when deciding if and how to adapt to a flood. A combination of these factors is regularly utilized to model and understand human behavior in the context of flood risk.

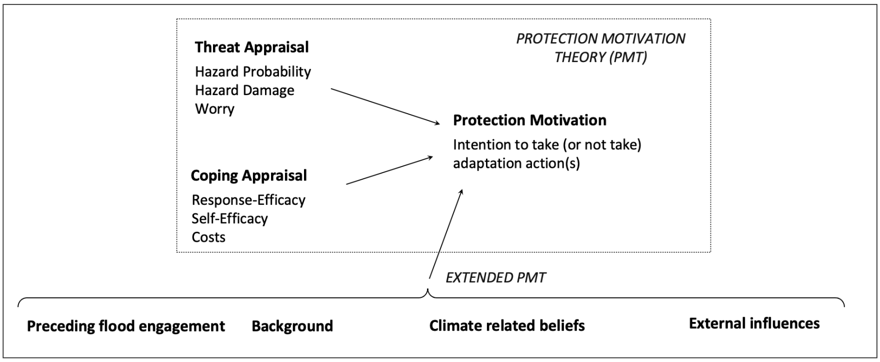

Figure 1.1: Graphical Representation of Protection Motivation Theory and the factors commonly used to extend the theory. Each component can be represented by one or multiple variables.

The extended version of PMT is the most commonly tested theory in the flood risk domain as it effectually contains the same components of TBP and stresses the importance of coping capacity, which is consistently shown to play a salient role in driving behavioral intention (Bamberg et al., 2017). However, while many of the factors included in PMT have consistently been shown to be effective in explaining adaptation intention and behavior (van Valkengoed & Steg, 2019), the theory's contemporary popularity could be in part, a case of popularity begetting popularity; testing PMT allows comparison to extensive past work, and therefore is more often selected. In this dissertation, I primarily test an extended version of PMT, with occasional comparison to other theories, such as TPB.

1.2 Gaps in Knowledge

Climate change will threaten nations across the globe. However, the devastating impacts of climate change, such as floods, will disproportionately affect the countries least responsible for emissions, primarily in the Global South (IPCC, 2014). Lack of data has been noted as a key bottleneck for robustly understanding human behavior (de Ruig et al., 2022), both in designing useful models and informing policy. Hence, while the conceptual importance of household adaptation in various contexts in fostering a resilient society is broadly acknowledged (Adger et al., 2005; Adger, Huq, Brown, Conway, & Hulme, 2003), household adaptation in diverse environments, across countries, and under assorted conditions is not well researched.

Surveys are typically used to collect data to study the factors that drive and inhibit household adaptation behavior. Despite the Global South being disproportionately affected by the impacts of climate change, most household flood surveys have been conducted in Europe and North America (Noll et al., 2020). Due to the data available in the field at present, it is not well understood how contextual factors such as culture or institutional decisions affect household-level behavior. Further, to what degree drivers and barriers of adaptation are consistent across contexts, is a noted research gap often touched upon in qualitative research (i.e. Olazabal et al. (2018)), but largely ignored in quantitative research in the flood risk domain.

While data availability is a key factor affecting the robustness of understanding household adaptation behavior, methodological and analytical choices by adaptation researchers likewise greatly impact the collective knowledge in the field. Linkages and co-benefits between adopting multiple adaptation measures had been previously discussed (Babcicky & Seebauer, 2019), but lack explicit analytical consideration. Furthermore, prior standard practices when dealing with and cleaning survey data, with limited exceptions (Rufat et al., 2022), had generally not considered the methodological choices of dealing with item non-responses and their potential meaning.

Finally, while there are some exceptions (i.e. Bubeck, Berghäuser, Hudson, and Thieken (2020); Mondino et al. (2021); Osberghaus and Fugger (2022); Seebauer and Babcicky (2020a)) most surveys are cross-sectional; meaning a one-off study. This is due in large part to the greater costs and logistical challenges involved in launching a panel or longitudinal survey (Hudson, Thieken, & Bubeck, 2019). This limits the analysis of the survey to associations, rather than causal inference. Further, this engenders that surveys have to depend on “stated intention” rather than “reported action” when estimating household adaptation intention due to the feedback that past actions can have on present perceptions (Bubeck, Botzen, & Aerts, 2012; Bubeck, Botzen, Suu, & Aerts, 2012). This method of data collection inhibits the empirical analysis of different elements that affect people’s adaptive decisions over time - including the transition from intention to action, responses to new/ varied stimuli, and causal attribution.

1.3 Research Goal

The goal of this dissertation is to advance the growing body of work on households’ adaptation behavior to floods. In this dissertation, I do not differentiate among the different types of floods - coastal, pluvial, and fluvial - but instead, focus on household behavior when threatened by an excess of water. In each chapter, I posit a unique question that contributes to addressing the gaps outlined above to offer a more holistic understanding of human behavior when it concerns floods. All research presented in this dissertation cumulatively makes strides toward a central research focus:

To progress toward an understanding of how households perceive, are affected by, and adapt to floods in various contexts over time.

To approach this complex goal from various perspectives I employ diverse approaches and make use of various data sets. The aforementioned goal was broken down into sub-questions presented below. Each (set of) research questions corresponds to the research presented in the chapters described in Section 1.5.

1.3.1 Research questions:

1. What is the state of household flood adaptation research? Can we observe patterns in the effects of various adaptation drivers by culture?

2. Can adaptation strategies be extrapolated across countries uniformly? Do adaptation drivers vary by the type of adaptation considered?

3. Are adaptation actions independent of one another as is typically modeled and presumed in prior work?

4. Is being risk-aware random, or can we find associations with select groups? How does being risk-uncertain about an event, like flooding, influence other perceptions and adaptation behavior?

5. How do household risk perceptions change over time? Does the intention to implement structural flood adaptation measures lead to action? What characteristics are associated with the household adaptation intention-behavior gap?

1.4 Methods

In selecting the method to answer each of the five aforementioned research questions, I considered both at what level the analysis should take palace and the data required to address the question.

1.4.1 Meta-Analysis

To address the first research question, I systematically searched for and collected all past quantitative survey research on household flood adaptation. My search was in 2019 and was conducted exclusively in English. From the collected published research, I recorded the statistical effects of various factors on adaptation to create a data set of effect sizes and conduct my own meta-(regression) analysis.

1.4.2 Case studies

Expansive empirical data from varied contexts over time was required in order to answer research questions 2 - 5; hence, running a (longitudinal) survey was the only feasible data collection method. Before designing the survey, however, it was essential to understand the context in which the survey will take place. I selected large coastal urban areas as the overarching area of focus due to the unique threat they face, as outlined in Section 1.1. In selecting which coastal urban centers to study, I sought to select case studies that represented diverse social, institutional, cultural, and geographic contexts. Hence, in meeting these ends I selected six major cities in four countries across the globe: the United States, the Netherlands, China, and Indonesia (Figure 1.2). All four countries are front-runners in escalating flooding risk (Tiggeloven et al., 2020), yet vary in the frequency of flood experiences: from nearly annual (Indonesia) to once-in-a-lifetime (the Netherlands).

Figure 1.2: Case study cities.

The USA and the Netherlands are Global North nations where theories of behavior such as Protection Motivation Theory, were developed and tested (Bamberg et al., 2017; Grothmann & Reusswig, 2006), and floods surveys have been predominately run (Noll et al., 2020). China and Indonesia, on the other hand, are two nations where limited prior survey work on household flood adaptation behavior exists. The four countries additionally host very different cultures and vary in the role governments take in adapting to climate-induced floods; outlined below.

The United States of America: Miami, Florida; Houston, Texas; and New Orleans, Louisiana all are major coastal cities in the United States and are prone to flooding from storms, and hurricanes (Brody et al., 2017). The cities and their respective "greater areas" vary in size from New Orleans, which has 1.3 million residents, to 6.1 and 6.3 million in Miami and Houston, respectively (Government, 2020). Miami is on Florida's Atlantic coast, while Houston and New Orleans are both contained within the Gulf of Mexico. All three cities, located in or near 'hurricane alley' are annually threatened by floods due principally to hurricanes and tropical storms (Lim, 2022); a risk projected to increase (Tiggeloven et al., 2020). While there are examples in all cities of large-scale projects designed to mitigate flood risks (e.g. elevating roads and installing storm surge barriers), yet in each location, a substantial risk of household flooding remains, for which household adoption and insurance purchase is encouraged (Brody et al., 2017). Hosting a diverse mix of households, economic livelihoods, and environments these three coastal cities provide a good representation of coastal urban regions in the United States.

The People's Republic of China: Shanghai, China, is home to 25 million residents and is one of the most flood-exposed cities in the world (S. Du et al., 2020; Nicholls et al., 2011). This is due to a combination of an average elevation of 4 meters above sea level paired with the increased exposure of having the Huangpu River run through the city (Xu et al., 2021). The city currently relies heavily on extensive top-down measures to protect itself from floods (S. Du, Gu, Wen, Chen, & Rompaey, 2015) and is considered one of the more well-protected coastal cities under current climate conditions (S. Du et al., 2020). However, public flood infrastructure can create such as the 'dike paradox' (Hartmann & Driessen, 2017) that increases potential damage. Without additional action under future climate conditions, Shanghai could quickly lose its title of a well-protected city as climate change aggravates flood risk globally, especially in coastal cities (S. Wang et al., 2021). Shanghai is a global economic powerhouse and one of the world's largest mega-cities. As the current Chinese administration tightens down on the information that leaves China, empirical research in this region becomes increasingly challenging. The survey data collected and analyzed in this thesis offers unique insight into a key global city with a growing flood risk.

The Republic of Indonesia: Jakarta, Indonesia, known as the "sinking city", is one of the most flood-prone major cities in the world. The threat of flooding is rising annually with that of the sea level and by land subsidence (5-10 cm annually) (Tiggeloven et al., 2020; Wijayanti, Zhu, Hellegers, Budiyono, & Ierland, 2017). While public infrastructure designed to reduce flood risk is in place, 5.9 million people annually are threatened by floods (Mcleod et al., 2010). An effective combination of adaptation across scales is essential in leading to any substantial reduction in projected damage. Household adaptation is essential (Esteban et al., 2017). The risk is expected to increase under future climate projections which is one of the principal reasons the country has taken steps to move the capital to Nusantara; however, most of the residents are expected to remain (Burke & Siyaranamual, 2019). Hence with the government shifting investment elsewhere, Jakarta is an ideal case study location to examine household adaptation.

The Kingdom of the Netherlands: Rotterdam metropolitan region in the Netherlands is home to 2.6 million inhabitants and is Europe's largest port. While much of the Netherlands lies below sea level, the country hosts one of the most expansive and comprehensive dyke systems in the world. The lowest dyke standard in the Netherlands is built to withstand a 1 in 1,250-year flood (a .08% chance of happening) with most dykes being built to assure 1:2500, 1:5000 and 1:10000 safety levels here (Aerts et al., 2014). The Dutch government is historically responsible for dealing with coastal and river flooding (Mees, Uittenbroek, Hegger, & Driessen, 2019), meaning that the approach to flood management is very top-down and a contributing factor as to why flood insurance from sea level rise is unavailable. This further engenders that household-level adaptation in the Netherlands is limited (Mol, Botzen, Blasch, Kranzler, & Kunreuther, 2020), despite the growing threat resulting from global warming and evidence that top-down flood defenses can not be relied upon 100% of the time (Tiggeloven et al., 2020) and can result in misconstrued feelings of safety (Mol et al., 2020). As the port of Europe, and one of the countries with the greatest proportion of land below sea level, perceptions and behavior from households of Rotterdam in the Netherlands offer unique insight into the residents of a country that's very existence depends on flood adaptation measures.

Figure 1.3 visually shows flood events that occurred in or near each case study city, highlighting the relevance of selection. While the six case study cities are coastal, this dissertation considers all types of floods (i.e. sea level rise, pluvial, fluvial, etc.). With all of the case studies expected to face an increasing threat due to climate change (Tiggeloven et al., 2020), the large urban coastal centers described above offer diverse governance, environmental, economic, and cultural contexts to study household flood adaptation with a large-scale, multi-national survey.

1.4.3 Primary survey, panel data

In April 2020, I finalized writing and designing the first survey wave. Via YouGov's platform, I launched surveys in the United States, the Netherlands, China, and Indonesia. The surveys are focused on soliciting information on households' socio-economic background,

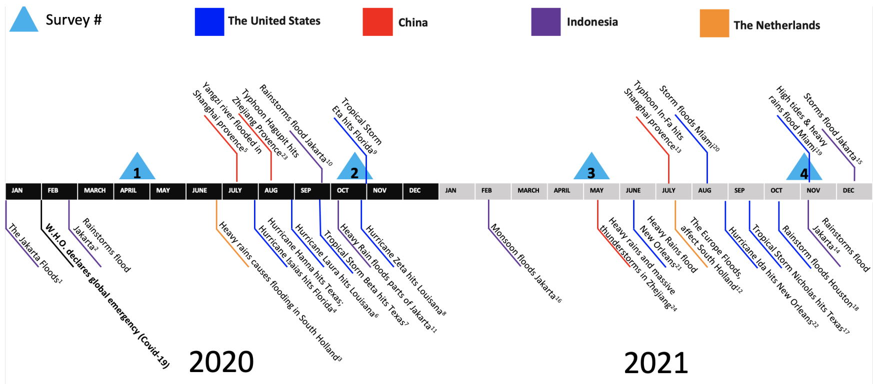

Figure 1.3: Timeline of floods that occurred in or around the four case studies during the survey timeline 2020-2021. Numbers correspond to links to events that can be found in the Appendix, Section 8.1.

perceptions, capacities, and behavior surrounding floods. The surveys were conducted online by YouGov and the data analyzed and presented in this paper are from identical, translated questions in the respective languages of each country. The survey was written in English by the authors, one of whom is a native speaker from the USA. For the non-USA respondents, the survey was professionally translated by YouGov field experts in each country, and the translation was reviewed by a climate adaptation scientist from each of the four case studies countries to help ensure the cross-national relevance of the measures and aid in avoiding cultural bias. Further, YouGov field experts provided relevant information on the national context, culture-specific ethical considerations, and legislation that aided in the design of the survey.

Based on national statistics, YouGov forms representative panels. In China, Netherlands, and Indonesia we specifically controlled for gender representation, and age and gender in the USA. YouGov has a number of quality assurance measures in place, including excluding "speeding-respondents" (respondents who click through too rapidly to allow reading), inviting future panelists to participate, before announcing the topic - helping avoid the self-selection bias and the verification of personal details given when respondents are registered for the panel. Further, respondents who consistently click the same (i.e. the first) answer are additionally filtered out. Finally, YouGov limits the number of surveys that respondents participate in monthly to reduce survey fatigue and conditioning (*More Detail on YouGov Research Methods*, n.d.). The YouGov platform for online surveys is accessible via mobile phones, as such, according to the field teams, a lack of internet at home is not a barrier to reaching a diverse sample. As our research was focused on major urban centers, internet access was not a limiting factor (Lin, 2020; Nabila, 2019). Employing an external company is a necessity when running such a large-scale, cross-national survey in a reproducible way. However, it is expensive and mandates outsourcing sampling and quality assurance. With YouGov's extensive history of conducting high-quality surveys for both academic, government, and corporate entities, we are confident that sample and data quality are properly upheld.

The first survey was launched in April 2020, and a subsequent survey followed every six months for a year and a half; in October 2020, April 2021, and November 2021. The spacing was specifically designed to allow sufficient time for the households to realize their adaptation intentions, yet still, be in frequent enough intervals to encourage continued household participation. Each of the four surveys can be found at the end of the Appendix.

1.4.4 Surveying household adaptation measures

To address research questions two and three I utilize data from the first wave exclusively (N>6400). For the fourth research question, I utilize primarily data from the first survey wave to maximize sample size but additionally include data and analysis from the second wave to support the segmentation classification. For the fifth and final research question, I use data from all four survey waves. By the fourth wave, the number of household respondents had attenuated to around 1500 households, still leaving one of the largest longitudinal samples that has been analyzed to date (Hudson et al., 2019).

In each chapter, outlined below, I utilized different factors, depending on the research question to examine adaptation behavior and perceptions. In this thesis, I focus exclusively on adaptation measures that households can take to further protect and prepare their property and themselves from floods. I intentionally selected these measures instead of insurance purchase and migration for two specific reasons. Insurance is not available in the Netherlands for floods resulting from sea or river inundation. In Chapters 3 - 6, which analyze the case study data, I wanted to make use of the full data set and not exclude the Netherlands. The reason I chose not to analyze migration in this thesis is that migration can be a decision that is years or even decades in the making; engendering it a less reasonable action to study via repeated surveys over a 1.5-year time period. Hence, depending on the chapter I analyze how various factors contribute to (a sub-set of) the 18 adaptation measures asked in the survey, listed below:

1. Raising the level of the ground floor above the most likely flood level
2. Strengthen the housing foundations to withstand water pressures
3. Reconstructing or reinforcing the walls and/or the ground floor with water-resistant materials
4. Raising the electricity meter above the most likely flood level or on an upper floor
5. Installing anti-backflow valves on pipes
6. Installing a pump and/or one or more system(s) to drain flood water
7. Fixing water barriers (e.g., water-proof basement windows)
8. Installing a refuge zone, or an opening in the roof of your home or apartment
9. Keeping a working flashlight and/or a battery-operated radio and/or emergency kit in a convenient location
10. Purchasing sandbags, or other water barriers
11. Buying a spare power generator to power your home

1

12. Being an active member in a community group aimed at making the community safer
13. Coordinating with the neighbors in case you are not home when a flood occurs, they would know what to do
14. Storing or placing important possessions (such as documents or expensive furniture) in such a manner to avoid flood damage
15. Asking someone (local government, Civil Defense, etc.) for information about what to do in case of emergency
16. Asking/ petitioning government representatives to increase the public protection measures
17. Storing emergency food and water supplies
18. Moving/ storing valuable assets on higher floors or elevated areas

I briefly give an overview of the contents of each chapter, corresponding with the research questions, below. Further in each chapter description, I state which adaptation measures were analyzed, provide information on groupings of the measures, and explain why certain measures were assessed, based on the research question.

1.5 Outline of dissertation

In **Chapter 2** I use secondary data collected from previous empirical household flood adaptation studies to examine the state of the field of research and explore to what extent culture can explain the variance that various factors have in driving household adaptation. In this chapter, due to data availability, all adaptation measures were studied together. This idea was inspired by past work that had, in general, qualitatively analyzed the connections between culture's links with risk (Hoffman, 2015), institutions (Hofstede, Hofstede, & Minkov, 2010), and especially hazards and disasters (Bankoff, Cannon, Kruger, & Schipper, 2015; Cannon, 2015; Kruger, Bankoff, Cannon, Orlowski, & Schipper, 2015). The approach presented in this chapter utilizes, to the best of my knowledge, a unique statistical methods approach in the flood risk domain - cultural meta-regression with various factors and effects on adaptation.

In **Chapter 3**, I analyze the first wave of my four-country data set to examine differences in effects across our case study countries and between measure types. I used a novel method of modeling adaptation, formulated as a ratio, and group the adaptation measures under two categories: High Effort measures (#'s 1 - 8, from the list of adaptation measures) and Low Effort (#'s 9 - 18). These two categories were selected based on the effort and resources required to undertake each measure and to enable comparisons between the types of adaptation in addition to the context. This analysis built upon the household flood adaptation literature that had previously been generally constrained to single country surveys (Bamberg et al., 2017; Bubeck, Botzen, Suu, & Aerts, 2012), primarily located in the Global North (Noll et al., 2020) to examine the factors driving household adaptation intentions.

Next, in **Chapter 4** I narrow my focus to study the effects of past and additionally-intended adaptive actions on one another and observe how correctly accounting for these effects affects other explanatory variables and statistical models. I specifically elected to use just one wave of survey data for this chapter as cross-sectional data is predominately how household adaptation behavior is analyzed; however, I build on this idea further in Chapter 6, when I use a lagged dynamic panel model to estimate adaptation. The question built on past work (Babcicky & Seebauer, 2019; Seebauer & Babcicky, 2020b) that suggested that adaptation actions could be linked via the economic benefits that could result from joint implementation of some actions. The hypothesis, however, was not explicitly tested, nor a focus of their past work. To explicitly examine the potential for economic feedback, I chose to focus on High Effort measures (#'s 1 - 8, from the list above). This is because all these measures require substantive financial and or temporal investments and are more likely to bring economic benefits when multiple are undertaken in succession or concurrently. Other work by P. Jansen, Snijders, and Willemsen (2020) aided in inspiring the method of using individual models for each possible adaptation measure to ensure I was capturing and controlling for, the within-person effects of the employed coping appraisal variables.

In the following section, **Chapter 5** I examine the concept of risk awareness and risk-uncertainty in the context of flooding. I assess if certain groups are more likely to be risk uncertain and how this affects their perceptions and actions. I was inspired by prior work in the field of medicine (Dolnicar & Grün, 2014; Ellis, Ferrer, & Klein, 2018), risk psychology (Roy, School, & Zeckhauser, 2013), and survey methods research (Groot & Thurik, 2018; Mata et al., 2018). As risk is one of the most commonly tested factors driving adaptation behavior, this study offers material insight into the characteristics and intentions of the risk-uncertain. To study the differences in adaptation intentions of the risk-uncertain, vs. risk-aware I utilized two groups of adaptation High Effort measures (#'s 1 - 8, from the list above) and Low Effort (#'s 9 - 18) and two types of modeling methods to estimate the factors driving adaptation intention for each group.

In **Chapter 6**, the final section of the original work presented in this thesis, I analyze all four waves of the survey. In this chapter, analyzing data I collected over 1.5 years, I study household perception dynamics, the intention-behavior gap, and the characteristics associated with specific intentions and behavior. In this chapter, I studied the intention and reported behavior of actions (#'s 1 - 7, from the list above), in the chapter referred to as "structural measures." I specifically chose these actions for the reason that these seven actions require structural modifications to the household AND prevent damage to the home (this is the reason why measure # 8 was excluded from this analysis). Since threat perceptions dynamics were one of the pillars of this paper, I wanted to only study measures that could possibly have feedback with the variables capturing a household's threat perception.

The analysis presented in this chapter has been a key objective since the genesis of the project and the design and was inspired by (Bubeck et al., 2020) and (Osberghaus, 2017) who offered suggestions at the conceptualization stage, based on their previous panel survey knowledge. Furthermore, over the course of the survey, other longitudinal flood work was published (i.e. (Hudson et al., 2019; Mondino et al., 2021; Seebauer & Babcicky, 2020a)) that advanced my understanding of the subject and motivated me in formulating these previously un-asked research questions. While prior work in this domain has utilized panel modeling techniques, it has stopped short of examining the attributes associated with specific intention and behavioral combinations in-depth, as I do here. I believe this additional component offers novel insight into household adaptation behavior and can be used to advance both models and inform targeted policies.

Finally, **Chapter 7** presents conclusions from the analysis in Chapters 2 - 6. In examining the aggregate findings from the previous chapters, Chapter 7 offers a broad perspective on household adaptation behavior while discussing practical implications for both policy and science. Throughout the process of this project - from designing the research plan, to the data collection, method selection, and analysis - I have sought to make the research accessible and viable for both scientists and policymakers alike. Extensive work has been conducted to accomplish both of these sub-objectives via publishing open-source code and through publishing and publicly presenting non-technical findings from several of the papers. Furthermore, I have worked to directly link findings from the research on human behavior to climate models to better account for heterogeneity in societies when planning for climate change. This concluding chapter makes note of the main research findings by chapter and how the work here can continue to be practically utilized and the future. Finally, in Chapter 7, I finish with a brief discussion on possible avenues for future work in the areas of adaptation, survey research, and incorporating household adaptation in climate models.

2

2 Does private adaptation motivation to climate change vary across countries? Evidence from a meta-analysis

Natural hazards, exasperated by climate change, increasingly affect societies worldwide. Accelerating risks necessitates private adaptation to complement more traditional public climate change adaptation measures. Culture plays an important role in framing how individuals' experience hazards and behave toward them. Yet, empirical research explicitly measuring whether and how climate change adaptation varies across cultures is lacking. To address this gap, we collect meta-analytic data on factors motivating individual flooding adaptation from 25 countries and more than 50 publications. By employing Hofstede's Cultural Rankings as a metric of national culture, we model the effect of culture on adaptation motivation of individual households using meta-regression analysis. We find a number of statistically significant relationships between culture and factors motivating private climate change adaptation. Hence, the cultural context is vital to consider when designing and implementing climate change adaptation policies, assessing limits of private adaptation empirically by means of decision-support models, and when simulating an uptake of individual hazard prevention measures. The findings are among the first to provide empirical evidence on the interaction effects between culture and private climate change adaptation motivation.

This chapter is based on: Noll, B., Filatova, T., & Need, A. (2020). How does private adaptation motivation to climate change vary across cultures? Evidence from a meta-analysis. International journal of disaster risk reduction, 46, 101615.

2.1 Introduction

Adaptation to climate change is at the forefront of both political and academic environmental discourse (Brown, Alexander, Arneth, Holman, & Rounsevell, 2019; Conway et al., 2019). Research has shown that public adaptation measures on their own, are insufficient to address projected impacts of climate change (Fankhauser, Smith, & Tol, 1999; Mendelsohn, 2000; N. Stern, 2007). Coordinated adaptation across scales, where private anticipatory actions, including individual household behavior, complement public adaptation measures, offers the best prospect for confronting adverse climate change impacts (Kreibich, Bubeck, Van Vliet, & De Moel, 2015; Mendelsohn, 2000; N. Stern, 2007).

To date, much of the empirical work on private climate change adaption has taken place in Europe and North America (Hopkins, 2015). This is problematic as the nations' least responsible for the global emissions, primarily located in the Global South, will be disproportionately impacted by climate change (IPCC, 2014). The numerous appeals for more cross cultural research, arise from the growing understanding that the success of adaptation strategies and policies is dependent on taking into account social, political, cultural, and demographic factors (Wolf & Moser, 2011). Individual perceptions of climate-induced risks, decisions whether to adapt to them and how are mediated by culture (Adger, Barnett, Brown, Marshall, & O'Brien, 2013). Recent cross-national studies on climate change perception and public adaptation explicitly highlight the need to consider cultural and geographical differences when looking at individual perception and adaptation to climate change across countries (Hinkel et al., 2018; Lee, Markowitz, Howe, Ko, & Leiserowitz, 2015; Poortinga, Whitmarsh, Steg, Böhm, & Fisher, 2019). Yet, these differences have been insufficiently addressed when looking at individual adaptation to the impacts of climate change.

Among climate change impacts, floods are among the most devastating and costly (Aerts et al., 2014; Hoegh-Guldberg et al., 2018). Public flood adaptation measures such as levees or governmental refund programs that have been successful in the past, may face limits in the new climate-altered reality (Filatova, 2014a; Keating et al., 2014). Similar to the broader field of climate change adaptation, there is a strong agreement that culture influences natural flood risk perception and individual adaptation behavior (Kruger et al., 2015; Renn & Rohrmann, 2000). However, with a few exceptions, cross-national empirical research has been limited in both the number of publications and number of countries included in the surveys (Boamah et al., 2015; Gierlach, Belsher, & Beutler, 2010; Hanger et al., 2018; Paton, Okada, & Sagala, 2013). Similar responses in individual adaptation to disasters are found on a case by case basis (Bubeck, Botzen, Suu, & Aerts, 2012), a deficit of research in much of the Global South and across multiple countries, means that generalizations across countries and cultures fundamentally lack empirical support.

The vast majority of flood surveys neglect cultural or national differences when examining individual adaptation behavior to floods. Hence, the question whether there are patterns in how various aspects of culture affect individual climate adaptation behavior, remains open. Two recent and prominent meta-analysis deliver an ample overview of the empirical work on disaster adaptation motivation. (Van Valkengoed & Steg, 2019) provide insights on climate adaptation motivation toward *all* natural hazards while (Bamberg et al., 2017) focuses solely on flooding, exclusively through the lens of *Protection Motivation Theory* (PMT). However, neither review reveals how may different cultures influence private adaptation to climate change. Individual risk perceptions and behavioral changes vary per type of hazard an individual faces; obscuring whether the observed variance in the review by (Van Valkengoed & Steg, 2019) is due to the hazard differences or the study location (Eiser et al., 2012; Ho, Shaw, Lin, & Chiu, 2008; Renn & Rohrmann, 2000, p.28). (Bamberg et al., 2017) provides a comprehensive review on flooding, but focuses exclusively on five PMT factors influencing adaptation and omits factors out of this scope. Moreover, that review utilizes a limited number of independent surveys, diminishing the suitability to explore cross-cultural differences. Importantly, both meta-analyses use a random effects model, indicating that a distribution of effect sizes exists for each of the factors motivating individual climate change adaption behavior. Furthermore, both meta-analyses state that some of the variance in the choice model would be explained through the further inclusion of descriptive and social norms. These norms describe what people perceive others as doing as well as the ‘unwritten’ behavioral rules of society. Direct study of these norms requires place-specific research as both norms strongly inform and are influenced by culture (Kruger et al., 2015; Smith, Bond, & Kagitcibasi, 2006)

Culture can yield a better understanding of individual behavior through contextualizing the norms that affect it. However, methods to analyze culture at a focused scale often require ethnographic and observational research and yield qualitative data that is more frequently utilized by anthropologists and sociologists, rather than climate and disaster researchers (Adger et al., 2013; Cannon, 2015). When looking at culture on a national level however, there are several approaches that quantitatively characterize different national cultural dimensions. A few, in particular, stand out: Hofstede’s Cultural Dimensions (Hofstede, n.d.), the "GLOBE Project" (GLOBE, n.d.) and several other rankings created from, or validated by, the Worlds Value Survey (WVS) (Inglehart et al., 2014). All utilize empirical data collected from extensive cross-national surveys allowing for comparisons across a broad scope of countries. We selected Hofstede’s Rankings for its suggested superior ability to predict behavioral frequencies when compared to GLOBE (Smith et al., 2006) and for the greater data availability for countries in which flood surveys were conducted when compared to the WVS’ rankings.

This paper aims to quantitatively examine if there are observable patterns for different factors motivating individual climate change adaptation behavior in empirical data that can be explained by national culture. To test this, we collect bi-variate associations of factors motivating individual adaptation, from 53 independent studies. Based on the country where the survey data was conducted, we then plot them against Hofstede’s national cultural rankings. The innovative contribution of this paper to the literature is two-fold. First, to the best of our knowledge, for the first time the interaction effects between culture and factors motivating private climate change adaption are measured with a sufficiently large country sample - more than 10 countries (Hofstede et al., 2010, p.30) - to distinguish cultural differences. Second, our extensive meta-analytic review statistically supports a previously contradicted difference in the effect size of risk perception toward intended vs. undergone adaptation. Since the distinction between actual and intended adaptation to climate-induced risks is important, it may influence an assessment of culture impacts on adaptation. Our review also reveals a significant affluence bias in survey locations, towards the Global North. Overlaid with statistically significant differences in the effects of culture on private climate change adaptation, this has implications for extrapolating empirical evidence from surveys run in developed countries towards anticipating what influences individual adaptation behavior in the Global South where adaptation to climate change is most needed.

The remainder of the paper is organized as follows: Section 2 outlines the methods used to collect and transform the data. In Section 3 we test for a difference in factors motivating intended vs. undergone adaptation to floods, sample size permitting. Following this, we present the meta-regression analysis to measure the interaction effects between factors motivating private adaptation and Hofstede's six cultural rankings. Finally, Section 4 discusses the implications of this research and draws conclusions.

2.2 Methods

2.2.1 Literature Search

To obtain data on individual behavior and flooding in a multinational context, we conducted a thorough literature search for surveys reporting individual households adaptation to flooding published as peer reviewed articles in English. Six different keyword combinations of "Individual", "Household", "Flood", "Adaptation", "Protection", "Motivation", and "Survey" were searched on SCOPUS and Web of Science (WoS), and Google Scholar in April, 2019. The search returned more than 100,000 results on Google Scholar, and, in total, just over 200 for WoS and SCOPUS. The first 100 results for each search were reviewed on Google Scholar and all results were reviewed on SCOPUS and WoS.

If the title or abstract mentioned a survey, a sample size, empirical data, or factors motivating adaptation, the article was screened to determine if it contained quantitative, bivariate associations or *effect sizes* (ES) of factors motivating individual flooding adaptation. ES are a way to measure the strength of an association and once standardized, allow for cross-study comparisons of the effects that the different factors have on adaptation motivation. We collected several different means of reporting ES: *Pearson's r, Spearman's rho, Kendall's Tau*, other test statistics: *chi squared (df = 1), odds ratios* and linear and logistic *standardized regression coefficients* (β). Only articles reporting ES in any of these formats were included in our evidence base. We removed duplicates and excluded or combined articles reporting data from the same survey before merging all search results into a single dataset.

Further, if a survey measured individual adaptation toward multiple hazards such as a hurricane and a flash flood, we included it as long adaptation to any type of flood adaptation was explicitly surveyed (flash flood, coastal flooding, dam/levee over-topping, etc.). The reported individual adaptive actions towards flooding varied greatly and included: insurance purchase, emergency preparedness measures, information acquisition, alterations to own home, and many other actions. Factors motivating individual adaptation were additionally manifold. A quantitative meta-regression analysis requires that a factor is reported sufficiently frequent to be eligible for inclusion. If 10 or more surveys reported a factor of interest, we included it in our analysis. Ultimately the aforementioned criteria yielded selected seven factors that were reported sufficiently frequent. Two factors: 'Risk Perception' and 'Self Efficacy' were asked often enough that we were able to distinguish between their effect in motivating intended, vs. undergone adaptation. Undergone adaptation is measured when the survey asks about action that has already taken place or is concurrent; whereas intended adaptation is an action that has not yet happened, but the individual aspires to accomplish it. Additionally, for Risk Perception, whenever possible we distinguished between its two components by recording whether it was the *probability* of the flood or the expected *damage* of the flood that was motivating adaptation. These subcategories led to a total of 13 collected factors that motivate individual flooding adaptation (Table 2.1).

Table 2.1: Thirteen factors motivating individual adaptation used in our meta-analysis of reported ES worldwide. 'Social Influence' and 'Institutional Faith' are comprised of multiple reported ES to achieve a sufficiently large sample of observations; more than 10.

Factors Motivating Adaptation	*Explanation*
1. Risk Perception (RP)	All reported ES for Risk Perception are included here. Combines ES for intended and undergone adaptation and ES probability and damage
2. RP: Undergone Adaptation	Combines both the ES for probability and damage given that adaptation has already occurred
3. RP: Intended Adaptation	Combines both the ES for probability and damage given a reported intention to pursue adaptation
4. RP: Probability of flood	Combines both the ES for intended and undergone adaptation
5. RP: Damage of flood	Combines both the ES for intended and undergone adaptation
6. (Prior) Flood Experience	ES were collected for any mention of flood experience
7. Age	ES were not collected if there were multiple age categories ES reported
8. Gender (Female)	ES were collected or transformed for the Female gender
9. Self Efficacy (SE)	All reported ES for Self Efficacy are included here. Combines ES for intended and undergone adaptation
10. SE: Undergone Adaptation	ES collected undergone adaptation
11. SE: Intended Adaptation	ES collected indented adaptation
12. Social Influence	'Information received', 'expectations', 'social support', and 'perceived stigma(s)' from family, friends, neighbors, and/or the local community)
13. Institutional Faith	'Information' provided by a governmental body/ the media, and/or the individual's 'trust' in the government, and/or 'adaptive actions' undertaken by a governmental body

Narrowed down to these 13 factors, we found a total of 72 relevant surveys. We excluded three studies where the *only* adaptation measured was relocation, out-migration or evacuation as these are fundamentally a different type of adaptation (Koerth, Vafeidis, & Hinkel, 2017). Furthermore another study was excluded since it grouped the results from two different countries, while our intention is to compare the differences between countries. Finally, surveys were further excluded if they did not report standardized ES, or the ES of a factor's *direct* impact on motivating flooding adaptation. To maximize the number of data points, we used the supplemental flooding adaptation motivation data provided by (Van Valkengoed & Steg, 2019) that they received by contacted authors for data not available in the original publications.

Following these search criteria, we compiled a dataset based on 53 independent publications (56 surveys) from 25 different countries, and the total number of respondents N=38,619. If a study reported multiple ES (e.g. several ES of risk perception motivating different adaptive actions), or two studies used the same survey population to measure different types of adaptation they were averaged so as to maintain the independence of each recorded ES, a critical component in a meta-analysis (Borenstein, Hedges, Higgins, & Rothstein, 2009). However, if within a study two independent factors were reported with

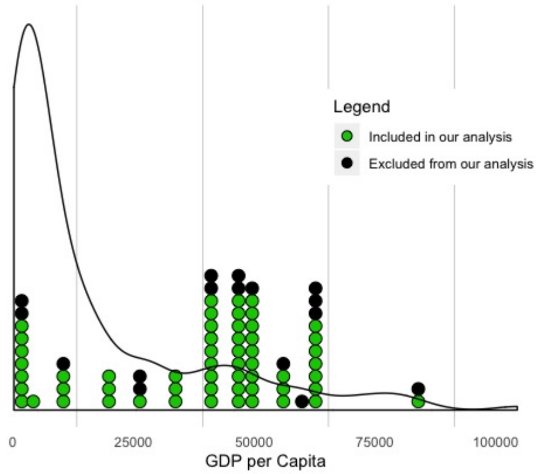

Figure 2.1: The probability density curve of global GDP per capita and individual level flooding adaptation studies that were found during the systematic literature search (N=72) Each dot represents a survey; in some cases several surveys results were published in the same study.

different N's - for example for 'Risk Perception' and 'Prior Flood Experience' - they were recorded separately with their respective N's to ensure precise weighting, as discussed in detail below.

At this stage we noticed a strong Global North bias in the survey locations. Figure 2.1 illustrates this distribution by displaying the number of individual flood adaptation studies we found in our search (both those included, and not included for quantitative or different type of adaptation reasons (i.e. did not report a transformable effect size or exclusively measured out-migration) against the probability density curve of global GDP per capita. One may question whether this distribution of surveys reflects the objective flood hazard exposure in the world, however data from (*EM-DAT*, n.d.) shows that floods are common in all regions of the world and that the current state of research is bias toward wealthier countries. The wealth of a country is intertwined with its culture (Hofstede et al., 2010) and two of Hofstede's cultural rankings - Individualism and Power Distance - are correlated with GDP per capita, thus we were unable to control for this skew in survey wealth distribution. We discuss some of the implications in Sections 2.3.2 and 5.3.4.

2.2.2 Cultural Rankings

Culture itself is not static. Rather it is shaped by a dynamic set of social relations and complex practices that influence individual behavior and inform decision making processes. These complexities make culture a "messy", but crucial concept to consider when looking at individual behavior surrounding disasters (Bankoff et al., 2015). Hofstede's ranking are suggested to be superior in predicting behavioral frequencies when compared with other cultural measurements (Smith et al., 2006) and was therefore selected as the culture metric for this study. The cultural ranking scores for each of Hofstede's cultural dimensions are based on the empirical data collected from internationally comparable surveys (Hofstede et al., 2010). For the purpose of our meta-analysis we rely on the data from the Hofstede's web-site (Hofstede, n.d.). We use six cultural dimensions in our analysis:

I. **Individualism** vs. Collectivism: In Individualistic societies, people are more autonomous and the ties between members of the society are less rigid. Individuals are primarily responsible for themselves and immediate family. In Collectivist societies, members are born into clearly defined groups, to which they belong, protect, and are protected by throughout their life.

II. **High Power Distance** vs. Low Power Distance: The "degree of acceptance" from less powerful members of society for an unequal power distribution and authoritarian decision-making vs. individual expectations to participate in decisions impacting them.

III. **High Uncertainty Avoidance** vs. Low Uncertainty Avoidance: The degree to which members of society are adverse to unknown situations. Cultures that avoid uncertainty prefer a clear set of rules, laws and regulations that offer structure and a possibility to plan so that possible risks are minimized.

IV. **Masculinity** vs. Femininity: A Masculine society has distinct, stereotypical gender roles, a strong focus on material success, individual achievements, strength and wealth. A feminine society has more loosely defined gender roles and members are typically more concerned with quality of life, nurturing for each other and for the environment. Feminine cultures resolve disagreements through negotiations rather than forcing solutions typical for the masculine ones.

V. **Long Term Orientation** vs. Short Term Orientation indicate the role of time for different cultures: Long Term Oriented societies prioritize future gains and value persistence, ability to adapt and long-term fulfillment. Shorter Term oriented values focus more on immediate and even past rewards such as tradition and preservation of face.

VI. **Indulgence** vs. Restraint: Indulgence is societies' acceptance of activities that are hedonistic and cherish enjoyment. In more restrained cultures personal happiness and freedoms are disapproved by social norms as these activities are seen as needing to be restrained.

Within each dimension, a country can score between 1 - 100, relative to other countries. A higher score indicates *more* of the characteristic highlighted in bold above. For example, a country with a score of 75 for the Individualism vs. Collectivism category is more individualistic than a country with a score of 50.

2.2.3 Data Processing

To compare the collected ES of the 13 factors motivating individual adaptation with the cultural scores we first needed to standardized them. First, we transformed all ES into Pearson's r,[1] and then converted using the variance-stabilizing Fisher's r to z transformation (Borenstein et al., 2009). Once transformed, we apply the random effects model on the factors in the dataset, weighted by the inverse variance, within and between the surveys.

[1]The equations used to transform the data can be found in the supplemental material.

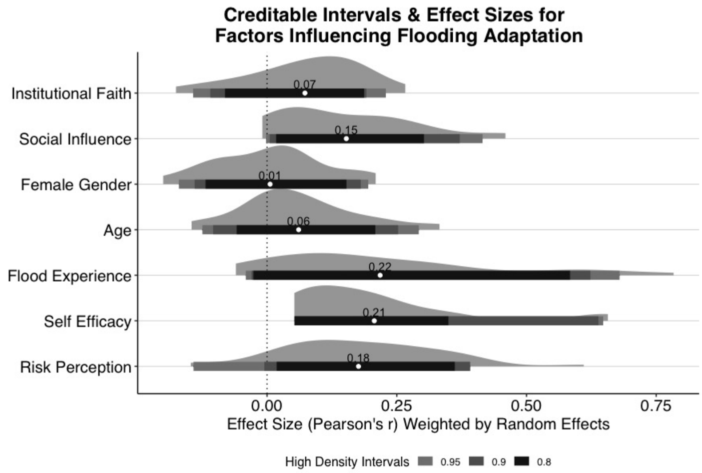

Figure 2.2: The Effect Sizes for the 7 primary collected factors motivating flood adaptation (both intention *and* undergone action grouped together) after weighting by random effects.

A random effects model, as opposed to a fixed effect model reflects a belief that there is more than one “true" ES. Encouraged by the findings of (Veroniki et al., 2016), we selected Paule-Mandel’s estimator for calculating the between study variance. The random-effects-weights for the individual and pooled values were calculated in R (3.6.1) using the "Metafor" package (Viechtbauer, 2015). We applied the assigned weights (percentages) to each study, then multiplied by the number of studies that reported an ES for a given factor to have the appropriate random effect weights for each *individual* study. This permits us to run analysis with the individual studies weighted by random effects (e.g. meta-regression analysis) and not simply consider the pooled effect size. Then the sum of the weighted individual study values was used to cross-check the pooled random-effect-weighted means. Finally, the weighted z-transformed correlations were re-converted into the commonly used ES of Pearson’s r for the analysis with culture and the reporting on meta-analytic findings. The pooled random-effect-weighted of the 7 main ES in Pearson’s r can be seen in Figure 2.2.

Bayesian Credible Intervals provide a more conservative and precise estimated range for each factor in comparison to frequentist confidence intervals (Morey, Hoekstra, Rouder, Lee, & Wagenmakers, 2016). Figure 2.2 displays the mean ES and the Bayesian Credible Intervals for the seven principle factors affecting individual adaptation motivation. The ranges do not test if there is a statically significant effect (i.e. if zero is captured in the interval), but rather where the averaged ES plausibly falls. We chose to use uninformed priors for the pooled effect sizes for two reasons. First, we collected data from studies included in both recent meta-analysis’ and therefore could not use them to create informed priors. Secondly we present the most conservative estimate so that future studies that seek to use Bayesian methods have the confidence to use these ES as priors.

Several factors have especially broad intervals. Variation in adaptation(s) measured, question phrasing and response, and time since the last flood all contribute to suspected error in our meta-analysis (Borenstein et al., 2009; Harzing, 2006). Due to sample size restraints (with adaptation actions measured) and lack of reported information (with the number of years since the last flood) we could not control for any of the above mentioned suspected sources of variance. We hypothesize however, that a substantial part of the variance is actually caused by cultural characteristics and from lack of differentiation between intended and undergone action. These two sources of variance suggest the need to look beyond the aggregated values and focus in on potential differences within each factor.

Figure 2.2 presents the pooled ES for seven factors. Here we do not differentiate between adaptation intention and action due to limited sample size for many of these factors in our dataset. It is valuable however, when pursuing empirical research on evolution of risk perception and changing adaptation motivation over time to consider the temporal dimension of individual choices. Risk Perception and Self Efficacy were the only two factors asked in sufficient frequency to differentiate between the intention to adapt and the actual adaptation action pursued by households across the world.[2] One hypothesis is that individuals with high Risk Perception in the past could have already taken adaptation actions, and thus perceive present flood risks as lower (Bubeck, Botzen, & Aerts, 2012). Likewise, Self Efficacy felt presently, could be based on the relative success of previously undergone adaptation. However, it is methodologically challenging to test these temporal feedbacks between Risk Perception, Self Efficacy and individual adaptation to floods. (Bamberg et al., 2017) uses meta-analytic data collected from PMT surveys measuring intention and undergone adaptation to test the hypothesis on risk perception contingency on previous adaptation actions. With a larger sample, unconstrained by PMT, we retest this assumption. Due to the non-normal distribution, sample size, and a desire to accurately communicate the size of effect, we again select Bayesian methods to examine the means of the ES of Risk Perception effect on intended and undergone adaptation; this time with Bayes' Factor (George Assaf & Tsionas, 2018). We calculate Bayes' Factor in R using the "Statsr" package (Clyde, 2018) and again assume flat priors based on the aforementioned justification. The results are presented below in Section 2.3.1.

