A SERIOUS GAME TO STUDY FLOOD RISK MITIGATION DECISIONS

DECISION GAME: A SERIOUS GAMING APPROACH TO UNDERSTANDING HOUSEHOLD FLOOD RISK MITIGATION DECISION-MAKING

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LAY ABSTRACT

We develop a research tool to help understand what drives people to protect themselves against flooding. This tool is a computer-based role-playing game experiment in which people take on the role of a homeowner tasked with choosing where to live and how to distribute their income. We log the decisions that people make in the game and use statistical analysis to figure out which factors are important in driving the decisions to insure against floods and to invest in protective structural measures. We find that experiencing a flood in the game has the largest positive effect on these decisions. The results of the model are used to inform a case study where we investigate potential outcomes of policy decisions in Calgary, Alberta. The development of this research tool and the findings contributes to optimizing policies to improve flood risk management through household interventions.

ABSTRACT

Household flood risk mitigation is an important component of Integrated Flood Risk Management. Voluntary household decisions about whether or not to structurally mitigate or insure can directly and indirectly influence vulnerability to the flooding of a community. Serious games can augment existing data collection methods in the flood risk context by operating in the space in between stated and revealed preference, through observing decisions as opposed to asking abstract hypothetical questions, while allowing for complete control over experimental conditions.

We look to answer the question of which individual and contextual factors contribute to the decision to mitigate against floods. We gather household decision-making data using a serious game role-play experiment named the *Decision Game*. Participants spent about 20 minutes making decisions about where to live and how to distribute limited income, given geographical information, including flood risk, about the city. We use a generalized linear mixed modelling approach to analyze the data. Among other findings, we see that experiencing an in-game flood had a strong positive effect, compared to a much weaker effect of a participant having experienced a real-life flood; our key observation is that incentivizing flood risk mitigation should be done quickly following a flood event. We find that real-life low-income individuals were no less likely to implement in-game mitigation measures

than their higher-income counterparts, suggesting that subsidies to address an income barrier may be an effective method of encouraging low-income household mitigation.

We apply the model to a case study of Calgary, Alberta finding that the insurance market could maintain cross-subsidization after a flood, making insuring higher risk areas more feasible. Moreover, we find that Calgarian policymakers should be encouraged to limit subsidy coverage to high-risk areas to avoid inefficient use of funds in low-risk areas which were projected to have the clear majority of program uptake.

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DECLARATION OF ACADEMIC ACHIEVEMENT

I, Julien N. Gordon, declare this thesis to be my own work. I am the sole author.

To the best of my knowledge, the content of this document does not infringe on anybody's copyright.

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LIST OF ABBREVIATIONS

ABM	Agent-Based Model
DG	Decision Game
FRM	Flood Risk Management
GLM	Generalized Linear Model
GLMM	Generalized Linear Mixed Model
IRL	In Real Life
LPHC	Low-Probability High-Consequence
WTP	Willingness to Pay

Introduction

In this thesis, we try to understand what factors contribute to household flood mitigation decisions. We do this using a digital serious game role-playing experiment to collect data. We use this tool to generate decision-making data which can be difficult to obtain in the real world. The experiment, called the *Decision Game*, was implemented across Canada both online and in-person. We model decisions to mitigate using the data from the experiment, discuss the significance of the findings and then apply the model to a case study of Calgary, Alberta.

Government policy has been putting more flood risk management responsibility on homeowners. Two key household flood risk management decisions are buying insurance and implementing structural mitigation measures. With climate change increasing the frequency and severity of flood events, it is increasingly important to make use of all aspects of flood risk management. As such, the household is being increasingly recognized as important for managing flood risk.

Investigating how to increase the voluntary implementation of household-level mitigation measures can be complicated. We know from advancements in behavioural economics that people do not always make decisions that are in their interest, particularly when it involves technically complex information. People have biases and take cognitive shortcuts to make decisions, some of which can result in decisions with a high long-term cost. In the case of flood risk management, this could mean living in flood-prone areas, not buying insurance when it is available and affordable, and not taking advantage of cost subsidies to mitigate against future flood damage. Given the complexity of assessing flood risk, improving the decision-making of households at risk of flooding presents an important challenge.

Researchers have gathered data and developed models of flood risk mitigation decision-making to try to figure out and contextualize what drives the choice to mitigate. Researchers generally have stated preference and revealed preference data collection methods at their disposal. Stated preference methods can have the issue of hypothetical bias, wherein what people state their decisions would be may not line up with what they actually do. Revealed preference methods can be expensive and are usually limited to natural experiments and for floods, the availability of natural experiments can be limited given their low probabilistic nature.

Arguably operating in a space between stated and revealed preference methods, serious games, or games developed for a purpose other than purely entertainment, can be used as a data collection tool to study decision-making under flood risk. In this thesis, we implement a serious game role-playing experiment as a research tool for gathering data on flood risk mitigation decisions. In Chapter One, we outline the methodology of the serious game and analyze the data collected. In Chapter Two, we apply the model generated in Chapter One to a case study of Calgary, Alberta to display how these data could be used in a real-world context.

Our primary research question asks which individual and contextual factors contribute to the decision to insure or structurally mitigate against floods at the household level. In addressing this question, we hope to better understand and implement household flood mitigation policy instruments and avoid unintended policy consequences. We approach this problem by conducting a serious game role-play experiment and logging the decisions that people make over time. In this experiment, participants are homeowners tasked with choosing where to live and how to distribute their income. They are given certain information about the fictional city's neighbourhoods and are exposed to in-game events which change their situation. We are especially interested in the decisions of whether to purchase flood insurance and structurally mitigate against floods and how these decisions change after the in-game events.

In Chapter One, we explain the justification for the research tool and the gap in knowledge it addresses. Furthermore, we detail the creation of the tool itself, the experimental procedure, and the recruitment methodology. We also outline how we model and analyze the data collected and report the results. We discuss the findings in detail, and additionally note the limitations of the research tool, future applications, and improvements. In Chapter Two, notwithstanding the limitations of the model, we apply it to Calgary, Alberta to investigate the predicted uptake of insurance and floodproofing under several scenarios. In discussing the findings, we focus on the implications to the insurance market and policymakers in Calgary.

CHAPTER 1

Decision Game: A Serious Gaming Approach to Understanding Household Flood Risk Mitigation Decision-Making

Background

The Context of Flooding

Flooding is costly, dangerous, and projected to increase in severity, emphasizing the need for research into managing flood risk. In Canada, flooding is the natural hazard most often responsible for economic and social losses (Nastev and Todorov 2013). The Canadian federal government and insurance companies alone paid out over $6.1 billion in flooding costs since 2008 (Government of Canada 2016). In addition to monetary costs, floods cause displacement to populations, can disrupt quality of life, can damage both physical and mental health, and can cause loss of life. Even though floods are hazardous, people tend to live near potentially dangerous bodies of water. Borchert (1992) found that German towns exceeding 5000 in population were twice as likely to be located next to a river (Kreibich, Christenberger, and Schwarze 2011). In Canada, the majority of villages, towns, and cities are found next to rivers, streams or other water bodies (Shrubsole 2013). Moreover, climate change is expected to create more extreme weather conditions. While some places are expected to experience more drought conditions, more extreme rainfall events are expected in most areas of the world (Zevenbergen et al. 2010). This may lead to more flood events in the short term, while also putting pressure on drainage infrastructure, creating a feedback loop of increased vulnerability (Zevenbergen et al. 2010). The context of increasing risk and high exposure to floods highlights the need for improving and developing interventions against flooding in Canada.

The urban context of flood risk management is of particular salience. Urbanization can create impermeable and hydraulically smooth surfaces and deforest catchment areas. These factors generally result in less infiltration, increased runoff, and runoff water being brought to river channels faster than usual (Zevenbergen et al. 2010). Moreover, high population density and population growth in urban locations increases pressure to develop into the flood-prone areas of those regions (Dieperink et al. 2016). In addition, Güneralp, Güneralp, and Liu (2015) estimate that, compared to 2000, the amount of urban area in low elevation coastal zones is expected to increase 230% to 234 000 km^2 by 2030. Additionally, the researchers estimate that in 2030, half of the global urban expansion from 2000 is expected to be in high-frequency flood zones. Furthermore, most urban expansion, especially in developing countries, is largely unplanned from a flood risk management perspective (Zevenbergen et al. 2010). Considering the increased flooding consequences from the urban environment, combined with urban expansion into floodable areas, urbanization can be considered a significant factor for flood risk. This threat highlights the need for studying flood risk management in the urban context.

Integrated Flood Risk Management

In the context of climate change, increasing urbanization, and the reality of exposure to floods, managing flood risk is of critical importance but has changed over time. Shrubsole (2013) highlights that in Canada, there was a focus on structural controlling of floods between 1953-1970, with a geotechnical and cost-benefit driven decision process. Shrubsole (2013) notes that environmental concerns, public participation, cooperation between different levels of government, and the introduction of non-structural measures like insurance, were factors which drove the transition away from this era of structural control. Including these other non-structural considerations ultimately led to the concept of integrated flood risk management (FRM). Integration in FRM means to diversify aspects of managing flood hazards, including decision-making criteria, involved stakeholders, and structural and non-structural measures. The question of who and what should be integrated into a flood risk management strategy is not always consistent in the literature but often includes:

- Reducing reliance on a solely structural approach that eliminates risk, and increasing use of methods including non-structural measures to adapt to hydrological and social uncertainties to minimize risk (Serra-Llobet, Conrad, and Schaefer 2016; Morrison, Westbrook, and Noble 2017; Butler and Pidgeon 2011).

- Moving beyond rigid political and geographical boundaries to involve all stakeholders in a river basin or catchment area in the FRM process (Serra-Llobet, Conrad, and Schaefer 2016; Samuels et al. 2010).
- Integrating FRM with other aspects of water resource management, such as storm drainage, sewage, storage, and treatment (Serra-Llobet, Conrad, and Schaefer 2016; Samuels et al. 2010).
- Emphasizing all temporal aspects of flood management i.e. pre, during, and post (Serra-Llobet, Conrad, and Schaefer 2016; Morrison, Westbrook, and Noble 2017).

Dieperink et al. (2016) note that the literature supports the concept that the diversification of FRM strategies, as well as moving from a fail-proof system to a safe-fail system, leads to more resilience against flood hazards. Moreover, Aerts et al. (2008) have shown in a case study in The Netherlands that a diversification of flood management assets is the most effective way of managing flood risk when faced with uncertainties in the flood hazard and operation of those assets. These findings reinforce the idea that an effective FRM strategy should make use of many available policy options and approaches.

Investigating Policy Options for Integrated FRM

Understanding the landscape of available options and tools for managing floods provides insight into why studying private household mitigation is justified. Managing risk against floods effectively involves building capacity and competency in many interrelated areas. For example, investing in integrated FRM can be thought of as improving in threshold, coping, recovery, and adaptive capacities. Threshold capacity refers to the ability of a city's infrastructure to absorb variation in flooding conditions with minimal disturbance. Coping capacity is the ability of a city's population, institutions, systems, and services to manage a flood event once it has occurred. Recovery capacity, also commonly referred to as resilience, is the ability of a city to return to the same or similar conditions that it was in before the event. Finally, adaptive capacity is the ability of a city's population, and relevant organizations and institutions to adapt to uncertainties (e.g. climate change, population growth, and urbanization) in the future that may impact flood risk in the long term (Zevenbergen et al. 2010). One consequence of this multifaceted nature of integrated FRM is that there is no single policy to effectively address flood risk in all those areas. In the next few sections, the major areas of FRM policies are investigated with a critical lens to demonstrate some pitfalls of relying on a single policy tool. Additionally, this provides context and justification for researching the optimization of private household interventions as done in this study.

Land-use and spatial planning

Governments use land-use and spatial planning to influence the use of land to achieve goals such as greater economic efficiency. The tools of land-use and spatial planning include regulations, social conventions, and rules used to differentiate functional and legal aspects of land (Zevenbergen et al. 2010). Policies such as building codes can be important for preventing new developments from being built without adaptive qualities (Greiving and Angignard 2014). In addition, land-use decisions to place non-critical infrastructure in flood-prone areas, or for storing or rerouting flood water when possible are valuable FRM policies (Zevenbergen et al. 2010).

While land-use and spatial planning play a vital role in an FRM portfolio, they may not be a complete remedy for managing flood risk. For example, removing people from floodplains using buyout legislation, and preventing future residential or critical infrastructure development in floodplains using zoning regulations can virtually eliminate risk for fluvial events (Greiving and Angignard 2014). Land-use planning can thus be considered the most effective policy tool to eliminate flood risk, in theory. However, flood risk is usually a low-ranked consideration when creating zoning regulations or land-use policy (Zevenbergen et al. 2010). Planners face economic pressure and may even find cost-beneficial trade-offs to developing in flood-prone areas (Baubion 2015). Furthermore, land-use policies that eliminate exposure in flood-prone areas may not be feasible when considering cities that are already developed. For example, the City of Calgary identified buying out 980 residential buildings in the floodway as a potentially attractive measure for reducing exposure to floods, but it had a negative benefit-cost ratio in addition to ranking low in their sustainability criteria (Calgary 2016).

Land-use planning for water management also tends to suffer from transboundary and trans-jurisdictional problems. Catchment areas rarely fit well with other administrative units of governance (Green 2017). Competing interests and administrative complexity often limit land-use to a subtler role in FRM. For example, catchment areas may span multiple metropolitan areas and various government departments may have differing interests in managing the floodplain, resulting in the stalling of basin-wide management choices (Green 2017). A study by Hegger et al. (2013) found that most countries nominally participating in the EU STAR-Flood project had limited integration of flood management practices in their spatial planning policies. The authors cited the assumption that water managers would technologically solve flooding problems as a potential reason for this lack of integration, in addition to the overall lack of communication between water managers and spatial planners.

Flood Defences

Flood hazard can be addressed by protecting certain areas to an acceptable service level of risk via structural measures (Kreibich et al. 2015). These service levels are typically framed as protecting against a flood with a "one in x" return period. For example, a one in one hundred flood refers to a flood which is expected to happen once in a given hundred-year period. These structural projects include infrastructure such as dams, upstream reservoirs, and dikes. Prior to 1970, structural measures were the preferred policy tool of the Canadian government (Shrubsole 2013). The efficacy of structural flood defences in reducing flood hazard from a technical standpoint is well documented, and flood defences are an integral part of an FRM portfolio.