2.3 Results

2.3.1 Intention vs. Action

Acknowledging the potential feedback from previously undergone adaptive actions on individual risk perception is important for understanding individual adaptation motivation. (Bamberg et al., 2017) find that the effect of risk perception on undergone action was generally higher than the effect on intended adaptation. This finding contradicts the original assumption of (Bubeck, Botzen, & Aerts, 2012), that individual risk perception should diminish after one has taken a flood adaptation measure. The data from our meta-analysis relies on larger sample of studies compared to (Bamberg et al., 2017)'s and our findings reveal a greater effect of risk perception in motivating an individual's intent to adaptation, than in explaining previously undergone adaptation (Figure 2.3). Hence, in contrast to the previous meta-analysis (Bamberg et al., 2017), it supports the original

[2]We could not do the same with Flood Experience (the other factor with a relatively large N) due to a lack of studies that measured intended adaptation and reported on the ES of Flood Experience.

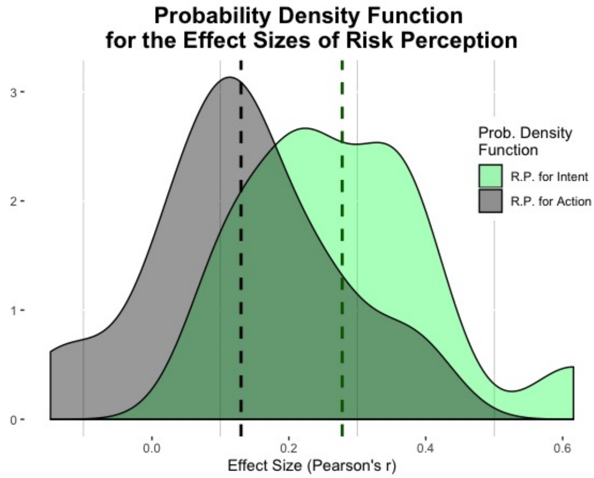

Figure 2.3: Probability density functions for the effect size of risk perception in influencing intention to adapt and undergone adaptation. The mean value for effect size of risk perception toward **intent** is: .28 (N = 14 surveys) and for (undergone) **action** is: .13 (N = 30 surveys).

assumption (Bubeck, Botzen, & Aerts, 2012) has regarding feedbacks between adaptation to floods and individual risk perception unfolding over time.

Here we use Bayes' Factor to represent the difference between the mean ES of Risk Perception and intended vs. undergone adaptation. Bayes' Factor is 16.47, which according to the inventor of the test, (Jeffreys, 1998), is a "strong" indication that the ES for Risk Perception is greater for intended adaptation to floods than it is for already undergone or concurrent action. For frequentist statistics comparative purposes, we also conducted a 2-group Mann-Whitney U Test, which confirms with 99% certainty that the ES of Risk Perception measuring intended adaptation is statistically different with that of undergone adaptation ($p < .01$). We find no statistically significant difference between Self Efficacy and intended vs. undergone adaptation when running the same tests.

2.3.2 Cultural Analysis

Further, we use Hofstede's six cultural rankings to empirically test if there are observable patterns for different factors motivating individual adaptation that can be explained by national culture. We plot the converted ES of factors motivating individual adaptation against the cultural rankings based on the country where the survey was conducted. In doing so we find that a number of the ES for factors motivating adaptation have a significant relationships with different cultural dimensions.[3] Table 2.2 reports the statistically significant meta-regression coefficients for all of the ES of the factors influencing adapta-

[3]All of the cultural ranking scores were taken from (Hofstede, n.d.) with two exceptions: Ethiopia did not have scores for two cultural dimensions: Long Term Orientation and Indulgence; and was thus excluded from the analysis on these two categories. Cambodia has no scores for any cultural dimension, however using a recent article (Berkvens, 2017) that discusses Hofstede's cultural dimensions in relation with Cambodia's ranked neighbors, we calculated coefficient estimates for each cultural dimension. See supplementary material for further explanation.

tion and cultural rankings. In what follows, we discuss the influence of different cultural dimensions in explaining the some of the statistically significant relationships between individual motivation to pursue adaptation to floods and flood experience, institutional faith, and flood probability.

Table 2.2: Regression coefficient estimates for the random effects weighted effect sizes of different factors motivating adaptation. Here we list values only for those that have a statistically significant relationship with Hofstede's Cultural Rankings:
(**I**): Individualism - Collectivism, (**II**): High - Low Power Distance, (**III**) High - Low Uncertainty Avoidance, (**IV**): Masculinity - Femininity, (**V**): Long - Short Term Orientation, (**VI**): Indulgence - Restraint. (N= number of surveys, n= number of respondents, c= number of countries)

	Hofstede's Cultural Rankings:					
	I	**II**	**III**	**IV**	**V**	**VI**
1. Risk Perception (RP) (N=41, n=26856, c=16)						
2. RP: Undergone adapt. (N=30, n=21954, c=13)						
3. RP: Intended adapt. (N=14, n=5182, c=7)						
4. RP: Probability (N=15, n=7082, c=10)				-0.3^{-2*}		0.7^{-2**}
5. RP: Damage (N=15, n=5626, c=11)					-0.6^{-2*}	
6. Flood Experience (N=27, n=18257, c=16)	-0.5^{-2***}	0.6^{-2**}	-0.4^{-2*}			
7. Age (N=18, n=14294, c=15)		0.2^{-2*}				
8. Gender (Female) (N=17, n=17870, c=15)		-0.2^{-2*}				
9. Self Efficacy (SE) (N=21, n=10658, c=15)	-0.3^{-2*}	0.4^{-2*}				
10. SE: Undergone adapt. (N=14, n=7290, c=11)	-0.3^{-2**}					
11. SE: Intended adapt. (N=10, n=3648, c=7)						
12. Social Influence (N=13, n=6866, c=10)						
13. Institutional Faith (N=20, n=19599, c=12)		0.4^{-2***}				

$^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$

Flood Experience and Culture

Natural hazards are culturally constructed events. Namely, how an individual experiences a natural hazard and the manner in which a society prepares, is impacted, and recovers from an event is strongly influenced by aspects of culture (Bankoff et al., 2015; Cannon, 2015; Oliver-Smith, 2015). In general, personal exposure to a flood is a strong indicator of future adaptation (Siegrist & Gutscher, 2006; Wachinger, Renn, Begg, & Kuhlicke, 2013). Our results indeed support this idea, however the magnitude of the effect appears to be mediated by culture. Several cultural dimensions: *Individualism*, *Power Distance* and *Uncertainty Avoidance* have statistically significant linear relationships with prior Flood Experience (Figure 2.4).

The *Individualism* dimension is the most highly correlated to the ES of flood experience motivating adaptation and explains the most variance in a linear model. In individualistic societies the ’group’ an individual is responsible for, and socially answers to, is much smaller than in more collectivist ones. Additionally, in individualistic societies public areas are less frequently utilized for family and social gatherings (Hofstede et al., 2010; Triandis et al., 1986). The lessened use of public space, and smaller social circle effectively diminishes the area that a flood can have a personal impact for an individual. Personal connection to a flood affected area is an important factor in determining if a flood experience will influence future adaptation (Barnett & Breakwell, 2001; Eiser et al., 2012), thus contributing to the negative relationship that Individualism has with the ES of Flood Experience motivating individual adaptation 2.4.

High Power Distance conversely has a positive relationship with flood experience motivating adaptation. This is expected as Power Distance and Individualism have an inverse relationship with one another. Furthermore, both cultural dimensions are correlated with GDP per capita (a positive relationship with Individualism and a negative one with High Power Distance). Wealth and culture are inextricably linked in many ways, especially with these two dimensions, thus we elected not to control for GDP per capita (Hofstede et al., 2010, 108). We do however represent GDP per capita in the graphs with the intra-dot shading (2.4).

We suspect *GDP* per capita does indeed contribute to how flood experience affects an individual. GDP per capita contributes to a nation’s capability to allocate resources to the communities and individuals impacted by floods (Gardoni & Murphy, 2010). This support could lessen the traumatic impact, and thereby contribute to prior flood experience being less of a motivating factor in countries with higher GDP per capita. It is also likely that if a government has more resources to allocate, individuals may expect to receive aid, and thus there could some incentive to ‘free-ride’ (Wachinger et al., 2013). Despite GDP’s importance, Individualism is more highly correlated and explains slightly more variance than GDP per capita, further reinforcing the necessity of considering culture in disaster adaptation (Eiser et al., 2012; King, 2004; Kruger et al., 2015).

The final cultural dimension to have a significant relationship with flood experience motivating adaptation is *Uncertainty Avoidance*. Uncertainty Avoidance measures how averse to unknown situations members of a society are. A flood occurrence may serve as a communication vehicle, since people get an updated information on the nature of this hazard event and their vulnerability to it, as also confirmed empirically in the hedonic analysis literature (Bin & Landry, 2013). Hence, experience with a flood and the damage it

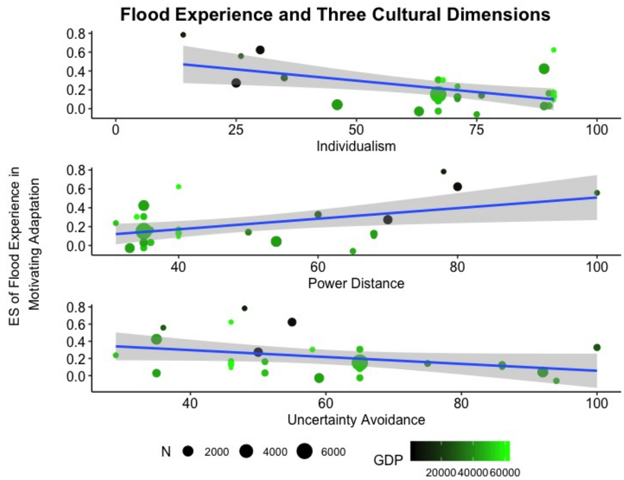

Figure 2.4: The effect sizes for flood experience in motivating adaptation plotted against three of Hofstede's cultural dimensions: Individualism (top), Power Distance (middle) and Uncertainty Avoidance (bottom). "N" is the size of the survey and "GDP" represents GDP per capita for the country in which the survey was conducted.

brings reduces uncertainty surrounding the event. The increased clarity around flooding that follows an event, could result in a lessened adversity to flooding and explain the diminished effect that Flood Experience has in motivating adaption in societies with higher Uncertainty Avoidance. This idea is supported by (Hofstede et al., 2010, 198) as they note that individuals from high Uncertainty Avoidance societies can paradoxically engage in risky behavior to in order to "reduce ambiguity" in their lives.

Since Flood Experience shows a statistically significant relationship with multiple cultural rankings, we select a multiple regression model to explain the most variance in the ES of Flood Experience motivating adaptation. Power Distance and Individualism cannot be in the same model due to issues with co-linearity. Thus, using step-wise model building logic, we select Individualism (the most highly correlated cultural factor) and then Uncertainty Avoidance for our model. In Equation 2.1 we explain the size of the effect of Flood Experience (ES_{Exp}) on adaptation motivation by using the cultural ranking score (C) of the two previously described cultural dimensions - Individualism and Uncertainty Avoidance - with the intercept and error (e).

$$ES_{Exp} = -0.0056(C_{Ind}) - 0.0052(C_{Unc}) + 0.90 + e \tag{2.1}$$

Following the data from 27 surveys from 16 countries with the total number of 18,257 respondents, the two cultural dimensions explain 39% (adjusted r^2, $p<.001$) of the variance in the size of the effect of Flood Experience motivating adaption. With inclusion in this equation, the p-value of Uncertainty Avoidance increases its significance level to .05, further suggesting its value to the model.[4] The credible interval for the ES of Flood Experience

[4]Pearson's r correlation estimate between the two variables is reasonable at .27 and the adjusted r^2 between Individualism and Uncertainty Avoidance is 0.06 (with our sample of countries); suggesting co-linearity is not a concern.

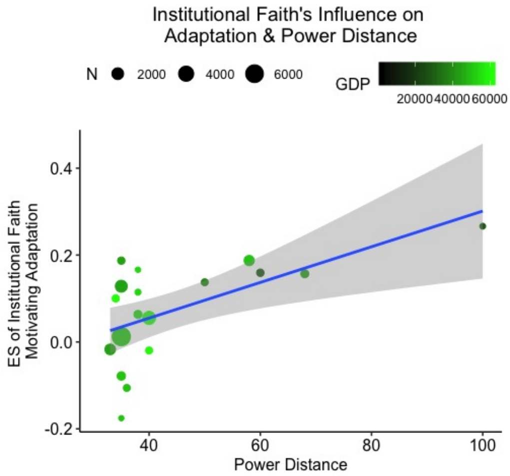

Figure 2.5: The effect sizes for 'Institutional Faith' plotted against the counties' Power Distance rank. ($p<.001$ and the adjusted r^2 is .33)

motivating adaptation is the largest among all the factors we measured (Figure 2.2). Thus, the cultural dimensions' explanation of 39% of this variance contributes to a significant increase in accuracy both for future cross-national research on the role of hazard experience in the uptake of climate adaptation measures by individuals and, consequently, a better frame of reference for policies and disaster research.

Institutional Faith and Power Distance

Institutional Faith (defined in section 2.2.1) is another factor consistently reported to influence individual adaptation motivation. Notably, Institutional Faith, has a positive, significant relationship with the cultural dimension *Power Distance*. In the sample of publications reporting the households surveys papers, over 12 countries elicited Institutional Faith across 19599 respondents. Within these studies, there is a large over-representation of countries that fall on the "lower" side on the power distance scale. This is related to the previously discussed skew toward higher GDP per capita (Figure 2.1). Therefore the positive trend in Figure 2.5 is contingent on limited results, giving way to a wide standard error.[5] Yet the p-value is very strong ($p<.001$) and the trend is theoretically logical. Thus, we discuss this finding with the cautionary note that further research is needed in countries with high Power Distances.

The larger effect that Institutional Faith has in countries with a higher Power Distance is in-line with Hofstede's characterization of this dimension. In cultures with a high power distance, the idea that power is a justification in itself, is rooted at the basis of the society (Hofstede et al., 2010, p.77). Strong leaders are respected, and individuals with less

[5] Malaysia has a score of 100 to represent the Power Distance in the country. Few surveys have been conducted in countries with such high Power Distance, and as a result, the survey in Malaysia is an outlier. To see how influential the point is we constructed models with and without the data point. The model is statistically significant in both cases, and the slope change is not especially dramatically (.004 with and .005 without.) However, the adjusted R^2 does drop from .33 to .21, indicating it is indeed an influential point.

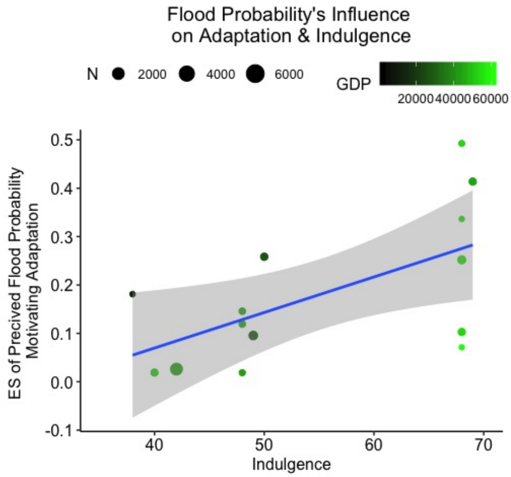

Figure 2.6: The effect sizes for the perceived Probability of Flooding plotted against the Indulgence ranking of the country. ($p<.05$ and the adjusted r^2 is .30)

respective power, expect to be told what to do, suggesting that adaptation motivation for individuals in high power distance societies may not be innate. The model in Figure 2.5 further indicates the effect that government/central media supply information or promotes a particular adaptation action has a much greater inspiring effect in countries where Power Distance is high.

Flood Probability and Indulgence

A final relationship between culture and adaptation motivation we wish to highlight is that of *Indulgence* and the perceived *Probability of Flooding* (Figure 2.6). Maps reporting probabilities of a flood is a common statistic published by governments to alert individuals of their respective flood hazard exposure. The relationship between Indulgence and perceived Flood Probability suggests that that this method of communication is not equally effective in all societies and governments and risk managers should be considerate of where their respective society falls on this cultural scale when considering the contents of risk communication.

Indulgence has a significant, positive relationship with the perceived Probability of Flooding motivating adaptation. One of the principle sub-components of an indulgent society is that its members share the belief that they have control over their lives (Hofstede et al., 2010, p.281). It is therefore logical that the elevated self-agency in higher indulgent cultures, has a greater effect inspiring action. Individuals with higher perceived life control, are more likely to believe that while they cannot lower the objective probability of a flood, they can alter its impact, hence the greater effect. When Masculinity, the other cultural dimension with a statistical relationship with the Probability of Flooding is added to a linear model, both variables lose significance and the adjusted R^2 is less than when just explained by Indulgence.

2.4 Discussion and Conclusion

As the Global Commission on Adaptation's pleas for taking action to address climate change intensify, understanding how individual households' actions and motivations vary across countries becomes increasingly important. Previous work examining disaster risk management has emphasized the influence that cultural factors have on a society's relationship with disasters (Kasdan, 2016). On an individual level, flooding adaptation studies across multiple countries further highlight the importance of these context specific factors in influencing behavior (Boamah et al., 2015; Bradford et al., 2012; Hanger et al., 2018). While these works note the importance of context, they do not specifically attest to patterns across regions or countries. There is an understanding that culture plays a role in individual assessments of risks (Gierlach et al., 2010; Kruger et al., 2015). However, a systematic analysis on how different dimensions of culture influence people's perceptions of climate-driven hazards and motivation to adapt to growing risks, is lacking.

Culture is a complex, multidimensional concept that can be difficult to measure. These challenges have led policy makers, international aid agencies/NGOs, and researchers to frequently shy away from the inclusion or explicit consideration of culture's influence in climate change adaptation work (Bankoff et al., 2015; Cannon, 2015). Yet, culture directly influences many aspects of adaptation motivation and is absolutely essential to include in the discourse (Adger et al., 2013; Bankoff, 2004). Transferring successful cases of climate adaptation from one cultural context to another may prove ineffective should cultural dimensions and differences be ignored. Furthermore, professionals who work with disaster policies, management, and research are, themselves, indoctrinated by their own culture and without explicit consideration of the unique context in the area they are working, people tend to view the world through the cultural lens in which they were raised (Hoffman, 2015). The bias resulting from the exclusion of culture can lead to inaccurate results and more importantly may increase vulnerability and risks for the affected populations (Hoffman, 2015; Mercer et al., 2012; Oliver-Smith, 2015).

Our meta-analysis provides empirical evidence supporting the importance of considering culture when looking at individual adaptation behavior with respect to the most devastating climate-driven hazard: flooding. Through the use of meta-regression, using Hofstede's cultural rankings as the independent variable, we find that national level culture does indeed affect factors that motivate adaptation behavior in climate change adaptation analysis. For example, significant variation in the effect that prior *Flood Experience* has on adaptation motivation is explained by several cultural dimensions: Individualism, Power Distance and Uncertainty Avoidance. The multiple-regression cultural model that predicts the effect of prior Flood Experience on motivating individual adaptation, explains almost 40% of the variance in the collected effect sizes of Flood Experience affecting adaptation. This finding provides a clear incentive for modelers, disaster researchers, and policy makers alike to utilize the easily accessible national level culture data available for inclusion in their work and models.

Furthermore, two cultural dimensions - *Power Distance* and *Indulgence* - exhibit statistically significant relationships with the factors that influence Institutional Faith and perceived Flood Probability have on motivating individual adaptation, respectively. The probability of a flood is a commonly published statistic used to warn individuals of their risk and how Indulgent a society is, has a strong relationship with the degree to which it affects an individuals' motivation to take adaptive action. Furthermore, the degree of Power Distance in a society is a good predictor as to how information and/or action taken by the government and media will influence an individuals' adaptation behavior. Both of these cultural relationships have important implications for researchers and policy makers seeking to motivate citizens to take preparatory action against the adverse effects of climate change. Not all disaster cues are received equally. Climate change strategies and campaigns that are successful in one country cannot be applied to another, without regard for cultural differences. Ignoring this fact will likely lead to less acceptable climate change adaptation measures that are less successful in achieving their intended objectives and may exacerbate the target population's risks.

Equally important are the patterns in relationships between factors affecting individual adaptation to floods and cultural dimensions that we did not witness. Data from 38,619 respondents across 25 countries in our meta-analysis sample does not explain variations in Social Influence and several measures of Risk Perception by any of the Hofstede's cultural dimensions. This does not necessarily indicate that culture has no influence on these factors; as differences in Risk Perception specifically have been found in previous cross cultural contexts (Gierlach et al., 2010; Renn & Rohrmann, 2000). Rather it suggests that either more localized culture is at play, or a larger sample of surveys across cultures is potentially needed to identify trends in these factors motivating individual adaptation.

In examining the state-of-the-art work in flooding adaptation, we explicitly highlight the need for more work in nations with a smaller GDP per capita. Nations in the Global South, with generally lower GDP per capita, will be disproportionately impacted by climate change. Compared to more economically affluent countries, they are also more dependent on private adaptation to floods, given the lower adaptive capacity at national levels to invest in large-scale climate change adaptation measures. Yet, household level surveys eliciting factors behind individual adaptation to floods are largely underrepresented for this group of nations. This gap has resulted in a wide standard error in several of the cultural models. Our models provide a significant increase in accuracy for extrapolating flood adaptation strategies to data scarce countries and regions where individual adaptation research is scarce or non-existent. This work however, should not be seen as a replacement for on-the-ground research. Future work should seek to focus on these data-scare regions, especially in the Global South where the risks of floods and adverse effects of climate change is disproportionately large.

We additionally find a strong difference between individual Risk Perception toward undergone and intended adaptation. The higher effect sizes in Risk Perception toward intended adaptation, compared to undergone adaptation is likely due to the feedback the completed/ concurrent action has in lowering one's perceived risk once the action is completed. (Bubeck, Botzen, & Aerts, 2012) propose that longitudinal data would be a revealing method to study this feedback. We agree and further suggest that this method would be useful in illuminating the *extent* to which intention leads to action. Several behavioral theories posit intention as a precursor to action (Ajzen, 1985; Rogers, 1975), however, the extent, and time it takes for individuals to follow through on these intentions remains unclear. Future work should consider the pathway between intention to adapt and undertaking the action (e.g. through the use of longitudinal methods) especially in diverse settings. Just as culture is shown to influence the factors affecting individual behavior, it is possible that the transition from individual intention to action is additionally mediated by culture and/or other variables.

Individual level adaption, complementing government action, is essential to address the increasing flood risk. Understanding how and why individuals adapt is critical for information transmission and motivation. Culture offers a unique insight into the shared patterns of thinking and learning of individuals that can provide important context for their behavior. While culture has previously been used to explain vulnerability to disasters (Duckers, Frerks, & Birkmann, 2015), to our knowledge, this is the first article to statistically demonstrate the merit of including culture in climate adaptation analysis when explaining differences in the effects of factors motivating individual level behavior across a large sample of countries. Researchers, disaster workers, and policy makers alike can make use of these findings to better tailor their message, plan, or model and thereby more effectively motivate individual adaptation. We hope that the effect of this work will both inspired further investigation into culture (potentially on a finer scale) and motivated the inclusion of culture as variable in future disaster research.

2

2.5 Acknowledgements

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3

Contextualizing cross-national patterns in household climate change adaptation

Understanding social and behavioral drivers and constraints of household adaptation is essential to effectively address increasing climate-induced risks. Factors shaping household adaptation are commonly treated as universal; despite an emerging understanding that adaptations are shaped by social, institutional, and cultural contexts. Using original surveys in the United States, China, Indonesia, and the Netherlands (N=3,789) - we explore variations in factors shaping households' adaptations to flooding, the costliest hazard worldwide. We find that social influence, worry, climate change beliefs, self-efficacy, and perceived costs exhibit universal effects on household adaptations, despite countries' differences. Disparities occur in the effects of response efficacy, flood experience, beliefs in governmental actions, demographics, and media, which we attribute to specific cultural or institutional characteristics. Climate adaptation policies can leverage on the revealed similarities when extrapolating best practices across countries, yet should exercise caution as context-specific socio-behavioral drivers may discourage or even reverse household adaptation motivation.

This chapter is based on: Noll, B., Filatova, T., Need, A., & Taberna, A. (2022). Contextualizing cross-national patterns in household climate change adaptation. Nature climate change, 12(1), 30-35. To comply with journal formatting requirements the Methods can be found at the end of the article.

3.1 Introduction

Worldwide, escalating climate-induced hazards inflate economic damages (Coronese, Lamperti, Keller, Chiaromonte, & Roventini, 2019), undermine livelihoods (Tanner et al., 2015), and force migration (Siders & Keenan, 2020). The approaching new climate reality calls for an urgent and ambitious adaptation at all levels: from government-led actions to household climate change adaptation behavior (Adger et al., 2005; Aghakouchak et al., 2020). Understanding how and why households adapt is critical for diminishing adaptation deficits and overcoming socially-constructed adaptation limits, (Berrang-Ford et al., 2021), for fostering societal resilience, (Michel-Kerjan, 2015) and risk communication (Clayton et al., 2015). Recent research on households' adaptation behavior to climate-induced hazards provides valuable insights in factors shaping individual motivations to adapt (Bamberg et al., 2017; van Valkengoed & Steg, 2019). Growing empirical evidence indicates that perceptions, experience, and self-efficacy could facilitate or inhibit households' adaptation to hazards (Seebauer & Babcicky, 2020b; Wilson, Herziger, Hamilton, & Brooks, 2020).

Flooding is the most widespread and costliest climate-induced hazard worldwide (Hirabayashi et al., 2013). Previous work has advanced our understanding of the empirical drivers of household flood adaptation, but has primarily focused on single countries; with rare exceptions that utilize non-synchronous and non-identical surveys (Bubeck, Botzen, Laudan, Aerts, & Thieken, 2018; Koerth et al., 2013). Furthermore, while climate change disproportionately impacts Global South countries, most surveys on households' flood adaptation are conducted on the Global North (Noll et al., 2020). Yet, adaptation is locally shaped, and social, institutional, and cultural factors likely affect individual adaptation behavior (Berrang-Ford et al., 2021; Schill et al., 2019; van der Linden, 2015; Wilson et al., 2020). In exploring these influences, past work has faced data limitations (Noll et al., 2020; Wilson et al., 2020), with the result that household adaptation and its drivers and constraints are often discussed uniformly across diverse contexts.

Household adaptation involves different actions, ranging from seeking information to hazard-proofing one's property. Previous studies suggest that households' adaptation behavior that varies in effort and costs could trigger different decision pathways (Babcicky & Seebauer, 2019; Seebauer & Babcicky, 2020b). Yet, research that specifically tests to what extent the drivers of different adaptations vary is notably missing. Hence, extrapolating a universal theoretical and empirical understanding of household adaptation behavior in diverse and understudied contexts remains a key challenge in the field of climate adaptation (Adger et al., 2013; Wilson et al., 2020).

To address this gap, we question to what extent commonly theorized factors of household adaptation have analogous effects across (a) different contexts and (b) adaptation types that require varying degrees of implementation efforts. To gather sufficient data to answer these research questions, in March-April 2020 we conducted identical household surveys (N=3,789) in four countries: the United States (USA), China, Indonesia, and the Netherlands. We focus on coastal urban areas, which are vulnerable to flash, river and coastal floods, and to sea level rise (See Supplementary Material Table 8.3 for specific survey location details) (Tiggeloven et al., 2020). The four countries represent unique social, institutional, cultural, and geographic contexts. USA and the Netherlands are two Global North nations where theories of behavior under risk were developed and advanced (Bamberg et al., 2017; Grothmann & Reusswig, 2006), and floods surveys are repeatedly administered (Noll et al., 2020). China and Indonesia are two Global South nations where prior surveys on factors motivating households' flood adaptation behavior are limited. All four, however, are front-runners in escalating flooding risk (Tiggeloven et al., 2020), yet vary in the frequency of flood experiences: from nearly annual (Indonesia) to once-in-a-lifetime (the Netherlands). The four cases differ culturally, and in the role governments take in adapting to climate-induced floods (stronger centralized protection in the Netherlands and China vs. more individual responsibility in Indonesia and USA).

To measure adaptation intention, we examine 18 household-level actions (details in Methods). Drawing on prior findings on the differences in adaptation motivation towards flooding based on the type of measures and potential synergies (Babcicky & Seebauer, 2019; Seebauer & Babcicky, 2020b), we classify our 18 measures into two groups (supported by confirmatory factor analysis, Supplementary Material Table S.6). High Effort measures (8) involve structural, usually irreversible modifications to one's home, and Low Effort measures (10) comprise less intensive non-permanent protection and communication actions. For both groups we estimate the proportion of intended actions from the remaining actions – not yet undertaken actions per case-study. Adaptation intention for these two groups are the focus of our analysis ('Dependent Variables' in Methods).

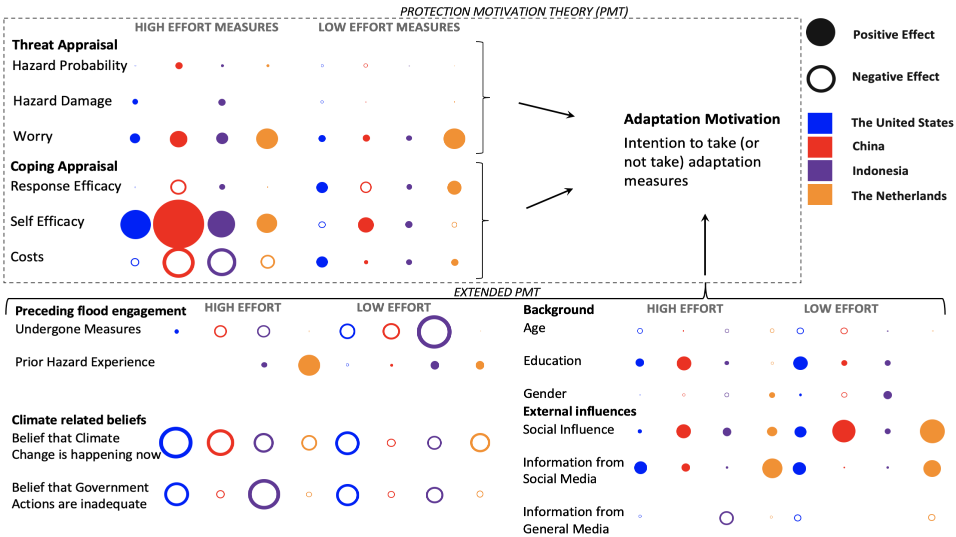


Figure 3.1: Social and behavioral factors motivating household climate change adaptation in four countries: USA (N=1,139 survey respondents), China (N=842), Indonesia (N=1,080), and the Netherlands (N=728). All 16 variables under the categorical groupings (bold) are included in the Bayesian beta regression models. The circles demonstrate the effects of these variables on households' adaptation intentions for High Effort and Low Effort Measures. The size of the circle is proportional to the size of the effect, which if negative, is presented by a hollow circle; the colors denote the four countries. The effect sizes and standard errors are presented in detail in Figure 2 and in Section S.4 in Supplementary materials.

To determine what drives and hinders households' adaptation decisions, we build on Protection Motivation Theory (PMT) (Bamberg et al., 2017; Grothmann & Reusswig, 2006; Rogers, 1975). Following previous work (Bamberg et al., 2017; Bubeck, Botzen, Suu, & Aerts, 2012; van Valkengoed & Steg, 2019), our survey examines perceived hazard probability, perceived damage, and worry about flooding driving Threat Appraisal, and self-efficacy, response efficacy and perceived cost shaping Coping Appraisal (Figure 1). We expand the original PMT model to account for preceding engagement with hazards (prior actions, experiences) (Botzen et al., 2019; Osberghaus, 2017), external influences (media, peers) (Poussin et al., 2014), climate-related beliefs (Mol et al., 2020), and demographic background (Bubeck et al., 2013). Hence, our 16 explanatory variables (Figure 1; see details in Methods) go beyond interpersonal factors to account for some intra-personal cues considered essential for behavioral adaptation (Wilson et al., 2020). To quantify the effects of these 16 socio-psychological factors on household adaptation intentions we estimate and analyze the effects from Bayesian beta regression models (details in Methods), separately by country and measure group.

We find that while a few drivers have universally consistent effects across countries and measure groups (i.e. social expectations and worry), others exhibit salient difference across countries (i.e. response efficacy) or measures (i.e. self-efficacy and cost) (Figures 1, 2). Key similarities and differences in the drivers across countries, when properly contextualized, could help strategies aimed at extrapolating household adaptations to data-scarce regions.

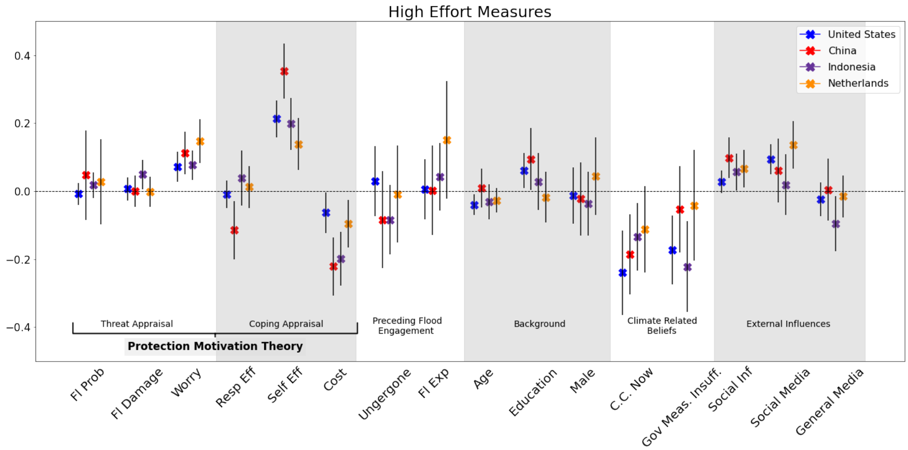
3.2 Patterns in primary drivers of household adaptation

The perception of a greater threat, is generally associated with an increased likelihood to take adaptive action (Rogers, 1975). In line with past empirical works (Babcicky & Seebauer, 2019; Bubeck, Botzen, Suu, & Aerts, 2012; Seebauer & Babcicky, 2020b), our analysis affirms that emotional, rather than analytical, reasoning drives household decisions. The former is intuitive and fast (Slovic et al., 2004), while probabilities requiring cognitive efforts, are abstruse to the public (Weber, Blais, & Betz, 2002). Perceived probability and damage, offer little power in explaining households' intentions to adapt across all four countries ('Fl Prob' and 'Fl Damage' in Figure 2). The effect of perceived damage in Indonesia presents an exception when estimating High Effort measures; possibly due in part to the vulnerable position and high exposure to flood damage many households face in Jakarta annually (Wijayanti et al., 2017). Yet, even in Indonesia, 'Worry' offers more explanatory power than the calculated risk variables ('Fl Prob' and 'Fl Damage'). 'Worry' has a consistently positive relationship with adaptation intention for both High and Low Effort measures across all counties (Figure 2).

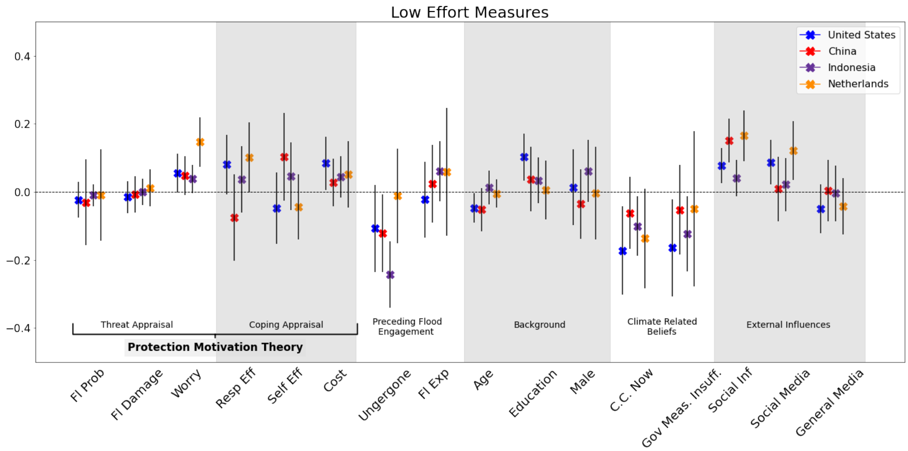
Coping Appraisal is generally a strong predictor of action (Babcicky & Seebauer, 2019; Bamberg et al., 2017). Among the three Coping Appraisal variables, the effects of two - self-efficacy and perceived costs - on household intention to take High Effort measures, are universally consistent across the four countries (Figure 2.a). In line with PMT and with past research (Bamberg et al., 2017), households who report greater capability and view the measures as generally less expensive ('Self Eff' and 'Cost', Figure 2.a), are more likely to intend adaptation for High Effort measures. Notably, in the two economically-wealthier Global North countries, USA and Netherlands, perceived cost is 2-4 times less of a deterrent in household adaptation compared to the two Global South countries - China and Indonesia (Section S.4, Supplementary Materials), calling for innovative climate finance solutions that support adaptive capacity in Global South.

The effect of response efficacy on intending to undertake High Effort measures, differs among countries (Figure 2). In USA and the Netherlands it likely has no effect on adaptation intentions; in Indonesia, the effect is marginally positive. In China however, we observe a negative effect meaning that households that, in general, view these household adaptation measures as less effective overall, paradoxically are more likely to adapt. While a null or negative response efficacy is not unheard of when estimating a grouped adaptation variable (Bubeck et al., 2013; Poussin et al., 2014), past empirical work usually demonstrates positive effects of 'Resp Eff' on adaptation intentions (van Valkengoed & Steg, 2019). Chinese culture, in comparison to the other three case-studies, is more long-term oriented (Hofstede et al., 2010). Longer-term oriented cultures situate their beliefs in a broader temporal context, potentially situating the way people assess efficacy in the longer term. Possibly, flood-aware respondents in China, who see property-level adaptions as less effective in the long term, may yet recognize the short-term utility of some measures - and hence are driven to adapt to remedy the more imminent adversities.

For Low Effort measures, in contrast to PMT, perceived costs have a reverse effect on households' intentions to adapt in all four countries (Figure 2.b; Section S.4, Supplementary Materials). Likewise, compared to High Effort measures, we see a universal substantial decrease in the effect of self-efficacy on intentions for Low Effort adaptations. The change in effects is likely due to the fact that several of the measures in this group are free and require minimal effort, (i.e. coordinating with neighbor or moving expensive furniture to a higher floor). Hence, measures that require less time and resource investments likely have different psychological drivers and/or are made using varying



(a)



(b)

Figure 3.2: The 'X's' report the mean effect sizes of for factors influencing households' intentions to adapt to flooding. The vertical bars indicate 95% credible intervals. The effects are calculated from Bayesian beta regression models; run separately by adaptation type - **(a)**: High Effort, **(b)**: Low Effort - in four countries (United States (N=1,139), China (N=842), Indonesia (N=1,080), the Netherlands (N=728).

heuristic shortcuts (Siegrist & Gutscher, 2006; Slovic et al., 2004). Further, we also find larger standard errors and slightly greater variance in effects of 'Resp Eff' among countries for Low Effort measures compared to High Effort - possibly due to more accurate reporting on intentions to undertake High Effort measures (Bubeck et al., 2020). Intentions to pursue Low Effort adaptations by households in USA and the Netherlands and, to a lesser degree, Indonesia are positively affected by 'Resp Eff', while the negative effect in China remains, though lessened.

3.3 Role of experience, background, beliefs, and social influence

In Indonesia and USA, 46% and 48%, respectively, of the households included in this analysis reported having experienced a flood, in stark contrast with China (19%), and the Netherlands (15%) (Table 8.3, Supplementary Materials). Yet, prior flood experience is a weak predictor of High Effort adaptations among our respondents everywhere, except the Netherlands ('Fl.Exp', Figure 2.a). In China, Indonesia, and USA, floods occur annually throughout the country. Dutch residents, by contrast rarely experience them, except occasionally with heavy rainfall or in unembanked areas. Since beliefs and personal baselines are formed in the context of own experiences (Kahneman, 1992), for a Dutch household, a flood is a unique experience creating a memorable availability heuristic (Siegrist & Gutscher, 2006)) that positively influences (95% likely) adaptation intentions.

Our data demonstrates that 17.7%-39.5% of households in four countries have already undertaken High Effort adaptation measures, and almost twice as many (43.2%-78.6%) have adopted Low Effort measures (Figure 3). The effect of prior adaptation on intending additional Low Effort measures has a strong negative effect everywhere, except the Netherlands (null effect for 'Undergone', Figure 2.b). Whereas for High Effort, the likely negative effect is lessened, and is only present in China and Indonesia (Figure 2.a). Both countries suffered major floods in the preceding nine months before our survey: 2019 Typhoon Lekima in China, and 2019 Jakarta Floods in Indonesia. Possibly, households in these countries have more *recently* undergone High Effort flood adaptation measures - lessening the likelihood that they would need to intend others in the immediate future.

While the effect is not included in the models (to maintain model independence for comparative purposes), it is worth noting that households who have *not* undergone Low Effort measures are more likely to intend High Effort measures (Wilcox Rank-Sum: for each individual country, $p< 0.001$). Still, households who have not undergone High Effort measures - in USA (Wilcox Rank-Sum: $p< 0.001$), China (Wilcox Rank-Sum: $p< 0.01$) and Netherlands (Wilcox Rank-Sum: $p< 0.01$) - are more likely to intend Low Effort measures. This is not the case in Indonesia (p=n.s.), where due to the relatively high flood exposure households that feel at risk, have likely already taken at least some Low Effort measures.

The effects we observe from the demographic variables are mixed and generally weak (Figure 2). In USA, Indonesia and the Netherlands, 'Age' has a small negative effect on intentions to pursue High Effort measures, perhaps due to discounting of implementation efforts over the remaining lifetime in own property. Age also discourages Low Effort measures in USA and China. That elder respondents are less likely to intend adaptation than the younger is concerning: they are more vulnerable and require specific attention during and following disasters (Malik et al., 2017). 'Education' has a positive effect on adaptation intentions only for households in USA (>99% likely for both High and Low Effort measures) and China (98% likely for High Effort measures), while in other countries it matters less. Gender has a likely null effect everywhere except Indonesia where men appear more likely than women (92% certainty) to intend Low Effort measures. Our sample respondents are slightly more educated than the general population, and in China and Indonesia somewhat younger; possibly influencing effects (Supplementary Material, Tables S.3, S.4). However, since other work has likewise found inconsistent effects for demographics, we don't foresee any substantial bias in the effects of

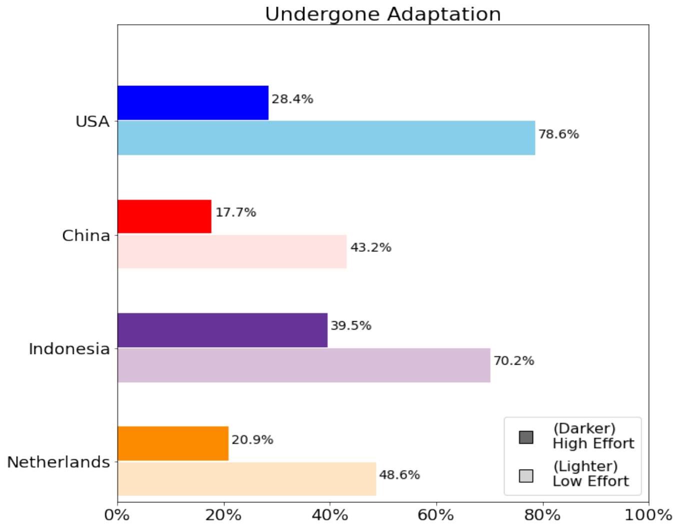


Figure 3.3: The percentage of households who have previously undergone at least one adaptation in each category.

measured variables (Bubeck et al., 2018).

Across the four countries, between 62%-79% of respondents believe that climate change is happening now (Table 8.3, Supplementary Materials). Past work however has shown that belief in climate change often does not translate into action (Sousa-Silva et al., 2018), can deter action (Hall, Lewis, & Ellsworth, 2018), and does not necessarily have a strong cognitive link with extreme weather events (Hornsey, Harris, Bain, & Fielding, 2016; Whitmarsh, 2008). Here the belief that climate change is happening now, ('C.C.Now', Figure 2) has a negative direct effect consistently in all four countries. The reason could be that households who believe in urgency of climate change, have already taken some actions - as many in our dataset have (Figure 3). Notably, the belief in climate change is associated with having previously undergone Low Effort measures (χ^2=123, p=0.0). While there is no discernible relationship between belief in climate change and previously undergone High Effort measures, as noted with past action, having undertaken Low Effort measures is associated with less intention for both High and Low Effort. Hence, it likely quells protection motivation (Bubeck, Botzen, Suu, & Aerts, 2012) and possibly explains the negative relationships.

Government adaptation many influence households' intentions. Previous research often found negative effect on households' adaptation intentions of trust in governmental protection or of belief that it is governmental responsibility (Bubeck et al., 2013). We go beyond measuring general beliefs and asked specifically whether households think actions already taken by their respective governments were sufficient (Table 8.3, Supplementary Materials). In Indonesia and USA the belief that the current government measures are inadequate discourages household adaptation intentions for both measures (>98.5% likely); whereas in China and the Netherlands the effect is small and uncertain, hence likely null ('Gov Meas. Insuff.' Figure 2).