However, structural measures are not without drawbacks and issues. Structural measures can have unintended consequences, such as increasing demand for development in floodable areas due to the decreased risk (Kreibich et al. 2015). For example, Husby (2016) identified that the Deltaworks project in the Netherlands, which involved large infrastructure projects including dikes, resulted in increased exposure to floods in protected areas over the long term. Additionally, reducing the hazard through engineering interventions such as flood walls may increase individual vulnerability to an extreme event by reducing individual capacity to react through reduced flood memories (Baubion 2015). There may also be some contexts in which large-scale infrastructure projects are not appropriate, such as sprawling coastal areas of development in the U.S. (Brody, Lee, and Highfield 2017), or when development displaces risk from one place to another. While costs are high, the benefit is lower when development is less dense. In this circumstance, the cost-benefit of targeted private mitigation may be comparatively higher.

Dieperink et al. (2016) highlight that an advantage of flood defences is the that there tend to be fewer political barriers to their implementation, but caution that this is not always the case. Flood defences are typically allocated in a process involving probabilities, population density, and economic damages. This process can create winners and losers, however, and pushback from property owners and citizen groups can limit implementation of defences which have aesthetic or property value-reducing impacts (Dieperink et al. 2016). To illustrate, consider property owners who may resent the erection of a floodwall which obstructs a river view. As a tangible example, a risk assessment for the City of Calgary found that an upstream Springbank Reservoir was the most effective method of flood mitigation for the Elbow River. While this project was found to be feasible and cost-beneficial, local advocacy groups such as DontDamnSpringbank have arisen as detractors of the project (Bryant and Davies 2017).

Flood Emergency Preparedness

Flood preparedness requires competency in responsible actors such as forecasters, warning disseminators and respondents, and emergency and social services (Dieperink et al. 2016). Competency in preparedness entails having quality flood monitoring and forecasting systems, as well as assigning crisis roles, highlighting vulnerable populations and key stakeholders, and knowing basin characteristics before a flood happens (Zevenbergen et al. 2010). The Canadian federal government requires municipalities to have emergency plans to respond to flood events, but the specifics of these plans are left largely to the discretion of those municipalities (Shrubsole 2013). Emergency preparedness within the population can also contribute to flood-preparedness overall, such as households having an emergency kit (Dieperink et al. 2016). However, cognitive factors and attitudes towards hazards, as well as a sense of connectedness to one's community can influence motivation to use those preparedness strategies (Levac, Toal-Sullivan, and O'Sullivan 2012).

Private Household Mitigation

There is a trend in FRM to encourage private households to engage in mitigation to supplement public efforts (Babcicky and Seebauer 2017). Private mitigation generally includes lot-level interventions by a household that lower the financial impact and physical damage of a flood. These efforts are generally structural alterations to a dwelling or purchasing flood insurance when available. After a flood event, buildings that are resistant against floods generally exhibit the following: sustaining only minor and easily repairable damage and utility disruption; the foundation remaining in fully functional condition; the building envelope remaining unimpaired; and a high degree of accessibility and livability (Zevenbergen et al. 2010). Table 1 provides examples of structural household mitigation measures which can aid in achieving the aforementioned traits. These efforts reduce vulnerability to flooding, lower the financial burden from an event, and allow for a more convenient return to normal life after a flood.

Table 1 - *Examples of household flood mitigation interventions (FEMA 2014)*

	Dry Prevents water from entering or reaching the building	**Wet** Assumes water will enter the building and reduces consequences
Active Requires action to use	• Temporary flood shields across doors and windows • Emergency sandbags	• Relocation of items stored below flood protection elevation level
Passive Functions without interaction	• Waterproof coatings and sealants • Sump pump and backflow valve	• Installment of openings to equalize hydrostatic pressure • Use of flood resistant materials i.e. concrete, stone, and ceramic

It is often assumed that structural private mitigation measures are cost-beneficial; however, studies of the costs and benefits of these measures are limited. One study by Kreibich, Christenberger, and Schwarze (2011), retrospectively surveyed participants after a flood and compared the relative amount of monetary damage incurred between those with protective measures and those without. The authors found certain measures to be economically reasonable depending on the risk level of the households, suggesting that large-scale implementation to drive down costs could improve the trade-offs to buyers. Kreibich et al. (2015) also note that few cost-benefit studies regarding private flood mitigation exist, and do not include a Canadian example in their review of cost studies of damage reducing measures at the building level.

Flood insurance can be a good source of rehabilitation after a flood event (Sandink et al. 2016), lowering the financial burden on a household of experiencing a flood. Flood insurance is not without its barriers and drawbacks, however. Insurance can be cost-prohibitive to higher-risk households, for whom the demand for insurance would arguably be greatest. Another problem is moral hazard, in which insured households take less precaution against floods, and are more willing to live in flood-prone areas, and less likely to engage in risk-managing strategies (Sandink et al. 2016). In addition, another form of moral hazard may exist in which households do not insure due to confidence in government compensation (Zevenbergen et al. 2010). Furthermore, Capano and Woo (2017) note that policies which induce a return to equilibrium, such as insurance, may not be appropriate when that equilibrium was the cause of instability or risk. In other words, insurance may allow unsustainably vulnerable households to avoid adaptation and remain vulnerable. Sandink et al. (2016) argue that flood insurance can be viable in Canada as part of a larger integrated FRM strategy while limiting coverage available to high-risk households.

The characteristic of private household mitigation that sets it apart from other tools in FRM is the voluntary aspect of its implementation. Private mitigation measures can be efficient and sustainable FRM tools, but robust government requirements and regulations for implementing them often do not exist (Dieperink et al. 2016). The voluntary aspect of having to choose to implement these measures results in unique barriers to their implementation. For example, the time and effort of implementing floodproofing interventions, especially if they are intrusive, are often not considered in analyses of mitigation measures (Heidi Kreibich et al. 2015). This may be one reason for which Bubeck et al. (2013) found that while people appraise the effectiveness of private mitigation highly, people often postpone these measures. Contrastingly, Buchecker, Ogasa, and Maidl (2016) found that respondents generally did not consider individual measures to be effective and did not know how to protect themselves. Consistent with other literature, respondents preferred engineering and structural interventions over individual or non-structural methods. This contrast suggests a context-dependent and complex decision-making process for implementing mitigation measures.

Aside from voluntary compliance from households, private mitigation faces further complexity from a governance perspective by often being dependent on multi-stakeholder agreements, encouragement of homeowner mitigation responsibility by local authorities, stressing local economic benefits of mitigation, and other voluntary programs and initiatives (Dieperink et al. 2016). Moreover, private mitigation may be susceptible to the discourse-related challenges around the shaping of the narrative that rationalizes the need for intervention (Dieperink et al. 2016). In other words, the public may not be open to the narrative that mitigation of floods is up to individuals. In line with this, surveys in Germany found evidence that people trusted government flood prevention measures much more highly than personal measures (Steinführer and Kuhlicke 2007).

The Role of Human Decision-Making in Private Household Mitigation

In most contexts, a universally appropriate and effective policy for managing flood risk is unlikely to exist. This underlines the need for households to partially take responsibility for mitigating risk for an integrated FRM approach. Private household mitigation often involves the voluntary implementation of structural measures and purchasing of insurance policies. In practice, it is well understood that humans often do not make decisions as rational actors in classical economic models, particularly under uncertainty. Especially in the case of natural disaster risk, people use various heuristics to ease the cognitive load of decision-making and are subject to biases, which can result in maladaptation (Kunreuther et al. 2013). As an example of this irrationality, a study of Dutch insurance policyholders showed that they preferred insuring for a high-probability-low-consequence event, bicycle theft, over a low-probability-high-consequence flood event, and that objective levels of risk did not strongly influence the insurance decision (Browne, Knoller, and Richter 2015). Furthermore, Botzen and van den Bergh (2013) identify that people rarely prefer to partially reduce risk, preferring to eliminate risk to zero, which may inhibit uptake of many mitigation measures. The complexity of human decision-making results in difficulty for policy-makers to encourage people to engage in private mitigation.

Researchers have attempted to model decision-making under flood risk using ideas from Protection Motivation Theory to inform risk communication and other policy interventions for increasing private mitigation uptake (Bubeck et al. 2012). Protection Motivation Theory was originally developed by (Rogers 1975) as a framework for understanding fear appeals. In the model, two key components drive adaptive responses, namely threat appraisal and coping appraisal. Generally, threat appraisal involves assessing the severity of and vulnerability to a threat, while coping appraisal is the process of assessing the effectiveness of potential interventions to the threat (Norman et al. 2005). Researchers have extended this Protection Motivation Theory to model the decision to privately mitigate against flooding, including factors like flood experience and socio-economic characteristics (Poussin et al. 2014; Grothmann and Reusswig 2006; Bubeck et al. 2013). These studies aim to identify the determinants of flood mitigation behaviour by connecting survey responses to reported or intended mitigation behaviour.

Highlighting the value of understanding flood risk decision-making, Brody, Lee, and Highfield (2017) suggest that implementation of adaptation programs by communities could be improved if the factors that trigger adoption of mitigation measures are known. To further highlight the value of understanding household decision-making under flood risk, consider that in Canada, disaster relief has been criticized for being akin to implicit insurance after flood events, funded by the larger tax-paying population (Sandink et al. 2016). Kreibich, Christenberger, and Schwarze (2011) suggest that relief should only be provided to households that have implemented a certain level of efforts to self-insure and self-protect. The authors suggest that mandatory building code regulations and "carrot and stick" incentives could be used to promote mitigation in conjunction with this policy. However, removing relief safety nets in this way, while not having a full understanding about mitigation decision-making could be problematic as financial incentives alone may not generate enough uptake of mitigation efforts, resulting in too many people without relief after a flood.

An understanding of decision-making under flood risk can be applied in sociohydrological models to investigate behaviour on larger scales like cities. For example, Di Baldassarre et al. (2015) develop a model to understand adaptation and levee effects. The adaptation effect describes the decrease in vulnerability associated with frequent flooding, and conversely, the levee effect describes the observation that lack of consistent flooding raises vulnerability (Di Baldassarre et al. 2015). The researchers develop differential equations based on the plausible assumptions of human-flood interactions which produce these adaptation and levee effects. The authors note that their findings can help direct the types of data that must be collected to understand human-flood interactions. Di Baldassarre et al. (2015) further note the need for validation of the sociohydrologic model through fitting of its findings on empirical test sites, in addition to evaluating whether the model can represent emergent behaviours such as the adaptation and levee effects. As another example of synthesizing data on decision-making under flood risk, Haer et al. (2016) use an Agent-Based Model (ABM) to explore the interaction between human behaviour and flood risk. ABMs use concepts from the social sciences and computer science to understand a large-scale outcome. They do this by assigning rules of behaviour to individual agents, often representing individuals or households. As the system progresses through time, emergent properties of the system are observed, often involving outcomes of and interactions between the agents and their environment (Axelrod and Tesfatsion 2006). The ABM developed by Haer et al. (2016) demonstrates that including people's decisions to invest in loss-reducing measures can more accurately estimate future flood risk under a number of cognitive assumptions. However, the authors remark upon the need to validate the decision models used in their ABM through empirical data that capture decision-making in the context of changing flood risk. In both modelling examples, the authors call for empirical data on decisions made in flooding contexts. This highlights the value of data collection on human decision-making under flood risk.

Introduction to A Serious Game Approach to Understanding Decision-Making

Understanding human decision-making in the context of flood risk can improve implementation of private mitigation programs, avoid maladaptation to floods, and improve our understanding of sociohydrological systems. This highlights the need for data on human decisions in the flood risk context. In this thesis project, we use a role-play experiment serious game for data collection, which differs from typically used methods for gathering information on preferences. Role-playing games involve taking on the role of a character in a fictional setting.

To understand the value of this data collection method, it is important to first discuss the ways in which researchers typically collect information on decision-making. Generally, researchers use stated preference and revealed preference methods for collecting data on human decision-making. Both methods generally gather information on how much people value goods and services, usually in terms of willingness to pay (WTP). Revealed preference methods involve observing market data to study people's decisions. This may include investigating purchase data to directly look at people's valuations, or researchers may infer WTP through methods like hedonistic pricing. Revealed preference methods are generally favoured over other methods, as the data are directly associated with individual decisions to purchase or valuation of a good or service; however, revealed preference methods can be prohibitively expensive and market data for certain natural experiments do not exist (Kimenju et al. 2006). Stated preference methods can be used when revealed preference methods are unavailable or unattainable and have some of their own advantages. Stated preference methods involve surveys, experimental choice auctions and discrete choice experiments like contingent valuation to elicit valuations of goods and services from participants. Researchers have noted that hypothetical bias and strategic bias are problems for stated preference methods which must be accounted for (Venkatachalam 2004). Hypothetical bias occurs when stated WTP differs from the participants' WTP for the good or service in real life. Strategic bias happens when participants believe that their valuation will affect the provision of an actual good or service, and so may over or under-report WTP to influence policy. An advantage of stated preference methods is that they can gather enriching information on psychological and situational factors that observable market data often do not provide (Hobbs and Mooney 2016).

Considering the presence of bias, the critical question asked of stated preferences is to what extent hypothetical responses can represent real-life behaviour, as this is ultimately what makes these data useful. This problem of predicting real-life action from participant responses is common in social science research. Meta-analysis of stated preference methods have shown that there are strong correlations between stated preference and revealed preference estimations, but stated preference tends to overestimate valuations of participants with varying degrees of magnitude and skew (Murphy et al. 2005; Carson et al. 1996). For example, in the flood risk context, Scolobig et al. (2012) note that the willingness to invest in flood mitigation measures was higher than actual investment.

While predictions from stated preference methods are known to be biased, some methods can minimize these discrepancies (Loomis 2014). These methods include measuring the uncertainty of participants' WTP (Loomis 2014; Braun et al. 2016; Champ et al. 1997) and calibrating stated preference data by assigning correction factors based on samples of revealed preference (Ben-Akiva and Morikawa 1990; Loomis 2014; Fox et al. 1998). Furthermore, providing options to participants, such as by using discrete choice experiments, reduce hypothetical bias (Murphy et al. 2005). Moreover, bias is further reduced if participants can make a non-choice to avoid forced decisions, since non-decisions are reflective of real market behaviour, especially when participants may be unfamiliar with choice categories (Adamowicz et al. 1998; Hensher 2010). Moreover, Hanemann (1994) argues that the plausibility and meaningfulness of the given scenario are key to successfully determining pricing preferences. In addition, he notes that concrete questions with specific commodities (i.e. "if it costs $1000, would you be willing to pay to reduce risk of flooding by 10%?") provide more useful and accurate information than open-ended questions with vague commodities (i.e. "what is the most you would pay to protect the environment?"), which ultimately result in more representative findings. Finally, Hensher (2010) highlights the value of reference alternatives or choice contexts in reducing hypothetical biases, such as using a trip to Paris to ground valuations of other goods.

While revealed preference methods are generally preferred, they require natural experiments, which in the flooding context are difficult to gather due to the low-probability-high-consequence nature of the event. This makes flooding scenarios an obvious candidate for using stated preference methods; however, decision-making biases are prevalent in the natural disaster context, where budgeting heuristics, learning failures, time discounting, postponement, and other factors can result in underinvestment in adaptation (Kunreuther et al. 2013). The prevalence of decision-making biases around flooding may contribute to why stated preferences for private flood mitigation decisions may considerably differ from actual behaviour. Given that availability of choice (including non-decisions), presenting plausible and meaningful scenarios, and providing grounding choice contexts are known to reduce hypothetical bias, using a serious gaming role-play experiment as a data collection method may be an effective alternative to existing stated preference methods.

The Serious Game Approach

Serious games can be defined as games used for a purpose other than purely entertainment (Wilkinson 2016). They have a variety of developed uses, including education, healthcare, mental wellness, social change, building social skills and cultural knowledge, professional learning and training, and supporting life decisions (Wilkinson 2016; Calderón and Ruiz 2015). One example from the health sector involves a video game used for the neuropsychological screening of children, where participants play through the familiar experience of a trip. The performance metrics of the game correlated with standardized neuropsychological tests, indicating the potential of the game as a screening tool (Rosetti et al. 2017). As a further example, a board game that tasks participants with building a skyscraper was designed with the purpose of training participants on concepts of supply chain management (van den Berg et al. 2017). A final illustration involves a computer model-assisted simulation of a river management scenario, in which participants negotiate for, try, and reassess river management measures with the purpose of promoting social learning (Van der Wal et al. 2016).

In this study, we use a serious game as a data gathering method for understanding decision-making under flood risk, which is outside of the typical uses of serious games. van den Berg et al. (2017) note that serious games often lack rigorous methods of assessing how and why certain player strategies are used. The authors identify that this can be done post-game, through surveys, but that these methods are reliant on the potentially unreliable opinion of the participants. Digital games have the advantage of being able to track decisions made throughout the process (van den Berg et al. 2017), such as how the neuropsychological screening tool game produces automatic test scores after gameplay (Rosetti et al. 2017). The tracking of choices means that the decisions can be investigated statistically as a more rigorous method of analysis. However, Calderón and Ruiz (2015) note that few serious games log in-game decisions, in practice. These logged data can be useful for comparing the effectiveness of financial product structures (Kunreuther and Michel-Kerjan 2015), and calibrating and validating social models like ABMs (Le Pira et al. 2017), among other uses. For example, Arnal et al. (2016) used a decision-making game to analyze the WTP for probabilistic flood forecasts when making a community flood mitigation decision. The participants competed against each other to make the best mitigation decisions with the least amount of money. The researchers quantitatively investigated the importance of certain in-game factors, such as the accuracy of the forecasts, on the WTP for those forecasts. Arnal et al. (2016) highlight that the use of these games fundamentally blurs the line between the typically dichotomous research methods of stated and revealed preference. It is possible that the benefits of the serious game role-play experiment approach could come from operating in the space between these two methods; they are easily controlled and offer the flexibility of stated preference methods, while potentially avoiding hypothetical bias by having participants actively engage in a scenario instead of thinking hypothetically about what they would do in that scenario. For example, in the case of studying decisions after a flood, an event in-game can have a consequence on the player's resources, which can elicit a more organic reaction than asking what would happen hypothetically in the case of a flood.

Within the context of understanding decisions under flood risk, serious games may have some unique advantages. Serious games can facilitate the experience of events that would otherwise be prohibitive due to time, cost, or safety concerns (van den Berg et al. 2017). Since floods are relatively low-probability events, the opportunities to collect empirical data from flood victims may be limited. Furthermore, specific phenomena related to coupled human and hydrological systems, such as the adaptation and levee effects studied by (Di Baldassarre et al. 2015), may be even rarer. Serious game environments can be adjusted with desired contexts and experimental controls to test hypotheses in an experimental setting. The games could also feature richer visual and interactive environments, and a less abstract narrative than a survey, which could result in better quality data. Moreover, the scalability of digital games could lend themselves to generating large datasets needed for powerful statistical models. Furthermore, Rosetti et al. (2017) highlight that the advantages of SGs can include the simulation of environments familiar to subjects, less required supervision, adaptive difficulty, decreased workload, and automatic report generation. Some studies caution that interacting with machines can change results when compared to paper counterparts (Rosetti et al. 2017). However, this finding may be tempered when considering that direct translations from paper to computer do not make use of the engagement advantages that digital SGs can offer (Rosetti et al. 2017).

Methods

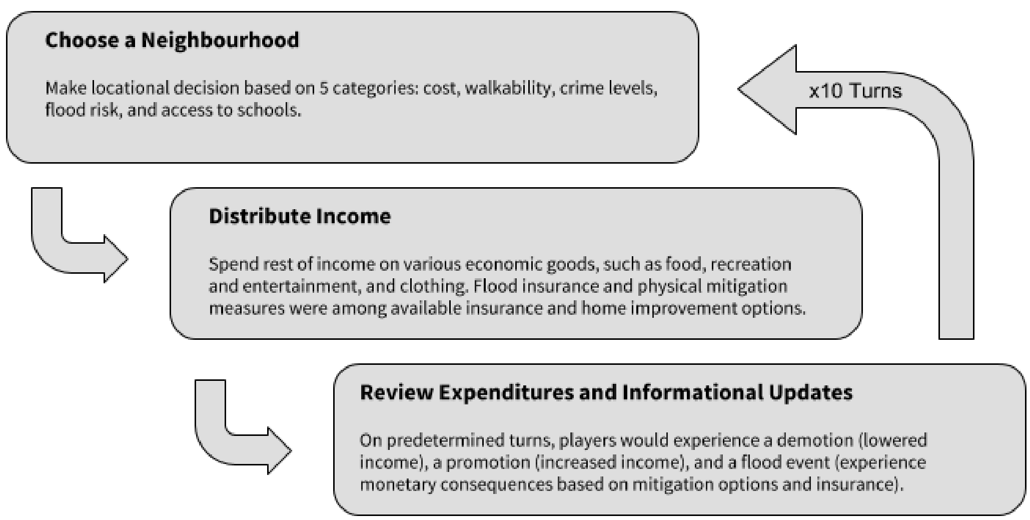
Research Tool Overview

In this study, we aim to answer the following research question:

Which factors predict the decision to invest in structural household-level flood mitigation or to purchase flood insurance?

To address the question, a web-based research tool named *Decision Game* was developed in 2017 to gather data about flood risk mitigation decisions, with the ultimate goal of modelling the decisions to purchase flood insurance or structural mitigation measures. The game was an internet browser-based experiment which put participants in the role of a homeowner tasked with making decisions about where to live and how to spend the rest of their limited resources. An overview of the role-play experiment can be seen in Figure 1. In addition to the experiment, participants responded to pre and post-game surveys that gave information about a variety of situational factors, attitudes, and demographic attributes relevant to decisions about flood risk. The questions asked, the targeted information, and the potential relationships with mitigation decisions are listed in Appendix 1. The combination of the in-game decisions and real-life information provided data about flood risk mitigation decisions within an experimental setting. We use these data to calibrate a statistical model to determine factors which predict the decision to mitigate against floods and purchase flood insurance. Furthermore, we investigate the consistency of the results of the model with previous findings in the literature on our independent variables, under the assumption that reasonable results suggest that the role-play experiment has potential as a method for collecting data about flood risk mitigation decisions.

Figure 1 - *Overview of the Role-Play Experiment*



Data Analysis

The analysis involves the estimation of two statistical models. The model structures are mostly congruent; however, one predicts the likelihood of structurally mitigating against floods, and the other predicts the likelihood of purchasing flood insurance. We use a generalized linear mixed model (GLMM) to analyze the data, choosing a binomial distribution with a logit link function. We use the lme4 package (Bates et al. 2015) in R (R Core Team 2017), choosing the glmer function to execute the analysis. We use the BOBYQA optimizer (Powell, 2009) with starting values for coefficient estimates obtained from bivariate versions of the model using one independent variable at a time as the predictor. We investigate the sensitivity of the model to both optimizer choice and starting values.

GLMMs can be thought of as an extension of Generalized Linear Models (GLMs). In GLMs, regression coefficients are typically treated as fixed, but there are some cases in which it makes sense for coefficients to be random (Jiang 2007). This can occur when observations are correlated due to multiple measurements from the same source. For example, in medical contexts when multiple measurements come from the same patients, a patient-level random effect would be estimated in addition to the fixed effects (e.g. the medical treatment) (Jiang 2007). GLMMs combine two often-used statistical frameworks of GLMs and linear mixed models which use random effects (Bolker et al. 2009). GLMMs are used in situations in which there are random effects and a non-normally distributed dependent variable (Bolker et al. 2009).

In our model, we assume fixed effects for psychological and situational factors (e.g. risk perception, real-life flood experience), and design effects for in-game events (e.g. in-game flood event, income changes). We also include a participant-level random effect which accounts for between-participant error that is not accounted for by fixed effects. The model we use is specified in (1). The fixed effects and design effects are all treated in the same way when estimating the model; however, we draw a distinction since the design effects are not independent *variables*, as they occur at the same time and in the same way for all participants. We also note that the fixed and design effects contain both in-game factors (in-game changes in income, flood event and neighbourhood flood risk) and real-life factors. This gives us an opportunity to compare the effects of in-game and real-life versions of income and flood-experience.

$$y_k = h(\sum_{i=1}^{n}(x_i\beta_i) + \sum_{j=1}^{m}(z_j\gamma_j) + \beta_0 + u_k + \epsilon) \qquad (1)$$

(1) specifies the GLMM that we use, where: y_k represents the probability of insuring or mitigating for a given respondent *k*; $h(\cdot)$ represents the inverse of the logit link function of the form $\frac{e^{(\cdot)}}{1+e^{(\cdot)}}$; n represents the number of fixed effects; x_i represents the fixed effects; β_i represents the regression coefficient of the fixed effects; m represents the number of design effects; z_j represents the design effects; γ_j represents

the regression coefficient of the design effects; β_0 represents the fixed intercept; u_k represents the random intercept for a given participant *k*, which can be thought of as the error *between* participants—note that we assume that $u_k \sim N(0, \sigma_u^2)$; and ϵ represents the residual error *within* participants, or the error not explained by u_k. We assume an unstructured variance-covariance matrix for within participant residuals.

Not all the original pool of variables that we surveyed for could be included in the final model (see Appendix 1). A large degree of collinearity existed between our survey responses, which was identified using chi-square tests of independence compiled in a correlation matrix (see Appendix 3). We selected independent variables from Appendix 1 for the final model based on a judgement—weighing their importance to the literature as well as their degree of correlation with other variables. The fixed effects we use in the model firstly include the player's real-life income level. Income is typically found to have a positive impact on mitigation decisions (Osberghaus 2014; Bubeck et al. 2012; Grothmann and Reusswig 2006; Botzen et al. 2009; Botzen and Van Den Bergh 2012), but it is important to note that the player's real-life income did not have an effect on the in-game income. We are therefore effectively examining differences in decision-making between lower-income and higher-income participants when they are given the same amounts of money to work with. Real-life risk perception and coping appraisal are two fixed effects included in the model which are informed by protection motivation theory (Rogers 1975). Flood risk perception is a key component of threat appraisal, which, in the context of flooding, involves assessing the severity of and vulnerability to flooding, while coping appraisal is the process of considering the effectiveness of potential interventions to flooding (Norman et al. 2005). It has been argued that risk perception and coping appraisal are both required to motivate protective action (Bubeck et al. 2013), but due to lack of convergence because of sample size, we were unable to include any interaction terms in the GLMM. Flood experience, or having been previously flooded in real life, has been found to have a positive relationship with mitigation decisions (Brody et al. 2017b; Osberghaus 2017), but that the effect fades over time (Atreya et al. 2013; Brody et al. 2017b; Tobin and Montz 1994). Personal measures, or having previously implemented a flood mitigation measure, is another fixed effect included in the model. There is some evidence of advantageous selection for flood mitigation, where flood insurance policyholders are more likely to implement mitigation measures, contrary to what one might expect due to moral hazard (Hudson et al. 2017; Osberghaus 2014). Having mitigation measures in place has been found to reduce risk perception and decrease the likelihood of implementing further measures (Richert et al. 2017; Poussin et al. 2013). Flood risk, or living in a high-risk neighbourhood in the game, is also included as a fixed effect. Flood risk levels have been found to be positively related with risk perceptions (Botzen et al. 2015; Botzen et al. 2009; Siegrist and Gutscher 2006), but the relationship with mitigation decisions has been found to be weak (Poussin et al. 2014; Siegrist and Gutscher 2006). The design effects were included to compare decisions made in the game after each game event. These events were a drop in income, a rise in income, and a flood event.