Two institutional and experiential differences between countries could explain the observed disparity in effects. First, the negative relationship in USA and Indonesia between the belief that governmental measures are inadequate and own adaptation intention aligns with other work that finds public and private adaptation can go hand in hand, especially for adaptations that entail structural property modifications (Bubeck et al., 2013; Poussin et al., 2014; van Valkengoed & Steg, 2019). This relationship has been previously rationalized by the logic that past flood events or close calls can trigger both public action and private household adaptation (Bubeck et al., 2013). Indeed, everywhere if our respondents have experienced a flood, they are more likely to have already undergone measures (High Effort: χ^2=123, p=0.0, Low Effort χ^2=61, p=0.0) possibly lessening the intention for further action. In Indonesia and USA more people have experienced floods than in the Netherlands and China (Supplementary Material Table 8.3). If a household has experienced a flood, they are also more likely to view the government measures as insufficient (χ^2=30, p<0.001). Second, China and the Netherlands have a similar, collectivist approach to flood management - that is in general, trusted by the populaces (White & Fu, 2012; Wiering & Winnubst, 2017; Zhong, 2014). In Indonesia and USA many disaster management programs are viewed generally more unfavorably and as insufficient (Darr, Cate, & Moak, 2019; Martono, Satino, Nursalam, Efendi, & Bushy, 2019; Sadiq, Tharp, & Graham, 2016; van Voorst, 2016; White & Fu, 2012). Our own data reflects these sentiments: 11% of Dutch and 22% of Chinese view flood protection measures already taken by the government as insufficient compared to 30% in Indonesia and 43% in USA.

Norms play a strong role in influencing behavior (Poussin et al., 2014; van der Linden, 2015; Wilson et al., 2020). Our analysis supports this notion: the perceived expectations of one's friends, family, and neighbors, as a prescriptive norm, positively influences the intention to implement both High and Low Effort measures across all four countries ('Social Inf', Figure 2, and Supplementary Materials). Differences between the four countries appear in the extent of social influence on households' adaptation, with USA exhibiting the lowest positive effect of social influence on High Effort adaptations, perhaps due to nation's individualistic culture (Hofstede et al., 2010). With Low Effort measures, we find that social expectations play a higher role in China and the Netherlands compared to USA and Indonesia; in spite of the mean of 'Social Inf' being lower in China (2.9) and the Netherlands (2.3) compared to USA (3.3) and Indonesia (3.3) (T-Tests: CN < IN/ USA: p< 0.001; NL < IN/ USA: p< 0.001). This phenomenon could be due to the influence of social norms that often go undetected by the influenced party (Nolan, Schultz, Cialdini, Goldstein, & Griskevicius, 2008). Alternatively, the higher effects of social expectations in China and the Netherlands could be due to the confirmation bias (Kappes, Harvey, Lohrenz, Montague, & Sharot, 2020), when respondents are more likely to report higher social expectations if they have already undergone a Low Effort Measure (T-value=3.7, p=0.0). In USA and Indonesia, households report higher social expectations, but also are significantly more likely to have already undertaken both High and Low Effort adaptations (Figure 3). As such, while they report a higher prescriptive norm, it is less likely to inspire action as many households already conform to the norm.

The traditional general media has a likely null effect/ slightly negative effect on household adaptation intentions across all countries, except Indonesia. There it distinctly discourages households intending High Effort measures ('General Media', Figure 2.a), possibly signaling distrust in information from the media (Esteban et al., 2017). Conversely, social media has, in general, a positive effect on adaptation intentions for High and Low Effort Measures for the Netherlands and USA and lower/ likely null in China and Indonesia. The internet in USA and the Netherlands are among the most 'free' and host generally unrestricted content. In Indonesia the internet falls on the lower end of the scale of 'partly-free' in terms of content restrictions and China's is one of most censored in the world (House, 2020). Differences in content restrictions could play a role in influencing what people can post and read on social media, how much they trust the information, and the effect it has on adaptation intention.

3.4 Discussion and Conclusions

Using unique surveys from four socially, institutionally, and culturally diverse countries we statistically study similarities in the drivers of household adaptations. Universally, affect (worry) and social influence drive adaptation intentions while perceived probability and damage has nearly no effect on motivating households' actions (except in Indonesia for High Effort measures). Self-efficacy and perceived costs are the strongest driver and barrier, respectively, for households' intentions to adopt High Effort measures. Beliefs in ongoing climate change have negative effects on adaptation intentions, perhaps because households with a sense of urgency have already adapted.

Disparities in the effects indicate that the social, institutional, and cultural contexts manifest meaningful differences in what motivates household adaptation intentions. Prior flood experience has little effect on household adaptation; except in the Netherlands where it is a rare experience. Negative effects of beliefs in insufficiency of governmental measures on households' adaptation intentions are 2-6 times stronger in USA and Indonesia compared to the Netherlands and China. Notably, education encourages adaptation only in China (High Effort measures) and USA; whereas social media facilitates household adaptation in the Netherlands and USA, but hardly in Indonesia and China. Several socio-psychological factors exhibit differences in effects between High and Low Effort measures, indicating that depending on the measures under consideration households may utilize various heuristics. Finally, while perceived costs universally discourage households' adaptation, it is 2-4 times a stronger barrier in the two Global South countries compared to the two in the more affluent Global North.

Our unique dataset and analysis across countries extends past research by refining assumptions about what commonly theorized factors of household adaptation are universal versus context-dependent, distinguishing between High and Low Effort measures. The coverage of four countries impedes a statistical attribution of cross-country variations in effects, limiting us to qualitative arguments of observed differences. Future work could consolidate existing fragmented survey data in joint globally-shared databases to permit numerical cross-country analysis, including structural models, to help unravel contextual, complex intra-variable relationships. Such datasets will permit a systematic analysis of contextually-shaped patterns in household adaptation behavior, and enable to meaningfully extrapolate to data-scarce regions when projecting households' adaptation progress or designing adaptation policies.

Further, future surveys should prioritize longitudinal designs to elicit if and how intentions lead to actions to assist in closing the intention-behavior gap. Panel data will permit monitoring the household adaptation progress' its speed and effectiveness - an important supplement to the adaptation tracking of government-led measures (Berrang-Ford et al., 2021; Hudson et al., 2019).

A recent review (Wilson et al., 2020) stresses the importance of complementing interpersonal factors with intrapersonal when studying households' responses to climate-induced hazards. Our study partially responds to this call by capturing prescriptive social norms, and finds a positive effect consistently in four countries. Future work could expand to study network and cohesion effects, and deepen to explore related social processes, like social amplification of risk (Kasperson et al., 1988; Lo, 2013) or information cascades in networks (ACEMOGLU, DAHLEH, LOBEL, & OZDAGLAR, 2011; Easley & Kleinberg, 2010). Computational social science methods, like network analysis and agent-based modeling, are especially adept to study dynamic feedbacks between intra- and interpersonal factors. Finally, the revealed uniform strong effects in self-efficacy and perceived costs underscore the need to investigate adaptive capacity further. Other elements theorized to constitute households' adaptive capacity – diversity, access to capitals, institutional capacity, and learning (Bennett, Dearden, Murray, & Kadfak, 2014) – should be systematically captured in future climate adaptation surveys.

Our findings have implications for climate change adaptation policies as well. To prompt household adaptation behavior, personalized narratives appealing to affect should complement communication of climate-driven risks. Since social expectations consistently facilitate adaptation, associating desired behavior with a positive group identity could aid households' adaptation diffusion and soften socially-constructed adaptation limits. Policies aimed at closing the adaptation gap by promoting diffusion of household-level action should target High and Low Effort actions differently. Importantly, knowledge on drivers and constraints of household adaptation should be transferred to new areas with caution as a driver in one context may be a constraint in another.

3.5 Methods

All research and data collection complies with the European Research Council Horizon 2020's data requirements and Research Ethics and Integrity policy. The research was approved by the Behavioral Management and Sciences Ethics Committee at the University of Twente, request number: 191249.

3.5.1 Data collection:

In March-April 2020 we ran household surveys in flood-prone coastal cities in the United States of America, China, Indonesia, and the Netherlands. The surveys were conducted online by YouGov and the data analyzed and presented in this paper are from identical, translated questions in the respective languages of each country (*YouGov Panel*, n.d.). The survey was written in English by the authors, one of whom is a native speaker from USA. For the non-USA respondents, the survey was professionally translated by YouGov field experts in each country, and the translation was reviewed by a climate adaptation scientist from each of the four case studies countries to help ensure cross-national relevance of the measures and aid in avoiding cultural bias. Further, YouGov field experts provided relevant information on national context, culture-specific ethical considerations and legislation that aided in the design of the survey.

Based on national statistics, YouGov forms representative panels. In China, Netherlands, and Indonesia we specifically controlled for gender representation, and age and gender in USA (see 8.3, Supplementary Material). YouGov has a number of quality assurance measures in place, including excluding "speeding-respondant" (respondents who click through too rapidly to allow reading), inviting future panelists to participate, before announcing the topic - helping avoid the self-selection bias, and the verification of personal details given when respondents are registered for the panel. Further, respondents who consistently click the same (i.e. the first) answer are additionally filtered out. Finally, YouGov limits the number of surveys that respondents participate in monthly to reduce survey fatigue and conditioning (*More Detail on YouGov Research Methods*, n.d.). The YouGov platform for online surveys is accessible via mobile phones, as such, according to the field teams, a lack of internet at home is not a barrier to reach the representative sample. As our research was focused on major urban centers, internet access was not a limiting factor (Lin, 2020; Nabila, 2019). Employing an external company is necessity when running such a large scale, cross national survey in a reproducible way. However, it is expensive and mandates outsourcing sampling and quality assurance. With YouGov's extensive history conducting high-quality surveys for both academic, government, and corporate entities, we are confident that sample and data quality are properly upheld.

3.5.2 Dependent Variables:

We study 18 household level flood adaptation measures (Supplementary Material Table S.5). We selected the relevant measures by reviewing prior empirical work guided by several meta analysis (Bamberg et al., 2017; Bubeck, Botzen, Suu, & Aerts, 2012; Noll et al., 2020; van Valkengoed & Steg, 2019), as well as case studies that looked in depth at adaptation in each country i.e. (S. Du et al., 2020; James, 2008a; wai Fan, 2015; Wiering & Winnubst, 2017). Here, we analyse adaptation intentions instead of already undergone actions to avoid issues with feedbacks with undergone measures on risk perception (Bubeck, Botzen, Suu, & Aerts, 2012). Prompted by recent research (Babcicky & Seebauer, 2019; Seebauer & Babcicky, 2020b), we group the adaptation measures into High Effort group - involving structural modification to ones home and necessitate significant time and financial investments; and Low Effort group - that include non-permanent flood mitigation actions as well as communication and information-seeking behavior. The two groups vary in the effectiveness of reducing hazard impacts and the extent of improving households' resilience (compare raising ground floor level with seeking hazard-related information). During the survey, within each group, we randomized the order in which the respondents saw the adaptation actions. The grouping on the survey likely contributes to some within group consistency. See section S.3 in Supplementary Materials for factor loading's and alphas on both groups.

For all adaptation measures, the respondent could select the following options:

1. I have already implemented this measure
2. I intend to implement this measure in the next 6 months
3. I intend to implement this measure in the next 12 months
4. I intend to implement this measure in the next 2 years
5. I intend to implement this measure in future, after 2 years
6. I do not intend to implement this measure

Options 2 - 5 were grouped together, by measure type, to indicate future intention. The questionnaire design allows us to construct a dependent variable based on the proportion of remaining measures a respondent can still pursue (the number not undergone) per measure group (Equation 4.1). This proportional formulation of the dependent variable helps maintain consistency across respondents and accounts for the fact that different respondents likely have already undertaken a number of different measures. Already reflected in the reported sample size, our analysis of adaptation intentions excludes all households who had already undergone all measures in a given group as they have nothing left to intend.

$$DV_i = \frac{Intended\ Measures_i}{Total\ Measures - Undergone\ Measures_i} \tag{3.1}$$

This specification of the dependent variable has several advantages over other approaches of modeling intention to take multiple actions. Ordinal logit models and count models do not explicitly incorporate the fact that many respondents may have already undertaken some of the measures asked and therefore cannot 'intend' to do something they have already done. Furthermore, count models such as binomial regression, assume Bernoulli trials, which we deemed potentially inappropriate in light of recent research that notes the connectivity between related measures (Babcicky & Seebauer, 2019; Seebauer & Babcicky, 2020b). Binary logistic/ probit regression (that groups any intention as a 1 and no intention as a 0) overcomes this issue; but in grouping all intended measures together, even if the intended adaptation measures are in subgroups, information about quantity is lost. Therefore, we choose a ratio of the intention to pursue adaptations proportional to the remaining in the corresponding measure group as the dependent variable (Equation 4.1). While acknowledging that the likelihood of observing differences in effects is subdued (Certo, Busenbark, Kalm, Lepine, & Certo, 2018) and for measure specific variables (i.e. self-efficacy) averages must be used (P. Jansen et al., 2020), we argue that this dependent variable is a good representation of household intention to pursue adaptation measures accounting for the ones already taken in the same group most accurately.

3.5.3 Explanatory Variables:

The presented analysis focuses on flood adaptation measures and factors driving household intentions to pursue them. The survey design relies on an extensive review of the empirical adaptation literature aided by several meta-analysis (Bamberg et al., 2017; Bubeck, Botzen, Suu, & Aerts, 2012; Noll et al., 2020; van Valkengoed & Steg, 2019). Six of the variables used in our analysis, make up the base PMT variables that often explains household adaptation intentions, and the remaining ten are variables frequently used to explain households' protective actions against flooding. While not exhaustive of all tested constructs, we identified these 16 variables as drivers of household adaptation motivation that were regularly found to be influential in past work (Botzen et al., 2019; Bubeck et al., 2013;

Bubeck, Botzen, Suu, & Aerts, 2012; Mol et al., 2020; Osberghaus, 2017; Poussin et al., 2014). The list of constructs, the questions used to solicit the variables, and their descriptive statistics are available in the Supplementary Material Table 8.3. Survey length limitations in the present study compelled mainly single-item previously validated questions (Botzen et al., 2019; Koerth et al., 2013; Poussin et al., 2014). While this is a tested, reliable method that produces comparable and quality data (Wanous, Reichers, & Hudy, 1997), future research could benefit from multi-item measurements. As all of these variables have been previously studied we were able to compare effects to past work to help ensure the constructs were understood. We checked the variance inflation factors (VIF) of all variables in the model to ensure that multi-co-linearity was not problematic (all VIFs < 2).

3.5.4 Data Analysis:

To model the proportions of measures that households intend to take from those remaining, we estimate a Bayesian beta regression model. It performs significantly better, based on WAIC scores (see Table S.5, Supplementary Material for more information), than other models we tested that can accommodate proportions as a dependent variable (linear and logistic regression). Previous work has found that adaptation intention can occur ‘in concert’ (Seebauer & Babcicky, 2020b), which can lead to bi-modal distributions. Our data confirm this finding and further support the beta regression model choice selection, as the beta family is very flexible with regards to the array of density forms it can accommodate (Branscum, Johnson, & Thurmond, 2007). Beta regression models cannot contain values exactly equal to one or zero, thus before estimating the model, we scale the dependent variable, the intention proportion values by group (Y), to fit *between* 0,1 Equation 3.2, (Smithson & Verkuilen, 2006).

$$Y_i = \frac{Y'(N-1)+0.5}{N} \tag{3.2}$$

The probability density function of the beta distribution is:

$$p(y|a,b) = \frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)} y^{a-1}(1-y)^{b-1} \tag{3.3}$$

where a, b >0, and Γ is the gamma function. We run all of our models in Python with the PYMC3 package (Salvatier, Wiecki, & Fonnesbeck, 2016). We parameterize the beta distribution in terms of its means (m) and standard deviation (σ). All coefficient priors in all models are broadly set as $\beta_i \sim N(0, 5)$ and all intercepts as: $\beta 0 \sim N(0, 10)$. We set the prior variance as $\sigma \sim$ halfN(0.5), bounded at the upper end with $\sqrt{\delta * (1-\delta)}$, where is the minimum value of y, transformed by the inverse logit function for each country that, when input into the above function, determines the upper limit on the value of sigma (Salvatier et al., 2016). Next, we transform the values to the Beta distribution shape parameters (*a, b*) using:

$$a = mk \qquad b = (1-m)k \qquad k = \frac{m(1-m)}{\sigma^2} - 1 \tag{3.4}$$

Constructed from the a and b parameters shown above, Bayesian beta regression models are typically reparameterized and represented with: $\mu = \frac{a}{a+b}$ and $\gamma = a + b$ (Branscum, Gardner, & Johnson, 2004; Branscum et al., 2007; Hanson, Johnson, & Gardner, 2003). Thus, where β is a vector of regression coefficients and intercept, $\beta = (\beta_0, \beta_1 ... \beta_i)$ and y = $(y_1, y_2 ... y_n)$, the Bayesian beta regression model we consider is:

$$y_i|\mu_i,\ \gamma_i,\ \sim Beta(\mu_i\gamma_i), \gamma_i(1-\mu_i) \tag{3.5}$$

$$\mu_i = F(\beta^{\top} x_i) \tag{3.6}$$

where F(·) is the inverse logit function that transforms our linear combination of independent variables (x_i).

In various places throughout the paper, we compare the relationship of a specific variable between countries via means testing with T-Tests or note the relationship between two variables either with a T-Test, Wilcox-Rank Sum test, or Chi-Squared test. For both epistemological reasons (this type of survey is repeatable) and ease of understanding, we use frequency statistics in these instances. Test scores and p-values are reported in the text.

3.6 Acknowledgments

This work was supported by the European Research Council (ERC) under the European Union's Horizon 2020 Research and Innovation Program (grant agreement number 758014). We thank YouGov, specifically Phil Newbold and Gavin Ellison, for their support with survey administration. We would also like to thank Dr. Daniel Osberghaus and Dr. Philip Bubeck for their feedback on the initial version of the questionnaire.

4

One and done? Exploring linkages between households' intended adaptations to climate-induced floods

As climate change increases the probability and severity of natural hazards, the need for coordinated adaptation at all levels of society intensifies. Governmental-level adaptation measures are essential, but insufficient in face of growing risks; necessitating complementary action from households. Apprehending the drivers of household adaptation is critical if governments are to stimulate protective behavior effectively. While past work has focused on the behavioral drivers of household adaptation, little attention has been paid to understanding the relationships between adaptation measures themselves - both previously undergone, and additionally (planned) intended adaptation(s). Using survey data (N=4688) from four countries - the United States, China, Indonesia, and the Netherlands - we utilize Protection Motivation Theory to account for the behavioral drivers of household adaptation to the most devastating climate-driven hazard: flooding. We analyze how past and additionally intended adaptations involving structural modification to one's home affect household behavior. We find that both prior adaptations and additionally intended adaptation, have a positive effect on intending a specific adaptation. Further, we note that once links between adaptations are accounted for, the effect that worry has on motivating specific actions, substantially lessens. This suggests that while threat appraisal is important in initially determining if households intend to adapt; it is households' adaptive capacity that determines how. Our analysis reveals that household structural modifications may be non-marginal. This could indicate that past action and intention to pursue one action trigger intentions for other adaptations; a finding with implications for estimating the speed and scope of household adaptation diffusion.

This chapter is based on: Noll, B., Filatova, T., Need, A. (2022). One and done? Exploring linkages between households' intended adaptations to climate-induced floods. Risk analysis.

4.1 Introduction

There is a growing realization of the need for household adaptation to complement public measures in addressing the risks of climate-induced hazards (Adger et al., 2005; Aerts et al., 2018). As household adaptation can have a marked impact on the expected damage following a natural hazard, understanding the drivers is important for designing effective policies and risk reduction strategies. Hence, a growing amount of research explores the drivers of household level adaptation, its speed and scope (Berrang-Ford et al., 2021).

Of all climate induced natural hazards, flooding is responsible for the most damage and impacts the most people (Hirabayashi et al., 2013). Unsurprisingly, empirical research on household adaptation to floods has been researched more frequently than any other hazard (van Valkengoed & Steg, 2019). Despite this, even in application to floods there are many understudied or still unknown aspects on the drivers of household adaptation. Protection Motivation Theory (PMT) is one of the most commonly utilized theories to explain how and why households intend to adapt to floods (Babcicky & Seebauer, 2017). Surveys are a commonly used medium to solicit different adaptation actions a household can take to floods as well as the drivers (Bubeck, Botzen, Suu, & Aerts, 2012; Koerth et al., 2017; Noll et al., 2020). Socio-behavioral theories, like PMT, are often operationalized to estimate if and explain why a household intends to take adaptation actions toward such climate-induced hazard as flooding. Contemporary research tends to focus on household adaptation *intention* as opposed to already undertaken actions due to possible feedbacks of past actions on current perceptions (Botzen et al., 2019; Bubeck, Botzen, Suu, & Aerts, 2012).

Traditionally, when estimating household adaptation intentions, researchers are faced with the decision to aggregate similar actions into a grouped dependent variable (Botzen et al., 2019; Bubeck et al., 2018; Poussin et al., 2014), or utilize independent regression models (Ahmad & Afzal, 2021; Babcicky & Seebauer, 2019; Brody et al., 2017). While grouping adaptations has the advantage of facilitating communication, it, however, inhibits the researchers' ability to distinguish between within person/ household and between person/ household effects. Yet, as recent evidence suggests (P. Jansen et al., 2020), the researcher is unable to discern differences between a household preferring one adaptation over the other vs. one household generally finding adaptation to be worthwhile. In contrast, independent regression models do not face this limitation. However, separate models fail to explicitly acknowledge either possible relationships or links between adaptation actions, and thereby can omit crucial information on drivers of households' adaptation intention.

Notably, the latest research contemplates that intention to take one flood adaptation measure could be linked to intention for other household adaptation actions (Babcicky & Seebauer, 2019; Seebauer & Babcicky, 2020b). For example, household adaptation, in particular actions involving structural modifications to ones home, can be intended in groups due to possible synergies between actions. This implies that the adaptation (co-)benefits of intention to pursue each individual adaptation action could be non-marginal, and if triggered, could amplify the speed and scope of households adaptation. In this same line of reasoning, past adaptation could help explain a households' current predisposition to intend (or not) other adaptation measures. While past work suggests that households update their threat appraisal upon undertaking adaptation action(s) (Bubeck, Botzen, Suu, & Aerts, 2012; Noll et al., 2020; Richert et al., 2017), a numerical analysis of direct feedbacks from past action is lacking (Kuhlicke et al., 2020; Richert et al., 2017).

To better understand the household decision making process and address this knowledge gap on the links between past and intended future adaptation actions, we launched household surveys across four countries. The first wave of this longitudinal survey was conducted in spring of 2020 and focused on densely populated coastal regions in the United States of America (USA), China, Indonesia, and the Netherlands (n>6000). In each country identical, translated surveys were issued through YouGov's online survey platform. In the survey we asked respondents about 19 different types of adaptation measures they could take to reduce the risk of flooding individually. Due to noted variation in effects contingent on the type of adaptation measures being considered (Babcicky & Seebauer, 2019; Seebauer & Babcicky, 2020b), here we focus only on measures that involve structural modifications to ones home (8 of 19 measures). Structural or *construction measures* seem to be more likely to be taken in groups due to cost efficiency and potential synergies that exist between certain actions (Kuhlicke et al., 2020; Seebauer & Babcicky, 2020b). The purpose of the current paper is to explore the effect that undertaken and additionally intended adaptations have on a households' intention to undertake a specific action.

Following the tradition of prior investigations into the household decision making process, we utilize PMT (Bamberg et al., 2017; Botzen et al., 2019; Bubeck et al., 2018; Grothmann & Reusswig, 2006; Rogers, 1975; van Valkengoed & Steg, 2019) to estimate household adaptation intention to reduce flood risk. PMT stipulates that two psychological processes drive households' intentions to take an adaptation action when facing uncertain consequences: threat appraisal and coping appraisal. In addition to the PMT variables, we control for country of residence and socio-economic variables. To study the potential influence that past and future (additional) adaptation actions can have on adaptation intention, we include two other variables in our analysis: the number of undergone and additionally intended construction measures a household has taken or intends to take respectively. We hypothesize that accounting for related past and future adaptation will significantly improve model performance and could significantly influence the effects of some key PMT variables - specifically the threat appraisal variables. To test our hypothesis, we estimate a unique logistic regression model for *each* construction adaptation - for a total of 8 models - while explicitly controlling for possible links between these adaptations. In comparison to previous work, this method affords us benefits from both grouped and non-grouped estimation methods, while alleviating their drawbacks. Since our aim is to explore the effects that past adaptation(s) and future additionally intended adaptation(s) have both independently and in conjunction, we estimate four sets of eight models. In each set, we account (or do not) for a different combination of past and future intended actions to elicit the unique effects that these actions have with household adaptation intentions.

The remainder of the paper is organized as follows: in Section 4.2 we outline the methods, Section 4.3 presents our findings, Section 5.3.4 discusses the findings and finally Section 4.5 draws conclusions and discusses strengths, limitations, and future work.

4.2 Methods

4.2.1 Survey

In March-April 2020 we launched household surveys through YouGov's online platform in flood-prone coastal cities in the United States of America (Miami, Houston, New Orleans), China (Shanghai and surrounding area), Indonesia (Jakarta and surrounding area), and the Netherlands (Rotterdam, Dordrecht and towns in the Zeeland province). We exhaustively reviewed past literature that utilized surveys to study household flood adaptation globally (Bamberg et al., 2017; Koerth et al., 2017; Noll et al., 2020). The survey was written in English by a native speaker, and was then professionally translated in the respective languages of each country by YouGov field experts. YouGov field experts provided relevant information on national context, ethical considerations and relevant national legislation that aided in the design of the survey. The translations were reviewed by a climate adaptation scientist from each of the four case studies countries to verify cross-national relevance of the measures and aid in avoiding cultural bias.

Based on national statistics, YouGov forms representative panels. In China, Netherlands, and Indonesia we specifically controlled for gender representation, and age and gender in USA (See Appendix Tables 8.17, 8.18 for sample vs. city representation) Within the panels YouGov has a several quality assurance measures such as blind selection from the participant pool to aid in avoiding self-selection bias. Their online platform for surveys is accessible via mobile phones, thus, a lack of

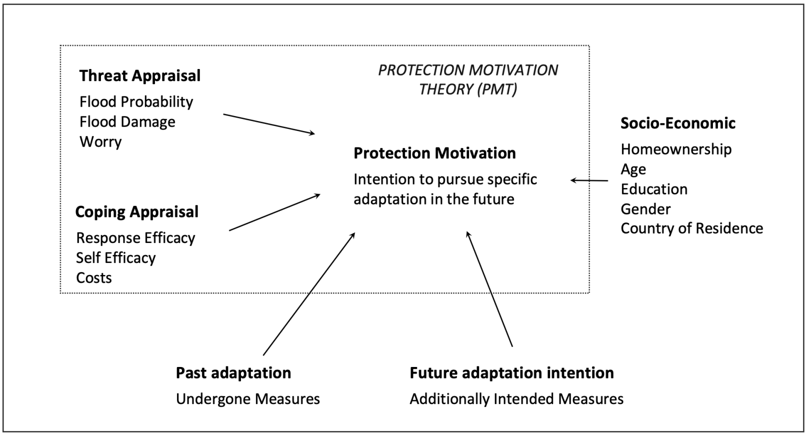


Figure 4.1: Factors driving households' adaptation intentions. Our analysis captures the six variables that comprise the basis of PMT, socio-economic control variables as well as the effects that past and additionally intended adaptation actions can have in influencing a protection motivation decision regarding a specific adaptation.

internet at home is not a barrier to reach the representative sample. As our research was focused on major urban centers, internet access was not a limiting factor (Lin, 2020; Nabila, 2019).

We have surveyed households in the areas highly exposed to floods in their respective countries (e.g. Miami in the US or Jakarta in Indonesia). This, however, does not imply that all respondents reside in officially designated and clearly communicated flood zones. Yet, all the surveyed cities will be affected by increasing severity and probability of floods, also due to sea-level rise in the future, blurring the boundaries of official flood zones that are often drawn on past hazards. Since our goal is to focus on analyzing links between adaptations to climate-induced floods, as opposed to mitigating damage of past floods, we perform the analysis on the full sample. In the Appendix, Tables A.2 and A.3 present the demographics of our survey and those from the surveyed cities, respectively, to allow for sample representation comparison.

4.2.2 Theory

While the decision to pursue different adaptation behaviors can follow different cognitive pathways (Babcicky & Seebauer, 2019), this paper focuses solely on estimating household intention to undertake eight different construction measures. We utilize PMT as a base theory (Grothmann & Reusswig, 2006) and expand it further to explicitly account for effects and linkages from past and intended future actions on households' adaptation motivation. Our survey captures respondents opinions corresponding to the two phases of households' decision making process about adaptation that PMT envisages: threat appraisal and coping appraisal (Figure 4.1). *Threat appraisal* is comprised of three variables: the perceived probability of a flood, perceived damage, and worry or fear of a flood. *Coping appraisal* concerns assessing self efficacy (how capable a person feels to take an action), response efficacy (how effective a given action could be) and perceived cost (how expensive an action is).

4.2.3 Dependent variables

Intensive household-level actions are increasingly necessary to effectively mitigate the growing global flood risks (Adger et al., 2005). Hence, this paper focuses on a specific sub-set of the elicited flood protection measures: Construction Adaptations. Measures involving structural modifications to ones home have been shown to have the potential to be taken in concert (Seebauer & Babcicky, 2020b); supporting the importance of analyzing links between measures. Our survey solicits information on eight Construction Adaptations (CA_i) that involve undergoing structural modification to ones house (Table 4.1).

For all adaptation measures, the respondent could select the following options:

1. I have already implemented this measure
2. I intend to implement this measure in the next 6 months
3. I intend to implement this measure in the next 12 months
4. I intend to implement this measure in the next 2 years
5. I intend to implement this measure in future, after 2 years
6. I do not intend to implement this measure

For this analysis we group options 2 - 5 together, by measure type, to indicate future adaptation intention for each of the eight CA. Already reflected in the reported sample sizes by country (total N = 4688), the analysis excludes all households who had already undergone all measures as they have nothing left to intend.

In Table 4.1 we observe that in China and Indonesia, a greater percentage of households generally intended to undertake a given CA in comparison to the USA and the Netherlands. This difference can, in part, likely be attributed to the fact that in both countries, the regions where our survey was issued suffered major floods in the previous nine months before the survey was issued: Typhoon Lekima in China, and Jakarta Floods in Indonesia. Across all eight measures, the respondents in Indonesia have taken more household-level adaptations than in the other three countries.

Table 4.1: Description of the eight different Construction Adaptations (CA_i) and the percentage, of households that intend to implement, and that have already undertaken a specific adaptation.

		Percentage of CA_i intended *(Percentage of CA_i Undergone)*			
Label	Description	USA (N=1577)	China (N=945)	Indonesia (N=1198)	Netherlands (N=968)
CA1	Raising the level of the ground floor above the most likely flood level	20% *(11%)*	39% *(4%)*	47% *(27%)*	24% *(6%)*
CA2	Strengthen the housing foundations to withstand water pressures	23% *(8%)*	45% *(4%)*	54% *(17%)*	26% *(2%)*
CA3	Reconstructing or reinforcing the walls and/or the ground floor with water-resistant materials	24% *(8%)*	56% *(5%)*	62% *(12%)*	28% *(3%)*
CA4	Raising the electricity meter above the most likely flood level or on an upper floor	25% *(12%)*	52% *(8%)*	51% *(20%)*	31% *(3%)*
CA5	Installing anti-backflow valves on pipes	27% *(8%)*	56% *(6%)*	54% *(11%)*	29% *(3%)*
CA6	Installing a pump and/or one or more system(s) to drain flood water	27% *(6%)*	54% *(4%)*	56% *(10%)*	30% *(3%)*
CA7	Fixing water barriers (e.g. water-proof basement windows)	24% *(8%)*	51% *(3%)*	55% *(11%)*	29% *(2%)*
CA8	Installing a refuge zone, or an opening in the roof of your home or apartment	29% *(11%)*	53% *(4%)*	59% *(14%)*	31% *(11%)*

4.2.4 Explanatory variables

Each PMT variable is solicited in the survey as a likert scale question (1-5) except perceived flood probability which asked respondents to select commonly used flood percentages and then scaled to a 5 point scale. See Appendix, Table 8.16 for the questions, scales, and summary statistics of all variables used in the analysis. The three coping appraisal variables, self efficacy, response efficacy, and perceived cost, were all asked for each specific Construction Adaptation measure (CA1-CA8).

We acknowledge that households adaptation may play out differently across countries (Adger et al., 2005; Noll et al., 2020). Exploring these differences would distract from the analysis of the paper thus, we additionally include three dummy variables to control for differences between the four countries. We do however ensure that our conclusions are robust against cross-country differences (Appendix, Figure 8.1). Further we include four socio-economic variables: age, gender, education, and home ownership in all our models. Finally, we add two adaptation variables in our analysis: the number of previously undergone adaptations and the number of additionally intended adaptations (Figure 4.1). In considering and controlling for the effects from past and future intended actions we portray a more holistic picture of the household adaptation process.

If a household has already undergone a measure, they are removed from that specific model when we are estimating the intention to undertake a specific measure; as one cannot intend to do something that has already been done. As such, the number of prior actions is consistent across all models. For the number of additionally intended adaptations, we only include the *other* measures that are intended (a count of adaptation measures *other* than the adaptation being modeled as the dependent variable). Thus depending on the specific adaptation being estimated, the variable can fluctuate by one. While this elimination is necessary for model specification and to accurately analyze the effect that past and additionally intended adaptation play in motivating a specific action, it does engender that households that have undertaken less measures are included more frequently in the analysis. This is noted as a shortcoming in the conclusions.

4.2.5 Data Analysis

To understand the relationship between the explanatory variables, and the eight possible construction measures, we estimate separate binary logistic regression models for each possible action (CA1-CA8). Estimating separate binary logistic regression models for each measure is selected as our primary method for several reasons. First, we individually look at the effects that the number of undergone and additionally intended adaptations have on construction intention. Prior work has shown that construction measures can be taken together (Seebauer & Babcicky, 2020b), suggesting that the each measure may not be entirely independent of another - a requirement for count models. Past research has additionally utilized ordinal least squares regression as it does not necessitate Bernoulli trials. However, in merging all measures together in a single 'count-like' dependent variable, the model can violate constant variance, a requirement for this type of regression (J. Du, Park, Theera-Ampornpunt, McCullough, & Speedie, 2012). While ordinal logit regression circumvents these issues (Bubeck et al., 2018), we asked measure-specific values for self efficacy, response efficacy, and perceived cost. As such, we are able to consider the *measure-specific effects* (P. Jansen et al., 2020). In using questions that are tailored to each measure (i.e. the self-efficacy score for *each* action, as opposed to a general self-efficacy score) and estimating specific measures, we can account for within household differences in choosing a specific climate change adaptation measure at the coping appraisal stage, leading to more accurate models in estimating protective intention (P. Jansen et al., 2020). Estimating separate models however, does not inherently account for the linkages between construction adaptations, the dependent variables. Therefore, we account for this link via the variable 'future or *additionally intended* adaptation', which further allows to explore possible relationships between household adaptation measures.

With these binary logistic regressions for eight adaptations (CA1-CA8) we estimate four *sets* of models:
Set-1: the six PMT variables + country dummies + socio-economic
Set-2: the PMT variables + country dummies + socio-economic + the number of past adaptation

actions,
Set-3: the PMT variables + country dummies + socio-economic + the number of additionally intended adaptation actions, and
Set-4: the full model with PMT variables + country dummies + socio-economic + the number of past adaptation actions + the number of additionally intended adaptation actions.

In each set we estimate eight logistic regression models; one for each of the eight construction adaptations. In all sets, for all models, if the respondent had already undergone a specific adaptation they are removed from the sample for that model. In estimating these sets, we are able to discern the effects that previously undergone, and additionally intended construction measures have in influencing a households' intention to take an adaptation action. To ensure the combination of previously undergone and additionally intended adaptations in Set-4 did not produce too much inter-correlation in the models (and skew the coefficient values), we checked the variance inflation factor (VIF) for all models: all VIFs for all variables in each model are <1.8.

Finally, we compare the Akaike Information Criteria (AIC) between the models and four sets to judge the degree of improvement that the inclusion of these two variables have in estimating the eight construction actions. As a model assessment criterion, AIC assists in determining the 'best' statistical model while penalizing for additional variables to avoid over-fitting (Cavanaugh & Neath, 2019).

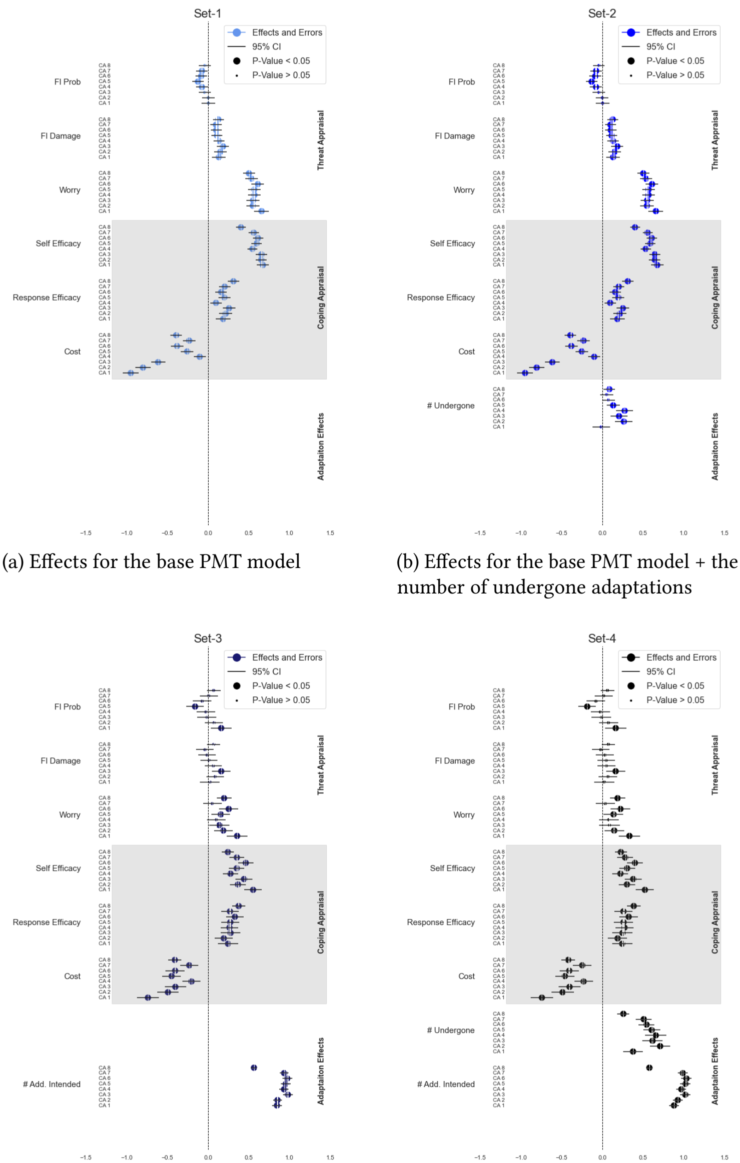
4.3 Results

In Figure 5.2 we present the effects of the main variables in our models for each set. To focus on the effects that pertain to our research questions, we remove the effects of the country dummies and the intercept from this visualization. The presented effects, however are from multivariate models which include the country dummies and the intercept and the numerical effects can all be found in the Appendix. The coefficient values and standard errors of the models in Set-1, Set-2, and Set-3 can be found in the Appendix and the results of Set-4 are in Table 4.2.

In Set-1 of eight models we estimate household intention to undertake each of the construction measures using only the six base PMT variables, controlling for the country dummy and socio-economic variables (Figure 4.2a). With respect to the role of threat appraisal, we observe that worry has the largest effect on adaptation intentions of households compared to the lessened effect of perceived probability and minor effects of perceived damage across all construction measures. Hence, the primary driver of threat appraisal for households is the affect heuristic rather than rational judgements about probabilities and damages (Slovic et al., 2004), as confirmed by other past work (van Valkengoed & Steg, 2019). The three coping appraisal variables perform as PMT posits across all eight models: self efficacy and response efficacy offer positive effects, while higher perceived cost reduces individual intentions to adapt. These effects too are in line with prior work that, in general, has found that coping appraisal offers slightly more explanatory power for household adaptation intentions than threat appraisal (Bamberg et al., 2017).

In looking at the effects for the eight models within Set-1, for the threat appraisal variables (perceived probability, perceived damage, and worry) the effects do not differ statistically across the eight adaptation adaptations (the 95% confidence intervals for each variable, overlap with the confidence intervals in all other models). However, the three coping appraisal variables (self efficacy, response efficacy, perceived costs) are measure-specific, meaning that the independent coping appraisal variables are able to tease out differences in preferences between the measures across households (see the shaded area of the 'Coping Appraisal' in Figure 4.2a).

Particularly with the effects of perceived cost on the households' intention to adapt, we observe some (significant) variation in the effects. Perceived cost has a generally stronger, demotivating role



(a) Effects for the base PMT model

(b) Effects for the base PMT model + the number of undergone adaptations

(c) Effects for the base PMT model + the number of additionally intended adaptations

(d) Effects for the base PMT model + undergone adaptation and additionally intended adaptations

Figure 4.2: Effects of different factors driving household intentions to adapt by means of construction measures, displayed in 95% confidence intervals. On the vertical axis are independent variables and a label CA_i corresponds to the construction adaptation being estimated. In addition to the displayed variables, the country dummy and socio-economic variables and an intercept are included in each model (Table 5.2). The horizontal axis indicates the size and the direction of the direct effect of the explanatory variables.

for CA1, CA2, CA3: adaptations that demand significant construction investment. In contrast, in CA4 (raising the electricity meter), an action that involves relatively little disruption, cost plays an insignificant role. However, in later sets once we account for the linkages between the dependent variables (CAs) the effect increases in its demotivating role. While some variation is present, each of the coping appraisal variables in general performs how PMT theorizes: considering a measure to be effective and feeling that it is in own power to implement it increase households' intentions to adapt, while perceiving costs as high demotivates households adaptation intentions.

Next, to explore any links between intention on a given measure and past adaptation in Set-2, we include the number of previously undergone construction adaptations Figure 4.2b. The number of previously undergone adaptations sometimes has a significant effect (5/8 of the models), but it is generally small. Importantly, controlling for previously undergone adaptations does not result in any statistically significant changes in effects for any of the six base PMT variables (Figure 5.2). The lack of change supports the notion that previously undergone actions are accounted for when households appraise their threat (Bubeck, Botzen, Suu, & Aerts, 2012). Otherwise, one could expect to see some differences as the two constructs - past action and threat appraisal - would explain similar variance in estimating intended adaptation.

As noted in Section 4.2, the models in Set-1 and Set-2 (Figures 4.2a, and 4.2b) do not control for the connection that the construction adaptation measures. To account for this and correctly specify the models, we add a variable that accounts for the number of additionally intended adaptations (Figures 4.2c and 4.2d). In Set-3, we control *only* for the relationship between a given adaptation and the number of other additionally intended adaptations (Figure 4.2c). Compared to the base models in Set-1 (Figure 4.2a), we observe differences with the threat appraisal variables; especially worry. Specifically, across all eight models in Set-3, compared to Set-1, the effect of worry on adaptation intention lessens by a significant margin when we control for additionally intended adaptation measures.

To explore the effects that both past actions and future adaptation intentions have on intending a specific measure, we include all explanatory variables in the models in Set-4. We observe the effect that the number of undergone adaptations has in explaining intention increases significantly across all eight models in Set-4 (Figure 4.2d) when compared to Set-2 (Figure 4.2b). Further, in Set-4 we continue to observe a significant change in the effect of worry compared to Set-1 - just as we did in Set-3. Table 4.2 lists the numerical values of effect sizes and errors from the Set-4 regression.

After estimating all the models in the four sets, we calculate AICs for each model, independently and present the results in Table 4.3. Controlling for undergone adaptations on their own (Set-2) offers little benefit in increased model performance; in heavy contrast with additionally intended adaptations (Set-3) (Table 4.3). However, when taking into account both undergone and additionally intended adaptations (Set-4), the model performs the best and represents a considerable improvement over the base PMT model (Set-1): more than 50% improvement in AIC. We discuss the implications of the models' performance in Section 5.3.4.

Finally, in Table 4.2 we note that for a number of the construction adaptations, the country variables from China and Indonesia sometimes have a significant effect, when compared to the reference category: the Netherlands. Cross country differences are an important subject in understanding how we can extrapolate survey data evidence on household adaptation from one region to another. However, investigating these differences requires extensive attention and other analysis beyond the scope of this paper. We present Set-4 results by country in the Appendix (Figure 8.1) for a robustness check. We analyze cross-country differences in a separate research article (Noll, Filatova, Need, & Taberna, 2021).

Table 4.2: The effects and (standard errors) for all eight Construction Adaptation (CA_i) models from Set-4.