Addressing Stayers

Based on the game dynamics, some participants may be exhibiting stayer behaviour, or choosing one strategy (i.e. always mitigate, never mitigate) throughout the entirety of the experiment. This contrasts with movers, who change their mitigation decision at least once in the game. It is difficult to know if stayer participants are expressing a genuine preference to not change any game options or are exhibiting a lack of engagement in the experiment. Determining the impact of stayer behaviour on a model is challenging. We use endpoints to extend the GLMM to consider the probability that an individual is a stayer. While random effects are typically expected to be normally distributed, endpoints extend the GLMM's model fitting process to include spikes of probability at the extremes of the expected probability distribution of the random effects. We first compare the log-likelihoods of equivalently specified models with and without endpoints to determine whether consideration of stayer behaviour affects the models. Currently, the lme4 package does not have the ability to explicitly address stayer behaviour. We used the SabreR (Crouchley et al. 2016) package to estimate the same GLMM specification as in (1) but including endpoints. Determining whether stayer behaviour is a result of a lack of engagement with the experiment or is indicative of a cognitively lazy decision-making process consistent with real-world behaviour is also challenging. We conduct chi-square tests of independence and a linear-by-linear test of association between the fixed effects in Appendix 1 and being a stayer to investigate whether stayer behaviour is associated with any specific groups of participants. We define being a stayer as having the same value (i.e. 0 or 1) for a dependent variable throughout the experiment. We are uncertain as to whether stayers at 0 and 1 should be classified as the same or different. These two groups of stayers are both potentially using similar types of cognitive laziness but with different decision outcomes. We consider three types of tests to capture multiple interpretations of stayers and movers. In the first case, there are two categories; one for stayers at 0 or 1, and movers, for which we use a two by two chi-square test of independence. In the second case, we consider stayers at 0, movers, and stayers at 1 as three distinct categories, for which we use a two by three chi-square test of independence. Finally, we consider the case that the stayers at 0, movers, and stayers at 1 may be ordinally related, for which we use a linear-by-linear test of association.

Recruitment

Recruitment was carried out both online and in-person, but all participants completed the tasks digitally on a computer or tablet. In-person recruitment was performed at 7 coffee shops and two community centres in Calgary, Alberta. The researcher approached the managers of the businesses and requested to come back at a later date to conduct research. A table was set up with laptops and an information poster for potential participants. The researcher approached patrons and asked whether they would like to participate in a master's research experiment, that it would take about 20-25 minutes, and explained the compensation. The response rate was not recorded but was estimated to be low, with about one in ten agreeing to participate. The researcher was present for the duration of the experiment, but did not provide unsolicited direction to the participants.

Online participants were recruited through a convenience sampling method using a number of approaches. Business cards with the experiment website were offered to people who did not want to participate but indicated interest in the project. Posters were put up in various locations in Calgary and Hamilton. Social media (Facebook, Twitter) was used to recruit participants, for example by reaching out to Calgarian homeowner-related groups, environmental groups, and community associations to "retweet" a recruitment post. In addition, two environmental groups agreed to include a recruitment paragraph in their email newsletters. All participants visited the webpage *http://www.decisiongame.ca* which directed them to a pre-game survey.

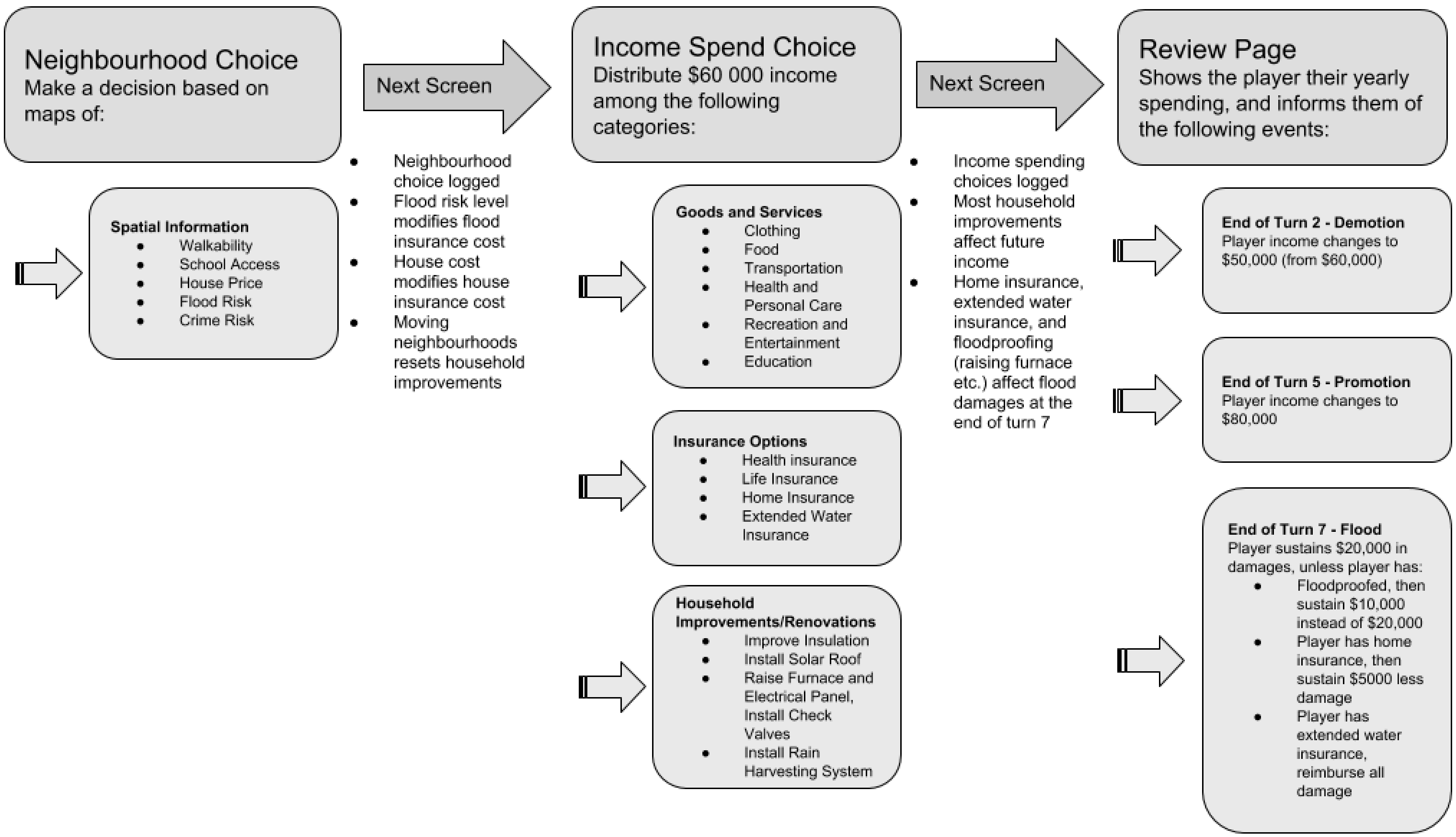
There were some minor differences between in-person and online participants. Firstly, the researcher was physically present for in-person participants, and so was able to answer clarifying questions should they have been asked. While the option to email the researcher was available to participants, no online participants asked clarifying questions. Finally, all participants were entered in a draw for a $500 Amazon.ca gift certificate, but in-person participants received an additional $5 gift certificate to Starbucks or Tim Hortons.

Experimental Procedure

Overview

All participants started by receiving basic information about the experiment and consenting to participate. A pre-game survey asked basic demographic questions and was followed by the role-play experiment. The game itself began with information on the context of the role-play and instructions on how to navigate the game. Participants assumed the role of a household decision maker charged with assigning income to various categories, prioritizing what they deem appropriate. The game was a sequence of ten turns, with each turn representing a year of life. The exact decisions available at each stage of the game are represented in Figure 2. An exit survey followed the game, which collected information about risk perceptions, attitudes, and a variety of other relevant information.

Figure 2 - *Detailed Role Play Experimental Procedure of a Turn*



Welcome, Intro Survey, and Instruction Page

Appendix 4.1 shows the page that one would view upon accessing the website. The page included basic information including the nature of the experiment and participation, the participation requirements, and the identity of the researchers. A clickable button directed participants to the intro survey. The intro survey provided a letter of information about the experiment and consent to participate consistent with the McMaster Research Ethics Board guidelines. Participants were also asked for their email, age, income and education level. Note that the description of the game was framed as a household decision-making experiment rather than an experiment designed to gather information about flood risk mitigation decisions. Following completion of the survey, the participants were emailed a unique link to participate at the Decision Game website. The intro survey can be found in Appendix 4.2. Upon clicking the DecisionGame link emailed to them, participants were directed to a basic instruction page shown in Appendix 4.3. This page informed the participants of the context of the game and their role as a homeowner, as well as the types of decisions they would be making. Meanwhile, a MySQL table was created, named according to their unique identifier, in which all the role-play experiment data was logged.

Neighbourhood Choice

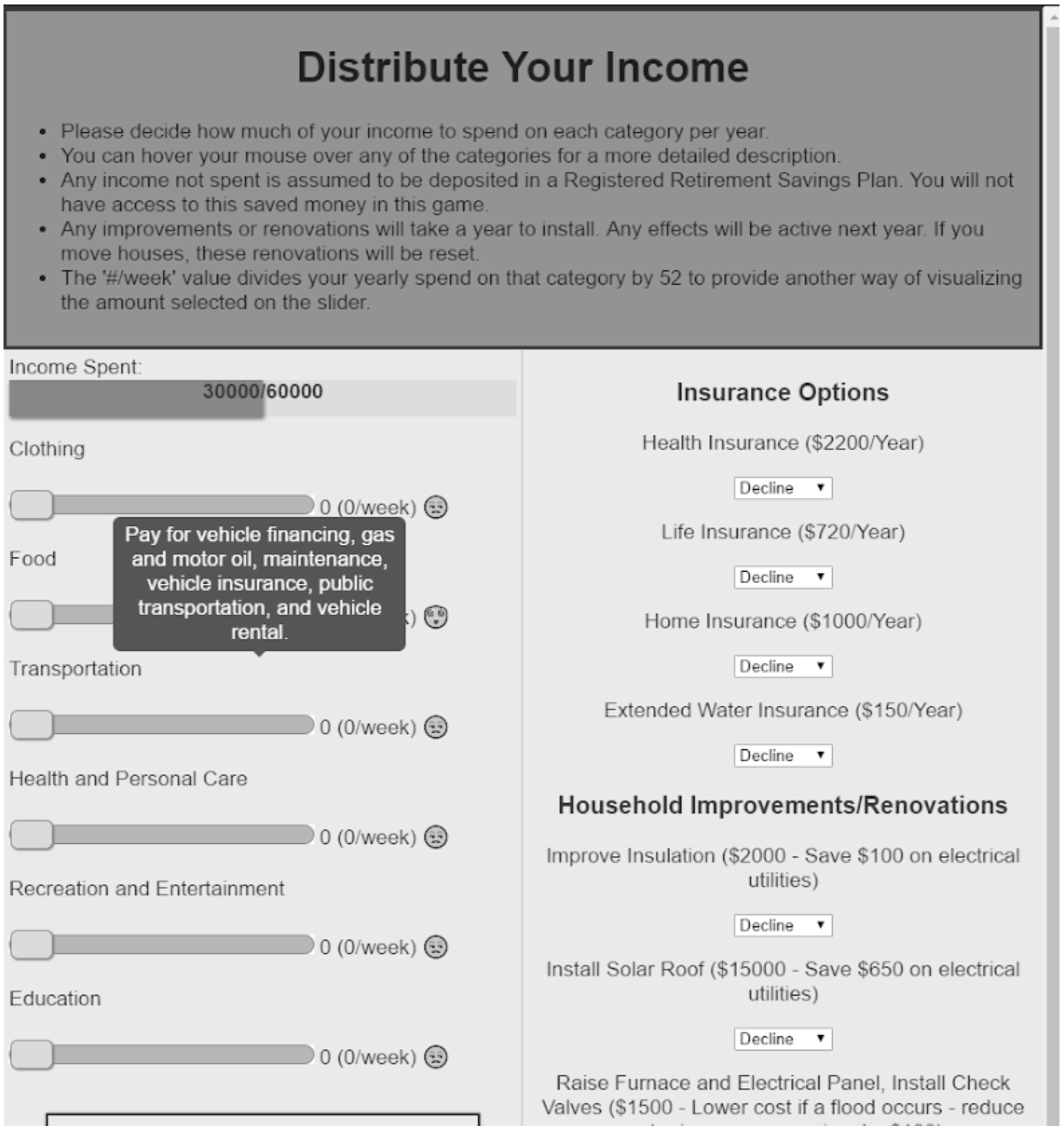
The first choice made every turn was to pick a location in which to live. Figure 3 shows the neighbourhood choice interface used to make this decision. Clicking through the tabs would display mapped information on the five different categories (see Appendix 6). The housing prices were based around the average housing prices in the census metropolitan area of Calgary. The neighbourhoods were balanced to not have an optimal choice. The effect on the yearly budget of picking a given neighbourhood would automatically update on the income bar at the bottom. Following this choice, the participant would be directed to the income distribution page.

Figure 3 - *Neighbourhood Choice Interface*

Income Distribution

The participants chose how to distribute the rest of their income using sliders and drop-down boxes on the interface (Figure 4). There was a degree of interactivity within the game; participants could see the immediate impact on their yearly budget as they selected spending levels on the various goods available. Additionally, players received instant feedback on their spending on goods through “emojis” which would change in happiness relative to the average amount spent in the census metropolitan area of Calgary on those goods. Most spending decisions did not affect the game in future turns; however, employing physical flood mitigation measures lowered the cost of flood insurance, and certain upfront purchases like solar panels could slightly raise future income through lower utility costs. Plausible insurance premiums were based on online insurance quotes using hypothetical values. Upon submitting their choices, the participants were directed to the review page.

Figure 4 - *Income Distribution Interface*



Review Page

Participants were provided with a summary of their most recent decisions prior to ending a turn (see Figure 5). This stage also served to inform players of the events that occurred on particular turns. There were three events that occurred in each game. In turn 2, participants saw a decrease in income from $60 000 to $50 000 associated with a demotion in their job, in turn 5 they experienced an increase in income to $70 000 due to a promotion, and in turn 7 the participant experiences a flood event. The flood event had a $20 000 impact on their income, however having purchased mitigation against the flood halved the monetary impact of the event, having home insurance lowered the impact by $5 000, and having flood insurance completely reimbursed the participant. After completing 10 turns of the game, the participants were directed to the exit page.

Figure 5 - *Review Page*

YEAR 3 OF 10

Summary of Spending

MORTGAGE AND HOUSING EXPENDITURES	CLOTHING	FOOD	TRANSPORTATION	HEALTH AND PERSONAL CARE	RECREATION AND ENTERTAINMENT	EDUCATION	HEALTH INSURANCE	LIFE INSURANCE	HOME INSURANCE	EXTENDED WATER INSURANCE	HOME RENOVATIONS DEDUCTED BY SAVINGS FROM IMPROVEMENTS
25000	3300	6700	4300	2200	400	4000	0	720	0	0	0

Start Next Turn

Exit Page and Survey

After completing the experiment, the exit page thanked the player and prompted the participant to click a button to complete the second survey. The exit page can be seen in Appendix 4.4. An exit survey followed the game, which collected information about risk perceptions, attitudes, and a variety of other relevant information. These data were used as inputs to the GLMM used in this analysis. The entire survey available in Appendix 5. We use question wording designed by Sobiech (2013) to identify how people rank on various factors identified in the literature as having an impact on mitigation decisions. A full list of variables targeted, their descriptions, the questions used to assess them, and connections with mitigation decisions from the literature are outlined in Appendix 1.

Software Used

DecisionGame was a browser-based application optimized for Google Chrome and Mozilla Firefox. The game was developed using PHP, JavaScript, HTML, and CSS, using a server-side MySQL database for storing participant decisions. Cookies tracked the turn number and the unique identifier of the participant, allowing them to return to the session later. All code is available from the authors. Participants were directed to Google Forms to conduct the pre and post-game surveys. The survey information was stored in a Google Sheet in a Google Drive accessible only by the researchers. The survey information and the game information were later linked with a unique identifier associated with the responses.

Results

Independent Variables and Sample demographics

123 participants were recruited for the study. Appendix 2 contains the frequency of responses to the survey questions. We present the distribution of the demographics of the participants in Figure 6 and compare them to the distribution from the 2016 Canadian census[1] (Government of Canada 2017a; Government of Canada 2017b; Government of Canada 2017c). The distribution of the sample demographics is quite different than the Census data. Participants were younger, wealthier, and more educated than the average Canadian. In addition, there were two separate recruitment modalities - online and in person. Approximately six out of every 10 participants performed the experiment online.

Dependent Variables

Table 2 shows the mean and variance of the dependent variables of the data. Figures 7 and 8 show the distribution of the number of turns out of 10 either insurance or floodproofing was used on the top. The distribution appears to be roughly normally distributed, with concentrations at the endpoints of 0 and 10. The plots on the bottom of Figures 7 and 8 show three categories, which, from left to right, show the number of respondents who never, sometimes, or always used the mitigative strategy. Even

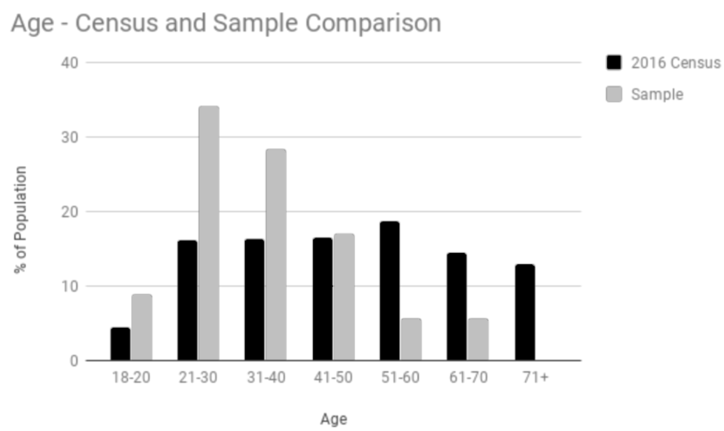
[1] Note that the census datasets for income and education contain people aged 15-17, which are not part of our sampling criteria

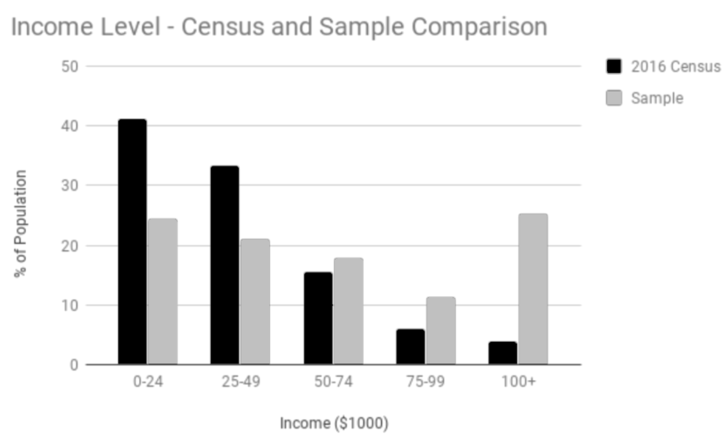
though the mean value of turns with flood insurance or floodproofing is around 4, the amount of people who insured or floodproofed for that particular number of turns is relatively low. 30 participants, or about one in four, did not insure against floods or floodproof at any point in the exercise.

Table 2 - *Simple descriptions of the dependent variables*

	Turns with Flood Insurance	**Turns Floodproofed**
Mean	**4.77**	**3.85**
Variance	**17.83**	**16.36**

Figure 6 - *Sample Demographics (Age, Income, and Education) compared to 2016 Census Levels*





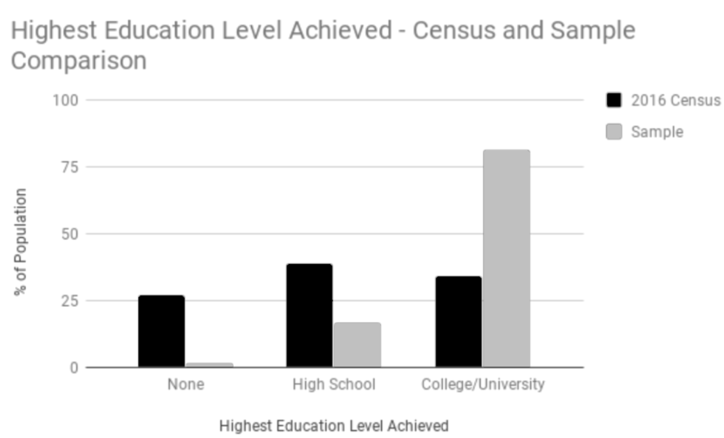
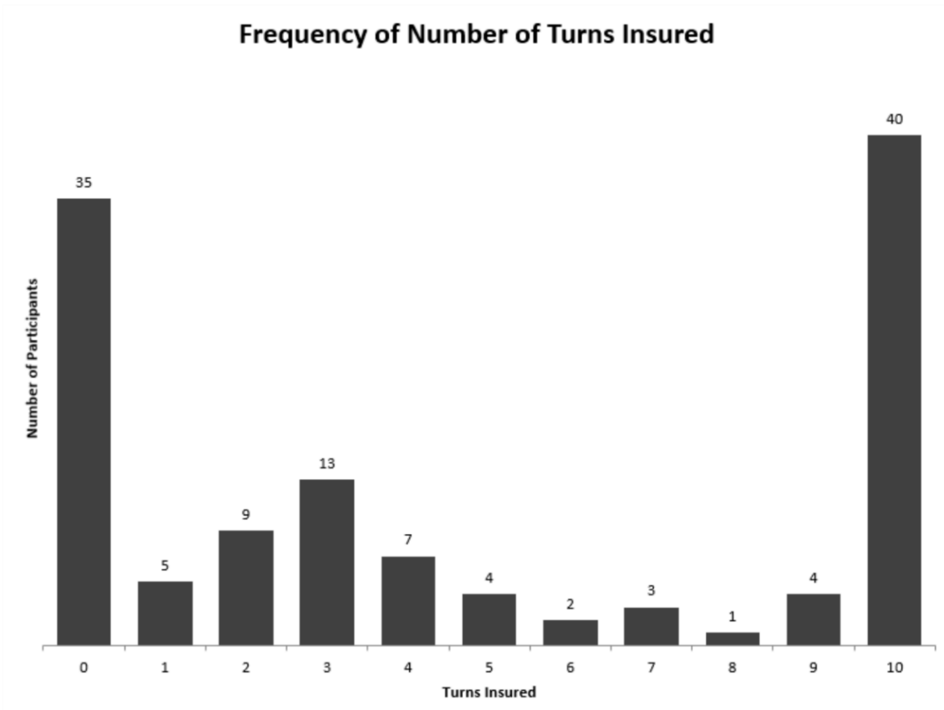


Figure 7 – *Flood Insurance Decisions Visualized*



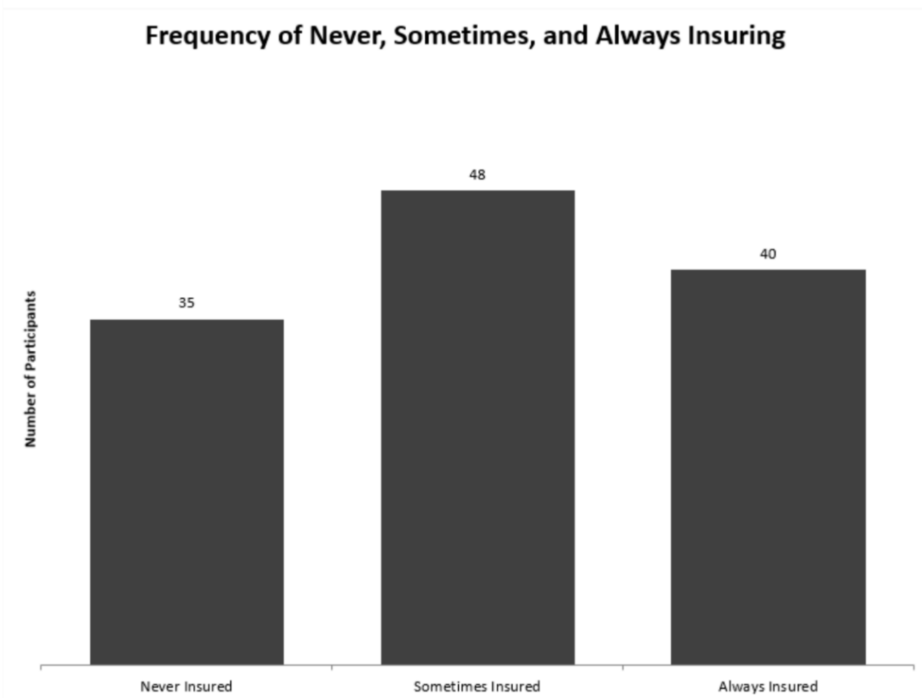
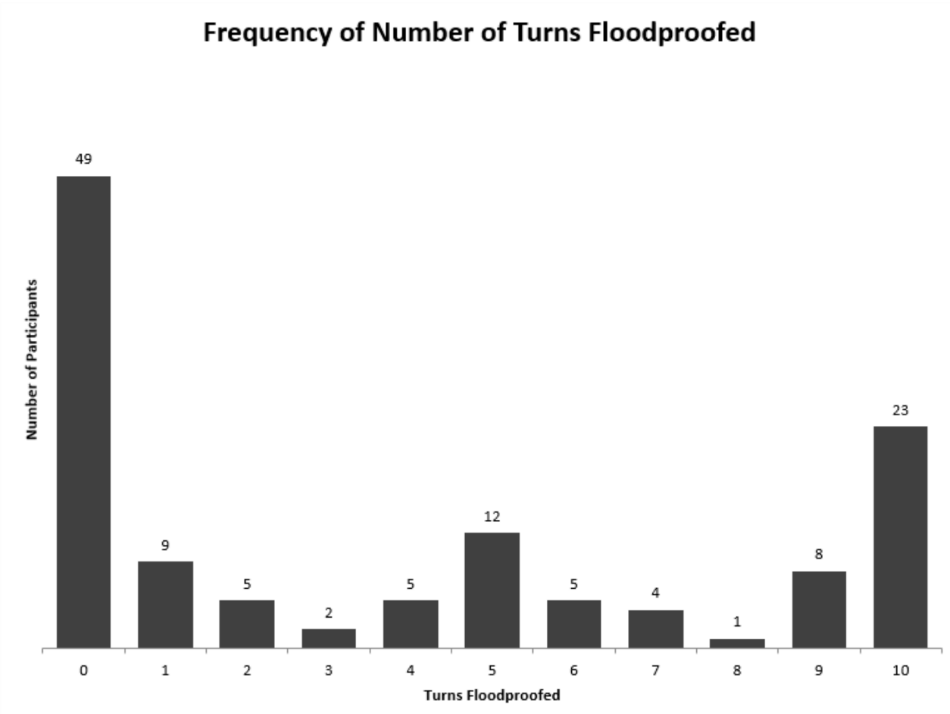
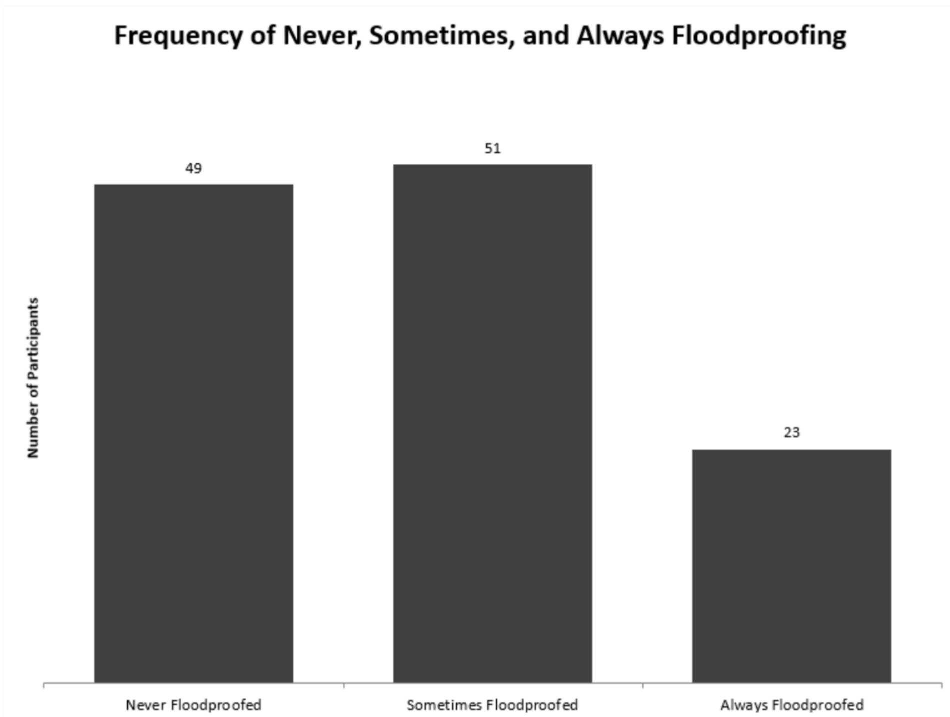


Figure 8 - *Floodproofing Decisions Visualized*





Model Results

Tables 3 and 4 contain the key results of the model. The model converges at a 0.01 tolerance level. The model estimates are robust to altering the starting values for the fixed effects to all zeroes, all sevens, all negative sevens, and random values. Moreover, the model estimates are quite robust to the use of various optimizers (see Appendix 8). For the full glmer output (Bates et al. 2015), including the correlation matrix of the fixed effects, Akaike Information Criterion (AIC), and log-likelihood values, see Appendix 7. Note that the standard error of the random effects is considerably larger than the estimate of the fixed effects. For example, the largest fixed or design effect size for both the insurance and floodproofing dependent variables is the post-flood design effect. This magnitude of the standard error of the random effect is approximately 1.25 and 1.51 times the size of the post-flood design effect for insurance and floodproofing, respectively. The largest fixed effect size was associated with having previously implemented mitigative measures in real life, which had a greater positive impact on mitigation decisions than having experienced a flood in real life for both insurance and floodproofing. We observe that all fixed and design effects have the same direction across both models, except for real-life flood experience. Risk perception and coping appraisal, which are both often cited as important in the flood mitigation determinant literature, had a positive impact on both dependent variables.