	Variable effects and (Standard Errors) for each Construction Adaptation model in Set-4							
Variables:	CA1	CA2	CA3	CA4	CA5	CA6	CA7	CA8
Intercept	-3.758	-3.553	-4.682	-4.270	-4.873	-4.923	-4.140	-3.533
Flood Percent	0.164*	0.076	-0.012	-0.024	-0.185**	-0.079	0.016	0.063
	(0.066)	(0.060)	(0.062)	(0.060)	(0.055)	(0.058)	(0.058)	(0.044)
Flood Damage	0.024	0.070	0.164**	0.049	0.047	0.033	-0.019	0.075
	(0.062)	(0.058)	(0.061)	(0.056)	(0.055)	(0.057)	(0.056)	(0.042)
Worry	0.333**	0.146*	0.088	0.079	0.138*	0.222**	0.036	0.188**
	(0.065)	(0.061)	(0.065)	(0.062)	(0.062)	(0.062)	(0.060)	(0.047)
Self Efficacy	0.524**	0.303**	0.380**	0.222**	0.305**	0.401**	0.281**	0.228**
	(0.056)	(0.052)	(0.054)	(0.050)	(0.050)	(0.051)	(0.050)	(0.037)
Response Efficacy	0.244**	0.188*	0.248**	0.272**	0.261**	0.324**	0.259**	0.386**
	(0.063)	(0.060)	(0.063)	(0.057)	(0.060)	(0.057)	(0.056)	(0.043)
Perceived Cost	-0.743**	-0.488**	-0.402**	-0.230**	-0.460**	-0.406**	-0.246**	-0.419**
	(0.069)	(0.070)	(0.070)	(0.059)	(0.061)	(0.061)	(0.059)	(0.042)
# Undergone	0.378**	0.710**	0.617**	0.656**	0.607**	0.543**	0.509**	0.259**
	(0.062)	(0.064)	(0.063)	(0.067)	(0.053)	(0.050)	(0.050)	(0.038)
# Additionally Intended	0.881**	0.927**	1.020**	0.971**	1.020**	1.034**	0.990**	0.578**
	(0.032)	(0.031)	(0.034)	(0.031)	(0.032)	(0.032)	(0.030)	(0.019)
Homeowner	0.241	0.219	0.336*	-0.087	0.003	-0.291*	-0.380**	0.028
Age	-0.150**	-0.041	-0.141**	-0.096*	0.037	-0.004	-0.069	0.051
	(0.055)	(0.051)	(0.053)	(0.048)	(0.048)	(0.049)	(0.049)	(0.036)
Education	0.014	-0.293**	-0.031	0.096	0.184*	0.058	0.072	0.075
	(0.098)	(0.093)	(0.098)	(0.091)	(0.089)	(0.090)	(0.088)	(0.067)
Gender (Male=1)	0.171	-0.090	-0.106	0.027	-0.019	-0.088	0.059	0.118
USA Resident	0.006	0.373	0.307	-0.230	0.338	0.082	-0.136	-0.114
China Resident	-0.650**	0.250	0.883**	-0.007	0.751**	0.353	-0.150	0.229
Indonesia Resident	0.612**	1.031**	0.949**	-0.573**	-0.331	-0.238	-0.209	0.475**
McFadden's Pseudo R^2	0.69	0.67	0.72	0.66	0.67	0.68	0.66	0.46
Significance Level:	*p<0.05; **p<0.01							

Table 4.3: AICs for all eight models in the four different sets. The Construction Adaptation measures (CA_i) and the four Sets correspond with those presented in Figure 5.2.

Sets:	Set-1	Set-2	Set-3	Set-4
	PMT+country+.	PMT+country+	PMT+country+	PMT+country+
	soc-econ vars.	soc-econ vars.+	soc-econ vars.+	soc-econ vars.+
		undergone	add.intended	undergone+
Models:				add.intended
CA1	3196	3197	1705	1670
CA2	3737	3714	2057	1914
CA3	3838	3823	1819	1709
CA4	4234	4208	2075	1965
CA5	4399	4391	2166	2027
CA6	4329	4327	2067	1945
CA7	4397	4397	2167	2061
CA8	4432	4428	3228	3184
Mean Set AIC Value	**4070**	**4061**	**2160**	**2059**

4.4 Discussion

4.4.1 Past adaptations are likely accounted for in threat appraisal

On its own, the number of previously undergone adaptations (Figure 4.2b) has a generally small and insignificant effect. If a household has undertaken some measures already that would improve their situation regarding flood preparedness, they have already incorporated this information into their threat appraisal - a finding supported by past work (Bubeck, Botzen, Suu, & Aerts, 2012; Richert et al., 2017). This feedback is further supported by the lack of significant interaction effects between 'worry' and previously undergone adaptations (Appendix Table 8.14). *Present* risk perception or worry about a flood would take into account any *past* actions that they had already completed. We test the interaction of worry over the other two threat appraisal variables (perceived probability and damage) as worry offers greater explanatory power than either perceived probability or damage - both in this analysis and in past work (van Valkengoed & Steg, 2019).

The lack of change in the three threat appraisal variables - perceived probability, perceived damage, and worry - between Set-1 and Set-2, further adds credence to this notion. The prior incorporation of the protection benefits of past adaptation also likely influences why in Set-4, the effects of additionally intended adaptations are consistently greater than the effects of previously undergone adaptations (statistically significant in 7/8 models) in explaining specific construction measures. Finally, due to the already incorporated feedback in threat appraisal, the nominal effect that undergone measures have in influencing adaptation intentions is clear from studying the AICs of Set-1 (PMT variables) vs. Set-2 (PMT variables + the number of undergone adaptations) in Table 4.3. The eight models across both sets have very similar performances to where the mean set AIC score differs nominally by 0.2%.

When the number of undergone adaptations is entered in the models with the number of additionally intended adaptations (Figure 4.2d), the effect of undergone adaptation increases by a statistically significantly margin across all eight models (Set-2 vs. Set-4). Naturally, the *number* of undergone construction measures reduces the *number* of additionally intended adaptations, as you can not intend to do something you have already done (Pearson r=-0.12, p<0.0001). However, when estimating the intention of a *specific* action, it does increase the likelihood of adaptation intention. Hence, it is logical that once we control for the measures a household additionally intends to take, undergone adaptations explain more variance when estimating a given adaptation action (Set-4, Figure 4.2d). Thus, while accounted for in the current assessment of threat (Bubeck, Botzen, Suu, & Aerts, 2012; Richert et al., 2017), implementing adaptations in the past, increases the likelihood of intending a specific future action, likely due to necessity resulting from external environmental factors (Bubeck et al., 2013). If a household has felt the need to take some adaptation action(s) in the past, or they live in a flood zone, it stands to reason that their flood risk - now made worse by climate change (Coronese et al., 2019) - contributes to a perception that they (may) need to do so again.

4.4.2 Threat appraisal likely influences *if* a household will adapt; coping appraisal determines *how*

When included in the models, additionally intended adaptations significantly reduces worry's effect on adaptation intention. Of the three threat appraisal variables, worry consistently explains the most variance in adaptation intention. It is therefore unsurprising that those who are more worried, intend to undertake a greater number of construction actions (Pearson $r=0.33$, $p<0.0001$). Hence, when we control for additionally-intended actions, and by doing so, explicitly account for the connection between the construction adaptations that households can intend, we observe a lessened effect that worry has in estimating the intention for a given construction measure.

Analysis of the interaction effects between worry and additionally intended adaptations further supports this notion. While the interaction effects in 2/8 models differ significantly from zero, all are relatively small ($> |0.08|$) suggesting that the two variables likely do not substantively moderate one another (Appendix Table 8.14). These results suggest that while threat appraisal and especially worry, does well in estimating *if* households intend to adapt, coping appraisal - undiminished in its effect by the inclusion of additionally intended variables - offers more explanatory power in estimating *which* action(s) households will take. The critical role of coping appraisal variables is a conclusion backed up by past work (Botzen et al., 2019; Kuhlicke et al., 2020; van Valkengoed & Steg, 2019); through our analysis here, what we offer is a possible reason why.

4.4.3 Household construction adaptation measures may be motivated in congregation due to co-benefits

Past work notes a lack of research on recursive feedbacks in the household flood adaptation domain (Kuhlicke et al., 2020). While longitudinal data is very adept to study these effects as we note below as plans for future work; our analysis shows that household flood adaptation intentions appear connected. The positive effect of intending other CA on households' adaptation intention is consistent across the surveyed countries, and suggests that households may see the co-benefits in taking adaptation measures in concert (Seebauer & Babcicky, 2020b). This has implications for the speed and scope of adaptation, since households do not seem to consider construction adaptation independently of one another. Instead, intending one construction adaptation measure could trigger intentions to pursue others - possibly due to new knowledge or awareness of an increase in protection.

Upon estimating all four sets of eight models, we calculated the AIC scores for each model. In each set, we took the mean AIC score to easily assess how the inclusion of previously undergone adaptations and/or additionally indented adaptations affects overall model performance. In comparing to Sets 2, 3, and 4 to Set-1 (the base PMT model) we draw several conclusions. First, on its own, previously undergone adaptations (Set-2 vs. Set-1) have a nominal effect on model performance - likely due to households already accounting for undergone actions when appraising their threat appraisal, discussed above. Second, as expected, in correctly specifying the model and accounting for additionally intended adaptations (Set-3) and again in (Set-4) improves model performance significantly as indicated by a much lower AIC across all models (Table 4.3). The dramatic improvement in the mean AIC via the inclusion additionally intended adaptation(s) highlights the importance of recognizing the linkages between various adaptation actions (Babcicky & Seebauer, 2019). In particular when considering structural adaptation, where there exist financial and practical motivations to consider a bouquet of actions (Seebauer & Babcicky, 2020b).

4.5 Conclusions

Prior research on household adaptation to floods has focused primarily on the social, psychological, and environmental factors that drive adaptation intention (Ahmad & Afzal, 2021; Babcicky & Seebauer, 2019; Botzen et al., 2019; Brody et al., 2017; Bubeck et al., 2018; Poussin et al., 2014). To further unfold the household adaptation decision making process, we analyzed what role past and additionally intended actions play in the household adaptation process.

To address these questions, we use the data from large-scale surveys conducted to explore drivers of household flood adaptation intentions of households in the Netherlands, USA, China and Indonesia. To elicit the role of undergone actions and additionally intended future adaptations involving structural modification to ones' home, we estimate four sets of eight binary logistic regression models: one model for eight possible construction adaptations that households can take to reduce their flood risk across four combinations regarding past actions and future intentions. We use an extended PMT model to estimate household adaptation intention and control for country of origin, and socio-economic variables. Comparing the effects within and between each set, we begin to disentangle how past and additionally intended adaptation(s) influence the decision-making process of a household considering a particular adaptation measure.

Our analysis suggests that households who perceive their threat to be higher and worry more do intend *more* adaptation. However once we control for additionally intended actions, the effect that worry plays in influencing a single adaptation is significantly reduced. At the same time, the effect of coping appraisal variables remains consistently significant. In line with PMT, if a household can afford the measure (perceived cost), deems it effective (response efficacy) and considers itself capable of undertaking it (self efficacy) they are much more likely to intend it. The general reduction in explanatory power of threat appraisal variables, in particular worry, paired with the relatively consistent effects of coping appraisal, suggest that while threat pushes people toward adaptation, coping appraisal determines how households will adapt.

While we make strides in this paper toward understanding how households adapt, longitudinal data (Bubeck et al., 2020; Mondino et al., 2021; Osberghaus, 2017; Seebauer & Babcicky, 2020a) - is aptly suited to tackle this issue in further depth (Kuhlicke et al., 2020). First, not all construction adaptations, when undertaken, are completed in a fixed period - some are improved upon over time. Research focused on specific measures in detail could offer a more nuanced picture on the evolution of how households adapt and be inclusive of improvements (i.e. *re*-sealing pipes and windows, *further* reinforcing the household's foundation, etc.). Additionally, a more measure-specific approach could shed light onto if specific actions are more likely to lead to other specific other actions being undertaken and would not necessarily require the exclusion of households that have already undergone a specific measure - a shortcoming of this analysis. An investigation of this nature would benefit from interdisciplinary research with residential engineers and could offer valuable insight for insurance companies and governments alike in formulating flood-proofing recommendations.

A second course in which longitudinal surveys could provide data that would build upon the ideas presented here, is in bridging the intention-behavior gap. In this article we used reported past actions and additionally intended adaptation to study linkages between possible adaptations. With longitudinal data, researchers could understand if these intentions are fulfilled and if in fact they taken in concert. If other environmental factors about households are tracked, such as flood experience and economic well-being, these contextual variables can be used, in conjunction with variables used in this analysis to apprehend what pushes a household from intention to action. This temporal component can assess if a household learns from experiences (i.e: are households more driven to action following a flood or a close call).

Both of these research directives necessitate that the survey solicits a subjective timeline for adaptation intention; as not everyone who plans to adapt will necessarily intend to do so on the timeline of the survey (unfortunately). As such, the researcher(s) should repeatedly solicit the dynamics of the households' intentions, perceptions, and any action to apprehend behavioral and psychological progression.

Household level action becomes increasingly necessary as climate change continues to magnify flood risk at a rate faster than many governments can contend with. The implications for policymakers and scholars working on assessing the costs of climate change and of adaptation are that household adaptation uptake may be non-linear. Namely, with the right push, households may be willing to undertake *several* measures to protect themselves from floods at once. Our analysis indicates that households primed to adapt, could consider taking more than one measure, possibly due to perceived co-benefits of taking actions in cohorts. Alternatively, intending multiple actions could arise from an expanding horizon - once a household explores options for adaptation, they are made aware of other possibilities that they consider as well. Hence, policies or insurance companies aiming to promote household-level adaptation, at least concerning construction measures against flooding, should consider the likely inter-connectivity in the decision making process and leverage triggers for multiple measures. Non-marginal benefits exist for implementing several measures; meaning that investing in communicating and providing incentives for one type of construction adaptation, could lead to the adoption of multiple actions. To do so, fostering household capacity (via coping appraisal) remains crucial (while not forgetting the importance of threat appraisal to initially trigger adaptation (Kuhlicke et al., 2020)). Policies, future adaptation surveys and climate models including heterogeneous households should note these possible links between adaptation actions when promoting, studying, and modeling household adaptation behavior.

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5

Uncertainty in individual risk judgments associates with vulnerability and curtailed climate adaptation

Risk assessments are key for the effective management of potential environmental threats. Across probabilistic phenomena, climate change is an exemplar of paramount uncertainties. These uncertainties have been embraced in supporting governments' decisions; yet receive scarce attention when studying individual behavior. Analyzing a survey conducted in the USA, China, Indonesia, and the Netherlands (N=6242), we explore socio-economic, psychological, and behavioral differences between individuals who can subjectively assess risks, and those who are risk-uncertain. We find that risk-uncertain individuals are more likely to belong to societal subgroups classically considered as vulnerable, and have reduced capacities and intentions to adapt to hazards - specifically floods. The distinctions between risk-aware and risk-uncertain individuals indicate that ignoring differences in individuals' capacity to assess risks could amount to persistent vulnerability and undermine climate-resilience efforts. While we use floods emblematically, these findings have consequences for the standard practice of dropping or bootstrapping uncertain responses, irrespective of the hazard, with implications for environmental management.

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5.1 Introduction

People regularly face decisions involving probabilistic outcomes and trade-offs. From choosing what to wear to deciding what to do with their life, individuals rely on a variety of mechanisms ranging from heuristics to social norms (Groot & Thurik, 2018; Mata et al., 2018; Slovic et al., 2004). Consistent across a range of disciplines - sociology, psychology, biology, engineering, and economics - the (perceived) likelihood and (perceived) consequences of varying outcomes are generally considered the foundation of the decision-making process under *risk* (Groot & Thurik, 2018; Kahneman, 1992; Rogers, 1975; Slovic et al., 2004). Risk assessments directly influence individual action (Rogers, 1975) and governmental policies.

Often risks cannot be estimated precisely by citizens, policy-makers, nor experts alike (Monasterolo, Roventini, & Foxon, 2019). It is especially relevant in the context of climate change, where past patterns of adverse events are not representative of what people are to experience in the current 'new normal.' When probabilities and consequences are unknown, *uncertainty* must be acknowledged and embraced (Folke, 2006; Kahneman & Tversky, 1984; Tversky & Kahneman, 1992). A differentiation between risk and uncertainty is supported by statisticians (Machina et al., 2014), sociologist (Young, 2012), psychologists (Windschitl & Wells, 1996), and neuro-biologists (Groot & Thurik, 2018) alike. Different methods have been proposed and tested to classify general uncertainty (i.e. (Hanea, Hemming, & Nane, 2021; Harrington, Schleussner, & Otto, 2021; Olazabal et al., 2018; Oppenheimer, Little, & Cooke, 2016)) and understand its consequences in climate adaptation research (Berkes, 2007; Kettle & Dow, 2016). Uncertainty is increasingly embraced in supporting governments' decisions (Haasnoot, Warren, Kwakkel, Warren, & Kwakkel, 2019; Wing, Pinter, Bates, & Kousky, 2020; Zarekarizi, Srikrishnan, & Keller, 2020). Yet, understanding uncertainty in individual climate-related risk judgments has received limited attention (Rufat et al., 2022), despite the fact that this is where many climate adaptation decisions take place. Individual uncertainty about the two components of risk – *risk-uncertainty* hereafter – manifests itself when the likelihood and/or consequences of an event or outcome are unknown and consequently cannot be (subjectively) assessed by a person (Chow & Sarin, 2001; Groot & Thurik, 2018; Hanea, Burgman, & Hemming, 2018; T. Jansen, Claassen, van Kamp, & Timmermans, 2019; Mata et al., 2018; Roy et al., 2013; Zeckhauser, 2010). While peoples' judgments are known to deviate from objective risks, here we focus on individuals' inability to form subjective judgments as these are key factors in motivating behavior.

Evidence from laboratory experiments has shown how and when individuals are uncertain (Andersen, Harrison, Lau, & Rutström, 2008; Kahneman, 1992) and has quantified the consequences of individual uncertainty. A downside of these controlled methods is that researchers need to inform the participant, at least in part, about said risk (Roy et al., 2013) - possibly altering original judgments. Furthermore, as these experiments occur in a controlled lab setting, they are difficult to scale up or subject to external validity tests. Conversely, social surveys are a common method to assess a wide range of people's perceptions of risk and behavioral responses (Ellsberg, 1961; Kahneman & Tversky, 1984; Slovic, 1987; Tversky & Kahneman, 1992) while reaching broad audiences and inquiring about their actual decisions. Particularly, perceptions about climate risks and associated adaptation behaviors are frequently studied via surveys (Bamberg et al., 2017; van Valkengoed & Steg, 2019).

The behavioral theories that are often operationalized via surveys to study decisions in risky situations generally include elements of individual risk perception, threat appraisal, or likelihood and consequence assessment (Ajzen, 1985; Bandura, 1998; Rogers, 1975; van Valkengoed & Steg, 2019). Yet, the theories used to guide survey designs when looking at climate-related perceptions and actions do not take into account circumstances in which individuals cannot assess a risk or threat for whatever reason. Instead, prior work operationalizing these theories has frequently utilized question formulation that either force a response (Vannette, 2015) or used bootstrapping/ imputation during the analysis to incorporate respondents that selected 'I don't know'(Efron, 2012). When applied to risk perception, both methods treat risk-uncertain respondents analogously to those with the capacity to, at least subjectively, assess their risk - i.e. the 'risk-aware' (Konstantinidis & Shanks, 2014). Yet, a growing body of work in social and medical sciences has shown not only that including 'I don't know' options for questions in surveys improves data quality (Dolnicar & Grün, 2014), but selecting this option can genuinely represent uncertainty about given perceptions (Montagni, Cariou, Tzourio, & González-Caballero, 2019; Rufat et al., 2022; Young, 2012). Since the majority of climate-related surveys still pool risk-aware and risk-uncertain respondents in their analysis, it remains unknown whether individual risk-uncertainty plays a substantial role in some of the most acute decisions of the 21st century (IPCC, 2022).

Departing from the conventional practice in the climate change adaptation domain - of merging risk-uncertain with risk-aware respondents - this paper differentiates between the two; focusing on flooding as the most costly and widespread climate-induced hazard (Hirabayashi et al., 2013). Specifically, we address the following previously unanswered questions in the climate adaptation literature: Which characteristics contribute to the likelihood that an individual can assess climate risks? How does risk-uncertainty affect individual perceptions and adaptive capacities? And, to what extent do we find differences between risk-aware and risk-uncertain individuals in the effect of drivers of adaption and adaptive capacity on climate change adaptation behavior?

To understand what, if any, differences exist between risk-uncertain and risk-aware individuals and how these differences affect their decision-making process, we rely on two theories to guide our variable selection from widely used to explain climate adaptation behavior: Protection Motivation Theory (PMT) (Rogers, 1975) and the Theory of Planned Behavior (TPB) (Ajzen, 1985). In both theories, individuals' assess their respective threats or attitude toward the phenomenon and their ability to cope with or control the outcomes. TPB additionally includes subjective norms that incorporate the effects of opinions and expectations of others. While the original PMT does not contain this explicitly, it is often extended (van Valkengoed & Steg, 2019) to include social elements, as we do here.

To explore whether risk-uncertain and risk-aware individuals differ in their characteristics and in climate adaptation behavior, we analyze data from a large-scale, multi-country survey (N=6242) executed in 2020 to explore individuals' adaptation to floods. We group adaptations into two types: High Effort measures (involving eight structural, irreversible modifications to one's home) and Low Effort measures (comprising ten less intensive non-permanent protection and communication actions, like purchasing sandbags or coordinating with neighbors in making a flood plan), see Supplementary Material, Table S.5 for details.

When studying perceptions and behavior, we narrow our focus to exclusively analyze 'I don't know' responses for two key variables related to risk: perceived likelihood and perceived consequences; though this analysis can be expanded to other variables as well (Rufat et al., 2022). Namely, we label respondents who answered 'I don't know' on one or both of the two subjectively assessed questions about risk - perceived likelihood or perceived consequence of a flood - as "risk-uncertain". While this method has been used to classify uncertainty in medical and survey methods research (Dolnicar & Grün, 2014; Ellis et al., 2018; Montagni et al., 2019; Young, 2012) and has been included in the analysis in climate adaptation research (Rufat et al., 2022), to the best of our knowledge this is the first applications differentiating between individuals who can assess risks and those who cannot. To compare adaptive capacity and behavioral traits of risk-uncertain and risk-aware individuals, we analyze socio-economic data paired with commonly-studied socio-behavioral drivers of adaptation. First, we examine how socio-economic factors and self-reported emotions and perceptions differ between the two groups using a Bayesian hierarchical regression model and differences-of-means tests, respectively. Next, by estimating multiple Bayesian regression models, we study how risk-uncertain individuals differ in their adaptation decision-making processes from their risk-aware peers.

5.2 Methods

5.2.1 Survey data collection

In March-April 2020 we ran household online surveys in coastal cities in the United States of America (Miami, Houston, and New Orleans), China (Shanghai), Indonesia (Jakarta), and the Netherlands (Rotterdam). YouGov managed the survey dissemination and the principle results presented in this paper are from identical, translated questions in the languages of each country (*YouGov Panel*, n.d.). To aid in the validation of our risk-uncertain classification, we briefly use data from the second wave of this longitudinal survey. This wave was issued to the same respondents six months following the first survey, in October 2020. Both surveys were written in English by the authors, one of whom is a native speaker from USA. For the other three countries, the survey was adapted into the respective countries' languages by YouGov professional translators. This version was then reviewed by climate scientists from each country to help mitigate cultural bias and verify the relevance of the measures. YouGov field experts additionally offered perspectives on the national context, culture-specific ethical considerations, and legal considerations.

In the YouGov panels in China, Netherlands, and Indonesia we specifically controlled for gender representation, and age and gender in USA (see Tables 8.17 and 8.18, Supplementary Material). In their panel YouGov has a number of measures in place including excluding "speeding-respondents" (people who click through too rapidly to allow reading), inviting panelists to participate before announcing the topic - helping mitigate self-selection bias, and they verify personal details when respondents are registered for the panel. Further, respondents who consistently select the same answers are additionally filtered out. Finally, YouGov limits the number of surveys that respondents participate in monthly to reduce survey fatigue and conditioning (*More Detail on YouGov Research Methods*, n.d.). According to the field teams, a lack of internet at home is not a barrier to reach a broad selection of households because the YouGov platform is easily accessible via mobile phones. As our research was focused on major urban centers, we did not consider internet access a major limiting factor (Lin, 2020; Nabila, 2019). Employing an external company was essential to run such a large-scale, cross-national survey in a reproducible way. With YouGov's long track record of conducting high-quality surveys for academic, government, and corporate entities, we are satisfied that sample and data quality are properly upheld.

5.2.2 Theoretical Foundations

In line with considerable past work on flood adaptation, here we utilized (an extended version of) Protection Motivation Theory (PMT) and Theory of Planned Behaviour (TBP) to inform our survey question formulation and variable selection in our analysis (Ajzen, 1991; Rogers, 1975; van Valkengoed & Steg, 2019). Both PMT and TBP are decision theories that are commonly employed when studying adaptation decisions (Bamberg et al., 2017; Zhang et al., 2020) and share three components that are fundamentally similar: Threat Appraisal/ Attitude, Social Influence/ Subjective Norm, and Coping Appraisal/ Perceived Behavioral Control. We expand on the variables that comprise each component in Section 5.3.2.

5.2.3 Categorizing risk-uncertainty

We determine if an individual is risk-uncertain based on the responses to two survey questions about the likelihood and consequences of flooding, with "I don't know" response for either or both questions signifying risk-uncertainty (Table 5.1). Across the four countries, a significant share of the sample appears unable to subjectively assess risks: between 8% in Jakarta Indonesia where floods are annual, to 18.3% in the Rotterdam area in the Netherlands where floods are once-in-a-lifetime event. Notably, everywhere more individuals are uncertain about the likelihoods of climate-induced floods more than of their adverse consequences, probably because the latter is more in their control.

Table 5.1: Distinction between risk-aware and risk-uncertain individuals. Individuals who selected “I don’t know” for one or both of these survey questions were classified as risk-uncertain (N=1139), all others were classified as risk-aware (N=5103); from the total sample (N=6242)

Survey Question	Response Options	USA (N=1880)	China (N=1156)	Indonesia (N=2021)	Netherlands (N=1185)
How often do you think a flood occurs on the property on which you live (e.g.due to rivers or heavy rain, storms and cyclones)? Which category is the most appropriate?	My house is completely safe 0.0% chance annually, Less often than 1 in 500 years ~ 0.1% chance annually, Once in 500 years or a 0.2% chance annually, Once in 200 years or a .5% chance annually, Once in 100 years or 1% chance annually, Once in 50 years or a 2% chance annually, Once in 10 years or 10% chance annually, Annually ~ 100% chance annually, More frequent than once per year ~ 100%,	1625	1011	1864	985
	I don’t know	255	145	157	200
In the event of a future major flood in your area on a similar scale to ___‡ how severe (or not) do you think the physical damage to your house would be?	(1) Not at all severe (2) (3) (4) (5) Very severe	1664	1040	1850	1080
	I don’t know	216	116	171	105
Risk-Uncertain: (Individuals who selected “I don’t know” for one or both questions)		**19.1%**	**18.6%**	**13.8%**	**20.5%**

‡USA: “the flooding from Hurricane Harvey in 2017"; China: “the 2017 China floods in Hunan"; Indonesia: “the 2020 Jakarta floods"; Netherlands: “the North Sea Floods of 1953"

To verify that our classification of risk-uncertainty was not a one-off occurrence, nor due solely to the tendency of a specific group to mark “I don’t know” (Rufat et al., 2022) we asked about four other situations involving decisions under risk (Covid-19, car and plane accidents, lottery) in the follow-up survey (see Supplementary Material Section 1.5). The second survey was issued six months later to the same respondents and also allowed us to differentiate between the likelihood and consequences uncertainty.

From the 3488 respondents that responded to both survey waves, we found that if an individual was uncertain about flood risk on the first wave, they were very likely to be uncertain about *at least one* of the other risky choices in the second wave (χ^2= 160, p=0.0). Equally as important, however, only 1.2% respondents were uncertain about all aspects of all risks - indicating that the vast majority of respondents *can and do* differentiate between risks they believe they can assess and those they cannot (Young, 2012). This suggests that risk-uncertainty, as we have classified it in this paper, is not simply a by-product of individuals who are more likely to select “I don’t know,” but instead represents a context-specific uncertainty regarding risk.

5.2.4 Who is risk-uncertain - Hierarchical Bayesian Logistic Regression and Odds Ratios

Using the aforementioned classification, we estimate who is risk-uncertain using 6 socio-economic factors (Gender, Education, Age, and Income Quintile, length of time in home, and household ownership) and flood experience as explanatory variables (Table 5.2, Table 8.16 - Supplementary Material). A hierarchical Bayesian Logistic regression model is used with risk-uncertainty as the dependent variable. The hierarchical variable is the country (C_i) where the survey took place, and the Country level prior is set as HalfCauchy(β=4). The prior for the intercepts are set at N(0,10) and the prior for each β_n estimate is set at N(0, C_i); where β_n is the effect for a given variable. All Variance Inflation Factor (VIF) for variables used in the regression $<$ 10.

In Table 5.1 we present the Odds for each socio-economic category and if an individual has experienced flooding to be risk-uncertain. The Odds Ratios are calculated from the the model coefficients by exponentiating the mean of a given coefficient as effects are Gaussian distributed): $e^{\mu(\beta_n)}$. Odds Ratios are a more intuitive method of presenting results and the numerical effects and variances can be found in Table 8.15 in the Supplementary Material.

5.2.5 Comparison of Means

To compare the means of the seven socio-behavioral divers commonly utilized to study individual climate adaptation behavior we utilize Bayesian T-Tests - see Supplementary material for a full description of the variables used and questions asked to solicit them. When soliciting income in the survey we were able to pre-construct quintiles for all countries ahead of time from publicly available data, except for Indonesia. For Indonesia, we asked an open-ended question and then estimated our own quintiles. For this reason, however, many respondents left this question blank. Instead of cutting them from the analysis, we bootstrap in the mean income quintile, by country, for these responses. While this does artificially shrink the S.D. of the variable, as it is not a primary focus of the analysis, and thus we do not view this as detrimental to our conclusions.

For the Bayesian T-Tests the prior mean for variables was set using a Gaussian distribution (N) at the medium for the variable scale used, with a bounded, uniform (U) standard deviation prior. Priors for worry, risk adversity, and social expectations: μ=N(3,1) σ=U(0.5,2); Self-Efficacy, Response Efficacy, and Perceived Cost (all combined score of maximum 90 and a minimum score of 18 so: (90 + 18)/2 = 54), hence μ=N(54,10), σ=U(5,25); Social Network μ=N(3,1.5), σ=U(0.5,3). For the Bayesian T-Tests we then subtract the sampled distributions from one another to find the likelihood of difference.

To plot the variables all on the same scale we normalize the differences using:

$$|(\mu(\omega_i) - \mu(\psi_i))/\lambda)| \tag{5.1}$$

where ω_i is i^{th} variables' μ from the risk-aware group, ψ_i is i^{th} variables' μ from the risk-uncertain group, and λ_i is the scale in which the i^{th} variable was measured on.

5.2.6 Differences in adaptation motivation - Bayesian logistic and linear models

To estimate adaptation, we utilize two regression models, Bayesian Logistic and Linear Regression. For explanatory variables we utilize all previously discussed variables: the four socio-economic variables, reported flood experience, (Table 5.2 and the seven variables, which we selected guided by PMT and TPB applied to study adaptation behavior (Figure 5.1) and separate by risk-aware vs. uncertain (Table 5.1. See Table 8.16 in the Supplementary Material for a list of all variables.

We use these explanatory variables to estimate two different types of flood adaptation. We selected the relevant measures by reviewing prior empirical work guided by several meta-analysis (Bamberg et al., 2017; Bubeck, Botzen, Suu, & Aerts, 2012; Noll et al., 2020; van Valkengoed & Steg, 2019), two theories, Protection Motivation Theory (Rogers, 1975) and Theory of Planned Behavior (Ajzen, 1985), as well as case studies that looked in depth at adaptation in each country i.e. (S. Du et al., 2020; James, 2008b; wai Fan, 2015; Wiering & Winnubst, 2017). Here, we analyze adaptation intentions instead of already undergone actions to avoid issues with feedbacks with undergone measures (Bubeck, Botzen, Suu, & Aerts, 2012). In light of recent work (Babcicky & Seebauer, 2019; Seebauer & Babcicky, 2020b), we classify adaptation measures into High Effort group - involving structural more resource intensive changes to the respondent's home, and Low Effort group - that include non-permanent flood mitigation actions as well as communication and information-seeking behavior. The two groups vary in the effectiveness of reducing hazard impacts and the extent of improving households' resilience (compare raising ground floor level with seeking hazard-related information). During the survey, within each group, we randomized the order in which the respondents saw the adaptation actions - likely contributing to some within-group consistency (see Supplementary Material 8.19).

For all adaptation measures, the respondent could select the following options:

1. I have already implemented this measure
2. I intend to implement this measure in the next 6 months

3. I intend to implement this measure in the next 12 months
4. I intend to implement this measure in the next 2 years
5. I intend to implement this measure in future, after 2 years
6. I do not intend to implement this measure

Options 2 - 5 were grouped together, by measure type, to indicate future intention. Where a (1) indicates intention to undertake any adaptation in that specific measure group, and (0): none. Already reflected in the reported sample size, our analysis of adaptation intentions excludes all households who had already undergone all measures in a given group as they have nothing left to intend.

For the Bayesian Logistic Regression Model if an individual intended *any* adaptation measure from a given category, they were coded as having adaptation intention (1), otherwise (0). For the Bayesian Logistic Regression Model we used the variables in a count-like fashion - summing the number of intended measures. Using linear regression for count data can be problematic to skew and sparsity of the data. Linear, count, and ordinal logistic models alike all may not be appropriate in estimating individual adaptation however as adaptations may be intended in concert, potentially violating the heteroscedasticity, independence, and proportional odds assumptions, respectively (Seebauer & Babcicky, 2020b; **?**).

Yet, we feel it is important to include the linear model in our analysis as it is one of the most popular methods to estimate effects in prior work (Bamberg et al., 2017; Bubeck, Botzen, Suu, & Aerts, 2012). Thus, we present the results of the Bayesian Linear Model to enable comparability with the warning of possible assumption violations. Further, in comparing effects side by side with a binary classification of adaptation, we take care to ensure that our findings are robust and any noted patterns are less likely to be due to our choice of methods or dependent variable formulation.

Before we estimate individual adaptation intention, we first center the three coping appraisal/ perceived control variables (Self-Efficacy, Response Efficacy, and Perceived Cost) at zero to reduce issues of multi-co-linearity. After centering, we check the VIF of all variables in the regression models: All VIF < 10. For both types of regression models, estimating both High and Low Effort measures, and for both risk-uncertain and risk-aware individuals, we set the intercept prior as $\beta_0 = N(0, 10)$, and explanatory variables are set as $\beta_i = N(0, 5)$. We estimate separate models for risk-aware and uncertain individuals. In Figure 5.2, the likelihood of differences are calculated by subtracting the distribution of the effects from one another and are reported if >90%.

In our analysis, we additionally use two frequency statistics tests: Wilcox rank-sum and χ^2 test. In all cases, the p-value and test statistics are reported.

5.3 Results and Discussion

5.3.1 Socio-Economic and Experiential determinants of individual risk-uncertainty

To reveal which individuals have the ability to assess climate risks, we estimate a hierarchical Bayesian logistic regression model with risk-uncertainty (Table 5.1) as a dependent variable, determined by four socio-economic characteristics and one experiential variable (Table 5.2). To assure our estimates are robust across countries, we use a hierarchical model to separate country specific effects. We communicate our results (Table 5.2) using the odds ratios transformed from the mean beta coefficients for each of the five variables from the Hierarchical Bayesian Logistic Regression Model (see the model specifications in Methods), estimating if a respondent is flood risk-uncertain, where 1 indicates risk-uncertainty. An odds ratio of < **1** means that for every unit the variable is higher, the likelihood that a respondent is risk-uncertain decreases by |1 - the odds ratio|, whereas an odds ratio > **1** signifies an increase in likelihood. An odds ratio of 1 implies indifference between risk-aware and risk-uncertain groups.

Table 5.2: Impact of socio-economic characteristics and hazard experience on the likelihood of individual risk-uncertainty communicated by odds ratios and (95% credible intervals). (Total N=6242).

		Odds Ratios			
Variable	Description	USA (N=1880)	China (N=1156)	Indonesia (N=2021)	Netherlands (N=1185)
Gender	Female = 0 Male = 1	0.55 (0.43-0.70)	0.73 (0.54-0.97)	0.73 (0.57-0.93)	0.85 (0.64-1.12)
Education	1: < High School, 2: High School 3: College degree, 4: Post Graduate	0.90 (0.77-1.05)	0.72 (0.54-0.95)	0.77 (0.63-0.96)	0.71 (0.56-0.88)
Age	1: [16-24], 2: [25-34], 3: [35-44], 4: [45-54], 5: [55-64], 6: [65+]	1.03 (0.95-1.12)	1.08 (0.92-1.26)	1.12 (0.98-1.28)	1.12 (1.02-1.23)
Income Quintile	1: Lowest 20% of country - 5: Highest 20% of country	0.80 (0.72-0.90)	0.90 (0.78-1.04)	0.95 (0.84-1.07)	0.81 (0.70-0.95)
Flood Experience	No prior flood experience = 0 Prior flood Experience = 1	0.44 (0.35-0.57)	0.55 (0.36-0.85)	0.62 (0.48-0.79)	0.56 (0.35-0.89)
Yrs in home	Number of years lived in home	1.00 (0.99-1.01)	1.02 (1.00-1.04)	1.02 (1.01-1.03)	0.98 (0.97-1.00)
House Own	Do not own home = 0 Own the home = 1	0.62 (0.48-0.81)	0.44 (0.31-0.63)	0.50 (0.38-0.66)	0.77 (0.57-1.05)

Our analysis reveals that risk-aware and risk-uncertain people exhibit distinct differences in terms of the socio-economic and experiential variables (Table 5.2). Notably, in general, women are more likely to be risk-uncertain, or at least more willing to admit it when responding to the survey. Likewise, less educated, lower-income individuals, and those lacking flood experience are all more likely to be risk-uncertain. The latter is unsurprising as past work has demonstrated the strong influence that experience plays in learning (Barron & Erev, 2003; Hertwig, Barron, Weber, & Erev, 2004). Finally, while the number of years in one's home, surprisingly, appears to have no effect, house owners are generally less likely to be risk-uncertain.

Alarmingly, in general, women, the lower educated, the economically poorer, and individuals who do not own their homes - all groups considered more vulnerable to adversities, including floods (Adger, 2006; Adger et al., 2007; Chau, Gusmano, Cheng, Cheung, & Woo, 2014; Cutter, 2016; Malik et al., 2017) - are generally more likely to be risk-uncertain. Further, while older age appears to have a slightly positive effect, in most countries the credible intervals contain 1, and therefore we can not confidently discuss its effect. Hazards perpetuate or exacerbate existing inequalities in society, leading to fundamentally different outcomes for different groups (Adger et al., 2007; Berrang-Ford, Ford, & Paterson, 2011), and risk-uncertainty may amplify or be a key factor in perpetuating these vulnerabilities.

Notably, the cross-country consistent effect of being a woman, lower educated, and economically poorer offers strong support to the idea of an underlying pattern. (Table 5.2). If risk-uncertain individuals were risk-uncertain simply because they objectively faced less risk and therefore had not needed to contemplate the likelihood or consequences, we would not likely have observed the cross-country consistency in the socio-economic variables. This suggests that risk-uncertain individuals could be a generic behaviorally-distinct category. This consistency encourages us to discuss risk-uncertainty for the remainder of the analysis universally across the four countries (while still controlling for country-specific effects) and to focus on generic differences between the risk-aware and risk-uncertain individuals.

5.3.2 Risk-uncertain individuals differ in adaptive capacities and drivers of adaptation decisions

On its own, noting socio-economic and experiential differences that help explain peoples' inability to assess risk aids little in designing vulnerability reduction strategies and promoting climate-change adaptation behaviors that increase community resilience. It is vital to additionally examine whether the ability to assess risks is associated with the social-behavioral factors that are commonly theorized to drive individual adaptation decisions (Ajzen, 1985; Rogers, 1975). Therefore, we test for mean differences between risk-uncertain and risk-aware individuals in key explanatory decision factors defining behavioral heuristics.

Specifically, understanding variations in the social and behavioral *drivers* of climate adaptation behavior is essential as recent work has noted that psychological differences can affect (perceived) vulnerability outcomes (Babcicky, Seebauer, & Thaler, 2021), and consequently influence a desire to take action (van Valkengoed & Steg, 2019). In turn, the benefits of individual-level adaptation actions in reducing flood vulnerability are well-documented (Adger et al., 2005; Wilson et al., 2020). Notably, individual intentions to adapt often depend on both personal drivers (Bamberg et al., 2017; Bubeck, Botzen, Suu, & Aerts, 2012) - like worry, self-efficacy, perceived costs - and social factors (Wilson et al., 2020) - including social network or expectations. To apprehend what differences exist in social-behavioral drivers of adaptation between risk-uncertain vs. risk-aware individuals, we compare mean differences in the reported scores for the two groups (Figure 5.1; Table 8.16 in the Supplementary material provides variables descriptions).

5

In comparing the reported 'Worry' values, (Figure 5.1), our results show that risk-aware individuals report a higher worry toward potential flooding than risk-uncertain individuals (95.4% certainty from the Bayesian T-Test). Typically, initial emotional responses *precede* deeper thought process (Lerner, Li, Valdesolo, & Kassam, 2015). Past research notes that affect, such as worry, complements the subjective rational judgments regarding perceived probabilities and damages (Slovic et al., 2004), and often serves as a key driver triggering individual adaptation (van Valkengoed & Steg, 2019). Our findings support the notion that individuals who worry more may actively seek out information (Fischhoff, Bostrom, & Quadrel, 1993; Turner, Rimal, Morrison, & Kim, 2006), possibly making them less risk-uncertain. Furthermore, risk-uncertain individuals report being less willing to take risks than their risk-aware peers (6% more 'Risk Adverse', Figure 5.1). Indeed, past medical work has shown that uncertainty of outcomes can be accompanied by risk adversity (I' & Sainfort, 1993).

Meanwhile, social influences and subjective norms can additionally spur individual climate adaptation behavior (Wilson et al., 2020). We compare two variables means here: 'Social Expectations', i.e. expectations from friends and family that one should take some individual adaptation measures, and 'Social Network', i.e. the number of people in one's social network who have already taken some flood adaptation measures. We find between-group differences for both social drivers. Compared to risk-uncertain individuals, the risk-aware report 6% stronger feelings of social expectations and know 18% more people that have taken flood adaptation measures (Figure 5.1). Notably, past research evidence suggests that such social influences are decisive in motivating individuals to take adaptation measures ((Bubeck, Botzen, Suu, & Aerts, 2012; Noll et al., 2021)).

Had we only examined social expectations, the relationship between social expectations and risk-uncertainty would be difficult to assess: the capacity to assess risk could lead to greater feelings of social influence - as individual perceptions or beliefs can be rationalized as norms by the holder (Fehr & Schurtenberger, 2018). However, reported social expectations increase with the number of people in an individuals' network who have taken adaptation measures (Pearson's r=0.38). As such, it is likely that a greater number of people who have adapted to floods in the network of risk-aware individuals (Figure 5.1) lessen the likelihood of an individual being risk-uncertain - a hypothesis aligned with prior network analysis and social research (Almaatouq et al., 2020; Kasperson et al., 1988; Yuan, Alabdulkareem, & Pentland, 2018).

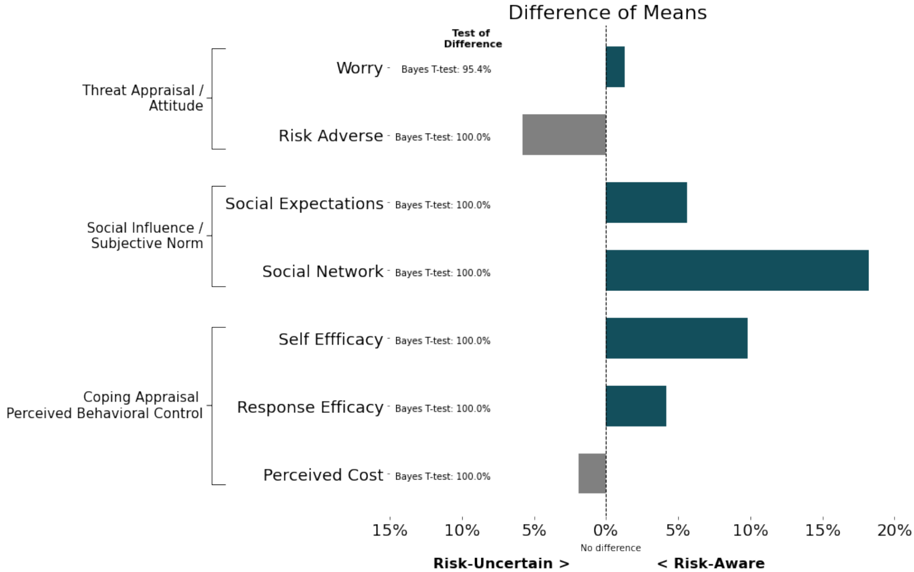


Figure 5.1: Differences in the socio-behavioral factors motivating individual climate change adaptation, compared between risk-aware (N=5103) and risk-uncertain (N=1139) respondents. To display differences in a comparable manner between variables that are measured on varying scales (N=6242), we take the difference of the risk-uncertain and risk-aware variable means and divide by the scale of measurement to get a cross-scale comparable, percentage difference.

While threat and social drivers can prompt a need to take risk-reduction actions, having sufficient coping appraisal/ perceived behavioral control to appropriately respond is equally critical (Kuhlicke et al., 2020). Self-efficacy, response efficacy, and perceived cost variables together, often represent an individuals' capacity to cope with a given threat such as flooding (Ajzen, 1991; Bandura, 1998; Grothmann & Reusswig, 2006; Rogers, 1975). Past medical survey research has found that a lower, health-related self-efficacy is associated with a greater likelihood to be risk-uncertain (Ellis et al., 2018). We corroborate this finding in our own data; where risk-uncertain respondents self-report being 10% less able to undertake flood adaptations (Figure 5.1, 'Self-Efficacy'). This finding, echoed by prior work, (Carr & Umberson, 2013; Flemming, Feinkohl, Cress, & Kimmerle, 2015; Yohe & Tol, 2002) offers strong evidence that the ability to appraise risk is linked to the perceived capacity to address it. Risk-uncertain respondents are additionally less likely to report that flood-adaptation measures will be effective in mitigating their risk ('Response Efficacy') and generally perceive adaptation to be more costly ('Perceived Cost') than risk-aware individuals (Figure 5.1). Our finding that risk-uncertain individuals have lower coping appraisal/ perceived behavioral control over a risky situation, is in line with both past medical and psychological research on adaptation (P. C. Stern, 2000; Turner et al., 2006)

5.3.3 Risk-uncertain vs. risk-aware adaptation drivers

An individuals' decision on whether or not to adapt can play a critical role in influencing both individual vulnerability and aggregate flood outcomes (Haer, Botzen, de Moel, & Aerts, 2017; Jongman, 2018; Taberna, Filatova, Roy, & Noll, 2020). Yet, our analysis reveals that, risk-uncertain individuals are significantly less likely to intend at least one of both High Effort (χ^2=130, p=0.0) and Low Effort

(χ^2=106, p=0.0) adaptations and intend fewer measures on average as well: High Effort (2.2 vs. 3.3; Wilcox rank-sum = 10.1, p=0.0) and Low Effort (3.6 vs. 4.6; Wilcox rank-sum = 8.8, p=0.0). To analyze if risk-uncertain and risk-aware individuals exhibit different cognitive decision-making processes in addition to the mean differences in drivers, adaptive capacities, socio-economic factors and reported experience, we utilizes these variables to estimate what drives different types of behavioral adaptation (High and Low Effort actions).

We measure individual adaptation intention with two commonly used statistical methods, Bayesian binary logistic regression and Bayesian Linear Regression, to ensure that differences in the drivers of adaptation decisions are corroborated across models and are therefore more robust. We estimate eight models - for both risk-uncertain and risk-aware for High Effort and Low Effort adaptations using these two regression methods. The explanatory variables are identical across models and consist of the variables previously discussed: seven socio-economic/ experiential variables, two variables represent threat appraisal/ attitude, two social influence/ subjective norm variables and three coping appraisal/ perceived control variables. Additionally we include country dummies in all models to control for cross-country variation, which could affect behavioral drivers of adaptation (Noll et al., 2020). The country effects are not shown in the figures, but all numerical effects are reported in the supplementary material (Table 8.20). For a given measure type, we drop respondents who reported having completed all measures in the category from the analysis - as there is nothing left to intend.

5

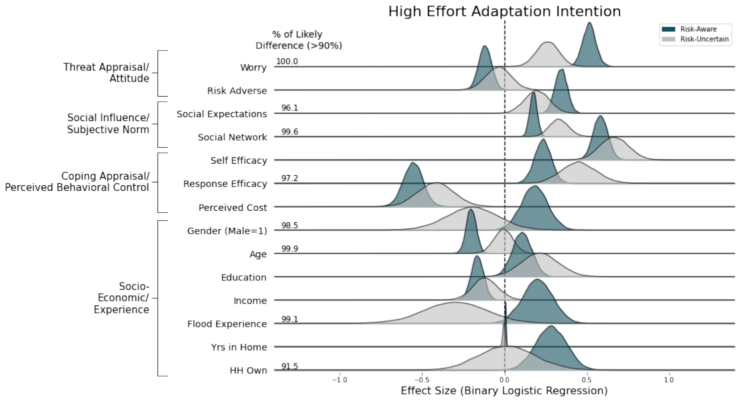
Comparison of the effects of Threat Appraisal and Attitude

Most, though not all, drivers of behavioral adaptations' intentions both risk-aware and risk-uncertain individuals exhibit effects of the same sign in both Bayesian models ((Figure 5.2). In some instances however the magnitude of the effect varies between the two groups. Specifically, when risk-uncertain individuals are contemplating High Effort adaptation measures, the reported worry about a flood ('Worry') has a diminished effect compared to that of the risk-aware (>95% likely) (Figure 5.2a/c). In line with decision, analysis (Lerner et al., 2015) and adaptation theories (Ajzen, 1991; Grothmann & Reusswig, 2006), the effect is still positive for risk-uncertain individuals. The lessened degree to which risk-uncertain individuals rely on affect is in line with some past work (Baas, de Dreu, & Nijstad, 2012; Tiedens & Linton, 2001), but contradicts another (Faraji-Rad & Pham, 2017a). This reduced reliance on worry of risk-uncertain individuals when deciding on whether to intend High Effort measures is possibly due to increased personal insecurity in their own feelings or judgments. With ('Risk Adversity') we note no cross-model consistent, likely differences (Figure 5.2b/d).

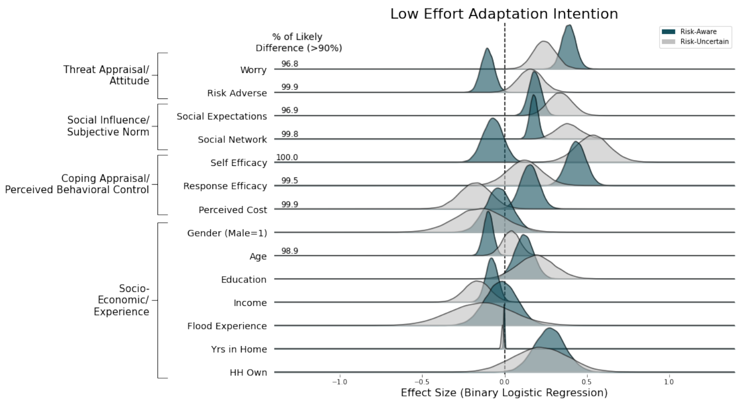
Comparing effects of Social Influences/ Subjective Norms

In contrast to a reduced reliance on worry - the number of people an individual knows that have taken an adaptive measure - has a greater effect (> 99% likely) on motivating adaptation for the risk-uncertain, possibly to compensate for lack of faith in personal judgment. This result is consistent for *both* High and Low Effort adaptation and across both Bayesian models (Figure 5.2.a, b,c,d). Risk-uncertain individuals may look more at their peers when deciding if and how to adapt as they feel less equipped to judge the risk on their own. They imitate peers when uncertain phenomena are theorized and documented empirically (Rendell et al., 2010; van Duinen, Filatova, Jager, & van der Veen, 2016).

With 'Social Expectations', we note consistent differences in effects on individual adaptation intentions for both High and Low effort actions across both models. Despite the likely difference in effects for risk-uncertain vs. risk-aware, the effect of an individuals' perception of what is expected of them is consistently positive (Figure 5.2b,d). The results suggest that social expectation has a greater effect on low effort measures for the risk-uncertain as when there is considerable social pressure to adapt, they are more likely to opt for an easier-to-accomplish measure.



(a) High Effort Measures -Bayesian Binary Logistic Regression



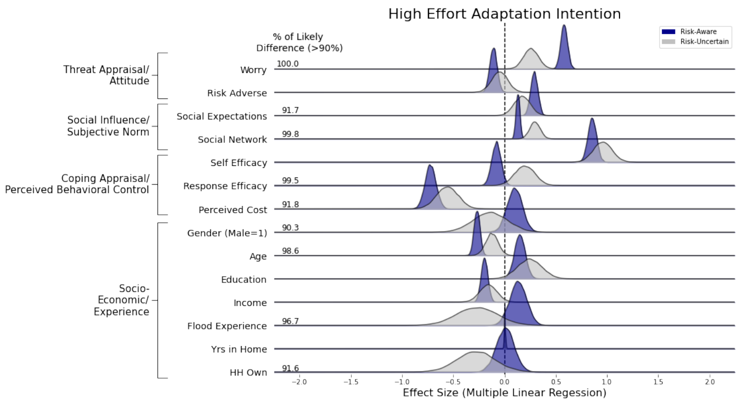
(b) Low Effort Measures -Bayesian Binary Logistic Regression

Comparing effects of Adaptive Capacity/ Perceived Behavioral Control

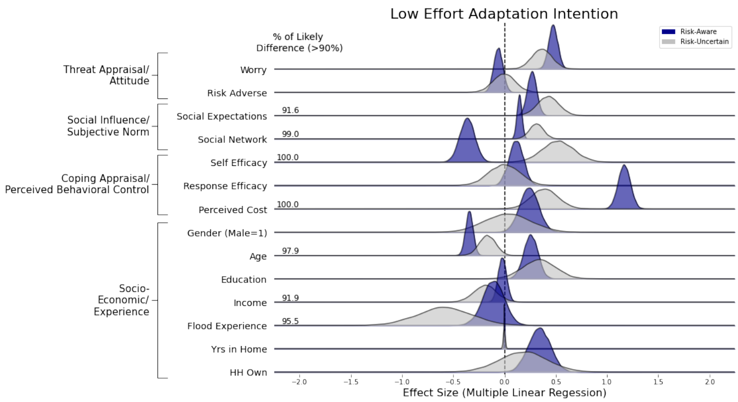
Here, as we estimate models where adaptation intention represents multiple measures, we take the mean score of the Coping Appraisal/ Perceived Behavioral Control variables (see Supplementary Material Table S.2). Hence, what we measure is the likelihood of indenting to adapt by individuals who generally perceive themselves as having a greater self-efficacy, generally see the measures as more effective, or typically perceive flood-adaptation measures as costly (P. Jansen et al., 2020). This clarification is important as these variables are often among the greatest driver/ barrier for adaptation (Bamberg et al., 2017).

For High Effort measures we find that only Response Efficacy has a consistently higher effect on adaptation intentions for risk-uncertain vs. risk-aware individuals across both model types (Figure 5.2a,c). With Low Effort adaptation however, we note the remaining two Coping Appraisal/ Perceived Behavioral Control variables have consistent differences (Figure 5.2b,d): ‘Self-Efficacy’ and ‘Perceived Costs.’ These differences are especially noteworthy because of the likely opposite coefficient signs for both variables, between risk-aware and risk-uncertain.

When considering Low Effort measures we note that the effect of self-efficacy is likely positive and the effect of perceived cost is likely negative - in line with the effect theorized by both PMT and TPB. These variables have the opposite effect for risk-aware respondents. This suggests that when



(c) High Effort Measures - Bayesian Linear Regression



(d) Low Effort Measures -Bayesian Linear Regression

Figure 5.2: Distributions displayed are Bayesian effect sizes estimated from separate models: grey for risk-uncertain and colored for risk-aware respondents. Figures 5.2.a/b are results from a Bayesian binary logistic regression models, whereas Figures 5.2.c/d are from Bayesian linear regression models. N=1139 for risk-uncertain, and N=5013 for risk-aware individuals. In addition to the effects displayed, all models include country dummies to control for cross-country differences. We subtract the distributions from one another and if the likelihood of a difference is >90%, we report the likelihood of difference in effects between the two groups next to the variable name - with the direction being visually indicated by the distributions.

risk-aware respondents have the self-efficacy and financial capacity to adapt, they are more likely to turn to High over Low Effort measures (Figure 5.2b,d).

Comparing effects of Socio-Economic and Experiential Drivers

Prior work has continually found inconsistent effects in demographic variables, such as age (Bubeck, Botzen, Suu, & Aerts, 2012). For risk-aware individuals the older a person is, the less likely they are to intend either High or Low Effort adaptations. For risk-uncertain individuals, age has a decreased effect that is likely different across High and Low Effort measures and across both Bayesian models (Figure 5.2). Another variable that we observe likely differs in effects is ('Flood Experience') (Figure 5.2 a,c,d) - a ($\geq$ 95.5% likelihood for a) difference in effects for 3/4 models (a,c,d). For risk-aware individuals, the effect of experience is likely null or slightly positive. Individuals who have experienced a flood and are (still) risk-uncertain (N=274) are much less likely to adapt - suggesting that feelings of fatalism or hopelessness hinder actions (Babcicky & Seebauer, 2019).

Finally, for High Effort measures, we note two consistent differences in the effects of gender (likely $\geq$ 90%) and homeownership (likely $\geq$ 91%) between risk-uncertain and risk-aware respondents. Home ownership is likely to have a null or negative effect on adaptation for risk-uncertain individuals, whereas, for the risk-aware, the effect is null or positive; depending on the dependent variable, i.e. adaptation formation, used in the model. Gender exhibits consistent differences in effects across both regression models: for risk-uncertain individuals, women are more likely to adapt, while for the risk-aware, men are.

The differences in effects of the three socio-economic and experiential variables - flood experience, home ownership, and age - highlight the importance of further controlling for psychological variation to elicit patterns in the effects of demographic variables. We additionally observe one other likely difference for the effect of income in one model (Figure 5.2.d); however, the inconsistency across models leaves doubts about the robustness of this outcome.

5.3.4 Expanding results to a broader context

Our analysis suggests that people belonging to the socio-economic groups that are classically considered vulnerable to disasters are likely to be risk-uncertain, which in turn likely influences their climate adaptation behavior. The consequences of this finding is substantial since commonly the two groups are often treated analogously as "I do not know" answers are traditionally bootstrapped or omitted from the analysis. We elicit systematic differences not only in behavioral drivers but also in intentions to act between risk-aware and risk-uncertain respondents. Our results align conceptually with scattered evidence in the psychological domain (Flemming et al., 2015; Tiedens & Linton, 2001) and methodologically with prior survey methodological research (Montagni et al., 2019; Young, 2012). The differences in adaptation drivers between risk-uncertain and risk-aware individuals are starting to find support in the climate change adaptation domain (Rufat et al., 2022). Hence, generic risk communication strategies may be ineffective for the risk-uncertain; possibly partially contributing to their decreased likelihood to intend adaptations. Ensuring that risk-uncertain individuals are differentiated when formulating adaptation policies is critical for building climate-resilient societies - where individual actions complement public government-led adaptation (Adger et al., 2005; Bubeck, Botzen, & Aerts, 2012) to reduce damages and facilitate recovery should a hazard event occur.

As a consistently-tested driver of adaptation (van Valkengoed & Steg, 2019), the effect of worry is an important focus. While some past work has found a greater reliance on affect when individuals are uncertain (Faraji-Rad & Pham, 2017b), other studies find that uncertainty dampens negative affect and emotions (Baas et al., 2012; Dijk & Zeelenberg, 2006; Tiedens & Linton, 2001). Our findings support the latter: risk-uncertain individuals worry less (Figure 5.1) and are less motivated by the affect to intend High Effort measures (Figure 5.2.a/b/c). Barriers or lack of knowledge, even subjective, in cognitive risk assessments by individuals influence the impact of affect on adaptation (Turner et al., 2006), despite affect being widely recognized as a key driver. Hence, policy recommendations that focus on affect as a motivating factor in promoting High Effort adaption, we find, will be less effective in motivating risk-uncertain individuals. While risk-uncertain individuals are more likely to be generally risk-adverse (Figure 5.1), this tendency to avoid risks has a limited effect on adaptation (High and Low Effort) for both risk-aware and risk-uncertain individuals.

With regards to social factors/ subjective norms influencing adaptation, risk-uncertain individuals self-report less social pressure ('Social Expectations') and report knowing substantially fewer people who have taken adaptation actions ('Social Network') than risk-aware individuals (Figure 5.1). These differences in social environments are likely a contributing factor to an individual being risk-uncertain, and could be key inhibitors of actions - as both social factors strongly motivate individual intentions to adapt across all models (Figure 5.2). As such, messages or policies targeting community awareness (Centola, 2010) could have a two-fold benefit: individuals could feel greater social pressure to adapt and grow their network, leading to greater knowledge on flood risks and increasing the likelihood of taking adaptation measures on their own.

Coping appraisal/ perceived behavioral control is consistently noted as crucial in individual adaptation behavior (Bamberg et al., 2017; Kuhlicke et al., 2020). The perceived ability to complete an action ('Self-Efficacy') has the greatest effect on risk-uncertain individuals' intention of both High and Low Effort measures, and for risk-aware individuals intending High Effort measures. Critically, here we group self-efficacy together for the given adaptation type (High/Low), measuring between-person differences (P. Jansen et al., 2020). Risk-uncertain individuals report 10% less self-efficacy compared to risk-aware individuals, a finding supported by past work that has found a negative correlation between greater self-efficacy and uncertainty (Ellis et al., 2018; Flemming et al., 2015). When we consider the two remaining coping variables, we note that risk-uncertain individuals also believe measures to be less effective ('Response Efficacy'), and perceive adaptation as more expensive ('Perceived Cost') (Figure 5.1). As all three variables are influential in adaptation decisions, especially for High Effort measures, fostering coping appraisal/ perceived behavioral control would likely have a substantial positive impact on the likelihood of adaptation by risk-uncertain individuals.

Finally, the socio-economic groups that are considered more vulnerable to hazards - less educated, female, and lower income groups- (Adger, 2006; Adger et al., 2007; Chau et al., 2014; Cutter, 2016; Malik et al., 2017) are, in general, more likely to self-report being risk-uncertain (Table 5.2) and in general, less likely to adapt (Figure 5.2. When estimating flood-adaptation intention, the factors 'Age', 'Gender', 'HH Own', and 'Flood Experience' have a consistent, likely difference in their effect on adaptation between risk-aware and risk-uncertain individuals (Figure 5.2). The differences found here, offer possible insight to why past work has found socio-demographics to offer inconsistent explanatory power (Bubeck, Botzen, Suu, & Aerts, 2012); there may be additional underlying psychological differences, such as risk-uncertainty that have previously been unaccounted for.

5.3.5 Future Work

This analysis is an extension of the growing body of literature on climate change adaptation and individual uncertainty in decision-making (Berkes, 2007; Folke, 2006; Hanea et al., 2021; Kettle & Dow, 2016; Olazabal et al., 2018; Oppenheimer et al., 2016)). Uncertainty is not just to be embraced by policy-makers, but also affects the adaptation decisions of individuals. Continuing to indiscriminately drop or bootstrap respondents with possible psychological differences such as risk-uncertainty can lead to ineffective or counterproductive policy recommendations as their decision can be affected differently. Acknowledging these differences and their consequences for climate change adaptation, and beyond, is a necessary step in understanding individual decision-making and ameliorating differences in vulnerability.

Future work can build on this analysis and test if risk-aware differs from risk-uncertain individuals in their characteristics and action intentions generically across various risk contexts and over time. Doing so would additionally enable causal analysis between actions and experiences and risk-uncertainty and thereby be able to incorporate learning in the analysis. Furthermore, future efforts could consider incorporating individual risk-uncertainty into methods that explicitly embrace individual heterogeneity such as agent-based models. These models are increasingly utilized to explore different climate scenarios and adaptation strategies (Taberna et al., 2020), with an explicit treatment of learning and social network interactions, and offer ideal settings to explore how *individual* differences - such as risk-uncertainty - cumulate to varying social outcomes (de Koning & Filatova, 2020; Gawith, Hodge, Morgan, & Daigneault, 2020).

Our findings additionally have important implications for the growing body of work on joint adaptation, knowledge production, and context-specific adaptation i.e. (Muccione et al., 2019; Rufat et al., 2020; Wilson et al., 2020). Future work could consider how communal adaptation strategies function when psychologically distinct individuals interact (Rendell et al., 2010) and what the consequences are for social capital (Ingold, 2017). Given that not only flood preparedness, but any attempt at climate adaptation requires widespread citizen participation, acknowledging and further exploring the differences between those who are able to assess their own risks and those who are not, are crucial steps toward inclusive climate policies. Finally, risk-uncertainty, like all knowledge, is not a binary construct and we acknowledge that while our classification method is possibly capturing various types of risk-uncertainty.

Future work could build on this study by innovating a gradient or continuous method to measure individual risk-uncertainty and thereby further unfold ambiguity in judgments (Hanea et al., 2021; Harrington et al., 2021; Olazabal et al., 2018; Oppenheimer et al., 2016). Risk-uncertainty, as we have measured here, captures a spectrum: from a total absence of awareness about floods to a more nuanced, lack of specific information on their likelihood or damage. To advance our understanding of uncertainty in individual judgment, future studies should aim to differentiate between these various types of risk-uncertainty and test if the personal, behavioral, and social differences observed in this analysis hold.

5.4 Conclusions

Worldwide countries are experiencing an unprecedented increase in climate-induced risks, with which top-down, government measures on their own cannot contend. Individual adaptation is essential to reduce damage and ease a recovery, should a hazardous event occur. Hence, a systematic understanding of the factors that shape vulnerability and motivate individual adaptation actions is crucial for just, climate-resilient societies.

Here, using an international four-country survey (N=6242) we explore a previously conventionally ignored group - risk-uncertain individuals who have insufficient information or capacity to assess flood risk. Our analysis reveals that risk-uncertain individuals are more likely to belong to socio-economic groups that are generally more vulnerable to disasters, have less coping capacity, and are less likely to adapt to floods. In employing two grouping methods of adaptation estimating, we find consistent differences in the drivers of behavioral adaptation between risk-uncertain and risk-aware individuals. The cross-model consistency of findings lends credence to the notion that lacking the knowledge to assess risk has behavioral consequences. Previously, this idea has not been explicitly entertained in the households' climate change adaptation literature, with only scarce evidence from other domains relying on social surveys. Differences in vulnerability, adaptive capacity, and behavior have gone unrecognized due to analytical methods and practices that typically drop or group risk-uncertain individuals with those who can assess risk.

Besides these methodological implications, our findings have consequences for climate change adaptation policies. Namely, messages seeking to inspire individual adaptation by targeting worry may be less effective for risk-uncertain individuals compared to risk-aware. Further, the influence that social networks have on adaptation is amplified for the risk-uncertain, possibly because those who do not know, copy others.

Finally, we note a vulnerable sub-group of risk-uncertain individuals: those who have experienced a flood but still cannot assess risk. These individuals are less likely to take adaptation action, especially High Effort measures - possibly suggesting fatalism. Researchers, risk modelers, and policymakers alike can leverage these findings to better account for, and motivate individual behavior change in progress toward a climate-resilient society and when seeking to reduce risks by inspiring individual adaptation.

5.5 Acknowledgments

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6

A longitudinal study on the dynamics of household flood adaptation behavior

Floods affect millions of households annually. While government-led measures like levees/dikes help in reducing hazard probabilities, it is the on-site adaptation measures that determine the extent of damages and the speed and pathways of recovery, should an adverse event occur. With exacerbating climate-induced floods and sea-level rise in times of unprecedented urbanization, understanding and stimulating adaptation behavior of households are increasingly vital to curb growing global flood risks. Cross-sectional surveys are a common tool to understand households' adaptation. Yet, a one-time snapshot fails to capture behavioral dynamics and causal inferences or to validate households' stated intentions - conventionally used proximally for action. Using a longitudinal survey administered in USA, China, Indonesia, and the Netherlands (balanced panel data, N=1251), during which more than half of the households reported experiencing flooding, we study household risk perception dynamics and the intention-behavior gap. Using Protection Motivation Theory, we trace dynamics of household perceptions, competencies, socio-economic, and experiential factors. In doing so, we find that perceptions are relatively stable and that household perception dynamics have less explanatory power than between-households' variations. Depending, on the time period, between 17-32% deviate from their state intentions, using a dynamic panel model, we test to what degree intention causes reported action. We find a positive yet statistically insignificant effect - rendering to what degree intention leads to action, uncertain. Finally, to understand factors contributing to this intention-behavior gap, we estimate what factors contribute to households deviating from their stated intentions. Our work advances the sparse longitudinal survey literature by eliciting household flood adaptation behavior dynamics based on the data from four countries and offers insight into factors separating households' flood adaptation behavior from intentions. The findings reinforce the need to move away from risk-based messaging strategies, and leverage the salient role that social influence and affect play in driving action; as long as the household has sufficient resources.

This chapter is currently under review for publication.

6.1 Introduction

Anthropogenic climate change has set on a trajectory that demands massive adaptation in the coming decades, even if emissions are successfully curbed (IPCC, 2014, 2022). Climate change makes hazards more likely and more extreme (Kirchmeier-Young et al., 2019; Trenberth et al., 2015). Flooding, the most costly climate-driven hazard globally, especially in coastal areas (Vousdoukas et al., 2020), affects millions of households and causes trillions of (US) dollars worth of damage annually (Jongman, Ward, & Aerts, 2012). While urban areas globally continue to swell due to economic migration and agglomeration forces (Barragan & de Andres, 2015), coastal cities especially face tremendous accumulating risks from floods and sea level rise (Tiggeloven et al., 2020; Vousdoukas et al., 2020). The projected continued growth in both population and infrastructure thereby also increases risk and necessitates immediate action (Magnan et al., 2022; **?**). The latter is particularly needed in areas hit by recurrent hazards, which leave little time for recovery and could lead to economic gentrification and poverty traps (de Koning & Filatova, 2020; Hallegatte, 2007, 2009). To curtail future damages and address the rising threat, adaptation to floods is an urgent necessity (Coronese et al., 2019; Siders & Keenan, 2020).

Government-led adaptation measures - such as dikes, levees, or nature-based solutions - are essential to address the growing risks (Magnan et al., 2022). These large-scale measures on their own can never fully eliminate risk and in many circumstances are difficult due to various economic, environmental, and political barriers (Berrang-Ford et al., 2021; Hudson et al., 2019). Adaptation at the household level reduces damages and increases resilience in case an adverse event occurs, increasingly making it a critical component of climate change adaptation strategies (Berrang-Ford et al., 2021; Magnan et al., 2022; Michel-Kerjan, 2015).

6

In this paper, we seek to answer three research questions (RQs) that progressively build on one another to provide a robust understanding of household adaptation behavior concerning floods. (RQ1) What are the dynamics of perceived threats and do within-household dynamics or between-household differences have a greater effect on adaptation intention? (RQ2) To what degree does intention lead to action? (RQ3) What key factors are associated with households' adaptation intention and behavior, and do these factors help explain the observed variation in households' actions?

In the flood risk domain, when researching households' protective actions, surveys are the prevailing method (Hudson et al., 2019; Mondino et al., 2021). Cross-sectional, as opposed to panel surveys, are by far the most common method of data collection, largely due to the logistical challenges, attrition, and cost barriers that exist when designing, implementing, and managing a longitudinal survey (Hudson et al., 2019). Numerous articles identify longitudinal studies as a bottleneck of data availability, necessary to advance our understanding of household adaptation behavior (Hassan, Shiu, & Shaw, 2016; Hudson et al., 2019) and particularly better apprehend the intention-behavior gap (Bubeck et al., 2020; Osberghaus, Botzen, Martin, & Ekaterina, 2022; Seebauer & Babcicky, 2020a). Prior longitudinal or *panel* surveys that monitor household adaptations to floods typically have two - three waves and face issues pertaining to sample size (at times inhibiting analysis) and lack flood exposure (Bubeck et al., 2020; Hudson et al., 2019; Osberghaus et al., 2022; Seebauer & Babcicky, 2020a). Furthermore, prior longitudinal surveys have generally been conducted before or after a flood and therefore are unable to account for the impact of a flood experience on household perceptions and actions. Hence, as noted by (Hudson et al., 2019) in their review of longitudinal flood data research:

"...the ideal panel dataset would contain observations from before and after a flood event. This would allow the flood to act as an 'exogenous' event and allow researchers to identify changes in behaviour as well as temporal impacts."

This article reports the results of a comprehensive statistical analysis of such a unique dataset: **50%** of our survey respondents analyzed here reported experiencing at least one flood over the course of our survey (Figure 6.1). While we are scientifically privileged to be privy to such data, we emphasize the scope of the tragedy of experiencing floods and the pain their adverse impacts impose worldwide. Our research design did not focus exclusively on flood-prone areas for data collection just coastal cities; yet half of our respondents suffered floods during our two-year survey. Given that climate change exasperates hazards globally (Kirchmeier-Young et al., 2019; Wu, Wei, & D'Hondt, 2022), we hope this sobering reality highlights the urgency of adaptation and of understanding barriers to action, including household adaptation.

Our longitudinal survey was administered between April 2020 and October 2021 in four surveys, one every six months, which took place in major coastal-urban centers in the United States of America (USA), China, Indonesia, and the Netherlands. The survey solicited information on risk and social perceptions, coping capacity, adaptation behavior, and socio-economic information. A total of 1251 households across the four countries responded continuously and completely to all four survey waves. We rely on an extended version of Protection Motivation Theory (Grothmann & Reusswig, 2006; Rogers, 1975) to design the survey and to guide our analysis.

6.2 Methods

6.2.1 Survey

In March-April 2020 we launched the first household online surveys in coastal cities and surrounding areas in the USA (Miami, Houston, and New Orleans), China (Shanghai), Indonesia (Jakarta), and the Netherlands (Rotterdam). Every six months until October 2021 (Figure 6.1) we re-contacted the same households and re-surveyed them; asking them follow-up questions tracing reported actions, perceptions, and beliefs. YouGov managed the survey dissemination across all four waves and the results presented in this paper are from identical, translated questionnaires in the languages of each country (*YouGov Panel*, n.d.). Our questions in the surveys were inspired by prior work (Bamberg et al., 2017; Bubeck, Botzen, Suu, & Aerts, 2012) and were written in English by a native speaker from the USA. For the remaining three countries, the survey was translated into the respective countries' languages by YouGov professionals. These versions were then reviewed by our scientific colleagues from each country to help mitigate cultural bias and verify the relevance of the measures and questions asked. YouGov field experts additionally offered perspectives on the national context, and culture-specific ethical, and legal considerations.

YouGov has a number of quality control measures in place to support high-quality data collection. Their software and analysts exclude "speeding-respondents" (people who click through too rapidly to allow reading), and they invite panelists to participate before announcing the topic - helping mitigate self-selection bias. Further, YouGov verifies relevant personal details when respondents are originally registered for their panel, and those who consistently selected the same answers (i.e. all option 1) are filtered out. Finally, YouGov sets limits on the number of surveys that respondents can participate in to reduce survey conditioning and fatigue (*More Detail on YouGov Research Methods*, n.d.). A lack of internet at home did not appear as a barrier to reaching a broad selection of households because the YouGov platform is easily accessible via mobile phones, especially in large urban areas where our research is focused(Lin, 2020; Nabila, 2019).

Across all countries, in the initial panel sample, we specifically controlled for gender representation, and in the USA, we were additionally able to initially sample a representative age distribution. In the Appendix (Tables 8.21 and 8.22) we compare our sample demographics to census demographics. For obvious reasons we could not control which households decided to not continue to participate in our panel; as is the case with any large-scale panel survey, some respondents were unable to be recontacted. Our sample after four waves has a good balance of gender, but in the USA and the Netherlands, it has more older respondents than the normal populous. Conversely, in China and Indonesia, our sample lacks older respondents. In all countries, our samples are more educated than the average population. While not all socioeconomic demographics are equally represented, we control for these factors in all our models. We analyze and discuss the attrition from our survey

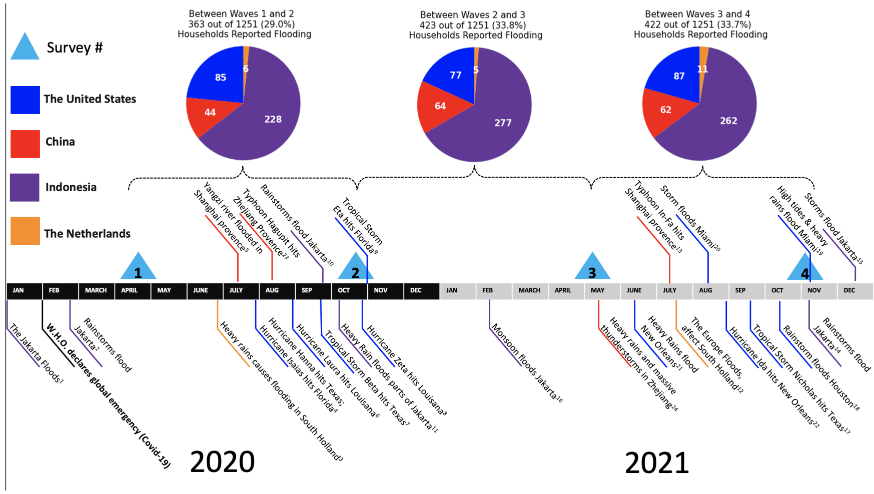

Figure 6.1: A timeline of the four survey waves over the past two years and the major flood events that have happened in or around our case study areas in four countries. The Superscripts correspond to information in the Supp. Material, section 8.6.

below in Section 6.2.2.

6.2.2 Survey attrition

Overall, 25% of the respondents who participated in our initial survey participated in all four surveys. To focus the analysis of our panel data on the dynamics and intention-behavior gap we use a balanced panel, consisting only of respondents who participated fully in all four waves (N=1251). Considering the limited past longitudinal research in the flood risk domain, survey attrition has received relatively little attention and has not consistently reported if an attrition bias is present in their samples (Hudson et al., 2019).

To cross-check our survey against past work, prior to presenting the results, we estimate a logistic regression model to see if respondents stayed through all four waves. Here, we use frequency statistics as it is in line with repeated longitudinal surveys from multiple sources. We estimate a model using the variables present in our later analysis, outlined below in Table 6.3.

In previous panel surveys that conducted a study of attrition, age was found to be one of the few factors that affected the likelihood of respondents continuing to respond (Hudson et al., 2019; Mondino et al., 2021; Seebauer & Babcicky, 2020a). Our data additionally supports the notion that older respondents are more likely to stay in the panel (Table 6.1). Likewise, more educated respondents and those who perceived structural flood adaptation measures as more expensive were also more likely to complete all four waves. Finally, Dutch respondents were much more likely to drop out compared to their American counterparts, while Indonesians were more likely to stay. There was no significant difference between American and Chinese respondents.

Not all socio-economic groups are equally represented here. Weighting or imputing data can aid in reducing bias, yet if the weighted data are used, incorrect confidence/ credible intervals will be produced (Schmidt & Woll, 2017). Further, it is likely, especially in our case, that our dynamic explanatory variables and time-dependent response variables changed in an unpredictable manner for respondents who dropped out. Thus, here we elect not to weight the data and introduce new biases in the pursuit of ameliorating other biases (Perkins et al., 2018). We instead present the results

Table 6.1: Binary logistic regression coefficients estimating if a survey respondent **stayed** through all four survey waves. N=1251

	Coefficient Est.	Standard Error	p-Value
Intercept	-3.662		
Flood Prob.	-0.001	0.001	0.305
Flood Damage	-0.005	0.034	0.874
Worry	-0.008	0.039	0.830
Self Efficacy	-0.062	0.040	0.119
Response Efficacy	-0.057	0.044	0.198
Perceived Cost	0.140	0.053	0.009
Exp. Fl. Dam.	0.018	0.084	0.832
Age	0.492	0.033	0.000
Male	0.010	0.076	0.892
Education	0.215	0.054	0.000
Years in Home	0.004	0.003	0.216
Soc. Expect	0.016	0.035	0.649
Netherlands	-2.139	0.173	0.000
China	0.023	0.127	0.856
Indonesia	1.122	0.110	0.000

from the analysis of the original sample, N=1251. While this decision can influence our findings, we discuss this as an avenue for future research in Section 6.5.

6.2.3 Adaptation measures

To collect information on adaption intentions and actions, in each wave we invited households to report if they had taken a given measure, (still) intended a given measure, or did not intend to take a given measure. If they intended to take a given measure for the first time, we asked them on what time scale they thought they would implement it. On Waves 1 and 2 (W1 and W2) respondents were presented all measures, except on W2 for those measures that households previously stated to be already implemented. Households could select:

- I have already implemented this measure
- I intend to implement this measure in the next 6 months
- I intend to implement this measure in the next 12 months
- I intend to implement this measure in the next 2 years
- I intend to implement this measure in the future, after 2 years
- I do not intend to implement this measure

Table 6.2 displays the percentages for intended and undergone actions among our respondents across the four waves. An in-depth analysis of differences in individual climate adaptation measures is important in the context of understanding within-households or between-household drivers (P. Jansen et al., 2020; Noll et al., 2021). However, to explore the dynamics of intentions over time depending on flood experience - to quantify the intention-behavior gap and to explore the reasons behind any observed discrepancies - we choose to aggregate the seven structural measures. Therefore, we measure the two dependent variables - intention to adapt and actual adaptation - at the group level as all these actions involve resource and time investment in modifying one's home to reduce household flood risk. Thus, the remainder of the paper uses either a dummy coded variable to signify intention (intending at least one action by a given wave) or no intention (no actions intended) or uses the number of adaptation actions intended.

Table 6.2: Percentage of household action and intentions from the total sample of N=1251.

#	Description	% of HH intending to complete action$_i$ by W$_i$ (*% of HH undertaking action$_i$ between W_i and W_{i-1}*) Wave 1 (April/May, 2020)	Wave 2 (Oct/Nov, 2020)	Wave 3 (April/May, 2021)	Wave 4 (Oct/Nov, 2021)
1	Raising the level of the ground floor above the most likely flood level	*(16%)*	3% *(13%)*	4% *(6%)*	3% *(2%)*
2	Strengthen the housing foundations to withstand water pressures	*(11%)*	2% *(14%)*	3% *(7%)*	2% *(3%)*
3	Reconstructing or reinforcing the walls and/or the ground floor with water-resistant materials	*(8%)*	3% *(13%)*	4% *(7%)*	3% *(3%)*
4	Raising the electricity meter above the most likely flood level or on an upper floor	*(15%)*	2% *(18%)*	4% *(6%)*	2% *(3%)*
5	Installing anti-backflow valves on pipes	*(9%)*	3% *(13%)*	5% *(5%)*	3% *(3%)*
6	Installing a pump and/or one or more system(s) to drain flood water	*(6%)*	4% *(12%)*	5% *(5%)*	4% *(2%)*
7	Fixing water barriers (e.g. water-proof basement windows)	*(7%)*	4% *(14%)*	4% *(6%)*	2% *(3%)*

6.2.4 Conceptualization

In line with past work on flood adaptation, we utilized Protection Motivation Theory (PMT) to inform our survey design and analysis (Rogers, 1975; van Valkengoed & Steg, 2019). PMT stipulates that decision-makers, like households, appraise their threat and coping options. Following the evidence from previous empirical studies (Grothmann & Reusswig, 2006), we utilize the extended PMT where the threat appraisal is measured by eliciting the perceived probability of an event, its perceived consequence or damage, and individual affect or worry about the adversity (Table 6.3). For coping appraisal - i.e. deciding whether and which actions to pursue - we measure the households' self-perceived ability to deal with the event and take action (self efficacy), their belief in the effectiveness of an action to mitigate risk in general (response efficacy), and their perceived assessment on how expensive the action is (perceived cost). In this article, we focus on the analysis of dynamics of the uptake of seven structural adaptation measures that are generally feasible at the household level (see Table 6.2 for details).

In addition to these theory-driven constructs, we also solicited socio-economic and experiential information to include in our analysis to better contextualize the heterogeneous conditions of households' climate adaptation decisions. Table 6.3 catalogs the variables we used in the analysis, and the corresponding survey questions used to solicit them.

Across the survey waves, we re-ask several questions. Factors like education and gender are very unlikely to change over the course of the survey, and age changes consistently across respondents. However, for the threat and coping appraisal variables we had to decide whether or not to ask each wave and in what manner to do so. For the coping appraisal variables, prior longitudinal analysis on flood adaptation had found the coping appraisal variable to be very stable (Bubeck et al., 2020), i.e. no statistically significant differences were found in the variables across waves. For threat appraisal variables, on the other hand, some (i.e. probability) were found to meaningfully differ. As coping appraisal is a measure-specific question, meaning that it is very time and space intensive to ask, we elected to only ask it on the first wave given its previously reported stable behavior. In contrast, we solicited the threat appraisal constructs for each wave. For the threat appraisal (the time-variant variables) after the first wave, we reminded the respondent of their response to the question on the previous wave and then asked them if their score had changed. If they indicated 'Yes' it had changed, they were prompted to fill in an updated score. As it is likely that households forget what number they selected the last wave, without the prompt, observed changes in reported scores due to chance. This method allowed us to better understand the effect of household internal changes in scores; an effect we test and discuss in Section 6.3.1.

Table 6.3: Variables utilized in this article, N=1251. See Table 8.21 for more information on the socio-economic characteristic variables.

Explanatory Variables	Question	Time	Wave(s) Measured	Measurement Scale
Adaptation Intention	Either formulated as binary (HH intended ≥1 action in wave$_i$)	Variant	1,2,3,4	0,1
	OR as the number of actions intended in wave$_i$	Variant	1,2,3,4	0,1,2,3...
Flood Probability	How often do you think a flood occurs on the property on which you live (e.g.due to rivers or heavy rain storms and cyclones)?	Variant	1,2,3,4	(cat.) 0-100%
Flood Damage	In the event of a future major flood in your area on a similar scale to ___‡ how severe (or not) do you think the physical damage to your house would be?	Variant	1,2,3,4	1-5
Worry	How worried are you about the potential impact of flooding on your home?	Variant	1,2,3,4	1-5
Self Efficacy	Do you have the ability to undertake this measure either by yourself or paying a professional to do so?	Invariant	1	$\frac{1-5\ for\ each\ adapt.\ measure}{7}$
Response Efficacy	How effective do you believe implementing this measure would be in reducing the risk of flood damage to your home and possessions?	Invariant	1	$\frac{1-5\ for\ each\ adapt.\ measure}{7}$
Perceived Cost	When you think in terms of your income and other expenses do you believe implementing (or paying someone to implement) this measure would be cheap or expensive?	Invariant	1	$\frac{1-5\ for\ each\ adapt.\ measure}{7}$
Experienced Fl. Dam.	Please provide an estimate of the total costs to your property that this flood caused AND if any medical expenses resulted from this flood, please include them in the estimate as well.	Variant	1,2,3,4	$\frac{Reported\ Financial\ HH\ damage}{Median\ country\ income}$
Age	YouGov collected this information	Invariant	1	(cat.) 1-6
Male	YouGov collected this information	Invariant	1	0,1
Education	YouGov collected this information	Invariant	1	(cat.) 1-4
Years in Home	In what year did you begin living in this accommodation?	Invariant	1	(2020 - answer) 1-N
Social Expectations	Do your family, friends and/or social network expect you to prepare your household for flooding?	Invariant	1	1-5
Netherlands	YouGov collected this information	Invariant	1	0,1
China	YouGov collected this information	Invariant	1	0,1
Indonesia	YouGov collected this information	Invariant	1	0,1
USA	YouGov collected this information	Invariant	1	0,1 (used as reference category)

‡USA: “the flooding from Hurricane Harvey in 2017”; China: “the 2017 China floods in Hunan”;
‡Indonesia: “the 2020 Jakarta floods”; Netherlands: “the North Sea Floods of 1953”

6.2.5 Data Analysis

To address our three research questions, we employ question-specific methods. For RQ1, we are principally interested in studying time-variant factors like perceived threat and experienced flood damage. The first step of our analysis is comparing, by country, the perceived threat appraisal variables across time. Next, to study the relationship between all extended PMT variables, - the four time-variant variables as well as the remaining time-invariant (Table 6.3) - and adaptation intention, we estimate our first-panel regression model. We initially estimate a fixed effects and random effects model in order to check for endogeneity within the regressors using the Hausman-Test.

The test statistic using this set of explanatory variables was insignificant, leading us to prefer the Random Effects model (Wooldridge, 2010). To test for a possible confounding relationship between the experienced flood damage and the dynamics of the three-time variant threat appraisal variables, we estimate separate models with interaction terms between flood experience and the three threat appraisal variables. Finally, to examine if within-household dynamics or the between-household differences with the three threat appraisal variables offer more power in explaining adaptation intention (P. Jansen et al., 2020), we estimate an identical model, but use the differences in reported scores between the waves for flood probability, flood damage, and worry. For example, the worry score from wave 1 is subtracted from wave 2 to get the difference and explain adaptation intention at wave 2. The effects of the differences in scores are compared to the reported scores.

Here we elect to estimate our models with Bayesian methods due to the increased estimate stability that has been found to be present in panel estimation (Beerli, 2006; Zyphur et al., 2021). While we use informed priors (outlined below), all coefficient and intercept priors are unbiased (centered at 0), thus the coefficient mean estimates are comparable with those from a Maximum Likelihood Estimation method. For RQ1 we estimate two models: A Bayesian linear and logistic regression model; where the intention is either the number of measures in the former model and binary (0 if no intent that wave, 1 if some) in the latter:

$$y_{it} = F \cdot (\alpha + BX_{it} + u_i + e_{it}) \tag{6.1}$$

where F· is the sigmoid function in the logistic regression model and is not present in the linear model. B is a column vector of regressor coefficients and X is a matrix of the explanatory variables and u is the individual random effect. The Hyperpriors for B are set as $\mu \sim N(0,2)$ and $\sigma \sim Exponential(0.3)$. The priors are then $B_k \sim N(\mu,\sigma)$. For the intercept a's prior $\sim N(0,5)$, and finally u the between-subject random effect was estimated deterministically from: $N(0,1) * Exponential(0.3)$. The model results are reported in the results section.

6

Next, to test the causal relationship between stated intent and household adaptation behavior - central to RQ2, we utilize a cross-lagged panel model with fixed effects (Allison, Williams, & Moral-Benito, 2017; Das, 2022; Moral, España, Allison, & Williams, 2018; Williams, Allison, & Moral-Benito, 2018). Here we use structural equation software (Semopy 2.0 (Meshcheryakov, Igolkina, & Samsonova, 2021)) to allow (and restrict) the correct covariances that allow us to avoid the estimation problems that can occur when estimating a cross-lagged panel model with fixed effects (Allison et al., 2017; Wooldridge, 2010). The vast majority of Structural Equation Modeling programs rely on Maximum Likelihood Estimation for their estimation and do not have Bayesian methods built in. Hence, while we use Bayesian methods in our regression models for estimation accuracy (and epistemology), for this research question we had to rely on the Maximum Likelihood Estimation approach. We selected our model after considering a number of other possible alternatives: Generalized Method of Moments (GMM) (Jung & Wickrama, 2008)) is a popular estimation method for panel data that has been previously used for other purposes in the flood risk domain (Bubeck et al., 2020). However, GMM models will provide biased estimates with dynamic panel models - using lagged dependent, or endogenous variables as explanatory variables as we wished to do here (Arellano, 2003; Moral et al., 2018; Williams et al., 2018) - as it is only logical that actions taken at time T-1 would influence actions at time T. Other past work has utilized a differences-in-differences approach with two time periods (Osberghaus, 2017); equivalent (when T=2) to fixed effects (Wooldridge, 2010). While this method is common to capture temporal changes between a population exposed to treatment vs the control group, it did not fit with our conceptual framing of the problem (i.e. that a household at T=1 was the 'control').