We observe that having a real-life income of $50 000 or above has a negative impact on both mitigation decisions; however, the increase in in-game income has a positive effect. Real-life flood experience had a negative impact for insurance and a relatively small positive impact for floodproofing, while the in-game flood event design effect had the largest effect size estimated in the model aside from the random effects.

Table 3 - *GLMM Results - Fixed and Design Effect Estimates*

Fixed/Design Effect	Estimate (Insurance)	SE	P-value	Estimate (Floodproofed)	SE	P-value
Intercept	-4.1698	1.7752	0.0188	-5.4371	1.2859	$2.35e^{-05}$
Turn 3-5 (Income Lower)	1.1695	0.4863	0.0162	0.7493	0.3529	0.0337
Turn 6-7 (Income Higher)	2.8059	0.5546	$4.21e^{-07}$	2.4267	0.4014	$1.49e^{-09}$
Turn 8-10 (Post Flood)	6.4629	0.6928	$<2e^{-16}$	3.5316	0.4109	$< 2e^{-16}$
Has Experienced a Flood (IRL[2])	-2.1455	1.9915	0.2813	0.5376	1.2395	0.6645
Income Greater than $50 000 (IRL)	-1.8447	1.8719	0.3244	-1.7832	1.2395	0.1503
Has Implemented Mitigative Measures Against Flooding (IRL)	5.6766	2.6914	0.0349	3.4505	1.4575	0.0179
Risk Evaluation of Community is "Medium" or Above (IRL)	1.5446	2.1652	0.4756	1.2910	1.4642	0.3779
Positive Coping Appraisal (IRL)	2.4329	1.9404	0.2099	1.3342	1.2194	0.2739
High Flood Risk Neighbourhood (In Game)	0.6533	0.5645	0.2471	0.7616	0.4505	0.0909

[2] In real life

Table 4 - *GLMM Results: Random Intercept Variance*

Dependent Variable of Model	Variance of Random Effect	Standard Deviation of Random Effect
Insured	64.82	8.051
Floodproofed	28.55	5.343

Visualizing the Results

Fixed Effects

Using the estimated models, we generate predictions of the likelihood of purchasing flood insurance and floodproofing using our sample data as inputs. In Figures 9 and 10, each plot visualizes the difference in predictions when separating the data by each fixed effect while holding other effects constant. Each pair of boxplots shows the difference in predictions at both levels of each fixed effect. The horizontal black lines represent the median prediction, the boxes contain the middle 50% of predictions, the whiskers represent the outside 50% of predictions, and the black dots represent outlier predictions. Each pair of boxplots contains predictions at different stages in time of the game, wherein each stage is separated by a design effect, showing how the predictions change as the participant experiences the events sequentially in the game. Note that the predictions do not include random effects, so they are underestimating the spread of data.

Generally, the greater the difference in the median predictions within a pair of boxplots, the greater the effect size of the fixed effect. Note that due to the nature of the logit link function, predictions are "squeezed" when closer to the extremes of probability estimates (i.e., 0 and 1). Conversely, this means that differences in predicted probability due to fixed effects, as well as the spread of predictions, are comparatively more exaggerated when closer to 0.5 than to one or zero. The maximum magnitude of fixed effect we observe is for personal measures when predicting insurance purchase. The minimum magnitude of the fixed effects is associated with real-life flood experience when predicting the likelihood of floodproofing, for which we observe much smaller differences in median predicted probabilities. In addition, as we observe pairs of boxplots further to the right, we see increases in predicted probability, reflecting the magnitudes of the design effect sizes. To illustrate the magnitude of the effect of the flood event, consider that all the median predictions of insurance likelihoods in the post-flood category are over 0.75.

Figure 9 - *Predictions of In-Game Likelihood of Purchasing Flood Insurance*

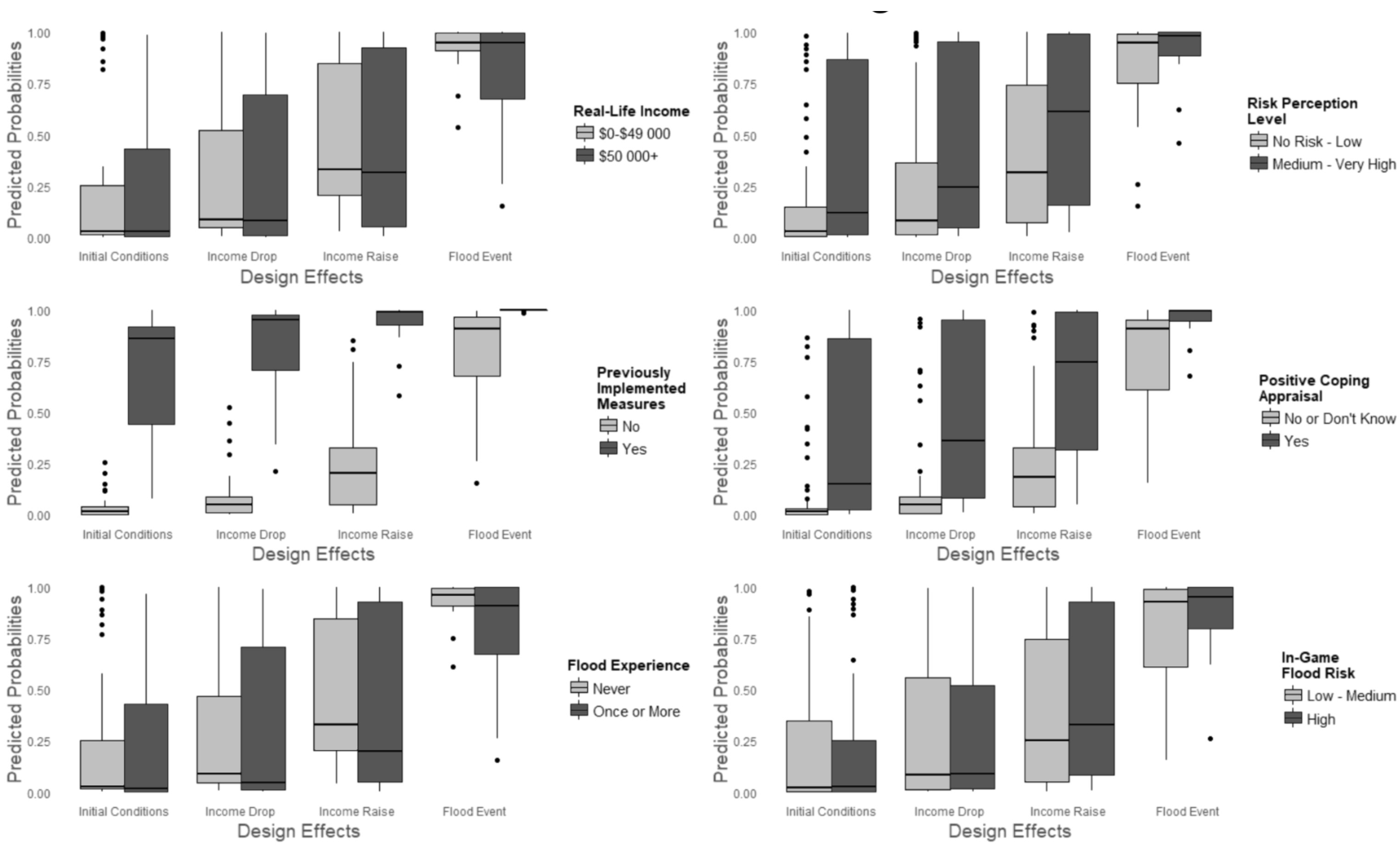
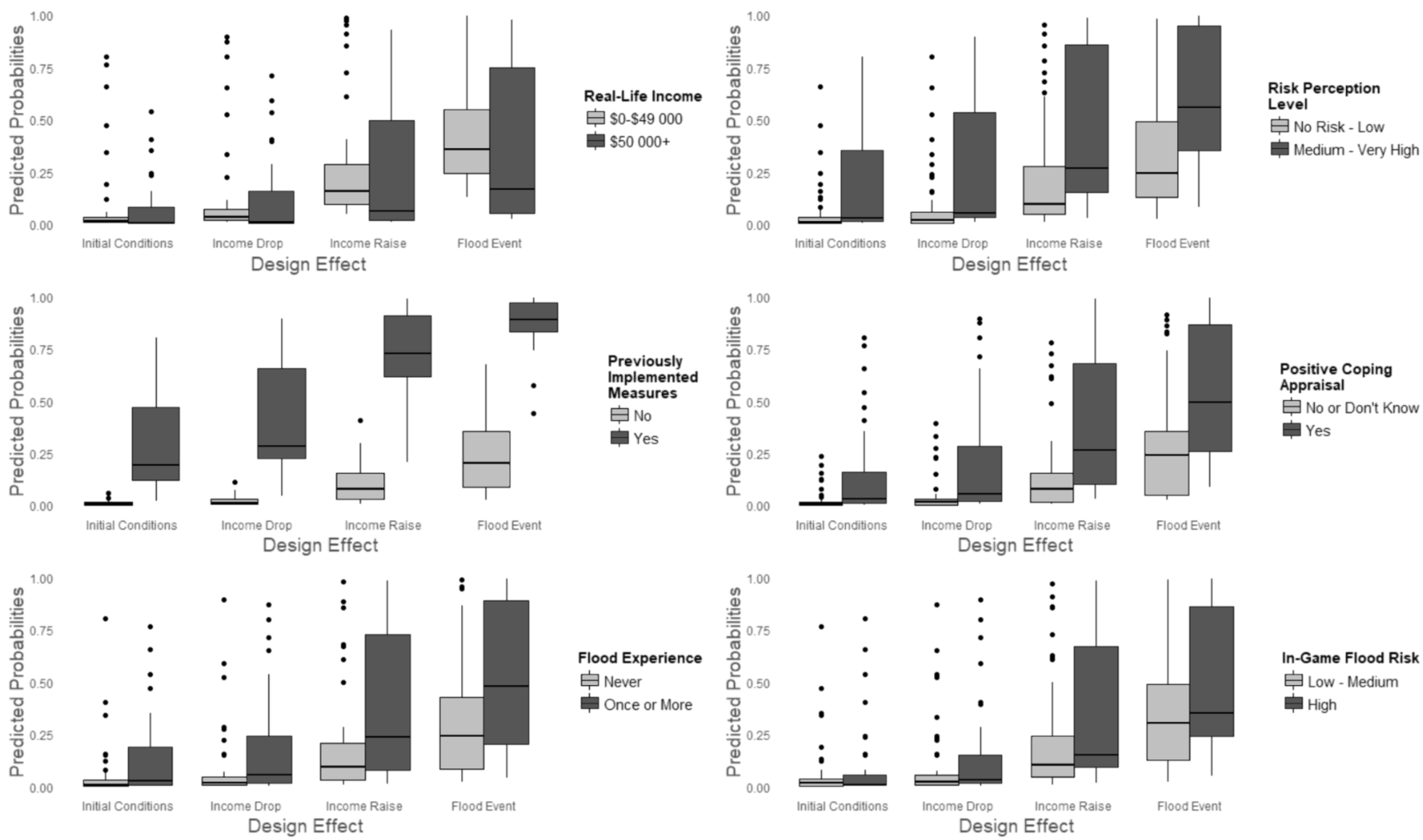


Figure 10 - *Predictions of In-Game Likelihood of having Floodproofing*



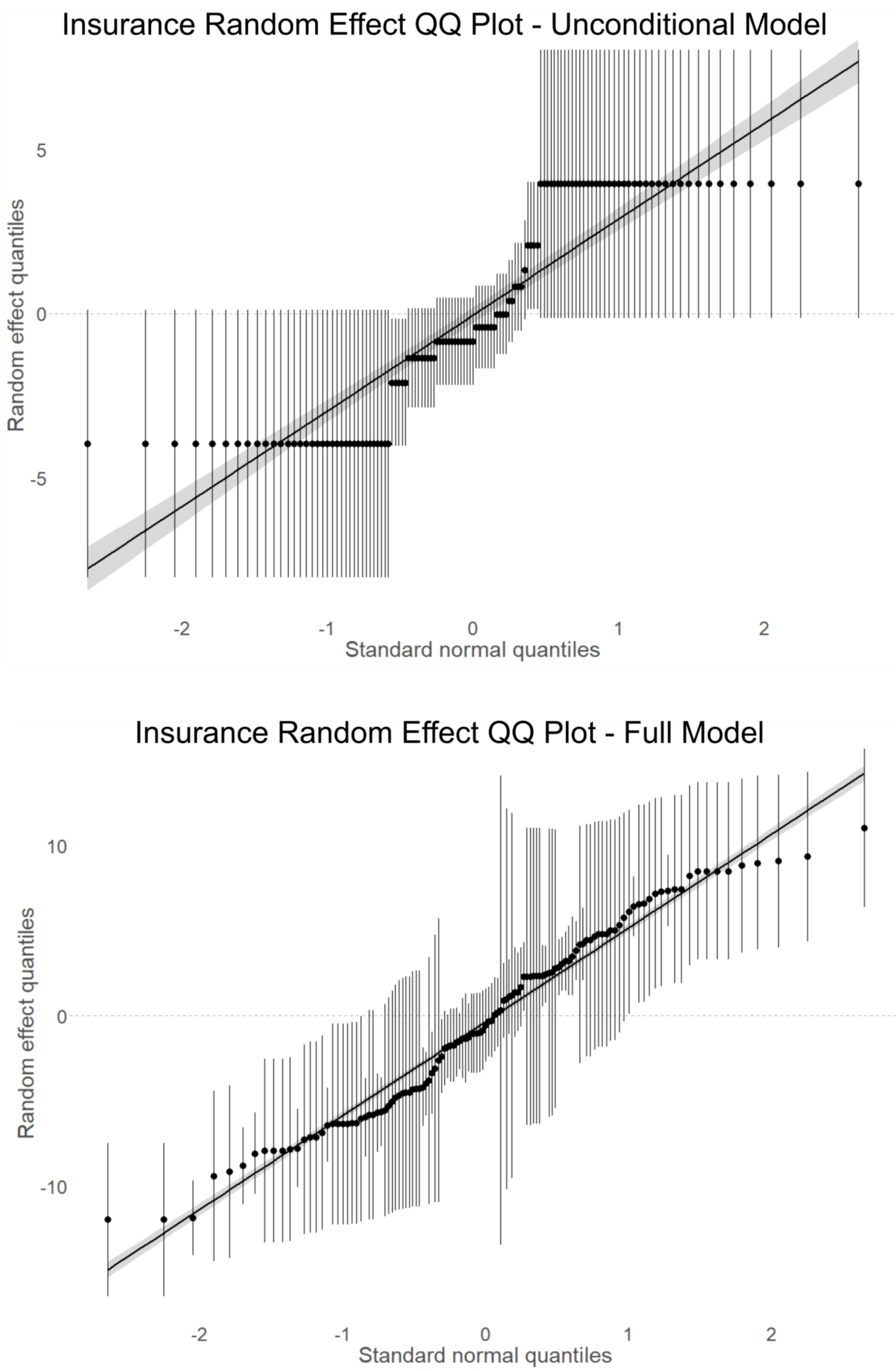
Random Effects

Although not a necessary assumption for GLMMs, we assume a normal distribution of random effects. Observing the qq plot[3] (see Figure 11, top) of the random effects for the unconditional models[4] of insurance indicates a bimodal distribution of random effects. When assessing the same qq plot for the complete model (see Figure 11, bottom) we see a smoothing of the random effects and an increase in the variance or spread of the points. See Appendix 10 for the same plots for floodproofing, for which we observe similar distributions.

[3] A qq plot is used to compare if two sets of data follow the same distribution. In this case, if points follow the trendline, then it is likely that the random effects are normally distributed.

[4] The unconditional model estimates only the random effects and a fixed intercept

Figure 11 – *Visualizing Insurance Model Random Effects*



Addressing Stayers

To address stayers, we estimate the same GLMM including endpoints. Appendix 9 contains the results of modelling the data using a GLMM with endpoints. We find that the log-likelihood of the model decreases for both insurance and floodproofing when endpoints are included. Appendix 11 contains the results of the two and three category chi-square tests of independence and linear by linear tests of association. The vast majority of variables were not closely associated with stayer behaviour under any of the tests. When we consider stayers to contain both those who always and never mitigated, we observe p-values of 0.085 and 0.047 for flood experience for insurance and floodproofing respectively. When using three categories of stayers and movers, namely never, sometimes, and always mitigating, we observe p-values of 0.148 and 0.093 for flood experience for insurance and floodproofing respectively. For the linear by linear tests of association considering ordinal effects, we do not observe any p-values below the 0.1 level. Age was also a notable variable connected to stayer behaviour, with p-values of approximately 0.15 plus or minus 0.05, being statistically significant at the 0.1 level for the three-category insurance chi-square test of independence. Generally, flood experienced, and younger participants were overrepresented in the mover categories.

Discussion

We set out to answer the following research question: which factors predict the decision to structurally mitigate against floods or to purchase flood insurance? To address this question, we modelled the decisions to purchase flood insurance and use structural floodproofing in a role-play experiment with various real-life and in-game factors. The literature on the determinants of property level mitigation decisions is well developed (Grothmann and Reusswig 2006; Botzen et al. 2009; Osberghaus 2014; Shah et al. 2017). While examples from the Canadian context do exist, they are limited in number and tend to be focused on structural measures or policy issues (Moghal and Peddle 2016; Robert et al. 2003; Thistlethwaite et al. 2018). In answering the research question, we hope to contribute to the knowledge of flood risk mitigation determinants in the Canadian context.

Furthermore, the use of a serious game as a research tool could offer a unique approach to understanding decision-making under flood risk, particularly where time, safety, or data availability constraints might limit our ability to collect real data. We explore the consistency of model estimates with findings from the literature to investigate whether we have a tool which can potentially reproduce and ultimately extend the results of other stated or revealed preference-based approaches. Moreover, we discuss some of the advantages, limitations, and future applications of the tool in the context of its potential to fulfill a niche in the role of data collection for low probability high consequence (LPHC) events.

Model Fitness

Absolute goodness-of-fit tests like R squared are problematic for GLMMs, for reasons including that residual variance is not easily defined for these models (Nakagawa et al. 2013). In the future, we suggest that with more data, comparison of predictions of the likelihood of insuring and floodproofing against a testing dataset could be used to assess the model. For this paper, we omit a discussion of absolute goodness of fit and use more exploratory methods to discuss the model. While not a rigorous test of model fitness, we expect the random effects of our model to be normally distributed. We see in the unconditional models (see Figure 11) that the random effects follow a bimodal distribution, which is to be expected when considering the tendency to always or never mitigate seen in Figures 7 and 8. Introducing the fixed and design effects of the final model (see Figure 11) results in a smoothing of the random effects to follow more of a normal distribution. The smoothing of the random effects suggests that introducing the fixed effects to the model explains the decision-making patterns considerably better than solely using the random effects; however, this seems to come at a cost of increasing the magnitude of the variance of the random effects. This finding suggests that there may be missing covariates that contain variability currently assigned to participant-level effects.

We have used reasonable, but not rigorously calibrated income levels and pricing of goods in the game. As such, we are more interested in the changes in predicted decisions and differences between subgroups of our sample as opposed to the absolute value of mitigation uptake. Moreover, the confidence intervals of model results are very large, with the size of standard errors similar to the size of the fixed effects themselves (see Table 3). In addition, the variance of random effects is larger in magnitude than the fixed effects (see Table 4). Practically, this difference means that the random effect term estimated for participants is more important than the fixed effects for an estimated likelihood of mitigation. Since the predictions found in Figures 9 and 10 are naïve to standard errors of the fixed effects and random effects, they underestimate the variability of predictions. The predictions are more of a visualization of the model coefficients as they apply to the dataset as opposed to a forecast of mitigation uptake, as the confidence intervals for predictions of the latter would be exceedingly large. Consequently, any further discussion of the fixed effects in this section must be taken with caution due to the magnitude of standard errors and random effects and is subject to future studies with larger sample sizes.

Individual Model Estimates

Income

This study provides an opportunity to compare whether real-life low-income participants are making different decisions than higher income participants when they are all given the same funds in the game. In the literature, effects of income on flood mitigation behaviour are typically positive (Osberghaus 2014; Bubeck et al. 2012; Grothmann and Reusswig 2006; Botzen et al. 2009; Botzen and Van Den Bergh 2012). In our results, real-life income was found to have a modest, negative effect on both in-game mitigation decisions. All else constant, low-income participants were making slightly more mitigation decisions compared to those with higher income. However, income was correlated with other demographics not included in the model. For example, in the lower income category of our sample, approximately two-thirds of the participants were 30 years old or younger. It is possible that the effects of income were being confounded by other demographics. To control for age, we could run the model on individual age sections of the sample to observe if the relationships hold. Testing for robustness of model estimates across age levels and other demographics was problematic due to a low sample size but is recommended for future studies.

When participants were given a higher income in the game, the model predicted that the likelihood of purchasing flood insurance or floodproofing increased, consistent with the literature. The contrast between the in-game and real-life income effects provide evidence that barriers to implementation of mitigative measures due to income are due to lack of funds rather than a psychological or behavioural difference of being in a lower income class. This provides support for any policies subsidizing flood mitigation or access to insurance which are graduated or contingent on income, as the evidence suggests that we can expect lower income people to make similar mitigation decisions when given the same purchasing ability. Not considered in this study, however, are social barriers to implementation. The cost of mitigative measures in the game was only represented in monetary terms. Low-income people may have time, knowledge and transportation barriers to accessing mitigation that are not represented in the game. This means that our results are likely underestimating the positive effect of higher income, as higher incomes would likely increase social access as well as financial means. This also tempers the potential effectiveness of using previously mentioned subsidies, as they fail to address these social barriers.

The drop in income did not have the expected effect on uptake of insurance and floodproofing, slightly increasing mitigation. This could be explained due to the up-front purchases players invested in at the beginning of the game. For example, investing in solar panels involved an upfront cost that would have freed up funds for later turns, perhaps coinciding with the drop in income. In the future, with a larger dataset, altering the order of the shocks randomly between participants could control for these confounding effects.

Objective Flood Risk

The participants had access to a flood risk map which had information about flood risk (see Appendix 6). The in-game flood risk did not impact the occurrence or severity of the game's flood event; however, the participants did not know this, so flood risk information should have the same effect as if it was accurate flood risk information. Living in an in-game high flood risk area had a small, positive effect on the decision to insure or floodproof, with a relatively small standard error for the insurance decision.

In a survey of flood-prone regions in France (Poussin et al. 2014) and Switzerland (Siegrist and Gutscher 2006), researchers found that objective risk levels did not have a significant impact on flood mitigation behaviour. However, it has been found that people living in flood-prone areas do have heightened risk perception of flooding (Poussin et al. 2014; Siegrist and Gutscher 2006; Botzen et al. 2009; Botzen et al. 2015). Several reasons could explain maladaptive responses including avoidance, wishful thinking, and postponement (Bubeck et al. 2013). A small positive effect of flood risk information on decisions to mitigate is therefore within reason, potentially reflecting awareness and maladaptive responses to the flood risk.

The effect of experiencing an in-game flood had an effect size several orders of magnitude higher than the effect of living in a high flood risk area in terms of the decision to insure or purchase floodproofing. Direct comparison of these effect sizes is problematic since the units of the two independent variables are different. With this limitation in mind, the results suggest that experiencing a flood has a greater impact on flood risk mitigation decisions than the objective information of living in a high flood risk area.

Real-Life Flood Experience

Arguably, the most surprising finding of the model was the effect of real-life flood experience. The effect of a participant having previously experienced a flood on decisions was negative for the insurance decision and positive, but relatively small, for floodproofing. This finding is contrary to what one might expect based on the literature. Many studies note the positive impact of flood experience on flood preparedness (Poussin et al. 2014; Bubeck et al. 2013; Kreibich and Thieken 2008; Siegrist and Gutscher 2008; Bradford et al. 2012), although the relationship may differ between local circumstances and contexts (Poussin et al. 2014; Bubeck et al. 2012). Moreover, Siegrist and Gutscher (2008) note that experiencing strong negative emotions and losses from floods are seemingly necessary for taking mitigative action, but are not sufficient for a response.

One explanation for the unexpected effect sizes and direction of real-life flood experience is that we did not ask about the severity of flood the participants had experienced. It is possible that many participants experienced only minor damage, skewing our results. In the future, clarifying the size of flood experienced in the survey is advised. Another explanation is that we did not ask when the floods were experienced by the participants. The contrary finding could be the result of a time-decay of the flood experience effect. Evidence from the literature suggests that over time, the positive effect of a flood on public interest and individual motivation for action wanes (Brody et al. 2017; Tobin and Montz 1994; Atreya et al. 2013). This time-decay may be due to the passive loss of flood memory over time but may also involve active forgetting due to reasons such as personal trauma, and the desire to increase housing price and attracting tourist and newcomers to the area (McEwen et al. 2012). Although, some observations of macro time-decay effects may be due to migration in and out of the area, with inadequate knowledge transfer resulting in a reduction in collective memory (Soetanto et al. 2008; Bradford et al. 2012). However, the migratory aspect of the time-decay effect would not apply to our flood-experienced participants. Since many participants were located in Calgary, where the last major flood occurred in 2013, it is possible that our sample contains many people past the time decay "expiry date." In the future, asking participants when they last experienced floods and the severity of the damages could allow one to observe the degree and progression of the decay effect within the game.

In-game Flood Experience

Contrary to real-life flood experience, in-game flood experience was by far the largest effect size in the model. The results indicate that the experience of the in-game flood had a great influence on a participant's likelihood of purchasing flood insurance or being floodproofed. The effect size was several orders of magnitudes larger than living in a high in-game flood risk area. This suggests that the experience of being flooded is more important than objective flood risk information with respect to taking mitigative action. Moreover, this finding is consistent with the idea of a time-decay and recency bias with respect to the effect of flood experience.

From a policy perspective, these findings are consistent with the idea that it may be important to highlight and market mitigation options in the time immediately after a flood. This may be especially effective when rebuilding or repairing homes in which construction must already take place. Grames et al. (2016) note that the politically best time to invest in flood protection is when stakeholders have immediate flood memory, even though, economically, the optimal time to invest is before the flood event occurs. Another option to combat the time decay of the effect of flood experience is to build sustainable flood memory to combat factors which influence forgetting (Garde-Hansen et al. 2017). Methods of mediating this collective memory include demarcating flood lines to show the water level during past flood events (Garde-Hansen et al. 2017).