Instead, we choose the cross-lagged structural equation panel model with fixed effects that allows us to use reported values of the time-variant regressors, as opposed to their differences (Arellano-Bond) (Allison et al., 2017). This is advantageous as it captures the between-household differences in effects (P. Jansen et al., 2020). This model allows us to control for the effects of both time-variant and invariant co-founders and test the direct causal effect of a time-variant variable; in this case "stated intention" on reported action. Hence the model we use to answer RQ2 is:

$$y_{it} = \lambda_t + B_1 x_{it-1} + B_2 y_{it-1} + \delta w_{it-1} + \alpha_i + e_{it} \tag{6.2}$$

where λ_t is an intercept that varies with time, B_1 and B_2 are both scalar coefficients estimates. x_{it-1} is, in this instance, intent to adapt - coded binary, and as the number of intended actions and y_{it-1} is the lagged dependent variable, reported undergone measures in the prior wave $t-1$. If a household intends to undertake y_i at time t, but did not complete it, we bump the household's intention to $t+1$ as long as they specify, at t, that they still intend to undertake the measure. δ is a column vector of time-variant coefficients with w_{it} being a row vector of $[1xj]$; where j is the number of regressors at time t that we specify below. e_{it} is the disturbance term free to vary with time and a_i includes all time-invariant effects not accounted for in the model. While an additional term can be included in the above model i.e. γz_{it-1} to incorporate time-invariant regressors directly, we do not do it. For this model to be identified, we need to assume that $cov(e,z) = 0$, an assumption that would not be upheld in this instance. However, as is noted in (Allison et al., 2017), time-invariant variables are fully controlled for as a part of the α term anyways, and since the time-variant variable, intention, is the focus of the analysis, we exclude time-invariant regressors from this model, while still controlling for the variance.

As already noted we include stated intention and lagged action in our cross-lagged structural equation panel model. We control for four additional time-variant threat variables (w): Perceived flood probability, flood damage, worry, and the amount of damage (in terms of monetary cost) a household experienced from floods in the previous time period (Table 6.3); all variables are centered prior to estimation.

The final part of our analysis concerns RQ3, which aims to apprehend what factors contribute to a household deviating from its adaptation plan. We group households into four distinctive groups (Figure 6.2):

1. **No intention, No Action**: Households who did not intent any action and did not take any
2. **Intention, but No Action**: Households who intended to take action in a given time period but do not follow through
3. **No Intention, but Action**: Households who acted without previously stating their intention or who took action either earlier than intended
4. **Intention and Action**: Households who follow through on prior intended adaptation plans (reference category)

The grouping for categories 1, 2, and 4 are straightforward. The reason that in category 3 we group those who 'spontaneously' took action with those who took action earlier is to denote households who act randomly without intent. We do believe that environmental, social, and contextual circumstances have caused these households to act earlier than previously intended or the intention, and subsequent action, was formulated between waves - thus not allowing the household to previously register the intention on our survey. In both scenarios, households acted in a shifted time frame, making them, an appropriate group for the purpose of this analysis.

Similar to RQ2, if a household intended to undertake adaptation$_i$ at time T, but did not complete it, we bump a household's intention to T+1. To better understand what factors motivated different decisions and deviations from stated plans, we estimate a Bayesian Generalised Linear Mixed Model (Gentle, Härdle, & Mori, 2012; Liu, 2016; Wooldridge, 2010). Specifically, we employ a Bayesian hierarchical multinomial panel model with random effects to answer RQ3. In this instance, we again select Bayesian estimation over Maximum Likelihood, because due to model complexity,

No Intention & No Action **W2: 752 *(60%)*** **W3: 855 *(68%)*** **W4: 977 *(78%)***	No (Previously Stated) Intention & Action **W2: 358 *(29%)*** **W3: 186 *(15%)*** **W4: 127 *(10%)***
Intention & No Action **W2: 37 *(3%)*** **W3: 102 *(8%)*** **W4: 90 *(7%)***	Intention & Action **W2: 104 *(8%)*** **W3: 108 *(9%)*** **W4: 57 *(5%)***

Figure 6.2: A break down of the four possible intention and behavior combinations. The numbers (and %) that are reported next to each wave W_i are the number (and %) of respondents *that wave* that fall into that category. The colors of the boxes correspond with those in Figure 6.5

Bayesian methods generally fair better in terms of accuracy (Beerli, 2006; Zyphur et al., 2021). An additional benefit of the use of random effects in this instance is the extrapolation outside our data set (Wooldridge, 2010). In our model, Y_{it} denotes the nominal categorical adaptation decision for the subject (household) i at time t with K as the categorical variable representing the four possible adaptation decisions described above in Figure 6.2, with households who followed through on prior intended adaptation plans as the reference group. Thus, using the explanatory variables presented in Table 6.3 as data X, the probability that $Y_{it} = k(k = 1, ...k)$ for subject i at time t is:

$$P_{itk} = Pr(y_{it} = k|X_{it}) = \left[1 + \sum_{l=1}^{K} exp(X'_{it-1}B_l + u_{il})\right]^{-1} exp(X'_{it-1}B_k + u_{ik}) \tag{6.3}$$

where X_{it-1} are the covariates for subject i at time $t-1$ and B_k is the vector of the regression parameters we estimate. u_{ik} is an N x 1 vector of between-subject random effects, where $N = i$ (the total number of households included in this analysis). The Hyperpriors for B are set as $\mu \sim N(0,2)$ and $\sigma \sim Exponential(0.3)$. The priors are then $B_k \sim N(\mu, \sigma)$. For the intercept priors delineating between different outcomes, K, we use $a \sim N(0,1)$, and finally u the between-subject random effect was estimated deterministically from: $N(0,1) * Exponential(1)$. All variables are centered prior to estimation and the analysis was carried out in Python v. 3.8.2 using PYMC3 v. 3.11.4 for the Bayesian estimation (Salvatier et al., 2016).

6.3 Results

6.3.1 Time-variant dynamics and the drivers of adaptation intention

Our analysis finds that threat appraisal - or risk perceptions - at the aggregated level are relatively stable over time (Figure 6.3), supporting prior findings (Seebauer & Babcicky, 2020a). When separated by countries, however, we do note differences in the mean country-level aggregated individual perceptions. Indonesian households (accurately) perceive the likelihood of them experiencing a flood to be the greatest in our sample, followed by households from the USA. Both the Dutch and the Chinese respondents perceive the likelihood of experiencing a flood as relatively low. Indonesian households likewise worry more about floods than households from other countries. Finally, Dutch households rank the damage that would occur to their household *if* there were a major flood, higher than their Chinese, USA, and Indonesian peers. Notably, despite flood occurrences in the four countries, all three measures of threat appraisal remain relatively consistent (Figure 6.3).

Utilizing these three threat appraisal factors and "Experienced Flood Damage" (all four are the time-variant variable collected each wave) as well as the other explanatory variables presented in Table 6.3, we estimate adaptation intention, across the four waves, using two types of Bayesian random effect panel models: linear and logistic. In one set of models, we include just the variables from Table 6.3. In the other set, to verify there is no confounding effect of experienced flood damage on any of the three time-variant threat appraisal variables, we include three interaction terms. Since all interactions-terms do not likely differ from zero (Appendix, Table 8.23), we present only the first set of the models in the paper (Table 6.4) and the second set in the Appendix, (Table 8.23).

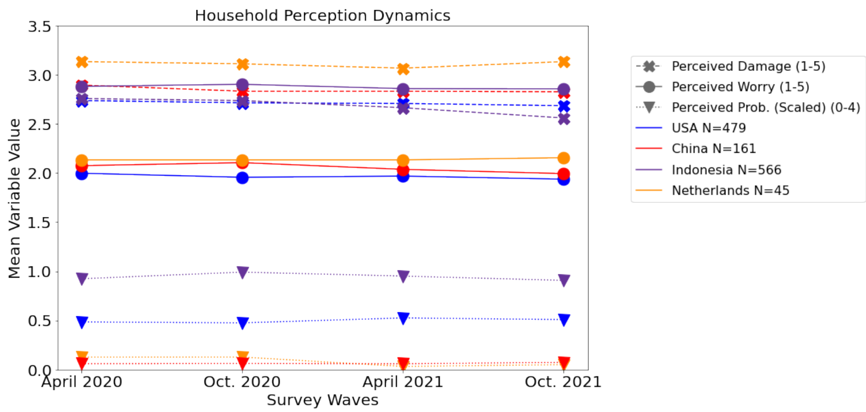

Figure 6.3: Dynamics of individual risk perception in four countries across the four survey waves.

We see that several PMT variables - perceived flood damage, worry, self efficacy, and perceived cost - have a likely effect on adaptation intention over time, across both models, as has been consistently found in cross-sectional studies (Bamberg et al., 2017; Botzen et al., 2019; van Valkengoed & Steg, 2019); supporting the persistent utility of these adaptation drivers in affecting household adaptation intention.

Finally, to examine how internal shifts in household threat perceptions and experiences affect adaptation intention over time, we compare the effects from two sets of models. One set (presented in Table 6.4) uses between-household differences to explain household intention, the other set (Appendix, Table 8.24) uses within-household changes, across the waves, in *households' experiences* and *threat appraisal* have on household intention to adapt. All other aspects of the models are identical. We note that the effects of the threat appraisal variables in the models that use the reported scores, and not the within-household differences between the waves are more likely to have an effect of greater magnitude and are more likely to differ from zero. Hence, between-household differences in threat perceptions explain adaptation intention more than internal changes (P. Jansen et al., 2020).

Table 6.4: Drivers and barriers of individual adaptation intentions. μ and σ stand for the mean coefficient effects and standard deviations of the variables from Table 6.3 estimated using the Bayesian linear and logistic random effects models across the four waves of surveys.

	Lin. μ	Lin. σ	Log. μ	Log. σ
Intercept	0.221	0.011	-10.656	0.065
Fl Prob.	-0.003	0.012	-0.001	0.041
Fl Dam.	0.039	0.012	0.175	0.048
Worry	0.058	0.013	0.222	0.050
Self Eff.	0.040	0.013	0.215	0.059
Response Eff.	0.007	0.012	0.039	0.061
Perc. Cost	-0.042	0.012	-0.182	0.050
Exp.Fl.Dam	-0.014	0.011	-0.083	0.065
Age	-0.021	0.015	-0.159	0.066
Male	0.023	0.011	0.090	0.045
Education	-0.002	0.011	-0.038	0.050
Yrs Home	-0.021	0.011	-0.124	0.048
Soc. Expect	0.015	0.012	0.118	0.053
China	0.003	0.013	0.148	0.066
Indonesia	0.085	0.016	0.488	0.080
Netherlands	0.001	0.011	-0.058	0.084

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6.3.2 Intention-Behavior gap

In a given time period$_i$, between 17-32% of households deviate from their stated plan: either by taking action when and previously reporting intention for time period t (10-29%), or not taking action when previously stating they intended to (3-8%). Of the household that *do* take action at time t, only 22-37% are doing so within their stated time frame. These percentages are in line with other panel research that finds that households adapt more than previously stated intention indicated (Osberghaus et al., 2022).

Hence, to understand to what degree intention actually leads to action, we estimate a dynamic panel model to measure intention's causal effect. As noted in the Methods, we formulate adaptation intention in two ways; as a dummy and as the number of intended measures. The dummy coded intention variable had a greater effect and constituted a better model (based on the RMSEA score - see Figure 6.4, and Figure 8.2 in the Appendix). We believe this is due, in part, to households not being good at assessing the quantity of their planned adaptation, and instead, when stating adaptation intention, expressing a more general sentiment. Hence, we focus our discussion primarily on that model and present the results of that model below. The description of the intention variable with the number of specific individual property adaptation measures can be found in Section 6.2.3.

While we see that intention is not statistically significant in its causal effect on action, it does have a positive, somewhat large effect ($\beta = 0.145, \sigma = 0.12, p - val = 0.22$, See green, Figure 6.4) that we can infer that there is a 78% chance that we would see this effect or larger not simply due to randomness. Thus, while it is relatively likely that stated intention has a positive effect on taking action, we cannot say with a high degree of confidence what it will lead to action. It is clear that there is an intention-behaviour gap that is not completely accounted for by our analysis so far. Therefore, we explore this gap in the following section to better understand what factors are correlated with a household deviating from its stated adaptation plans. We refrain from interpreting the remainder of the coefficient effects as, in the presented model, we have not estimated them causally and do not wish to fall victim to the "Table 2 fallacy" (Keele, Stevenson, & Elwert, 2020; Westreich & Greenland,

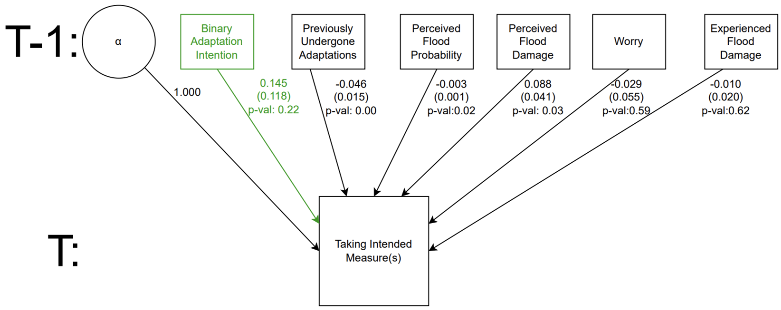

Figure 6.4: The effect of Binary intention on taking (an) adaptation measure(s) while controlling for all time-invariant effects and the depicted time-variant variables. Fit Statistics: DOF = 1; RMSEA: 0.115; chi2: 17.54, p-val $\leq$ 0.0001; AGFI: -96.88

2013). However, as noted in the Methods, we do control for these variable dynamics in estimating households' intentions' effect on action.

Next, to better understand this gap, we split intention and behavior into four groups outlined previously in Figure 6.2, and again in Figure 6.2, below. In distinguishing between those who acted with and without intent, and intended with and without following through, we delve further into the factors influencing household intention and behavior.

6.3.3 Plan without acting, Act without planning (and everything between)

What increases the likelihood that a household will act (or not act) with (or without) intent? In Figure 6.2 we show the four categories denoting the four possible combinations of intention and behavior (see Methods), with the number (and %) of households per wave in each category. While the scarce literature analyzing household flood adaptation panel data (Hudson et al., 2019) implicitly accounts for these possible combinations in their statistical models, to our knowledge this is the first explicit examination of these four categories to better understand the intention-behavior divide. In analyzing the differences between these categories, we begin to unfold the complex, causal relationship between intention and behavior and study if certain factors are likely to drive a household to belong to a specific category. Further in the Discussion, we explore behavior-specific variables - the factors that, regardless of intention, drive behavior. We are able to analyze households belonging to one of the four intention-behavior gap categories by estimating a Bayesian multinomial random effects logistic model, Figure 6.5, Table 8.25.

We begin by examining the influence of the threat appraisal variables on differentiating households' between the various types of adaptation behavioral adaptation decisions. While the differences in the variable effects are smaller in scale in this category vs. others, we still note several likely differences. Households who perceive flood likelihood to be lower are more likely to intend but not follow through (91% likely difference) and somewhat more likely (81% likely difference) to act spontaneously without intentions or earlier than intended, compared to those who adapt as intended. Households who perceive damage to be higher, however, are very likely to intend and adapt compared to the other three categories of the indention-behavior gap (89%- ~100% likely difference). Finally, the differences in the effects of worry, highlight it as a behavioral driver; as those who worry more are more likely to act, either with intention or without (≥ 80% likely difference). While lower worry makes it especially likely that a household will not intend or act (Figure 6.5).

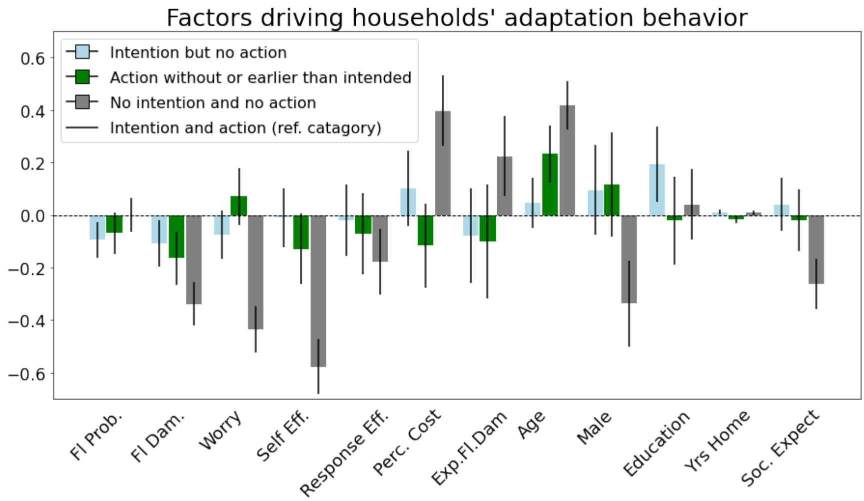

Figure 6.5: Effects and SD intervals from a Bayesian random effects multinomial model with the baseline being Households who follow through on prior intended (or not intended) adaptation plans (N=1251). Country dummies are also included in the model but excluded from the graphic. Numerical effects and variances are reported in the Appendix (Table 8.25).

In examining the coping appraisal variables, we also note several likely differences in effects between the four categories of intention-behavior gap. A lower self efficacy score makes it much more likely (~ 100% likely difference) that a household will not intend/ take any action (grey: no intent, no action, category (Figure 6.5). The effect of response efficacy, however, does not contribute to any differences between the four categories. In contrast, those who perceive the cost of adaptation to be generally higher are less likely to take action; whether they previously intended action (76% likely difference) and deviate or did not intend any (~ 100% likely difference).

In looking at the damage experienced in past floods (Exp.Fl.Dam) we note that a household who experienced more damage in a previous flood is more likely to do nothing (not intend nor take action) in the subsequent time period; perhaps because they are recovering and have limited resources for additional adaptation investments. When examining the socio-economic variables, compared to the baseline of intending and adapting as planned, older respondents are more likely to either adapt spontaneously (earlier or without intention), or do not intend nor adapt. Likewise, again compared to the baseline (reference category), men are less likely (98% likely difference) to not intend nor adapt and more educated households are slightly more likely to intend, but not act (91% likely difference). Like the variables 'worry' and 'perc. cost', the number of years a respondent has lived in their home is an intention-behavior partitioner. The more years a respondent has lived in their home, the more likely they are to not take action, whether they intended it (88% likely difference) or not (84% likely difference). Fewer years lived in a home increases the chances of taking more spontaneous action (95% likely difference). Finally, the greater social pressure a household feels from their network, the more likely (~ 100% likely difference compared to the baseline) they are to not belong to the group that neither intends nor takes action.

6.4 Discussion

In this article, we examine three research questions that progressively build on one another to advance the understanding of the intention-behavior gap, specifically in households-led climate adaptation to floods. Using a novel four-country panel data set (N=1251), we study household adaptation to floods measured in four waves with about 50% of the respondents reporting experiencing floods at least once over the course of the study.

In answering RQ1: *examining the dynamics of the perceived threat, and if within- or between-household differences have a greater effect on adaptation intention*, we look at a group of dynamic or time-variant drivers of intention: three threat appraisal variables and reported damage due to flood experience (Rogers, 1975). We see that perceptions of threat are relatively stable, in line with previous findings (Mondino et al., 2021; Seebauer & Babcicky, 2020a). Yet, they differ between countries. Notably, our study demonstrates that irrespective of the country (characterized by different flood occurrences, cultural and distributional settings), individual flood perceptions are stable even though 50% of the respondents experienced floods during our survey. It suggests that households were at least somewhat (accurately) aware of their risk prior to the floods, as has been found in prior work (Botzen et al., 2019) or have previously adjusted their risk expectations correctly to fit their environment. In our analysis, this is further supported by the fact that none of the interactions between the threat appraisal variables and experienced flood damage likely differed greatly from zero (Appendix, Table 8.23).

Another non-mutually exclusive possibility is that a longer time scale is needed to observe larger inter-household threat perception dynamics. Experiences and shifts in perceptions make take time to manifest, especially when households are bailed out by public funds, or do not yet detect changes in the hazards' severity or frequency. Analysis of what causes a shift in threat perceptions is a salient subject for future work which we note in Section 6.5. However, as climate change continues to increase the frequency in which hazards such as floods occur, it's possible that future observations will detect more fluctuation in households' threat perceptions, especially when changes to the status quo climate situation in different places will become apparent.

Next, guided by the extended version of PMT and building on the past work of household flood adaptation (Babcicky & Seebauer, 2019; Bamberg et al., 2017) we estimate several models seeking to explain household adaptation intention to floods. Over our study period, we find that perceived flood damage, worry, and self efficacy are key drivers while perceived cost is a key inhibitor of adaptation intention, in line with recent cross-sectional empirical work (T. Wang et al., 2022). However, the real objective of estimating intention with our panel data was to examine within and between-household differences. To our knowledge, for the first time in the household flood adaptation domain, we compare the effects of the three time-variant threat appraisal variables when we use the reported scores at wave$_i$ vs. household differences between the four waves. We find that the reported scores offer more explanatory power than the internal temporal household dynamics (Tables 6.4, 8.24).

Further, our analysis reveals no likely direct relationship between threat appraisal and the amount of actual damage from a flood experienced in the prior time period (Table 8.23). These two findings, paired with the relative stability of threat appraisal variables suggest that perceived threat does not necessarily manifest in behavioral responses and that it is a sturdy persuasion. It is very possible that the effect of the event could have been better observed at a later time period or that a longer survey is needed. Further, households may be anchored by their previous responses when reminded of them (Section 6.2.4), however when other longitudinal studies (i.e. (Bubeck et al., 2020)) did not prompt respondents of their previous responses, perceptions were still generally stable.

If threat perceptions are in general stable, it raises the question of if the stability is due to a prior, accurate understanding of their flood risk (i.e. recognizing that floods will happen and accounting for this in their threat appraisal) or a misunderstanding (i.e. incorrectly interpreting 1:100 probability as the next flood occurring in 100 years from now). Both possibilities lead to different futures as a misunderstanding would engender a more vulnerable society. Regardless of the reason, it reinforces the important role that coping appraisal, especially self efficacy and perceived costs, play in determining adaptation intention (Table 6.4, Figure 6.5), generally more than risk (Osberghaus & Hinrichs, 2021; Rufat et al., 2020). Intention to adapt however does not contribute to a flood-resilient society, action does. Hence we now turn to see, to what extent, intention actually leads to action.

Next, to address RQ2: *the degree to which intention leads to action*, we analyze the output of our intention-behavior model. In our study, 17-32% of households, depending on the wave, deviated from their stated plan (of either taking action or not) according to their previously recorded intention (off-diagonals blue and green squares, Figure 6.2). Here we go beyond simply noting this gap between intention and behavior and assess to what degree intention causes action (Orbell & Sheeran, 1998; Sheeran & Webb, 2016). We construct a causal model that, while controlling for our collected time-variant factors and other time-invariant factors, estimates the effect of intention on the action. Our analysis reveals that (binary-coded) intention's effect is relatively strong and positive (0.145), but insignificant. There is a 78% chance that intention's strong positive effect (or greater) is not simply due to random chance (Figure 6.4).

A number of reasons might explain this intention-behavior gap not accounted for in our model. We note that the RMSEA for our model (Figure 6.4 is higher than what is typically considered a "good" model: between 0.05-0.08 is often used as a cutoff, and ours is 0.11. Hence, there are likely missing components that influence a household moving from intention to action. First, implementing an action might require a longer time lag (Bubeck et al., 2020; Hudson et al., 2019). In some cases, if our respondents reported longer-term intention or intention after the first wave, not enough time has passed to realize their intention, possibly weakening the causal effect. Secondly, taking a non-protective response or maladaptation might be, in part, responsible for this gap (Seebauer & Babcicky, 2020a). In our survey, we do not focus on non-protective responses such as explicitly asking a household about 'denial' or 'fatalism.' Hence, including non-protective responses in future analysis may increase model performance, as we note in Section 6.5. Another factor that we omit in the present analysis is the *strength* of intention (Ajzen & Schmidt, 2020). While the perceived urgency or the firmness of a household's intention is likely partially captured by the threat appraisal variables included in this analysis (i.e. worry), there is still likely variance in the model that results from some households having stronger intention than others, and thereby having their intention more likely to lead to action. In the confines of the present variable selection, to explore the intention-behavior gap in greater detail we analyze the four possible categories of intention and behavior combinations (Figure 6.2) in the final part of our analysis.

6

In the final part of this paper, to respond to RQ3 and examine: *what are the key factors associated with households adaptation intention and behavior, and do these factors help explain the observed variation in households' actions*, we analyze differences between 1) Households who do not intend or act; 2) Households who intended to take action in a given time period but deviate and do not act; 3) Households who acted spontaneously without previously stating their intention or who took action either earlier than intended; and 4) *used as a reference category* - Households who follow through on prior intended adaptation plans (Figures 6.2, 6.5). To our knowledge, this is the first time this type of segregation analysis of the four intention and behavior combinations has been done in the flood risk domain. In comparing the differences in effects on likely categorization, several salient points are apparent.

Households that worry more about floods are the most likely to adapt without previous intent. As the only driver that separates action from no action - irrespective of prior intent - it is a factor of consequence. Worry drives *actual* household adaption, however, we also know that it plays a key role in driving intention (Table 6.4) - establishing the importance of affect in both decision formation and in a household's follow-through process(Slovic, 1987). While worry pushes households to act, adaptation costs and a longer tenure in ones' home, hold households back.

Households who perceive adaptation to be more expensive are unlikely to intend and follow through with adaptation - solidifying financial resources as a key barrier for both intention and action. However, our analysis here also reveals that if an action is affordable, a household may act spontaneously or quicker than previously expected. When considered in conjunction with the notion that adaptation can be intended in groups due in part to the cost-benefits of implementing several measures at once (Seebauer & Babcicky, 2020a), adaptation subsidies have the potential to rapidly escalate household flood preparedness. If paired effectively with an information campaign that induces a non-crippling growth in worry, a household level action strategy may prove to be a more rapidly scale-able solution to dealing with the accelerating, dynamics of climate change than a larger scale, top-down scheme.

While worry and perceived cost offer decisive insight into a household's actions, regardless of prior intent, several other variables offer clues that distinguish between-households who do not intend and take no action (grey-box, Figure 6.2) and those who both intent and take action (white-box, Figure 6.2). The three variables that comprise 'coping appraisal' as a construct are excellent predictors for differentiating between those who do not intend or nor adapt and the reference category who do both: self efficacy, $\sim$ 100% likely difference; response efficacy, 92% likely difference; perceived cost, 99.9% likely difference. The importance of coping appraisal is well recognized in driving adaptation intention, (Bamberg et al., 2017; van Valkengoed & Steg, 2019). However, its effect on motivating actual adaptation has received much less attention. Here, we likewise find that the coping appraisal factors are also important to bridging households' intention to actual behavioral adaptation (Figure 6.5).

In addition to coping appraisal, experienced flood damage, age, gender (male), and social expectations (All variables: $\geq$ 95% likely difference) all are effective in differentiating between no intention and no action, and intention and action. Older people and those who identify as female are also much more likely to not intend nor take action than their younger, male counterparts. As these two socio-economic groups already face disproportionate vulnerability (Adger, 2006; Chau et al., 2014; Cutter, 2016; Malik et al., 2017), it is pertinent to implement policy and/or messaging strategies that shrink this gap. Further, the greater damage that household experiences from a flood, the more likely it is that a household will not intend nor adapt. This underscores the debilitating impact that floods can have on households; as the more damaged is suffered, the fewer resources household have to devote to adaptation (Figure 6.5). Social pressure could be a partial solution to this barrier. While social pressure of course cannot overcome a lack of resources at the household level, when leveraged with fiscal policy to support households coping capacity, it could be a key driver aid in motivating investments following a flood to build back better (Barraque & Moatty, 2019; Filatova, 2014b; Mondino et al., 2021; Thanvisitthpon, 2017).

That low social expectations strongly increase the likelihood of a household not intending nor adapting (differentiating factor from all other categories (>99%) strongly supports the notion that both stated intention and/ or behavior are, in part, socially driven (Noll et al., 2021; Wilson et al., 2020). Heuristics have long been known to have a critical role in the decision-making process i.e. (Gigerenzer & Gaissmaier, 2010). The devastating effect suggests that like technology adoption/ innovation (Moore's Law), acceptance of the necessity of adapting to climate-induced hazards, such as floods could be slow at first, but once the early adaptors have taken measures and the influence disperses their social networks exponentially, household adaptation practice will diffuse rapidly.

6.5 Study Limitations and Future Work

Using novel data and analysis for the flood risk domain, this study made headway toward a more robust understanding of household adaptation dynamics. However, there are several limitations we acknowledge and avenues for future work we hope to inspire.

Our analysis offers a first glimpse of the factors standing between intentions and individual adaptation actions. Since surveys are costly, the scientific community and practice will likely, by and large, continue to collect data via one-short surveys capturing only intentions to adapt. What is important to recognize is that surveying respondents to merely state intention leaves a gap between intention and behavior. Future work should strongly consider soliciting the strength of the household's/ respondent's intention in implementing the adaptation measures (Ajzen & Schmidt, 2020). While this may complicate the models needed to analyze the data, the result will likely reflect a more accurate picture of the drivers of intention and ultimately behavior.

In this study, we only analyze respondents who completely answered all four waves; analyzing a *balanced* panel. Used by past studies (i.e. (Bubeck et al., 2020; Seebauer & Babcicky, 2020a)), it enables unit (in our case household) specific analysis. We stand by this method for the current study, yet recognize that future work on this data set should explore various imputations methods or run similar analyses using fewer waves, but with more respondents to examine if the results are comparable.

Next, in this paper, we present results from the first-panel analysis of this data set. As noted when presenting the results for RQ2 - the causal effect of intention on action - our model contains more error than what is typically considered for a well-fit model. Future work could expand this analysis and study the explanatory power of other dynamic variables by examining social perception (Wilson et al., 2020), beliefs (Osberghaus & Fugger, 2022), non-protective responses (Seebauer & Babcicky, 2020a), adaptation actions of different effectiveness (communication with neighbors vs. dry-flood proofing) as taking one adaptation may reduce the urge to take others (Noll et al., 2021), and perception both of self (Jones, 2019) and institutions (Mondino et al., 2021; Noll et al., 2021).

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Additionally, as we have done in the present analysis, further examination of the role of flood experience and the damage suffered is critical to understand. The time needed for recovery and the longer-term impacts of flood damage on adaptation (Jongman, 2018) are salient topics for future research.

Finally, as noted, in this paper we do not look at if the intention for a specific adaptation led to that adaptation; as this would require action-specific models. We instead examine if the intention of one or several actions at a given time period leads to action in that time period. We take this approach as we recognize that changing circumstances can lead a household to shift plans or select one action over another. Future work, however, could meaningfully examine if households accurately estimate specific actions they note that they intend (such as (Osberghaus et al., 2022)).

6.6 Conclusions

Climate change-exasperated floods continue to devastate people across the world; a phenomenon projected to increase in light of urbanization, sea level rise, and the externalities of climate change. In many contexts, household adaptation is essential to effectively reduce the societal risk of floods. Understanding what drives households to intend, and ultimately undertake adaptive measures is critical both for general resilience and to appropriately and rapidly respond to accelerating climate induced-hazards. Leveraging the unique surveys from four countries with half of the respondents experiencing floods over the observed period, we delve into the intention-behavior gap of household adaptation to floods and go beyond past work in unfolding the factors that contribute to it.

Specifically, we ask three questions aimed at collectively providing a clearer picture of the household adaptation decision-making process. We observe relatively stable threat perceptions and that intra-household differences in threat perception dynamics explain households' adaptation intentions better than inter-household. This means that policy interventions aimed at informing households' threat perceptions may not have immediate observable effects on intention as is often thought. Further, while intentions are critical to consider, on a given wave, between 17-32% of households deviate from their stated intent; rendering a quantifiable gap. Hence, next, we estimated a causal model to look at the extent of this gap and the effect of intention on behavior. While intention has a positive effect on action, the degree to which it influences cannot be stated with appropriate confidence with our model and leaves a hole in our understanding of what are all the important factors that link intention to action.

To assess this gap in knowledge, we use the factors included in an extended PMT model to distinguish households categorized by the four possible intention/ behavior combinations and thereby are able to begin to unfold this divide between intention and action. Worry and perceived cost stand out as a driver and an inhibitor that can offer effective insight into if households will take action or not, regardless of prior intent. Thus, the present analysis shows that these two factors are critical in motivating actual behavior and salient variables to include in future research in understanding intention-action gap.

Finally, we observe the detrimental effect that past flood damage can have on adaptation behavior as households appear too impacted following a flood to prepare for the next. Social influence and coping appraisal both are strong predictors of households taking actions. Hence, to facilitate a resilient household response following a flood, governments should consider combining socially based messaging (reinforcing that households should be a bit worried) with appropriate resource allocation to drive households to "build back better." Based on our analysis and data, and in contrast to many of the risk-centric messaging approaches currently employed, this strategy is likely to lead to a more flood-ready society.

6.7 Acknowledgments

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Conclusions

7.1 Conclusions

For the foreseeable future, the effects of climate change will continue to impact countries, regions, communities, and countless households globally. Floods, the most costly and damaging hazard, have a proven capacity to decimate societies and undermine livelihoods for generations. Any strategy aimed at curtailing the increasing risk brought on by climate-exasperated floods needs to invoke active participation at all levels. Government-led public adaptation measures cannot completely eliminate risk. Private adaptation or action taken at the household level increasingly must complement public action to improve societal resilience against floods

Ensuring adequate diffusion of adaptation at the household level can be challenging, as in many contexts it is difficult to study, mandate, and motivate household adaptation. Understanding how households perceive flood risk, their self-assessed abilities to curtail flood risk, and specifically what the additional key adaptation drivers and barriers are, is paramount for designing models and policies that can aid in constructing a flood-resilient society.

7.1.1 General Conclusions

This dissertation delves into household adaptation to floods using secondary and primary survey data, and varied statistical analytical approaches to address a range of research questions that culminate toward a response to a central research goal:

To progress toward an understanding of how households perceive, are affected by, and adapt to floods in various contexts over time.

The main findings of this thesis in response to this overarching goal are as follows:

1. Cultural, institutional, environmental, and social **context** impact household perceptions and adaptation decisions. In Chapters 2 and 3, using secondary and primary data and varied statistical methods, I find that adaptation drivers can vary based on the context. In Chapter 2 I present the results of a meta-analysis and analyze the data and cultural measurements to observe patterns across the previously conducted surveys studying household flood adaptation behavior. In Chapter 3, I use unique primary data collected across four countries to analyze and compare the statistical effects of adaptation drivers across countries. While in both cases there are salient differences in how various factors affect households' adaptation intentions - similarities in the effects of drivers were present

as well; offering promise to extrapolate existing household adaptation strategies to new, data-scare regions.

2. **Past adaptation actions** can help explain (future) household adaptation intended behavior. Chapters 3, 4, and 6 all highlight the relevant effect of past actions in modeling household adaptation intention. In Chapter 3, I find that past action, for both High and Low Effort measures has a likely pertinent effect in the majority of the case studies. In Chapter 3, I note that including past and additional intended actions in the analysis has a consistently positive effect on adaptation intention. While the inclusion of these factors in the model reduces the explanatory power of variables representing a household's threat appraisal, the importance of a household's coping capacity remains critical. This suggests that while threat appraisal may push a household to adapt, coping appraisal determines how the household will act. Further, in Chapter 6, I find, that prior adaptation experience is important to consider when linking intention with action. A lot of prior research ignores the influence of past actions when seeking to explain adaptation intentions and behavior. In the future, the inclusion of this component can help improve models seeking to accurately represent household decision-making processes and the accuracy of policy recommendations aimed at encouraging household adaptation behavior decisions regarding floods.

3. **Risk perception** is not born universally. Chapter 5 examines the inability of some households to subjectively assess risk. I find that risk-uncertainty is associated with belonging to populations - women, lower educated, lower income, renters - that are conventionally considered more vulnerable. I also find that individual risk uncertainty is associated with lower self efficacy, a lower likelihood of belonging to a social network that has taken adaptation actions, and a decreased probability of taking adaptation measures. This chapter presents a new way to look at survey data in the flood risk domain - one very often overlooked in previous studies.

4. A household's **coping capacity** and their perceived **social expectations** are consistent drivers of intention and action. Chapters 3, 4, 5, and 6 demonstrate the importance of considering a household's coping capacity and social network. While coping capacity is generally accounted for in behavioral theories, social network is not necessarily always present (i.e. in the original Protection Motivation Theory). The results from this dissertation highlight the salient role social norms play in influencing adaptation behavior, and suggests that its incorporation in behavioral theories would more accurately explain (adaptation) behavior.

5. The **intention-behavior** gap has a measured divide. In my analysis, I find that intention has a (likely) positive effect on adaptation. There is, however, a large degree of uncertainty in estimating the specific role it plays. To further investigate this issue, I studied the four combinations of intention and behavior and found that intention and action can be understood in conjunction via a few key factors being more likely to drive action vs. inaction (worry and perceived adaption cost). Furthermore, I find that other factors (namely: self efficacy, gender, and social expectations) can aid in distinguishing between households that do not intend nor act, and households who at least intend to act spontaneously, or without previously reporting their intent.

7.1.2 Answers to the Research Questions

In what follows, I provide detailed answers to each research question and summarize the key findings of each chapter.

Research Questions 1

What is the state of household flood adaptation research? Can we observe patterns in the effects of various adaptation drivers by culture?

I address these questions exclusively in Chapter 2. To gather the appropriate data, I reviewed 72 papers that presented results from distinctive household flood adaptation surveys and compiled the effects that various factors have on household adaptation to floods. In my examination of the state of the private adaptation literature, I find that a disproportionate number of studies had been conducted in the Global North; possibly skewing "generic conclusions" about household adaptation.

To examine this further I quantitatively analyze 53 of the 72 independent household surveys (due to available data reported in the published papers)(Household N=38,891) to study the effect of culture on household adaptation behavior. Drivers and barriers to household adaptation are often discussed generally in the field of climate adaptation. The role of culture has received some attention, however, the analytical method has almost exclusively been qualitative in its approach. This dissertation provides one of the first attempts in the flood risk domain to numerically examine if some of the variance observed in household flood adaptation data could be attributed to the cultural context of the country in which the study was conducted. To do this, I used meta-regression analysis with Hofstede's cultural rankings (Hofstede et al., 2010) as explanatory variables. In conducting this analysis of the 13 most prominently measured drivers of adaptation, I find that national-level culture can affect factors motivating household flood adaptation. The variance in the effect that flood experience has on adaptation motivation can be partially explained (up to 40%) by several cultural dimensions: Individualism, Power Distance, and Uncertainty Avoidance.

Furthermore, two other of Hofstede's cultural dimensions - Power Distance and Indulgence - exhibit statistically significant relationships with two factors that influence individual adaption motivation: faith in institutions and perceived flood probability, respectively. While the available data was limited by prior household survey work reporting the necessary information, it is likely that other household adaptation studies could have culturally dependent factors such as risk perception and self efficacy.

Research Questions 2

Can adaptation strategies be extrapolated across countries uniformly? Do adaptation drivers vary by the type of adaptation considered?

As noted when conducting the overview on the state household flood surveys in Chapter 2, I find that household flood adaptation research is disproportionately conducted in the global north; making this research question a salient one. In Chapter 3, I test for differences in drivers directly by comparing the effects of various factors motivating household adaptation intention across identical translated surveys across the four case study countries: the USA, China, Indonesia, and the Netherlands. This research presents the results from a novel survey and is the first article to directly compare identically translated questions across four case studies. Additionally, in formulating the dependent variable to represent adaptation intention, I use a ratio of the remaining possible actions that a household had not undertaken. This novel formulation allowed me to use a Bayesian beta regression to model the ratio while explicitly allowing me to account for past action's effect on current adaptive options in the dependent variable.

In the analysis, I find that a household's worry regarding floods and social influence drives adaptation intentions while perceived probability and damage have generally little effect on motivating households' actions. Self-efficacy and perceived costs are the strongest driver and barrier, respectively, for households' intentions to adopt High Effort measures; while beliefs in ongoing climate change have negative effects on adaptation intentions, perhaps because households with a sense of urgency have already adapted.

Disparities in the effects indicate that the social, institutional, and cultural contexts manifest meaningful differences in what motivates household adaptation intentions. Prior flood experience has little effect on household adaptation intention; except in the Netherlands where floods are exceptionally rare. Later on, however, in Chapter 6, I note that the severity of damage experienced does affect action. The negative effects of beliefs in insufficiency of governmental measures on households' adaptation intentions are 2-6 times stronger in USA and Indonesia compared to the Netherlands and China; whereas social media facilitates household adaptation in the Netherlands and USA, but less so in Indonesia and China. Education meanwhile encourages adaptation only in China (High Effort measures) and in the USA for both High and Low Effort measures. Finally, while perceived costs universally discourage households' adaptation, it is 2-4 times a stronger barrier in China and Indonesia compared to the USA and the Netherlands.

Despite the aforementioned differences, many of the effects of various factors, have likely similar effects on intention or, at least have the same effect sign (i.e. acts consistently as a driver). These similarities offer a baseline to extrapolate strategies to data-scarce regions where motivating household adaptation is needed, but little research exists.

The second part of this research question concerns the drivers of different types of adaptation: High Effort and Low Effort measures. In estimating separate models by type of adaptation I additionally note differences in the factors driving and inhibiting households intending to take adaptation measures. Several socio-psychological factors exhibit differences in effects between high and Low Effort measures, indicating that depending on the measure(s) under consideration households may utilize varying heuristics. I find the generally reduced influence of coping appraisal variables in deciding if to intend Low vs. High effort measures. Recognizing that decision-making processes can differ is a salient point if policymakers or risk mitigation strategists wish to encourage a specific type of behavior.

Research Questions 3

How do households consider adaptation - alone or in groups? Are adaptation actions independent of one another as is typically modeled and presumed in prior work?

In Chapter 4, I estimate household adaptation intention primarily using variables that measures a household's perceived threat and coping capacity while controlling for country of origin, and socio-economic factors. Comparing the effects within and between each set, I begin to disentangle how past and additionally intended adaptation(s) influence the decision-making process of a household considering a particular adaptation measure. While prior work has conceptually discussed possible links between household adaptation measures, this is one of the first works in the flood risk domain that uses empirical household data to broadly investigate this idea.

The analysis suggests that households who perceive their threat to be higher and worry more do intend *more* adaptation. However, once I control for additionally intended actions, the effect that worry plays in influencing a single adaptation is significantly reduced. At the same time, the effect of coping appraisal variables remains consistently significant. In line with Protection Motivation Theory, if a household can afford the measure (perceived cost), deems it effective (response efficacy), and considers itself capable of undertaking it (self efficacy) they are much more likely to intend it. The general reduction in the explanatory power of threat appraisal variables, in particular worry, paired with the relatively consistent effects of coping appraisal, suggest that while threat pushes people toward adaptation, coping appraisal determines how households will adapt.

Finally, the analysis indicates that households primed to adapt could consider taking more than one measure, possibly due to perceived co-benefits of taking actions in cohorts. Alternatively, intending multiple actions could arise from an expanding horizon - once a household explores options for adaptation, they are made aware of other possibilities that they consider as well. Hence, policies or insurance companies aiming to promote household-level adaptation, at least concerning construction measures against flooding, should consider the likely inter-connectivity in the decision-making process and leverage triggers for multiple measures. Non-marginal benefits exist for implementing several measures; meaning that investing in communicating and providing incentives for one type of construction adaptation, could lead to the adoption of multiple actions. To do so, fostering household capacity (via coping appraisal) remains crucial.

Research Questions 4

Is being risk-aware random, or can we find associations with select groups? How does being risk-uncertain about an event, like flooding, influence other perceptions and adaptation behavior?

Individual Risk-uncertainty has received considerable attention in behavioral psychology and economics. Yet in applied research, especially in the climate risk domain, risk uncertainty at the household or individual level has been hardly discussed. Utilizing "I don't know" responses on questions regarding the probability and consequences of floods as a proxy for individual risk-uncertainty, is a unique method that encourages a new perspective on threat perception in the flood risk and adaptation domain. My analysis demonstrates that people belonging to the socio-economic groups that are classically considered vulnerable to disasters are likely to be risk-uncertain. Notably, according to my analysis and data, women are more likely to be risk-uncertain, or at least more willing to admit it when responding to the survey. Likewise, less educated, lower-income individuals, and those lacking flood experience are all more likely to be risk-uncertain. The latter is unsurprising - as it reinforces the influential role that experience plays in learning.

In examining the role that individual risk-uncertainty, can play in adaptation, I find that risk-uncertain individuals are more likely to belong to socio-economic groups that are generally more vulnerable to disasters and have less coping capacity (risk-uncertain individuals report 10% less self-efficacy compared to risk-aware individuals). Furthermore, they are less likely to adapt to floods (significantly less likely to intend at least one of both High Effort (χ^2=130, p=0.0) and Low Effort (χ^2=106, p=0.0)).

Like in Chapter 3, I utilize two grouping methods of adaptation estimation - High Effort and Low Effort to test if the effect is similar across different types of adaptation decisions. I find consistent differences in the drivers of behavioral adaptation between risk-uncertain and risk-aware individuals. The cross-model consistency of findings lends credence to the notion that lacking the knowledge to assess risk has persistent behavioral consequences. Previously, this idea has not been explicitly entertained in the households' climate change adaptation literature, with only scarce evidence from other domains. Differences in vulnerability, adaptive capacity, and behavior have gone unrecognized due to analytical methods and practices that typically drop or group risk-uncertain individuals with those who can assess risk.

Besides these methodological implications, these findings have consequences for climate change adaptation policies. Namely, messages seeking to inspire individual adaptation by targeting worry may be less effective for risk-uncertain individuals compared to risk-aware. Further, the influence that social networks have on adaptation is amplified for the risk-uncertain, possibly because those who do not know, copy others.

Research Questions 5

How do household risk perceptions change over time? Does the intention to implement structural flood adaptation measures lead to action? What characteristics are associated with the household adaptation intention-behavior gap?

In Chapter 6 I use panel data, collected from the four case study countries over 1.5 years to address these questions. Initially, when looking at perception dynamics, separated by countries I note differences in the country-level aggregated means. For example, Indonesians accurately perceive the likelihood of them experiencing a flood to be the greatest, followed by households from the USA and both the Dutch and the Chinese respondents perceive the likelihood of experiencing a flood as relatively low. While there is variation at the group level between countries, within each country, despite floods occurring during the course of the survey, all three measures of threat appraisal remain relatively consistent. Next, in delving into the effects of these threat perceptions, I test the explanatory power of inter- and intra-household threat appraisal and find that intra-household differences in threat perception dynamics offer more power than inter-household when motivating household adaptation intention.

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Intentions are critical to consider, yet on a given wave, between 17-32% of households deviate from their stated plan (intending or not intending). Hence, next, I estimated a causal model to look at the effect of intention on action. While intention has a positive effect on action, the degree to which it influences cannot be stated with a high degree of confidence and leaves a gap in the understanding of what are all the important factors that link intention to action.

To analyze this gap, I test the factors included in an extended Protection Motivation Theory model to distinguish households categorized by the four possible intention/ behavior combinations and thereby are able to begin to untangle this divide between intention and action. This research is the first article in the flood adaptation domain, to my knowledge, that unfolds the four adaptation-behavior categories and examines the factors that contribute to each category. Worry and perceived cost stand out as a driver and an inhibitor that can offer effective insight into if households will take action or not - regardless of prior intent. I also observe the detrimental effect that past flood damage can have on adaptation behavior - households appear too impacted following a flood to prepare for the next. Social influence and coping appraisal both are strong predictors of households taking action. Thus, to facilitate a resilient household response following a flood, governments should consider combining socially based messaging (ideally induces a non-debilitating amount of worry) with appropriate resource allocation to drive households to "build back better." Based on my analysis and data, this recommendation is likely to be met with more success and is in contrast to many of the risk-centric messaging strategies currently employed.

7.1.3 Contributions to Science

The research presented in this dissertation makes several contributions to the empirical literature on climate adaptation behavior. First, I employed a novel methodology and collected and analyzed unique data to contribute a new perspective on the rich, largely qualitative literature, on culture, disaster risk, and adaptation (Adger et al., 2013; Gierlach et al., 2010; Kruger et al., 2015). The meta-regression analysis presented in Chapter 2 examined to what degree the cultural context in which the survey took place could explain variance in the statistical effects of various factors on adaptation. Previously due to data availability, much of the previous analysis on cross-country differences in adaptation drivers and barriers have been conceptual (Cannon, 2015) or perception-focused (Gierlach et al., 2010), rather than have a behavioral component. This was among the first attempts in the flood risk domain to quantitatively assess the impacts of country culture on a global scale; for which there is an urgent need (Hopkins, 2015). I then built on this idea in Chapter 3 where when analyzing the findings from the first wave of the four-country survey, I assessed differences in the statistical effects that various factors had on adaptation.

A second notable contribution this dissertation provides to science is that it offers a novel method of studying individual risk-uncertainty and reclassifies a group that had previously been all but ignored in the household adaptation literature. Different methods have been proposed and tested to classify general uncertainty (i.e. (Hanea et al., 2021; Harrington et al., 2021; Olazabal et al., 2018; Oppenheimer et al., 2016)), uncertainty in the modeling process and understand its consequences in climate adaptation modeling and research (Berkes, 2007; Kettle & Dow, 2016). Uncertainty is increasingly embraced in supporting governments' decisions (Haasnoot et al., 2019; Wing et al., 2020; Zarekarizi et al., 2020). Yet, understanding uncertainty in individual climate-related risk judgments has received limited attention (Rufat et al., 2022), despite the fact that this is where many climate adaptation decisions take place.

In Chapter 5, I classify and analyze how risk-uncertain affects individual adaptation perceptions and behavior and assess the consequences should the field continue to ignore this distinct group. The notion of uncertainty being an additional dimension to individual risk perception has implications for many behavioral theories that do not explicitly acknowledge uncertainty in individual judgements and postulate that a high perceived risk/ threat is directly linked to action. My research suggests that incorporating this dimension explicitly in individual behavioral theories would better explain individual behavior in situations that are probabilistic, such as flood and climate adaptation.

A final contribution that this dissertation makes to science is the analytical approach taken to study the intention-behavior gap. In Chapter 6, I analyze the panel survey data from the four-country survey and was especially interested in the intention-behavior gap, separating households' adaptation intentions from actually undertaking the action. I was fortunate to have a small, but quality sample of past longitudinal research in the flood risk domain to look to for knowledge and inspiration (Bubeck et al., 2020; Hudson et al., 2019; Mondino et al., 2021; Osberghaus et al., 2022; Seebauer & Babcicky, 2020a). However, while some of the previous work had measured the intention-behavior gap with statistical modeling techniques, the collective analysis had stopped short of unfolding this gap further and analyzing the factors contributing to households behaving in certain manners. The analysis presented in Chapter 6 goes beyond prior panel analysis, using statistical methods that had not been previously employed in this domain to offer a novel perspective on the relationship between intention and behavior. In doing so, I am able to provide an empirically-based estimate of how large the intention-behavior gap is and what factors contribute to its existence; the latter of which had not been previously analytically assessed in the flood risk domain.

7.1.4 Policy Implications

Motivating household adaptation behavior has been a salient topic of research in responding to climate change and fostering resilient societies (Adger, 2006). Governments cannot eliminate the risk of flooding; hence **household adaptation is critical** to respond dynamically to evolving threats. In this dissertation, I make strides to better understand how households think, what motivates household adaptation and how various contexts affect both perceptions and behavior. These findings have direct implications for policymakers seeking to motivate household adaptation. Depending on their objectives they can target the various factors that were strong drivers and inhibitors of varying actions.

While the survey offers an in-depth look at four case studies, the analysis presented in this dissertation offers critical insights into households outside these areas as well. I find that **certain factors are generically effective in driving or hindering adaptation**. Specifically, across the chapters, I note the continued importance of worry, perceived self efficacy, and perceived social expectations in motivating adaptation. As **these factors are perceptions, they are susceptible to information provision**. A focus on these factors will have a far greater effect on motivating households to take adaptation measures compared to traditional risk messaging.

Furthermore, research presented in Chapter 3 suggests that **adaptation measures are likely considered in consort**. When this idea is considered with the fact that perceived costs are a consistent barrier for households to take adaptation measures, subsidies or attractive government loans could tip a number of households to take multiple actions; dramatically increasing preparedness and/or reducing risk. Since flood risk can be very localized, bottom-up approaches have the potential to more effectively and dynamically respond to climate change in many contexts, complimenting large-scale government-led projects.

Finally, in Chapter 6, I present the analysis of the panel data from the four-country survey. In the analysis, I find that threat perceptions and emotions are, on a group level relatively stable, despite that a number of households experienced floods each wave. Country differentiation in perceptions likewise accurately reflects the comparative frequency that each case study experiences floods. This suggests that household perceptions are somewhat accurately based on context and on prior experience. This engenders that a single event is unlikely to cause a large shift in behavior or perceptions. In recognizing that perceptions are resilient to large shifts after a single event, policymakers should realize that **a single flood is unlikely to spur a dramatic shift in perceptions and (adaptation) behavior**. External messaging, support, or policy instruments are needed to shift behavior in a rapid manner.

7.1.5 Research limitations

One of the principle objectives of Chapters 2 and 3 is to study how culture can affect household-level adaption behavior. I curated two novel data sets to analyze the effect of culture on behavior and offer unique insights into how households adapt. However, both analyses were, in their respective way, limited by the available data. In Chapter 2, I exhaustively searched for all published statistical analyses of surveys that examined household adaptation to floods. There were many different manners in which the surveys were administered and all surveys did study the same type of adaptation measures. This engendered that when I collectively analyzed the effect sizes, I was grouping and comparing the effects of various measures and survey designs. I do not, however, have any reason to suspect that the solicitation of certain adaptation measures varied in a systematic manner across cultures. Hence, I believe there may be Type II statistical errors present in the analysis due to the variance caused by various measurements and measures. If in the future this analysis were repeated with a larger sample I suspect that more factors may be found to vary in their effect on adaptation by cultural context.

In Chapter 3, using the four-country survey I designed, I analyzed cross-country differences in the effects of various factors driving household adaptation. While this survey, in terms of the number of countries included in the study was the largest to date, the number of countries still proved a limiting factor. As there are only four countries, I was unable to statistically attribute the observed variation in the effects to differences across countries. Instead, I relied on extensive qualitative research to explain these differences. A larger sample would enable analysis that could offer more clarity as to exactly what contextual factors are associated with varying effects. I discuss avenues to build on the analysis presented in both Chapters 2 and 3 below, in Section 7.1.6.

In Chapter 5, I explore a new idea in the flood risk domain of risk-uncertainty. This concept offers a new way to think about household flood adaptation and advances our understanding of how risk perception affects adaptation decisions and how the analytical choices we make as scientists can greatly affect our results. In exploring this concept in the domain for the first time, I categorized households in a discrete manner: risk-aware (have the ability to subjectively assess risk), and risk-uncertain (do not/ cannot subjectively assess risk). There is undoubtedly a spectrum of risk-uncertainty; a nuance that the work presented in this chapter does not capture. Future work could build on the analysis presented in Chapter 5 by exploring additional methods of measurement and analysis. I explain the means of doing so in greater detail in Section 7.1.6.

Finally, in Chapter 6, I analyze the longitudinal survey data collected between 2020-2021. My research objective for this chapter was to make strides in understanding the intention-behavior gap. To study intention and behavior generally, and not focus on a specific measure, I modeled general adaptation and did not examine if households took a *specific* action they previously stated they intend. While the length is long for a survey, it is short in terms of the average human life. Hence, my analysis is limited by the data in that it only has four temporal data points and does not consider if a household changed their minds and undertook a different measure or implemented a different number of measures than originally intended. Simplifying household adaptation behavior was a necessary trade-off for the statistical approach that I selected, however, my analysis does not offer information as to if households are following through on the specific measures they state, only on adaptation generally. These limitations are discussed in greater detail in Section 7.1.6, below.

7.1.6 Perspectives for future research

At the root of climate change adaptation is the core question of how people interact with and make decisions concerning the environment around them. This dissertation makes strides toward understanding this complex and dynamic relationship. Of course, while taking these figurative steps, far more questions are left unanswered and new queries manifest. Below are a few of the salient lines of research that will provide a more in-depth and robust understanding of human behavior as it concerns climate adaptation.

Contextual factors influence on adaptation

In Chapters 2 and 3 I study the effect of culture and country-level differences on adaptation intent. A key purpose of this research was to aid in extrapolating findings from existing case studies to data-scarce regions. However, in the future with more survey data becoming available and surveys becoming more standardized (thanks to efforts like this: Rufat et al. (2022)). Standardized, hierarchical analysis both within and between countries would greatly advance our understanding of household adaptation behavior as it would enable researchers to tease out institutional, contextual, and environmental factors that affect individual perceptions and behavior when they concern adaptation and would be especially suited for a differences-in-differences approach.

Intentions

Adoption prioritization and strength of intention are additional areas in which future work could take strides in understanding household adaptation. As is standard practice in the flood risk domain, in this thesis, in the survey I designed, I measure intention as a binary: Yes the household intends this measure (and when); The household never intends this measure. As households could also indicated *the time frame in which* they intended to take the measures the binary method was chosen to not overwhelm the survey respondent. However offering households the opportunity to mark the strength of this intent may prove to be a missing link in the intention-behavior gap and can be assessed on a scale in a survey. Further, the strength of intention offers some insight into the prioritization of households - if a household has adaptation intentions that are (consistently) low strength, it would be logical to deduce that they are of low(er) priority compared to other issues the household desires to address. However, prioritization itself may prove to be a greater challenge to assess as it requires households to report flood adaptation against other facets of their life; many of which, are of course, unique. One method to assess priority that is worthy of consideration is risk ranking (Webster, Jardine, Cash, & Mcmullen, 2010). However, as I have shown in this dissertation, risk perception is not often the primary driver of adaptation (Chapter 3), and not all households have the capacity to assess their respective risk (Chapter 5), hence additional (proxy) measurements or other methods of research, such as qualitative interviews, may be needed to complement the survey to provide the whole picture.

Perceptions dynamics and behavioral consequences

In Chapter 6 I analyze threat perception dynamics and their effect on household adaptation intention. In the analysis, I find that most threat perceptions are steady and that within household threat dynamics matter less in explaining adaptation than between household differences. While I test if the effects of the threat perception dynamics are mediated by experienced flood damage, an insightful next step in the analysis of the dynamics of household perceptions would be to look at if flood experience or other factors cause a (+/-) shift in threat. Furthermore, *if* a household updates its perceptions, what are the (behavioral) consequences?

Going beyond examining the dynamics of threat perceptions, analyzing and incorporating further dynamic variables such as social expectations in the analysis of household intention to behavior additionally has the potential to more robustly bridge the intention behavior gap. In Chapter 6, I estimate the causal effect of intention on action. The lagged dynamic panel structural model is one of the first of its kind in the flood risk domain and incorporates the importance of considering past action(s) from Chapter 4. However, from the variables utilized in the analysis, it accounts for less variance than is typically considered a "good" predictive model in social science, and in part causes the estimate of intention's effect on behavior to have a large degree of uncertainty (wide σ).

Future research that explores different variables testing (i.e. with more/ different dynamic variables or different theories), or has more temporal data points, is likely to be able to eliminate additional variance and provide a more robust estimate of intention's effect on behavior.

Modeling and Uncertainty

As computational social science continues to grow in popularity, and the simulation models in climate change research utilized to study various phenomena increase in complexity, a more realistic representation of human behavior becomes increasingly important to accurately capture and depict risk. Especially as models become more open source and modular, this will (ideally) lead toward more cross-scale and cross-discipline integration. Analyzing model uncertainty (i.e. with sensitivity analysis) has received increasing attention due to advances in computational power. However, while measuring the variance in models is increasingly included in the discussion of model validation, the incorporation of uncertainty and diversity in human behavior lags.

In the last years, there have been marked efforts to improve upon representations of human behavior (i.e. (Aerts et al., 2018; de Koning & Filatova, 2020; Taberna et al., 2020)), yet many models examining climate adaptation still use "representative households" or, the select models that can incorporate heterogeneous households, typically use deterministic decision-making functions. Chapter 3 in this thesis, using Bayesian methods, presents and analyzes the variance (uncertainty) in the estimate of the statistical effects of various factors under varying conditions. Further, in Chapter 5, uncertainty in decision-making is explicitly analyzed and the effect is shown to be non-marginal in a variety of scenarios including who is uncertain and the effect that it has on adaptation. Future work wanting to explore the full space of uncertainty should consider incorporating it in models supporting climate change adaptation policies. By not forgetting about the uncertainty present in real individuals - not just in models - future work can make strides to depict more realistic climate adaptation behavior.

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8

Appendix

8.1 Appendix for Chapter 1

Flood events from Figure 1.3

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11. https://floodlist.com/asia/indonesia-floods-landslides-mid-october-2020
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8.2 Appendix for Chapter 2

Cambodia's Cultural Rankings

From Berkvens (2017) we have calculated the the scores for Cambodia's different cultural dimensions using the following logic:
Individualism: Thailand, Hong Kong, S. Korea and Taiwan are averaged due to their comparison to Cambodia. **Power Distance**: Cambodia has "a large power distance." Vietnam and Malaysia, two neighboring countries with high Power Distance are averaged. **Uncertainty Avoidance**: "is higher than Thailand," thus we average Thailand's score with S. Korea's -a country with a very high Uncertainty Avoidance ranking in the region. **Masculinity**: "a similar position to Thailand," we copied Thailand's score. **Long-Term Orientation**: Cambodia is more short term oriented than Thailand, we copied the Philippians score; a shorter term oriented neighboring country. **Indulgence**: This dimension was not included in the paper, thus we average Malaysia, Thailand, and Vietnam.

Equations for transforming effect sizes

Spearman's rho (ρ) converted to Pearson's r (Rupinski & Dunlap, 1996)

$$r = 2\sin(\frac{\pi}{6} * \rho) \tag{8.1}$$

Chi Squared (χ^2) (df =1) converted to Pearson's r (Rosenberg, 2010)

$$r = \sqrt{\frac{\chi^2}{n}} \tag{8.2}$$

Odds Ratio (OR) converted to Pearson's r (Field & Gillett, 2010)

$$r = \frac{\sqrt{OR} - 1}{\sqrt{OR} + 1} \tag{8.3}$$

Kendall's tau (τ) converted to Pearson's r (Walker, 2003)

$$r = \sin(0.5\pi * \tau) \tag{8.4}$$

beta (β) converted to Pearson's r (y = 1 when β is greater than or equal to zero, and 0 when β is smaller than zero) (Peterson & Brown, 2005; Van Valkengoed & Steg, 2019)

$$r = \beta + 0.05y \tag{8.5}$$

Logistic regression coefficients (λ) converted to Pearson's r (Field & Gillett, 2010; Ialongo, 2016)

$$OR = e^{\lambda} \qquad\qquad r = \frac{\sqrt{OR} - 1}{\sqrt{OR} + 1} \tag{8.6}$$

Pearson's r to Fisher's Z for variance stabilizing and then back to Pearson's r for reporting the values (Borenstein et al., 2009)

$$Z = 0.5 * ln(\frac{1+r}{1-r}) \qquad\qquad r = \frac{e^{2Z} - 1}{e^{2Z} + 1} \tag{8.7}$$

8.3 Appendix for Chapter 3

Specification and descriptive statistics of the 16 Explanatory Variables

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Table 8.1: Explanatory variables used in the analysis

			Country level descriptive statistics			
Construct (Abbreviation)	Question	Response Options	**USA** μ (s.d.)	**China** μ (s.d.)	**Indonesia** μ (s.d.)	**Netherlands** μ (s.d.)
Flood Probability (Fl Prob)	How often do you think a flood occurs on the property on which you live (e.g.due to rivers or heavy rain, storms and cyclones)? Which category is the most appropriate?	*6 point scale (Multiplied all % values by 5)* My house is completely safe 0.0% chance annually Less often than 1 in 500 years ~ 0.1% chance annually Once in 500 years or a 0.2% chance annually, Once in 200 years or a .5% chance annually, Once in 100 years or 1% chance annually, Once in 50 years or a 2% chance annually, Once in 10 years or 10% chance annually, Annually ~ 100% chance annually, More frequent than once per year ~ 100%	0.58 (1.29)	0.10 (0.42)	0.66 (1.39)	0.10 (0.51)
Flood Damage (Fl Dam)	In the event of a future major flood in your area on a similar scale to ___ ‡ how severe (or not) do you think the physical damage to your house would be?	*5 point scale* (1) Not at all severe - (5) Very severe	3.11 (1.25)	2.97 (1.07)	2.67 (1.21)	3.16 (1.17)
Worry (Worry)	How worried are you about the potential impact of flooding on your home?	*5 point scale* (1) Not at all worried - (5) Very worried	2.40 (1.12)	2.10 (0.96)	2.65 (1.15)	2.07 (1.12)
Self Efficacy (Self Eff)	Do you have the ability to undertake this measure either by yourself or paying a professional to do so?	*5 point scale for each measure** *High Cost/ Effort Measures μ and s.d. on top* *(averaged for all measures in same category)* (1) I am unable - (5) I am very able	3.34 (1.00) 3.68 (0.87)	3.52 (0.74) 3.67 (0.73)	3.58 (0.73) 3.73 (0.66)	3.09 (0.85) 3.27 (0.77)
Response Efficacy (Resp Eff)	How Effective do you believe implementing this measure would be in reducing the risk of flood damage to your home and possessions?	*5 point scale for each measure** *High Cost/ Effort Measures μ and s.d. on top* *(averaged for all measures in same category)* (1) Extremely ineffective - (5) Extremely effective	2.47 (1.20) 3.90 (0.83)	2.62 (0.94) 3.62 (0.72)	3.11 (0.89) 3.71 (0.66)	2.34 (0.98) 3.39 (0.85)
Perceived Cost (Cost)	When you think in terms of your income and other expenses do you believe implementing (or paying someone to implement) this measure would be cheap or expensive?	*5 point scale for each measure** *High Cost/ Effort Measures μ and s.d. on top* *(averaged for all measures in same category)* (1) Very cheap - (5) Very expensive	3.87 (0.75) 2.46 (0.99)	3.40 (0.61) 2.65 (0.77)	3.64 (0.60) 2.77 (0.72)	3.60 (0.76) 2.52 (0.79)
Previously undertaken measure(s) (Undergone)	I have already implemented this measure	Yes (1) or No (0) for *each* measure *(If Household has implemented $\geq$1 measure,* *in a category the dummy variable = 1* *High Cost/ Effort Measures μ on top*	0.28 0.79	0.18 0.43	0.40 0.70	0.21 0.49
Flood Experience (Fl Exp)	Have you ever personally experienced a flood of any kind?	Yes (1) or No (0)	0.48	0.19	0.46	0.15
Age (Age)	YouGov collected this information prior to the survey	1: [16-24], 2: [25-34], 3: [35-44], 4: [45-54], 5: [55-64], 6: [65+]				
Education (Edu)	YouGov collected this information prior to the survey	1: < High School, 2: High School, 3: College Degree, 4: Post Graduate	See Table S.2 for categorical percents for age, education, and gender.			
Gender (Male)	YouGov collected this information prior to the survey	Male (1) and Female (0) *The authors do not imply gender is binary,* *but did not receive other data*				
Belief on effects of climate change (C.C. Now)	There is a lot of discussion about global climate change and its connection to extreme weather events. Which of the following statements do you most agree with?	*Bold response a dummy (0,1)* ** **Global climate change is already happening** Global climate change isn't yet happening, but we will experience the consequences in the coming decades Global climate change won't be felt in the coming decades, but the next generation will experience its consequences Other opinion	0.79	0.62	0.72	0.62
Perception of Government Measures (Gov Meas. Insuff.)	Do you think the current measures that the municipal government have implemented are sufficient to stop the risk of floods and heavy rain?	*Bold response a dummy (0,1)* ** Yes – they are sufficient and will last for the foreseeable future (30+ years) Yes – but they will need to be updated within the next decade **No – they are not currently sufficient**	0.43	0.22	0.30	0.11
Social Influence (Social Inf)	Do your family, friends and/or social network expect you to prepare your household for flooding?	*5 point scale* (1) They do NOT expect me to prepare for flooding - (5) They strongly expect me to prepare for flooding	3.34 (1.25)	2.88 (0.99)	3.29 (1.02)	2.35 (1.21)
Effect of social media on household adaptation (Social Media)	How frequently do you read information about flooding and other hazards on social media? To what extent, if at all, do you trust the information about flooding and other hazards from social media?	*Two, 5 point scales averaged**** (1) Very infrequently - (5) Very frequently (1) Do not trust at all - (5) Trust completely	2.67 (1.76) α=0.80	3.16 (1.11) α= 0.51	3.49 (1.17) α=0.62	2.29 (1.56) α=0.76
Effect of general media on household adaptation (General Media)	How frequently do you read information about flooding and other hazards from the general media? To what extent, if at all, do you trust the information about flooding and other hazards from the general media?	*Two, 5 point scales averaged**** (1) Very infrequently - (5) Very frequently (1) Do not trust at all - (5) Trust completely	3.39 (0.95) α=0.60	3.21 (0.76) α=0.45	3.62 (0.76) α=0.62	2.87 (0.90) α=0.55

‡USA: "the flooding from Hurricane Harvey in 2017"; China: "the 2017 China floods in Hunan"; Indonesia: "the 2020 Jakarta floods"; Netherlands: "the North Sea Floods of 1953"

*Following the empirical adaptation research tradition ((Botzen et al., 2019; Bubeck et al., 2013)), for self efficacy ('Self Eff'), response efficacy ('Resp Eff') and perceived cost ('Cost') we average the response scores for the respective High and Low Effort categories across multiple adaptations actions in a model for all three Coping Appraisal variables. Using the mean score for each of the three variables provides information on the respondent's *general* beliefs on this aspect of flood adaptation rather than allowing for distinguishing *between* measures (P. Jansen et al., 2020).
**With regards to the two belief variables (Gov Measures and C.C. Now), we use dummies here as opposed to scales as we phrased the survey questions to capture time (i.e. 'Do you believe that climate change is happening now, believe it will happen in the near future, in the distant future...). Hence, each response is a dummy. We estimated the effects of all dummies from both questions across all four countries. The dummies we selected to use in the analysis represent beliefs that concern the present (now), and in turn, had the greatest effect on current intention. Thus to keep the number of explanatory variables reasonable, we selected only these dummy variables to include in the analysis.
***For social media and general media we use probability (frequency of media exposure) and affect (trust in observed media) to test the effect both information sources have on adaptation intention (two separate 1-5 likert scale questions). The two questions do not measure the same construct, hence the low Cronbach alpha scores in several of the counties. However, together the two variables provide information on the number of times a respondent is exposed to flood information (frequency) of exposure and the possible impact (measured by trust). The object of this analysis is to compare effects between countries and hence to keep the number effects compared reasonable, we combined these two variables on the basis frequency and impact.
For the remainder of the constructs we use a single item scale as is common practice (Botzen et al., 2019; Koerth et al., 2013; Poussin et al., 2014).

Survey Population Statistics

Table 8.2: Households' survey locations and sample sizes used in the analysis - after removing non-responses and respondents who had already completed all adaptation measures. For simplicity, throughout the paper we refer to each sample by the country name, however we acknowledge that our urban samples are not representative of the entire country.

Countries	Sample	Cities
The United States of America	N=1,139	Miami, Fl; Houston, TX; New Orleans, LA
The People's Republic of China	N=842	The greater Shanghai area
The Republic of Indonesia	N=1,080	The greater Jakarta area
The Kingdom of the Netherlands	N=728	The greater Rotterdam area

Table 8.17 shows the population statistics on the three "background" or socio-economic variables included in the analysis. In general, the survey sample is representative of the population. In Indonesia, the medium age is a decade younger than in the other three countries and in both China and Indonesia many elderly people

live with their children or younger family members. As our objective is to study household adaption, and only one member per household was allowed access to our survey, the lack of older respondents from these two countries was anticipated and we do not regard it as problematic for our analysis. While our sample is in general more educated than the general population, to help ensure that the distribution of these three 'background' variables does not bias the effects in the analysis, we control for age, education, and gender in all our models.

Table 8.3: Distribution of the survey respondents' gender, age, and education demographics by country from the data included in the analysis. Due to rounding, percents may not sum exactly to 100.

		Survey Percentages by Country			
Variables		USA (N=1139)	China (N=842)	Indonesia (N=1080)	Netherlands (N=728)
Gender	Female	52%	52%	45%	45%
	Male	48%	48%	55%	55%
Age	16-24	11%	19%	23%	20%
	25-34	22%	50%	42%	23%
	35-44	19%	23%	25%	17%
	45-54	19%	5%	7%	13%
	55-64	14%	2%	2%	11%
	65+	16%	1%	0.5%	17%
Education	< High School	3%	0.4%	1%	4%
	High School	39%	2%	41%	43%
	College degree	33%	69%	51%	44%
	Post Graduate	25%	29%	7%	9%

Table 8.4: Census data on gender, age, and education demographics in each of the surveyed cities (*City Population Rotterdam*, 2021; *Shanghai Municipal Bureau of Statistics*, 2020; *Shanghai Poeple's Government*, 2020; *Statistik Daerah Kota Jakarta Selatan 2016*, 2016; *United States Census Bureau*, 2019). Due to information scarcity and fragmentation, the age category does not exactly align with categories from our survey nor with data from other countries. Yet, these official statistics still provide a useful baseline picture to judge the representativeness of the survey sample. Percentages, due to rounding, may not sum exactly to 100.

	USA (2019)				**China** (2019)		**Indonesia** (2015)		**Netherlands** (2021)	
Variables	*Cat.*	New Orleans	Houston	Miami	*Cat.*	Shanghai	*Cat.*	Jakarta	*Cat.*	Rotterdam
Gender	F	52.5%	50.1%	51.4%	F	50.5%	F	49.8%	F	50.6%
	M	47.5%	49.9%	48.6%	M	49.5%	M	50.2%	M	49.4%
Age	5-17	20.1%	25.1%	20.2%	<17	12.3%	15-24	14.9%	10-19	10.4%
	18-65	59.9%	56.8%	57.3%	18-34	16.2%	25-34	20.5%	20-29	17.1%
	65+	14.1%	10.5%	16.7%	35-59	36.4%	35-44	17.4%	30-39	15.5%
					60+	35.2%	45-54	12.2%	40-49	12.6%
							55-64	7.0%	50-59	12.7%
							65+	4.1%	60-69	10.0%
									70+	10.9%
Education	<High School	13.5%	21.1%	18.6%	<High School	47.1%	<High School	39.3%	<High School	29%
	High School	48.9%	46%	51%	High School	19.0%	High School	40.9%	High School	37%
	≥College	37.6%	32.9%	29.8%	≥College	33.9%	≥College	20.0%	≥College	34%

S.3: Groups of Household Flood Adaptation Measures

When designing our survey, by referencing prior empirical work from several meta-analyses (Bamberg et al., 2017; Bubeck, Botzen, Suu, & Aerts, 2012; Noll et al., 2020; van Valkengoed & Steg, 2019), we were able to construct a list of 18 commonly used adaptation options, that we included in our questionnaire. While the list is not comprehensive, it does represent the majority of commonly practiced adaptation measures. For the purposes of the current research, we divide the 18 measures into two classes. Here we model intention over adaptation due to the feedbacks that can exist between current perceptions and previously undergone measures (Bubeck, Botzen, Suu, & Aerts, 2012).

Table 8.5: Factor Loadings from confirmatory factor analysis by country for both adaptation groupings. Factors analysis was conducted using Sklearn (Buitinck et al., 2013). Cronbach alpha is presented for each group, by country, at the bottom of each section.

	Factor Loadings			
High Effort Measures	USA (N=1139)	China (N=842)	Indonesia (N=1080)	Netherlands (N=728)
Raising the level of the ground floor above the most likely flood level	0.91	0.91	0.90	0.91
Strengthening the housing foundations to withstand water pressures	0.93	0.92	0.91	0.93
Reconstructing or reinforcing the walls and/or the ground floor with water-resistant materials	0.92	0.93	0.91	0.93
Raising the electricity meter above the most likely flood level or on an upper floor	0.93	0.93	0.91	0.94
Installing anti-backflow valves on pipes	0.93	0.92	0.92	0.93
Installing a pump and/or one or more system(s) to drain flood water	0.93	0.93	0.92	0.94
Fixing water barriers (e.g. water-proof basement windows)	0.93	0.93	0.91	0.94
Installing a refuge zone, or an opening in the roof of your home or apartment	0.90	0.89	0.89	0.91
Cronbach Alpha	*0.94*	*0.93*	*0.90*	*0.95*
Low Effort Measures				
Keeping a working flashlight and/or a battery-operated radio and/or emergency kit in a convenient location	0.91	0.93	0.92	0.93
Purchasing sandbags, or other water barriers	0.93	0.93	0.92	0.93
Buying a spare power generator to power your home	0.93	0.93	0.89	0.94
Storing or placing important possessions (such as documents or expensive furniture) in such a manner to avoid flood damage	0.93	0.94	0.92	0.94
Storing emergency food and water supplies	0.94	0.94	0.93	0.95
Moving/ storing valuable assets on higher floors or elevated areas	0.94	0.94	0.94	0.95
Being an active member in a community group aimed at making the community safer	0.95	0.94	0.93	0.94
Coordinating with the neighbors in case you are not home when a flood occurs, they would know what to do	0.94	0.93	0.94	0.94
Asking someone (local government, Civil Defense, etc.) for information about what to do in case of emergency	0.95	0.94	0.93	0.95
Asking/ petitioning government representative to increase the public protection measures	0.95	0.94	0.93	0.95
Cronbach Alpha	*0.90*	*0.92*	*0.90*	*0.93*

S.4: Coefficients of the Extended PMT model

Effect sizes presented in Figure 2 in the main text are estimated from Bayesian beta regression models. We present the mean of the effect distribution ($\hat{\beta}$), the standard deviation (σ) and a convergence diagnostic for the four monte carlo chains ($\hat{r}$). $\hat{r} = \hat{V}/W$ where W is the within-chain variance and $\hat{V}$ is the posterior variance estimate for the pooled traces. Values > 1 suggests that chains have not yet converged.

Table 8.6: Coefficients from the regression models of household adaptation with 16 independent variables.

USA (N=1139)

	High Effort			Low Effort		
	Mean of $\hat{\beta}$	σ	$\hat{r}$	Mean of $\hat{\beta}$	σ	$\hat{r}$
Intercept	-0.67	0.18	1.0	-0.44	0.21	1.0
Fl Prob	-0.01	0.02	1.0	-0.02	0.03	1.0
Fl Damage	0.01	0.02	1.0	-0.02	0.02	1.0
Worry	0.07	0.02	1.0	0.05	0.03	1.0
Resp Eff	-0.01	0.02	1.0	0.08	0.04	1.0
Self Eff	0.21	0.03	1.0	-0.05	0.05	1.0
Cost	-0.06	0.03	1.0	0.08	0.04	1.0
Undergone	0.03	0.05	1.0	-0.11	0.07	1.0
Fl Exp	0.00	0.04	1.0	-0.02	0.06	1.0
Age	-0.04	0.02	1.0	-0.05	0.02	1.0
Education	0.06	0.03	1.0	0.10	0.03	1.0
Male	-0.01	0.04	1.0	0.02	0.06	1.0
C.C. Now	-0.23	0.06	1.0	-0.17	0.07	1.0
Gov Meas. Insuff.	-0.17	0.05	1.0	-0.16	0.08	1.0
Social Inf	0.03	0.02	1.0	0.08	0.03	1.0
Social Media	0.09	0.02	1.0	0.09	0.03	1.0
General Media	-0.02	0.02	1.0	-0.05	0.04	1.0
model_err	0.40	0.00	1.0	0.40	0.00	1.0

China (N=842)

	High Effort			Low Effort		
	Mean of $\hat{\beta}$	σ	$\hat{r}$	Mean of $\hat{\beta}$	σ	$\hat{r}$
Intercept	-0.52	0.29	1.0	-0.03	0.26	1.0
Fl Prob	0.05	0.06	1.0	-0.03	0.07	1.0
Fl Damage	-0.00	0.02	1.0	-0.01	0.03	1.0
Worry	0.12	0.03	1.0	0.05	0.03	1.0
Resp Eff	-0.11	0.04	1.0	-0.08	0.06	1.0
Self Eff	0.35	0.04	1.0	0.11	0.07	1.0
Cost	-0.22	0.04	1.0	0.03	0.04	1.0
Undergone	-0.09	0.07	1.0	-0.12	0.06	1.0
Fl Exp	0.00	0.07	1.0	0.02	0.06	1.0
Age	0.01	0.03	1.0	-0.05	0.03	1.0
Education	0.09	0.05	1.0	0.04	0.05	1.0
Male	-0.02	0.05	1.0	-0.04	0.05	1.0
C.C. Now	-0.19	0.06	1.0	-0.06	0.05	1.0
Gov Meas. Insuff.	-0.05	0.07	1.0	-0.05	0.07	1.0
Social Inf	0.10	0.03	1.0	0.16	0.03	1.0
Social Media	0.06	0.05	1.0	0.01	0.05	1.0
General Media	0.00	0.05	1.0	-0.00	0.05	1.0
model_err	0.38	0.00	1.0	0.38	0.00	1.0

Indonesia (N=1080)

	High Effort			Low Effort		
	Mean of $\hat{\beta}$	σ	$\hat{r}$	Mean of $\hat{\beta}$	σ	$\hat{r}$
Intercept	0.26	0.24	1.0	0.04	0.22	1.0
Fl Prob	0.02	0.02	1.0	-0.01	0.02	1.0
Fl Damage	0.05	0.02	1.0	0.00	0.02	1.0
Worry	0.08	0.02	1.0	0.04	0.02	1.0
Resp Eff	0.04	0.04	1.0	0.04	0.05	1.0
Self Eff	0.19	0.04	1.0	0.05	0.05	1.0
Cost	-0.20	0.04	1.0	0.04	0.03	1.0
Undergone	-0.09	0.05	1.0	-0.24	0.05	1.0
Fl Exp	0.04	0.05	1.0	0.06	0.04	1.0
Age	-0.03	0.03	1.0	0.01	0.02	1.0
Education	0.03	0.04	1.0	0.04	0.04	1.0
Male	-0.04	0.05	1.0	0.06	0.05	1.0
C.C. Now	-0.14	0.05	1.0	-0.10	0.05	1.0
Gov Meas. Insuff.	-0.22	0.07	1.0	-0.12	0.06	1.0
Social Inf	0.06	0.03	1.0	0.04	0.03	1.0
Social Media	0.02	0.04	1.0	0.02	0.04	1.0
General Media	-0.10	0.04	1.0	-0.00	0.04	1.0
model_err	0.40	0.00	1.0	0.37	0.00	1.0

Netherlands (N=728)

	High Effort			**Low Effort**		
	Mean of $\hat{\beta}$	σ	$\hat{r}$	Mean of $\hat{\beta}$	σ	$\hat{r}$
Intercept	-0.82	0.23	1.0	-1.14	0.25	1.0
Fl Prob	0.02	0.07	1.0	-0.01	0.07	1.0
Fl Damage	-0.00	0.02	1.0	0.01	0.03	1.0
Worry	0.15	0.03	1.0	0.15	0.04	1.0
Resp Eff	0.01	0.03	1.0	0.10	0.05	1.0
Self Eff	0.14	0.04	1.0	-0.04	0.05	1.0
Cost	-0.10	0.04	1.0	0.05	0.05	1.0
Undergone	-0.01	0.07	1.0	-0.01	0.07	1.0
Fl Exp	0.15	0.09	1.0	0.06	0.09	1.0
Age	-0.03	0.02	1.0	-0.01	0.02	1.0
Education	-0.02	0.04	1.0	0.00	0.05	1.0
Male	0.04	0.06	1.0	-0.00	0.07	1.0
C.C. Now	-0.11	0.07	1.0	-0.14	0.08	1.0
Gov Meas. Insuff.	-0.04	0.09	1.0	-0.05	0.11	1.0
Social Inf	0.07	0.03	1.0	0.17	0.04	1.0
Social Media	0.14	0.04	1.0	0.12	0.04	1.0
General Media	-0.02	0.03	1.0	-0.05	0.04	1.0
model_err	0.40	0.00	1.0	0.39	0.00	1.0

S.5: Comparing the Expanded Model to PMT

We estimated a Base PMT model to which to compare the model presented in the paper for both High and Low Effort measures. See Methods for model.

1. Base PMT Model: Fl Prob, Fl Dam, Worry, Self Eff, Resp Eff, Cost

2. Extended PMT model: All 16 variables presented above.

To assess model performance, we utilize the expected log point-wise predictive density (elpd) WAIC score (Table 8.7). This fully Bayesian method of assessing a models predictive capacity adjusts for over-fitting through additional variable penalization (Salvatier et al., 2016; Vehtari, Gelman, & Gabry, 2017). When analyzing the variables' effects, all effects are contained with Bayesian 95% high density intervals.

Table 8.7: The elpd WAIC scores for each country and model. Higher scores indicate a better model. Scores are only meaningful when compared in same country and when estimating same dependant variable.

	High Effort elpd WAIC		*Low Effort elpd WAIC*	
Countries:	Base PMT	Full Model	Base PMT	Full Model
USA	3086	3117	1975	1999
China	1423	1433	1633	1644
Indonesia	2232	2243	1978	1994
Netherlands	1787	1801	1122	1137

8.4 Appendix for Chapter 4

Table 8.8: Explanatory variables used in the analysis

Construct (Abbreviation)	Question	Response Options	USA μ (s.d.)	China μ (s.d.)	Indonesia μ (s.d.)	Netherlands μ (s.d.)
			Country level descriptive statistics from our survey			
Flood Probability (Fl Prob)	How often do you think a flood occurs on the property on which you live (e.g.due to rivers or heavy rain, storms and cyclones)? Which category is the most appropriate?	*Scaled between 0-4, 5 point scale* My house is completely safe 0.0% chance annually Less often than 1 in 500 years ~ 0.1% chance annually Once in 500 years or a 0.2% chance annually, Once in 200 years or a .5% chance annually, Once in 100 years or 1% chance annually, Once in 50 years or a 2% chance annually, Once in 10 years or 10% chance annually, Annually ~ 100% chance annually, More frequent than once per year ~ 100%	13.29 (31.22)	2.59 (10.93)	15.77 (34.09)	2.51 (12.42)
Flood Damage (Fl Damage)	In the event of a future major flood in your area on a similar scale to ___‡ how severe (or not) do you think the physical damage to your house would be?	*5 point scale* (1) Not at all severe - (5) Very severe	2.96 (1.28)	2.93 (1.08)	2.65 (1.21)	3.15 (1.15)
Worry (Worry)	How worried are you about the potential impact of flooding on your home?	*5 point scale* (1) Not at all worried - (5) Very worried	2.23 (1.11)	2.06 (0.98)	2.63 (1.17)	2.03 (1.12)
Self Efficacy (Self Eff)	How Effective do you believe implementing this measure would be in reducing the risk of flood damage to your home and possessions?	*5 point scale for each measure (averaged for all measures)* (1) Extremely ineffective - (5) Extremely effective	2.43 (1.19)	2.58 (0.96)	3.13 (0.92)	2.27 (0.99)
Response Efficacy (Resp Eff)	Do you have the ability to undertake this measure either by yourself or paying a professional to do so?	*5 point scale for each measure (averaged for all measures)* (1) I am unable - (5) I am very able	3.25 (1.04)	3.47 (0.77)	3.59 (0.76)	3.06 (0.85)
Perceived Cost (Cost)	When you think in terms of your income and other expenses do you believe implementing (or paying someone to implement) this measure would be cheap or expensive?	*5 point scale for each measure (averaged for all measures)* (1) Very cheap - (5) Very expensive	3.87 (0.79)	3.39 (0.62)	3.62 (0.63)	3.61 (0.79)
Previously undertaken measures (# Undergone)	I have already implemented this measure Yes (1) or No (0) for *each* measure	*0-7 scale* (8 is dropped from analysis as there is nothing left to intend)	0.71 (1.55)	0.38 (1.07)	1.22 (2.00)	0.33 (0.94)
Additionally Indented Adaptations (Add. Intended)	I intend to implement this measure	*0-7 scale* (The measure estimated is not included) Yes (1) or No (0) for *each* measure	1.99 (2.90)	4.07 (3.18)	4.38 (3.03)	2.26 (3.09)
Included in all models in Sets 1-4, but effects not shown in Figure 2						
Homeowner (Homeowner)	Do you rent or own your accommodation?	Own(1), Rent or Other (0)	0.70	0.82	0.72	0.48
Age (Age)	YouGov collected this information prior to the survey	1: [16-24], 2: [25-34], 3: [35-44], 4: [45-54], 5: [55-64], 6: [65+]				
Education (Edu)	YouGov collected this information prior to the survey	1: < High School, 2: High School, 3: College Degree, 4: Post Graduate		See Table S.2 for categorical % for age, gender, and education.		
Gender (Male)	YouGov collected this information prior to the survey	Male (1) and Female (0) *The authors do not imply gender is binary, but did not receive other data*				
Country Resident	YouGov collected this information	From *country* (1), from another country (0) (Netherlands Control)	0.34	0.20	0.26	0.21

Demographics

Table 8.17 shows the population statistics on the three “background” or socio-economic variables included in the analysis. In general, the survey sample is representative of the population. In Indonesia, the medium age is a decade younger than in the other three countries and in both China and Indonesia many elderly people live with their children or younger family members. As our objective is to study household adaption, and only one member per household was allowed access to our survey, the lack of older respondents from these two countries was anticipated and we do not regard it as problematic for our analysis. While our sample is in general more educated than the general population, to help ensure that the distribution of these three ‘background’ variables does not bias the effects in the analysis, we control for age, education, and gender in all our models.

Table 8.9: Distribution of the survey respondents’ gender, age, and education demographics by country from the data included in the analysis. Due to rounding, percents may not add up exactly to 100.

		Survey Percentages by Country			
Variables		USA (N=1577)	China (N=945)	Indonesia (N=1198)	Netherlands (N=968)
Gender	Female	50%	52%	45%	49%
	Male	50%	48%	55%	51%
Age	16-24	10%	19%	23%	20%
	25-34	19%	50%	42%	23%
	35-44	18%	23%	26%	16%
	45-54	19%	5%	7%	13%
	55-64	16%	2%	2%	11%
	65+	18%	1%	1%	16%
Education	< High School	3%	0.4%	1%	4%
	High School	42%	3%	42%	44%
	College degree	32%	69%	51%	44%
	Post Graduate	24%	28%	7%	8%

In all model sets we, like past work (Brody et al., 2017), use home ownership as a socio-economic control (Table 8.16). We select home ownership over income as education and income are correlated (Spearman’s R = 0.4) and education offers more explanatory power in the number of adaptations intended than income (Spearman’s R = 0.12 vs. 0.09, respectively). Further, homeowners are more likely to belong to a higher income quintile (Wilcox Rank Sum = 77, p<0.0001) and ownership has a strong relationship with the number of intended adaptation actions (Wilcox Rank Sum = -24, p<0.0001).

Table 8.10: Census data on gender, age, and education demographics in each of the surveyed cities *City Population Rotterdam* (2021); *Shanghai Municipal Bureau of Statistics* (2020); *Shanghai Poeple's Government* (2020); *Statistik Daerah Kota Jakarta Selatan 2016* (2016); *United States Census Bureau* (2019). Due to information scarcity and fragmentation, the age category does not exactly align with categories from our survey nor with data from other countries. Yet, this official statistics still provides a useful baseline picture to judge the representativeness of the survey sample. Percentages, due to rounding, may not sum exactly to 100.

	USA (2019)				**China** (2019)		**Indonesia** (2015)		**Netherlands** (2021)	
Variables	*Cat.*	New Orleans	Houston	Miami	*Cat.*	Shanghai	*Cat.*	Jakarta	*Cat.*	Rotterdam
Gender	F	52.5%	50.1%	51.4%	F	50.5%	F	49.8%	F	50.6%
	M	47.5%	49.9%	48.6%	M	49.5%	M	50.2%	M	49.4%
Age	5-17	20.1%	25.1%	20.2%	<17	12.3%	15-24	14.9%	10-19	10.4%
	18-65	59.9%	56.8%	57.3%	18-34	16.2%	25-34	20.5%	20-29	17.1%
	65+	14.1%	10.5%	16.7%	35-59	36.4%	35-44	17.4%	30-39	15.5%
					60+	35.2%	45-54	12.2%	40-49	12.6%
							55-64	7.0%	50-59	12.7%
							65+	4.1%	60-69	10.0%
									70+	10.9%
Education	<High School	13.5%	21.1%	18.6%	<High School	47.1%	<High School	39.3%	<High School	29%
	High School	48.9%	46%	51%	High School	19.0%	High School	40.9%	High School	37%
	≥College	37.6%	32.9%	29.8%	≥College	33.9%	≥College	20.0%	≥College	34%

Set-1

Table 8.11: Set-1 Coefficients and (standard errors)

Variables:	CA1	CA2	CA3	CA4	CA5	CA6	CA7	CA8
Intercept	-1.307	-1.587	-2.580	-3.408	-3.619	-2.922	-3.330	-2.849
Fl Prob	0.003	0.002	-0.041	-0.074	-0.124	-0.086	-0.074	-0.040
	(0.043)	(0.039)	(0.038)	(0.038)	(0.036)	(0.036)	(0.036)	(0.036)
Fl Damage	0.133	0.152	0.184	0.134	0.110	0.101	0.098	0.126
	(0.042)	(0.038)	(0.038)	(0.035)	(0.034)	(0.035)	(0.035)	(0.034)
Worry	0.658	0.550	0.554	0.570	0.567	0.612	0.535	0.502
	(0.046)	(0.041)	(0.041)	(0.039)	(0.039)	(0.039)	(0.038)	(0.038)
Self Eff	0.674	0.653	0.657	0.545	0.596	0.614	0.561	0.404
	(0.038)	(0.035)	(0.035)	(0.032)	(0.032)	(0.032)	(0.032)	(0.031)
Response Eff	0.186	0.217	0.258	0.098	0.200	0.161	0.204	0.312
	(0.045)	(0.042)	(0.040)	(0.036)	(0.038)	(0.036)	(0.036)	(0.035)
Cost	-0.949	-0.800	-0.614	-0.102	-0.256	-0.381	-0.231	-0.391
	(0.049)	(0.047)	(0.045)	(0.037)	(0.039)	(0.039)	(0.038)	(0.035)
H.H. Own	0.364	0.238	0.257	0.160	0.186	0.053	0.088	0.231
Age	-0.323	-0.275	-0.304	-0.366	-0.299	-0.317	-0.289	-0.217
	(0.037)	(0.034)	(0.033)	(0.030)	(0.030)	(0.030)	(0.030)	(0.029)
Edu	0.184	0.088	0.162	0.182	0.214	0.170	0.185	0.178
	(0.066)	(0.060)	(0.059)	(0.056)	(0.055)	(0.055)	(0.055)	(0.054)
Male	0.228	0.146	0.158	0.250	0.173	0.145	0.209	0.210
USA	0.079	0.126	-0.067	-0.170	0.004	-0.041	-0.205	-0.173
China	0.409	0.649	0.695	0.683	0.832	0.794	0.599	0.573
Indonesia	1.064	1.291	1.204	0.627	0.727	0.892	0.681	0.886

Set-2

Table 8.12: Set-2 Coefficients and (standard errors)

Variables:	CA1	CA2	CA3	CA4	CA5	CA6	CA7	CA8
Intercept	-1.311	-1.569	-2.541	-3.415	-3.627	-2.907	-3.324	-2.855
Fl Prob	0.004	-0.000	-0.043	-0.077	-0.131	-0.088	-0.075	-0.042
	(0.043)	(0.039)	(0.039)	(0.038)	(0.036)	(0.036)	(0.036)	(0.036)
Fl Damage	0.133	0.151	0.184	0.133	0.114	0.104	0.100	0.128
	(0.042)	(0.039)	(0.038)	(0.035)	(0.035)	(0.035)	(0.035)	(0.034)
Worry	0.658	0.548	0.551	0.568	0.568	0.611	0.536	0.503
	(0.046)	(0.042)	(0.041)	(0.039)	(0.039)	(0.039)	(0.038)	(0.038)
Self Eff	0.675	0.643	0.644	0.533	0.589	0.608	0.557	0.402
	(0.039)	(0.036)	(0.035)	(0.032)	(0.032)	(0.033)	(0.032)	(0.031)
Resp Eff	0.186	0.216	0.252	0.096	0.196	0.158	0.202	0.313
	(0.045)	(0.042)	(0.040)	(0.036)	(0.038)	(0.036)	(0.036)	(0.035)
Cost	-0.949	-0.806	-0.614	-0.099	-0.252	-0.380	-0.231	-0.392
	(0.049)	(0.048)	(0.045)	(0.038)	(0.039)	(0.039)	(0.038)	(0.035)
# Undergone	-0.014	0.264	0.206	0.274	0.133	0.075	0.054	0.086
	(0.055)	(0.054)	(0.052)	(0.054)	(0.042)	(0.039)	(0.040)	(0.037)
Homeowner	0.366	0.201	0.226	0.116	0.160	0.041	0.077	0.220
Age	-0.323	-0.266	-0.304	-0.358	-0.298	-0.318	-0.289	-0.215
	(0.037)	(0.034)	(0.033)	(0.031)	(0.030)	(0.030)	(0.030)	(0.029)
Edu	0.184	0.078	0.156	0.173	0.209	0.166	0.183	0.174
	(0.066)	(0.061)	(0.060)	(0.056)	(0.055)	(0.055)	(0.055)	(0.054)
Male	0.228	0.127	0.153	0.237	0.173	0.141	0.206	0.209
USA	0.080	0.093	-0.090	-0.184	-0.006	-0.053	-0.210	-0.192
China	0.408	0.681	0.721	0.740	0.858	0.803	0.605	0.572
Indonesia	1.065	1.254	1.148	0.594	0.684	0.863	0.664	0.850

Set-3

Table 8.13: Set-3 Coefficients and (standard errors)

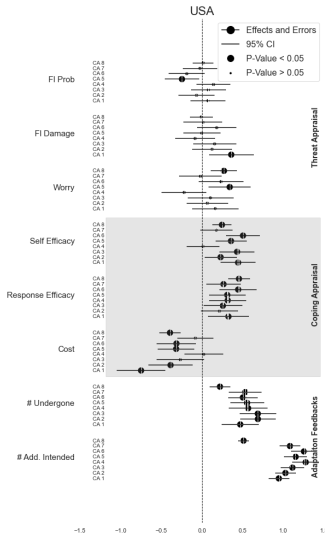
Variables:	CA1	CA2	CA3	CA4	CA5	CA6	CA7	CA8
Intercept	-3.726	-3.475	-4.821	-4.290	-4.605	-4.866	-4.225	-3.530
Fl Prob	0.162	0.073	-0.015	-0.026	-0.159	-0.073	0.008	0.069
	(0.064)	(0.057)	(0.059)	(0.059)	(0.055)	(0.057)	(0.057)	(0.043)
Fl Damage	0.024	0.087	0.162	0.064	0.014	-0.012	-0.039	0.070
	(0.062)	(0.056)	(0.058)	(0.054)	(0.053)	(0.054)	(0.054)	(0.041)
Worry	0.357	0.187	0.138	0.102	0.157	0.254	0.052	0.196
	(0.065)	(0.058)	(0.063)	(0.060)	(0.059)	(0.059)	(0.059)	(0.046)
Self Eff	0.554	0.368	0.442	0.276	0.353	0.464	0.354	0.244
	(0.055)	(0.050)	(0.052)	(0.047)	(0.048)	(0.048)	(0.048)	(0.037)
Resp Eff	0.246	0.193	0.277	0.263	0.274	0.330	0.269	0.376
	(0.062)	(0.058)	(0.061)	(0.055)	(0.057)	(0.055)	(0.054)	(0.042)
Cost	-0.739	-0.493	-0.402	-0.203	-0.448	-0.404	-0.230	-0.409
	(0.068)	(0.067)	(0.067)	(0.056)	(0.059)	(0.059)	(0.057)	(0.041)
Add. Intended	0.847	0.854	0.982	0.934	0.955	0.973	0.935	0.564
	(0.030)	(0.028)	(0.032)	(0.029)	(0.030)	(0.031)	(0.029)	(0.019)
Homeowner	0.333	0.327	0.433	0.090	0.194	-0.134	-0.161	0.068
Age	-0.172	-0.102	-0.173	-0.158	-0.019	-0.040	-0.102	0.035
	(0.054)	(0.049)	(0.050)	(0.046)	(0.045)	(0.047)	(0.047)	(0.035)
Edu	0.047	-0.196	0.021	0.139	0.218	0.120	0.123	0.099
	(0.096)	(0.088)	(0.093)	(0.087)	(0.085)	(0.086)	(0.085)	(0.066)
Male	0.191	0.026	-0.022	0.083	-0.017	-0.026	0.114	0.127
USA	0.074	0.513	0.466	-0.144	0.375	0.256	-0.029	-0.042
China	-0.650	0.120	0.716	-0.168	0.521	0.260	-0.187	0.240
Indonesia	0.646	1.166	1.227	-0.369	0.000	0.145	0.077	0.637

Interaction effects

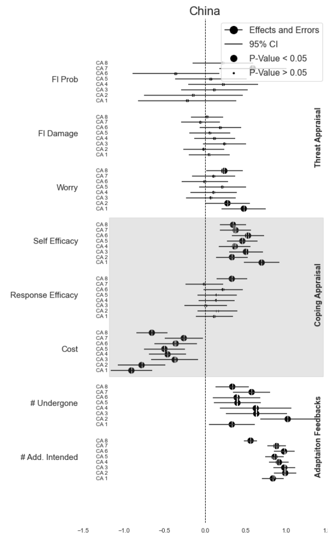
Table 8.14: Full Model (Set-4) + Interaction Effects Coefficients and (standard errors). Here we present the most complete, Set-4 model, with two interaction effects: "Worry * Undergone adaptation" and "Worry * Additionally Intended adaptation". As discussed in the main text, the interaction effects between "Worry * Undergone adaptation" are insignificant as are all but two between "Worry * Additionally Intended adaptation." As visible in the table these effects are very small and we argue, negligible.

Variables:	CA1	CA2	CA3	CA4	CA5	CA6	CA7	CA8
const	-4.117	-4.091	-4.883	-4.112	-4.934	-5.335	-4.567	-3.656
Fl Prob	0.158*	0.067	-0.011	-0.020	-0.187**	-0.079	0.005	0.055
	(0.065)	(0.059)	(0.061)	(0.060)	(0.055)	(0.057)	(0.056)	(0.044)
Fl Damage	0.022	0.068	0.157**	0.050	0.037	0.027	-0.033	0.069
	(0.063)	(0.058)	(0.061)	(0.056)	(0.056)	(0.057)	(0.056)	(0.042)
Worry	0.475**	0.373**	0.188	0.004	0.170	0.406**	0.245*	0.250**
	(0.128)	(0.125)	(0.116)	(0.109)	(0.108)	(0.109)	(0.113)	(0.069)
Self Eff	0.529**	0.309**	0.386**	0.226**	0.309**	0.409**	0.288**	0.231**
	(0.057)	(0.052)	(0.055)	(0.050)	(0.051)	(0.051)	(0.050)	(0.037)
Resp Eff	0.242**	0.188**	0.244**	0.270**	0.261**	0.319**	0.258**	0.386**
	(0.063)	(0.060)	(0.063)	(0.057)	(0.060)	(0.057)	(0.056)	(0.043)
Cost	-0.741**	-0.489**	-0.403**	-0.234**	-0.462**	-0.405**	-0.248**	-0.419**
	(0.070)	(0.070)	(0.070)	(0.059)	(0.062)	(0.061)	(0.059)	(0.042)
# Undergone	0.451**	0.900**	0.565**	0.412**	0.404**	0.565**	0.357**	0.193*
	(0.140)	(0.142)	(0.136)	(0.148)	(0.115)	(0.108)	(0.109)	(0.081)
Add. Intended	0.960**	1.044**	1.117**	0.954**	1.096**	1.178**	1.177**	0.650**
	(0.072)	(0.071)	(0.078)	(0.066)	(0.067)	(0.073)	(0.069)	(0.044)
Interaction	-0.030	-0.076	0.018	0.110	0.092	-0.010	0.069	0.029
Worry*# Undergone	(0.049)	(0.048)	(0.049)	(0.061)	(0.047)	(0.042)	(0.044)	(0.033)
Interaction	-0.033	-0.048	-0.040	0.008	-0.030	-0.060	-0.076	-0.030
Worry*Add. Int.	(0.026)	(0.026)	(0.029)	(0.026)	(0.025)	(0.026)*	(0.025)*	(0.017)
HH_own	0.247	0.223	0.336*	-0.089	0.006	-0.277	-0.376**	0.031
Age	-0.147**	-0.041	-0.141**	-0.095*	0.039	-0.002	-0.064	0.051
	(0.055)	(0.052)	(0.053)	(0.048)	(0.048)	(0.049)	(0.049)	(0.036)
Edu	0.017	-0.292**	-0.024	0.095	0.192*	0.065	0.074	0.078
	(0.098)	(0.093)	(0.097)	(0.091)	(0.089)	(0.090)	(0.088)	(0.067)
Male	0.173	-0.084	-0.109	0.026	-0.018	-0.084	0.059	0.124
USA	0.011	0.368	0.300	-0.218	0.327	0.065	-0.144	-0.121
China	-0.660**	0.229	0.859**	-0.004	0.722**	0.315	-0.207	0.200
Indonesia	0.613**	1.017**	0.929**	-0.573**	-0.364	-0.261	-0.244	0.452**
Significance Level:	$^{*}p<0.05$; $^{**}p<0.01$							

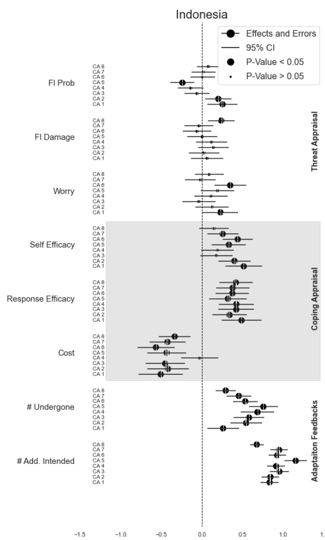
Robustness check - across countries



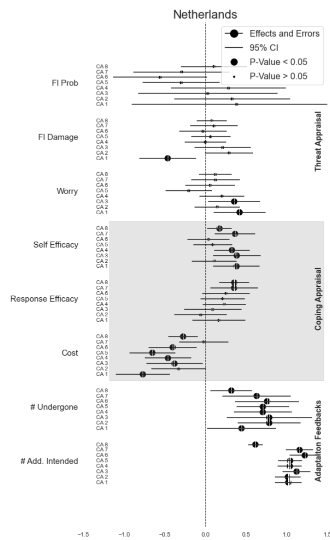
(a) United States of America (N=1577)



(b) China (N=945)



(c) Indonesia (N=1198)



(d) Netherlands (N=968)

Figure 8.1: Below are the effects and 95% confidence intervals for the "Set-4" model, separated by country. The sample size is smaller, hence the intervals are much wider. The important common characteristic to note is that the effects of the number of previously undergone measures and the effects of the number of additionally intended measures have on intended adaptation is consistently positive across countries. In the main research paper we control for cross-country differences via dummy variables. If the reader is interested in cross country differences we have another paper where we specifically explore differences in household adaptation drivers (Noll et al., 2021).

8.5 Appendix for Chapter 5

Heirarchical Bayesian logit model coefficients and standard errors

Table 8.15: The effects and standard errors of Socio-Economic Variables on Flood risk uncertainty from a hierarchical Bayesian logistic regression model.

		Bayesian mean effects and *(SD)* country estimates			
		USA	China	Indonesia	Netherlands
Label	Description	(N=1880)	(N=1156)	(N=2021)	(N=1185)
Gender	Female = 0	-0.597	-0.321	-0.316	-0.165
	Male = 1	*(0.121)*	*(0.145)*	*(0.124)*	*(0.141)*
Education	1: < High School, 2: High School	-0.106	-0.331	-0.258	-0.347
	3: College degree, 4: Post Graduate	*(0.077)*	*(0.138)*	*(0.106)*	*(0.112)*
Age	1: [16-24], 2: [25-34], 3: [35-44],	0.031	0.073	0.111	0.115
	4: [45-54], 5: [55-64], 6: [65+]	*(0.039)*	*(0.078)*	*(0.068)*	*(0.047)*
Income	1: Lowest 20% of country -	-0.217	-0.101	-0.052	-0.208
Quintile	5: Highest 20% of country	*(0.055)*	*(0.071)*	*(0.062)*	*(0.077)*
Flood	No = 0	-0.808	-0.595	-0.484	-0.580
Experience	Yes = 1	*(0.125)*	*(0.216)*	*(0.125)*	*(0.234)*
Years in home	Open Ended	0.001	0.016	0.016	-0.017
		(0.005)	*(0.010)*	*(0.005)*	*(0.007)*
HH own	Own home = 1	-0.475	-0.828	-0.686	-0.259
	rent or “other” = 0	*(0.133)*	*(0.179)*	*(0.136)*	*(0.155)*
Intercept	–	0.204	0.549	-0.606	0.087
Hyper-Prior	Country level variance	0.415			
for the SD		*(0.068)*			

Descriptive Statistics

Table 8.16: Variables used in the analysis

			Descriptive statistics	
			risk-aware (N=5103)	**Risk-uncertain** (N=1139)
Construct	Question	Response Options	μ (σ)	
Worry	How worried are you about the potential impact of flooding on your home?	*5 point scale* (1) Not at all worried - (5) Very worried	2.40 (1.18)	2.33 (1.15)
Risk Adversity	Are you generally ready to take risks in your life or do you avoid risks?	*5 point scale* (1) Very willing to take risks - (5) Not willing to take any risks	2.79 (1.08)	3.08 (1.06)
Social Expectations	Do your family, friends and/or social network expect you to prepare your household for flooding?	*5 point scale* (1) They do NOT expect me to prepare for flooding- (5) They strongly expect me to prepare for flooding	3.07 (1.19)	2.79 (1.10)
Social Network	Thinking about your friends, family, and neighbors, how many households have taken some adaptive actions toward flooding?	*7 point scale* (0) - (6+) I don't know (coded in analysis as 0)	1.74 (2.12)	0.65 (1.55)
Self-Efficacy	Do you have the ability to undertake this measure either by yourself or paying a professional to do so?	*5 point scale for each measure High Effort Measures μ and s.d. on top Low Effort Below; (both averaged by category)* (1) I am unable - (5) I am very able	2.67 (1.08) 3.66 (0.82)	2.28 (1.04) 3.27 (0.94)
Response Efficacy	How Effective do you believe implementing this measure would be in reducing the risk of flood damage to your home and possessions?	*5 point scale for each measure High Effort Measures μ and s.d. on top Low Effort Below; (both averaged by category)* (1) Extremely ineffective - (5) Extremely effective	3.37 (0.89) 3.60 (0.81)	3.22 (0.88) 3.42 (0.88)
Perceived Cost	When you think in terms of your income and other expenses do you believe implementing (or paying someone to implement) this measure would be cheap or expensive?	*5 point scale for each measure High Effort Measures μ and s.d. on top Low Effort Below; (both averaged by category)* (1) Very cheap - (5) Very expensive	3.65 (0.74) 2.61 (0.85)	3.67 (0.83) 2.73 (0.81)
Gender (Male=1)	YouGov collected this information prior to the survey	Male (1) and Female (0) *The authors do not imply gender is binary, but did not receive other data*	0.52	0.40
Age	YouGov collected this information prior to the survey	(1) [16-24], (2) [25-34], (3) [35-44], (4) [45-54], (5) [55-64], (6) [65+]	2.80 (1.47)	2.94 (1.56)
Education	YouGov collected this information prior to the survey	(1) < High School, (2) High School, (3) College Degree, (4) Post Graduate	2.77 (0.74)	2.60 (0.72)
Income	What was your total family income from all sources last year in 2019?	*5 point country specific scale income quintiles* 1: Lowest 20% of country- 5: Highest 20% of country	3.17 (1.31)	2.84 (1.24)
Flood Experience	Have you ever personally experienced a flood of any kind?	Yes (1) or No (0)	0.40	0.24
Years in Home	What year did you move into your current home?	2020 - ______	12.26 (12.02)	11.97 (11.9)
Household Ownership	Do you rent or own your accommodation?	Own = 1, Rent = 0 Other = 0	0.68	0.52

Sample Representativeness

Table 8.17 shows the population statistics on the three socio-economic variables included in the analysis. We present the results here by country for transparency in sample representativeness, In general, the survey sample is representative of the population. In Indonesia, the medium age is a decade younger than in the other three countries and in both China and Indonesia, many elderly people live with their children or younger family members. As only one member per household was allowed access to our survey, the lack of older respondents from these two countries was anticipated and we do not regard it as problematic for our analysis. While our sample is, in general, more educated than the general population, to help ensure that the distribution of these variables does not greatly bias other variable effects in the analysis, we control for age, education, and gender in our models.

Table 8.17: Distribution of the survey respondents' gender, age, and education demographics by country from the data included in the analysis. Due to rounding, percentages may not sum exactly to 100.

		Survey Percentages by Country			
Variables		USA (N=1880)	China (N=1156)	Indonesia (N=2021)	Netherlands (N=1185)
Gender	Female	54%	54%	54%	50%
	Male	46%	46%	46%	50%
Age	16-24	11%	20%	24%	20%
	25-34	19%	48%	42%	23%
	35-44	19%	23%	25%	18%
	45-54	18%	5%	7%	14%
	55-64	16%	2%	2%	12%
	65+	17%	1%	0%	14%
Education	< High School	3%	1%	2%	4%
	High School	44%	4%	42%	48%
	College degree	31%	69%	49%	41%
	Post Graduate	22%	26%	7%	7%

Table 8.18: Census data on gender, age, and education demographics in each of the surveyed cities *City Population Rotterdam* (2021); *Shanghai Municipal Bureau of Statistics* (2020); *Shanghai Poeple's Government* (2020); *Statistik Daerah Kota Jakarta Selatan 2016* (2016); *United States Census Bureau* (2019). Due to information scarcity and fragmentation, the age category does not exactly align with categories from our survey nor with data from other countries. Yet, this official statistics still provides a useful baseline picture to judge the representativeness of the survey sample. Percentages, due to rounding, may not sum exactly to 100.

	USA (2019)				**China** (2019)		**Indonesia** (2015)		**Netherlands** (2021)	
Variables	*Cat.*	New Orleans	Houston	Miami	*Cat.*	Shanghai	*Cat.*	Jakarta	*Cat.*	Rotterdam
Gender	F	52.5%	50.1%	51.4%	F	50.5%	F	49.8%	F	50.6%
	M	47.5%	49.9%	48.6%	M	49.5%	M	50.2%	M	49.4%
Age	5-17	20.1%	25.1%	20.2%	<17	12.3%	15-24	14.9%	10-19	10.4%
	18-65	59.9%	56.8%	57.3%	18-34	16.2%	25-34	20.5%	20-29	17.1%
	65+	14.1%	10.5%	16.7%	35-59	36.4%	35-44	17.4%	30-39	15.5%
					60+	35.2%	45-54	12.2%	40-49	12.6%
							55-64	7.0%	50-59	12.7%
							65+	4.1%	60-69	10.0%
									70+	10.9%
Education	<High School	13.5%	21.1%	18.6%	<High School	47.1%	<High School	39.3%	<High School	29%
	High School	48.9%	46%	51%	High School	19.0%	High School	40.9%	High School	37%
	≥College	37.6%	32.9%	29.8%	≥College	33.9%	≥College	20.0%	≥College	34%

Income
To solicit income quintiles from each country we asked the following questions in each respective country based. Initial information was found here: Institute and Institution (2018); Press (2018); Statline (2019) and then adjusted for inflation from data 2017 to 2019 levels.
The United States of America: What was your total family income from all sources last year in 2019?

- Less than 25730 Dollars
- Between 25731 and 49200 Dollars
- Between 49201 and 80995 Dollars
- Between 80996 and 132490 Dollars
- More than 132490 Dollars

China: What was your total family income from all sources last year in 2019 after taxes?

- Less than 14325 Yuan
- Between 14326 and 25625 Yuan
- Between 25626 and 35260 Yuan
- Between 35261 and 47140
- Between 47141 and 80475*
- More than 80475*

* *These are combined and together make the 5th quintile*
Netherlands: What was your total family income from all sources last year in 2019?

- Less than 26130 Euro
- Between 26131 and 42785 Euro
- Between 42786 and 66935 Euro
- Between 66936 and 102540 Euro
- More than 102540 Euro

Indonesia: What was your total family income from all sources last year in 2019? Please fill in your TOTAL annual income.

______ Ruipah*
* *We could not find publicly available information on Indonesian income quintiles thus, we asked open-ended questions and estimated our own.*

Adaptation Measures

Table 8.19: Factor Loadings from confirmatory factor analysis by risk (un)certainty for both adaptation groupings. Cronbach alpha is presented for each group, at the bottom of each section.

	Factor Loadings	
High Effort Measures	**Risk-aware** (N=5103)	**Risk-uncertain** (N=1139)
Raising the level of the ground floor above the most likely flood level	0.90	0.92
Strengthening the housing foundations to withstand water pressures	0.92	0.94
Reconstructing or reinforcing the walls and/or the ground floor with water-resistant materials	0.93	0.94
Raising the electricity meter above the most likely flood level or on an upper floor	0.92	0.94
Installing anti-backflow valves on pipes	0.93	0.94
Installing a pump and/or one or more system(s) to drain flood water	0.93	0.94
Fixing water barriers (e.g. water-proof basement windows)	0.93	0.94
Installing a refuge zone, or an opening in the roof of your home or apartment	0.89	0.91
Cronbach Alpha	*0.93*	*0.95*
Low Effort Measures		
Keeping a working flashlight and/or a battery-operated radio and/or emergency kit in a convenient location	0.92	0.93
Purchasing sandbags, or other water barriers	0.93	0.94
Buying a spare power generator to power your home	0.91	0.94
Storing or placing important possessions (such as documents or expensive furniture) in such a manner to avoid flood damage	0.93	0.94
Storing emergency food and water supplies	0.94	0.95
Moving/ storing valuable assets on higher floors or elevated areas	0.94	0.95
Being an active member in a community group aimed at making the community safer	0.94	0.95
Coordinating with the neighbors in case you are not home when a flood occurs, they would know what to do	0.94	0.95
Asking someone (local government, Civil Defense, etc.) for information about what to do in case of emergency	0.94	0.95
Asking/ petitioning government representative to increase the public protection measures	0.94	0.96
Cronbach Alpha	*0.91*	*0.93*

Model Effects

Table 8.20: Mean beta coefficients estimates and (standard errors) for Figure 5.2

	High Effort Adaptation Intention				Low Effort Adaptation Intention			
	Bayesian Binary Logit		Bayesian Linear Regression		Bayesian Binary Logit		Bayesian Linear Regression	
Variables:	risk-aware	risk-uncertain	risk-aware	risk-uncertain	risk-aware	risk-uncertain	risk-aware	risk-uncertain
Intercept	-1.166	-1.514	1.737	1.445	0.106	-1.388	2.732	1.598
Worry	0.514	0.262	0.581	0.259	0.389	0.242	0.475	0.365
	(0.04)	(0.068)	(0.033)	(0.073)	(0.043)	(0.067)	(0.044)	(0.096)
Risk	-0.118	-0.036	-0.109	-0.047	-0.103	0.157	-0.061	-0.004
Adverse	(0.039)	(0.075)	(0.035)	(0.078)	(0.039)	(0.073)	(0.044)	(0.106)
Social	0.343	0.197	0.290	0.173	0.184	0.338	0.268	0.426
Expectations	(0.037)	(0.073)	(0.035)	(0.079)	(0.038)	(0.073)	(0.045)	(0.104)
Social	0.175	0.331	0.131	0.297	0.178	0.388	0.145	0.312
Network	(0.022)	(0.058)	(0.019)	(0.052)	(0.025)	(0.075)	(0.024)	(0.068)
Self	0.583	0.666	0.855	0.959	-0.070	0.538	-0.364	0.522
Efficacy	(0.045)	(0.087)	(0.042)	(0.092)	(0.061)	(0.103)	(0.074)	(0.154)
Response	0.233	0.452	-0.080	0.198	0.435	0.122	0.114	-0.001
Efficacy	(0.051)	(0.105)	(0.045)	(0.098)	(0.058)	(0.102)	(0.07)	(0.151)
Perceived	-0.555	-0.417	-0.722	-0.557	0.153	-0.179	1.168	0.390
Cost	(0.059)	(0.109)	(0.053)	(0.106)	(0.056)	(0.095)	(0.059)	(0.132)
Gender	0.182	-0.195	0.100	-0.138	-0.035	-0.148	0.240	0.032
Age	-0.202	-0.007	-0.268	-0.123	-0.099	0.039	-0.344	-0.166
	(0.03)	(0.057)	(0.029)	(0.06)	(0.029)	(0.052)	(0.037)	(0.08)
Education	0.107	0.215	0.149	0.246	0.118	0.191	0.256	0.339
	(0.059)	(0.112)	(0.053)	(0.118)	(0.059)	(0.11)	(0.069)	(0.16)
Income	-0.165	-0.117	-0.196	-0.158	-0.078	-0.166	-0.022	-0.188
	(0.039)	(0.082)	(0.032)	(0.079)	(0.038)	(0.081)	(0.041)	(0.107)
Flood	0.201	-0.299	0.133	-0.270	-0.021	-0.140	-0.108	-0.585
Experience								
Years in	0.006	-0.003	0.002	0.006	-0.002	-0.012	-0.002	-0.002
House	(0.004)	(0.007)	(0.003)	(0.007)	(0.004)	(0.007)	(0.004)	(0.01)
HH Own	0.283	0.018	0.008	-0.277	0.274	0.220	0.340	0.184
USA	-0.528	-0.145	-0.509	0.057	-0.131	-0.197	-0.436	-0.571
China	1.055	0.796	1.242	0.935	0.646	0.672	1.337	1.309
Indonesia	0.575	0.907	0.514	1.096	0.474	0.571	-0.265	0.466
sigma	-	-	2.498	2.607	-	-	3.182	3.462
	-	-	(0.025)	(0.055)	-	-	(0.032)	(0.074)

Wave two additional risk questions: risk uncertainty robustness check

In wave two of the longitudinal survey we asked the following questions and cross referenced respondents answers on the second wave to uncertainty about flood risk in the first wave. We compare these uncertainty results to those presented in the paper in the beginning of the Discussion Section. Uncertainty is coded in the same manner as described in the Methods.
“The next several questions will ask about your perceptions of other situations that are uncertain. Please answer to the best of your knowledge."
Covid-19

- Please indicate how likely it is that you could contract Covid-19?
  ______%
  I dont know

- In the case you are diagnosed covid-19, how likely is it that you would beat/ overcome the disease?
  ______%
  I dont know

- In this scenario, how likely is it that you are a-symptomatic (i.e. don’t have any symptoms)?
  1 Very likely - 5 Very unlikely
  I dont know

Winning a Lottery

- The government of [*country specific answer*] is having a lottery where they randomly select [*USA: 33100, China:144000, Indonesia: 27350, European Union: 44800*] citizens to win [*USA: 50,000 dollars, China: 7,500 yen, Indonesia: 730 million Rupiah, NL: 50,000, Euro*]. Please indicate how likely is it that you will be one of the winners.
  ______%
  I dont know

Car Accident

- How likely do you think it is you could be involved in a car accident in the next 12 months?
  ______%
  I dont know

- How severely do you think a car accident would impact your life?
  1: Little, I am in good health and believe my body would most likely heal quickly-
  5: A crippling amount. I believe I would need extensive physical therapy
  I dont know

Plane Crash

- Hypothetically how likely is it that, on your next flight, the plane you are on crashes?
  ______%
  I dont know

- In the scenario where the plane you are on crashes, how likely is it that you survive?
  ______%
  I dont know

8.6 Appendix for Chapter 6

Survey sample

Table 8.21: Distribution of the survey respondents' gender, age, and education demographics by country from the data included in the analysis. Due to rounding, percentages may not sum exactly to 100.

		Survey Percentages by Country			
Variables		USA (N=479)	China (N=161)	Indonesia (N=566)	Netherlands (N=45)
Gender	Female	49%	42%	46%	53%
	Male	51%	58%	54%	47%
Age	16-24	1%	11%	15%	2%
	25-34	7%	34%	41%	13%
	35-44	9%	40%	33%	16%
	45-54	21%	8%	8%	27%
	55-64	29%	5%	2%	18%
	65+	33%	2%	0%	24%
Education	< High School	1%	1%	1%	2%
	High School	38%	2%	35%	49%
	College degree	34%	71%	56%	43%
	Post Graduate	28%	25%	8%	7%

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Interaction

Table 8.23: Interaction Terms from the Panel intention models

	Lin. Mean	Lin. SD	Log. Mean	Log. SD
Intercept	0.221	0.011	-10.655	0.066
Fl Prob.	-0.003	0.012	-0.003	0.042
Fl Dam.	0.039	0.012	0.173	0.048
Worry	0.058	0.013	0.224	0.049
Self Eff.	0.040	0.013	0.215	0.058
Response Eff.	0.008	0.012	0.041	0.062
Perc. Cost	-0.042	0.012	-0.181	0.050
Exp.Fl.Dam	-0.002	0.028	-0.016	0.147
Age	-0.021	0.014	-0.162	0.065
Male	0.022	0.011	0.090	0.044
Education	-0.002	0.011	-0.038	0.049
CN	0.003	0.013	0.143	0.066
IN	0.084	0.017	0.481	0.080
NL	0.000	0.011	-0.058	0.081
Yrs Home	-0.021	0.011	-0.124	0.049
Soc. Expect	0.015	0.011	0.118	0.054
Exp.Fl.Dam x Prob	0.000	0.011	0.006	0.042
Exp.Fl.Dam x Dam	0.000	0.029	0.015	0.150
Exp.Fl.Dam x Worry	-0.013	0.028	-0.116	0.147

Table 8.22: Census data on gender, age, and education demographics in each of the surveyed cities Jakarta2016, Shanghai2020, Shanghai2020a, Rotterdam2021, USA2019. Due to information scarcity and fragmentation, the age category does not exactly align with categories from our survey nor with data from other countries. Yet, these official statistics still provide a useful baseline picture to judge the representativeness of the survey sample. Percentages, due to rounding, may not sum exactly to 100.

	USA (2019)				**China** (2019)		**Indonesia** (2015)		**Netherlands** (2021)	
Variables	*Cat.*	New Orleans	Houston	Miami	*Cat.*	Shanghai	*Cat.*	Jakarta	*Cat.*	Rotterdam
Gender	F	52.5%	50.1%	51.4%	F	50.5%	F	49.8%	F	50.6%
	M	47.5%	49.9%	48.6%	M	49.5%	M	50.2%	M	49.4%
Age	5-17	20.1%	25.1%	20.2%	<17	12.3%	15-24	14.9%	10-19	10.4%
	18-65	59.9%	56.8%	57.3%	18-34	16.2%	25-34	20.5%	20-29	17.1%
	65+	14.1%	10.5%	16.7%	35-59	36.4%	35-44	17.4%	30-39	15.5%
					60+	35.2%	45-54	12.2%	40-49	12.6%
							55-64	7.0%	50-59	12.7%
							65+	4.1%	60-69	10.0%
									70+	10.9%
Education	<High School	13.5%	21.1%	18.6%	<High School	47.1%	<High School	39.3%	<High School	29%
	High School	48.9%	46%	51%	High School	19.0%	High School	40.9%	High School	37%
	≥College	37.6%	32.9%	29.8%	≥College	33.9%	≥College	20.0%	≥College	34%

within-household Differences

Table 8.24: Intention models with within-household differences for threat appraisal variables.

	Lin. Mean	Lin. SD	Log. Mean	Log. SD
Intercept	0.220	0.011	-10.609	0.064
Fl Prob. DIFF	-0.001	0.011	-0.010	0.038
Fl Dam. DIFF	0.011	0.011	0.049	0.039
Worry DIFF	-0.004	0.011	0.018	0.040
Self Eff.	0.036	0.013	0.201	0.057
Response Eff.	0.010	0.012	0.037	0.059
Perc. Cost	-0.035	0.012	-0.153	0.050
Exp.Fl.Dam	-0.009	0.011	-0.058	0.057
Age	-0.035	0.015	-0.211	0.066
Male	0.019	0.011	0.075	0.044
Education	0.001	0.011	-0.026	0.049
CN	0.002	0.013	0.153	0.067
IN	0.095	0.016	0.536	0.081
NL	0.004	0.011	-0.046	0.082
Yrs Home	-0.017	0.011	-0.116	0.049
Soc. Expect	0.029	0.011	0.189	0.052

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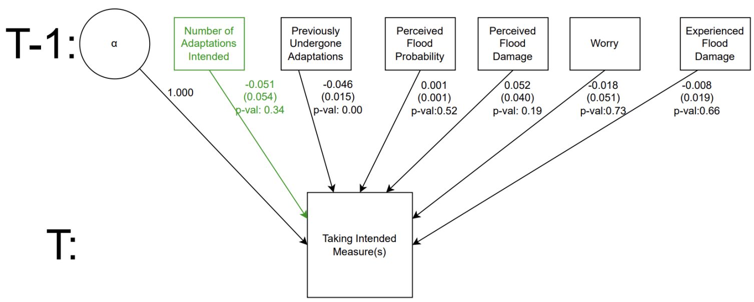

Figure 8.2: The effect of Binary intention on taking (an) adaptation measure(s) while controlling for all time-invariant effects and the depicted time-variant variables. Fit Statistics: DOF = 1; RMSEA: 0.128; chi2: 21.6, p-val $\leq$ 0.0001; AGFI: -104.12

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Table 8.25: Effects from the multinomial model, Figure 6.5

	mean	sd
Fl Prob. (Int, no act)	-0.095	0.069
Fl Prob. (Act no int)	-0.069	0.080
Fl Prob. (No int, no act)	-0.000	0.066
Fl Dam. (Int, no act)	-0.107	0.088
Fl Dam. (Act no int)	-0.165	0.102
Fl Dam. (No int, no act)	-0.339	0.084
Worry (Int, no act)	-0.076	0.091
Worry (Act no int)	0.071	0.109
Worry (No int, no act)	-0.437	0.088
Self Eff. (Int, no act)	-0.010	0.113
Self Eff. (Act no int)	-0.130	0.134
Self Eff. (No int, no act)	-0.579	0.105
Response Eff. (Int, no act)	-0.019	0.136
Response Eff. (Act no int)	-0.072	0.156
Response Eff. (No int, no act)	-0.178	0.124
Perc. Cost (Int, no act)	0.101	0.143
Perc. Cost (Act no int)	-0.117	0.161
Perc. Cost (No int, no act)	0.397	0.133
Exp.Fl.Dam (Int, no act)	-0.079	0.179
Exp.Fl.Dam (Act no int)	-0.102	0.217
Exp.Fl.Dam (No int, no act)	0.224	0.153
Age (Int, no act)	0.046	0.097
Age (Act no int)	0.232	0.108
Age (No int, no act)	0.418	0.091
Male (Int, no act)	0.095	0.171
Male (Act no int)	0.115	0.199
Male (No int, no act)	-0.338	0.163
Education (Int, no act)	0.193	0.145
Education (Act no int)	-0.022	0.167
Education (No int, no act)	0.040	0.135
CN (Int, no act)	0.816	0.262
CN (Act no int)	-0.323	0.289
CN (No int, no act)	-0.823	0.254
IN (Int, no act)	0.264	0.226
IN (Act no int)	0.109	0.252
IN (No int, no act)	-1.286	0.233
NL (Int, no act)	0.416	0.335
NL (Act no int)	-0.095	0.345
NL (No int, no act)	-0.196	0.305
Yrs Home (Int, no act)	0.011	0.009
Yrs Home (Act no int)	-0.018	0.012
Yrs Home (No int, no act)	0.009	0.009
Soc. Expect (Int, no act)	0.040	0.101
Soc. Expect (Act no int)	-0.021	0.118
Soc. Expect (No int, no act)	-0.263	0.097

Flood Events

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heavy-rains-after-tornadoes-kill-12-friday

8.7 Surveys

Attached to this thesis are a copy of the four surveys used in this dissertation to collect data

Curriculum Vitæ

Brayton Louis Noll

Brayton Noll was born on April 19, 1991, in San Jose, California. He completed his undergraduate studies at Willamette University, in Salem, Oregon in Environmental Science. He returned to school to get his Masters's degree and attended the MESPOM program, a consortium of universities that coordinate to form a joint program: Central European University, University of Lund, University of Manchester, and the University of Aegean. In late 2018 he moved to the Netherlands to acquire his Doctorate. The first two years he spent at the University of Twente, while the latter half of his Ph.D. was completed at Delft Technical University. During his Ph.D. he successfully wrote two scholarship proposals to attend the Inter-university Consortium for Political and Social Research summer school to advance his knowledge of statistics. He did a short research visit to the London School of Economics, where he deepened his resilience knowledge. He finished his PhD in late 2022.

Publications and Conferences

Peer-Reviewed Publications

1. Noll, B., Filatova, T., Need, A., & Taberna, A. (*Under Review*). Exploring the household climate adaptation intention-behavior gap: A longitudinal analysis
2. Noll, B., Filatova, T., Need, A., & de Vries, P. (2023). Uncertainty in individual risk judgments associates with vulnerability and curtailed climate adaptation. **Journal of Environmental Management**, 325, 116462.
3. Noll, B., Filatova, T. & Need, A. (2022). One and done? Exploring linkages between households' intended adaptations to climate-induced floods. **Risk Analysis.**
4. Noll, B., Filatova, T., Need, A. & Taberna, A. (2021). Contextualizing cross-national patterns in household climate change adaptation. **Nature Climate Change**, 1-6.
5. Taberna, A., Filatova, T., Roy, D., & Noll, B. (2020). Tracing resilience, social dynamics and behavioral change: a review of agent-based flood risk models. **Socio- Environmental Systems Modelling**, 2, 17938-17938.
6. Noll, B., Filatova, T., & Need, A. (2020). How does private adaptation motivation to climate change vary across cultures? Evidence from a meta-analysis. **International Journal of Disaster Risk Reduction**, 101615.

Included in this thesis.

Conference and Other Publications

1. Noll, B. (Dec. 2021). International insight into household behavioral adaptation to floods. Delta Links
2. Noll, B., Filatova, T., and Need, A. (2021). Adaptation in Context. UNESCO EAUMEGA, Mega Cities Alliance for Water and Climate.
3. Noll, B., Filatova, T., and Need, A. (2020). How does culture affect individual adaptation to climate-driven floods? The 4th European Conference on Flood Risk Management.
4. Noll, B., Filatova, T., and Need, A. (2020). Multi-Level Resilience: Community initiatives and individual behavior. International Resilience Conference, Session: A.s2. Towards a flood-resilient society: designing, assessing, and monitoring to increase flood resilience of systems.

Conferences and Talks

December 2022	[] Noll, B., Filatova, T., Need, A., Bell, A., & A. Taberna. “Household flood adaptation dynamics and the intention - behavior gap.” Society of Risk Analysis. Tampa, Florida. USA.
June 2022	Noll, B., Filatova, T., & Need, A. “Exploring linkages between households’ intended adaptations to climate-induced floods.” European Society of Ecological Economics. Pisa, Italy.
April 2022	Noll, B., Filatova, T., Need, A. & De Vries, P. “Household adaptation, behavioral uncertainty.” London School of Economics, Grantham Institute Talks. London, UK.
February 2022	Noll, B., Filatova, T., Need, A., & Taberna, A. “Cross-national patterns in household climate adaptation." RiskKAN workshop: Understanding and Modeling Complex Risks in Coupled Human-Environment Systems. Online.
January 2022	Noll, B., Filatova, T., Need, A., & Taberna, A. “Adaptation in Context." Mega Cities Alliance for Water and Climate. Paris, France/ Online.
July 2021	Noll, B., Filatova, T., & Need, A. “How does culture affect individual adaptation to climate-driven floods?" The 4th European Conference on Flood Risk Management. Budapest, Hungary/ Online.
November 2020	Noll, B., Filatova, T., & Need, A. “Multi-Level Resilience: Community initiatives and individual behavior." The 4TU Resilience Conference. Delft, Netherlands.

Won a travel award.