Personal Measures

The other real-life situational variable besides flood experience in the model is whether the participant had previously taken preventative measures against flooding. This study provides an opportunity to examine the psychological effects on decision-making of having previously implemented mitigation measures while controlling for the feedback effects of lowered risk perception of having flood protection. This controlling of the feedback effects occurs since real-life mitigation implementation had no impact on the parameters of the game.

One of the commonly cited feedback effects from insurance is moral hazard[5]. Moral hazard from flood insurance purchases has been found to be minor (Botzen 2015). There is evidence that people who have previously purchased insurance are no less likely to implement, and are in some cases more likely to implement physical mitigation measures (Hudson et al. 2017; Osberghaus 2014). This is evidence for advantageous selection, where insurance policyholders are more risk-averse, and therefore more likely to seek to reduce risk, particularly when incentives are present to lower premiums to people who structurally mitigate. For physical mitigation measures, there is evidence that having previously employed these measures lowers risk perception (Richert et al. 2017), and reduces the likelihood of further mitigation (Poussin et al. 2013), especially if those measures were successful in past flood events.

We find evidence that all other factors equal, people who had previously implemented measures were more likely to have employed mitigation measures in the game. This effect size was relatively large and positive for both dependent variables.

[5] Moral hazard occurs when there is an increase in risk-taking behaviour when exposure to risk is decreased (i.e., through insurance)

This finding lends credence to the idea that, ignoring feedback effects, those who have previously insured or mitigated are more likely to seek to reduce flood risk.

Risk Perception and Coping Appraisal

Risk perception has been found to have a positive relationship to flood preparedness (Fuchs et al. 2017; Miceli et al. 2008; Grothmann and Reusswig 2006). Messner and Meyer (2005) argue that a community with low risk perception would likely take little action to decrease risk or prepare for the occurrence of flooding, which can result in higher vulnerability to flood damages. Contradictorily, studies which find no relationship between risk perception and flood preparedness exist (Siegrist and Gutscher 2008; Steinführer and Kuhlicke 2007; Bradford et al. 2012; Bubeck et al. 2013). The relationship between risk perception and taking protective action has been found to be more complex than a straightforward indicator (Scolobig et al. 2012). A psychological framework known as Protection Motivation Theory has been adapted to the flood risk context by researchers to respond to this increased complexity (Bubeck et al. 2013; Poussin et al. 2014). An important factor in this framework is coping appraisal. Coping appraisal refers to the process after an individual perceives that they are at risk of a flood, wherein they consider the benefits of interventions, their personal competence of carrying them out, and the costs associated with implementation (Bubeck et al. 2012). Coping appraisal has been found to be an important, positive factor in influencing mitigation and preparation behaviour (Bubeck et al. 2012; Poussin et al. 2014).

Risk perception was found to have a positive effect on the insurance and floodproofing decision, although the standard errors were larger than the effect sizes themselves. This finding is generally consistent with the literature. Note that in our study, participants were not limited to those who lived in flood-prone areas. An example of a resultant implication is that the category group with low perceived risk includes both those whose perception is accurate and those who are underestimating their risk. It is unclear to what extent our model is sensitive to this issue. In the future, with more data, the model could be stratified based on subpopulations with differing levels of real-life flood risk to see if relationships hold. Moreover, the risk perception effect is more pronounced when putting "medium" in the reference category as opposed to the comparison category. However, few people responded that the risk evaluation of their community was high or very high, so the size of the group made the results too unreliable.

We also find a positive effect of coping appraisal on both dependent variables. Conceptually, this is consistent with the idea that people who believe that they can have an impact on their flood risk are more likely to act upon that risk. We did not include any interaction term between risk perception and coping appraisal in the analysis, as the model did not converge with these specifications. In the future with more data, this would be a necessary step to explore, as the protection motivation theory used in the literature suggests that mitigation action comes from a combination of risk perception and coping appraisal (Poussin et al. 2014).

Evidence for Stayers and its Implications

Figures 7 and 8 provide evidence for the existence of stayers—those who did not change their decision to purchase or decline flood insurance or floodproofing throughout the whole game, as opposed to movers—those who changed decisions at some point. In the context of flood risk mitigation decisions, stayers may suggest that the decision-making processes across participants may have been fundamentally different. For example, some people may have a more cognitively lazy process of decision making (i.e., insurance is important to me, or it is not), and some people's decision making may be more analytical and optimizing, considering pricing and context. The model developed in this paper is naïve to mover-stayer processes. The extent to which our model results are robust to this naïveté is uncertain. We estimated a GLMM (see Appendix 9), which was specified in a similar way but used endpoints which assigned a probability that the decisions by a participant would be all 0s or 1s. This estimation did not improve the fitness of the model. While being the only R package we know of to address stayers, SabreR (Crouchley et al. 2016) has been removed from the CRAN repository due to lack of author support. It is possible that updated modelling software might show improved model fitness when explicitly considering stayers.

We investigate whether stayer behaviour is associated with cognitive laziness due to lack of engagement with the game or due to other factors. We find that flood experience is associated with stayer behaviour in three out of the four chi-square tests of independence that we conducted at the 0.1 level of statistical significance. This suggests that flood experienced participants were making more measured decisions than their inexperienced counterparts. Note that this association between movers and breaks down when treating the categories of never, sometimes, and always mitigating as ordinal. This makes sense under the assumption that flood experience leads to more measured decision making since being a mover is the most cognitively active category while being second out of three categories in the ordering. While only statistically significant at the 0.1 level for the three-category chi-square test, age was consistently associated with stayer behaviour with the p-values around 0.15, relatively higher than the other variables. This seems to be indicative of two possible explanations warranting further investigation regarding stayer behaviour in the game. The first is that flood experience may have a lasting effect on being cognitively active when making flood risk mitigation decisions. The second is that younger people, who may be more familiar with computers and gaming environments, are more comfortable navigating the online game and changing their decisions with new information. It is also possible that both factors are occurring at the same time.

The Suitability of the Role-Play Experiment as a Research Tool

The use of a digital role-play experiment as a data collection tool for flood mitigation decision-making is a novel research method, as far as we know. The extent to which the role-play experiment can contribute to legitimate sources of data for flood risk mitigation decision-making research is discussed in the following sections. We explore the real-life representativeness of the decisions made in the game, validation of the tool's results, and some other advantages of the research method.

Reducing Hypothetical Bias

The experimental game approach used in this study could offer an alternative to existing data collection methods which could reduce hypothetical bias. Through increasing the plausibility and meaningfulness of the participant experience, the use of digital serious games with a role-play component can introduce a new level of detail and realism in data collection beyond many stated preference surveys or interviews. Additionally, the iterative nature of the turn-based role-playing game can allow participants to reflect more on the information presented and can even change their minds in certain game contexts. For example, consider a stated preference method of asking about post-flood after a given loss of funds; the role-play experiment equivalent more tangibly allows the player to experience the flood and the negative impact of the lost resources, potentially producing a response with less hypothetical bias. This type of experiment could blur the line between the stated preference and revealed preference methods, resulting in a compromise between the accuracy of revealed preference methods and the ease of collection of stated preference methods. Ultimately, however, validation is necessary to determine if the model can be trusted to predict real decision outcomes.

Avoidance of Demand Characteristics

It is plausible that the role-play experiment method is less susceptible to certain psychological biases than other forms of preference evaluations. Demand characteristics are a concept widely used, but arguably under-researched (McCambridge et al. 2012), concept in psychology, referring to the undesired effect on responses caused when the researchers' goal is perceived to be known to the participant (Nichols and Maner 2008). Moreover, a certain type of hypothetical bias can occur in contingent valuation surveys, in which the participant makes strategic estimates when he or she is both invested in the good being evaluated and has no stake in the survey (Murphy and Stevens 2004). These biases can arguably be mitigated in this role-play experiment format since the participant is not explicitly informed of the target variable, nor implicitly informed through asking direct questions until after the experimental component is complete.

Lack of Incentivization for Performance

DecisionGame did not include performance-based incentives to participants, which may be beneficial for the quality of the data. Participants were informed that there was no correct answer for this game and made choices as they saw fit. Incentivizing performance would have implied that there was a specific goal in mind at the outset of the experiment. Any performance metric used would have prescribed utility judgements for the participants instead of them revealing their own preferences. In addition, the heuristics, biases, and apathy that people may have used when making decisions under uncertain flood risk may have been lost if there was a competitive objective to the game, such as having the most consumption of goods while having the greatest amount of savings at the end of the game. Therefore, the role-play experiment could potentially be a better reflection of reality if participants take the game seriously.

While participants were compensated only for participation, the literature for using economic games suggests that incentivizing performance with large sums of money is important for ensuring that participants take games seriously (Kunreuther and Michel-Kerjan 2015). However, in the same way that the immersive experience of digital serious games can be helpful for engagement in training contexts (Zyda 2005), it is plausible that an immersive experience can substitute for performance incentivization in terms of influencing participants to take the experiment seriously. Moreover, several "sandbox" style entertainment video games, such as *Minecraft* are largely exploratory in nature and rely on the immersive experience of the game as opposed to a specific objective to capture player attention.

As evidence of the likelihood that participants were taking the game seriously, Yiannakoulias et al. (2017) compared in-person and online participants and found similar responses across groups. The groups were compared in terms of the time taken to complete the experiment and frequency of specific decisions within the game. For a typical economic experiment incentivized for participation, it is reasonable to expect that in-person participants would take the experiment more seriously than their online counterparts due to the social pressure of the researcher's presence. That Yianna

koulias et al. (2017) find that responses are similar between groups suggests that the game experience itself incentivizes serious participation. Consequently, the role-play experiment could be bypassing the downsides of incentivizing particular behaviour while retaining quality responses from players. Goals such as coffee stamps and reward certificates are powerful motivators for participation in programs, but their purpose is fundamentally to change natural behaviour (Kivetz et al. 2006). It is likely that our methodology could be improved if goal-setting and the role-play experiment could be reconciled to improve participation while not interfering with revealing preferences.

Limitations and Potential Improvements

Digital role-play experiments can be viewed as an innovative advancement in terms of the ability to gather rich data for the field of social hydrology. However, there are limitations and possible adjustments, which must be discussed in order to realize the full potential of the method. Validation tool is arguably the most important hurdle in assessing the reliability of the tool, which could be done with more data. Additionally, the representativeness of the sample prevents us from applying our findings to the entirety of the Canadian population. Furthermore, there are some statistical and experimental improvements which could contribute to more reliable results.

Discussion of Validation

Stated preference methods such as contingent valuation are typically validated through replication, comparison with results from other studies, and comparison with actual behaviour where possible (Hanemann 1994). These validation methods could be applied to using serious games for research. In this study, we did not use a rigorous validation method. Moreover, the pricing of the commodities in the game was not precisely calibrated in a way which lent itself to strict comparison to a real-world scenario. For this study, we were more interested in the direction of the fixed effects in the model and investigating the relative magnitudes of the effect sizes where applicable. In the discussion of the fixed effects, we find that results are reasonably consistent with the literature, but we would require a greater sample size to reduce the size of confidence intervals. We limit our claims of validation to suggest that this paper provides evidence that using role-play experiments to study mitigation and insurance decisions under flood risk shows promise as a research tool.

Since GLMMs generally lack a reliable endogenous validation metric such as an R squared value, exogenous validation methods should be used. Data could be partitioned into a modelling and testing dataset. The model built with the modelling data could be used to generate predictions of mitigation uptake in the testing dataset. The validation of the method could be assessed by comparing the predicted uptake to the actual uptake of mitigation. The sample size of 123 participants was not large enough to justify parcelling the dataset into modelling and testing sets and contributed to the large standard errors that we observed. Since Yiannakoulias et al. (2017) found that the online participation was of relatively high quality, online role-play experiments could be scaled up with less researcher involvement to increase participation and create large training and testing datasets to validate results.

The partitioning into training and testing data, prediction, and comparison is an example of internal validation. External validation, while more rigorous, would require testing the game results against real-world behaviour. The role-playing game would likely be an abstracted scenario of a real-world context of which the researcher had access to demographics and mitigation uptake values. One might reasonably question why a simulation would be necessary if real-world data has already been collected. As discussed previously, there may be a desire to collect data on decisions in a hypothetical extension of the real world, such as a policy intervention or after a flood has occurred. Should the research tool be validated in the existing socio-geographical context, findings from the hypothetical context could be better trusted as a forecast of decisions.

Representativeness of the Sample

The demographics of the sample differ from the Canadian average, limiting the generalizability of the results (see Figure 6). Specifically, participants were younger, wealthier, and more educated than the Canadian average. In-person recruitment was mostly done in Calgary urban coffee shops for convenience sampling, mainly due to the availability of reliable internet access, high volume of patrons, and a relatively high likelihood of finding participants with 25-30 minutes to complete the experiment. In addition, some online participants would have participated at a later time after having been given a recruitment business card at a coffee shop. Potentially, this targeting of coffee drinkers was responsible for some selection bias. The study participants were not primed with specific information about the game, so the selection bias was most likely not related to interest in flood risk, meaning that the findings on flood risk mitigation decisions may be fairly representative for this sample.

Improvement of Statistical Fitness through Stayer Models Conditional on Random Effects

Statisticians have used more advanced random effects models to understand arthritis progression, extended to include mover-stayer effects. These models allow stayer probabilities to be conditional on patient-level random effects (Yiu et al. 2017; O'Keeffe et al. 2013). In this medical context, stayers represent patients who have not experienced arthritis previously and are not susceptible to developing joint damage. The analogue for our study would be individuals who will virtually always or never purchase flood insurance or private mitigation. In the arthritis context, the scientific case for the existence of stayers is well established, while in the flood context, more work would need to be done to confirm that stayer behaviour has valid psychological justification. If this justification could be established, exploring various distributions of random effects, and mover-stayer submodels conditional on those random effects could be used to improve our model fitness.

The potential existence of stayers suggests that government communication or incentive programs could be optimized between movers and stayers if they could be identified. For example, movers may be more open to incentives such as subsidies for existing options. Contrastingly, subsidies for stayers who would mitigate anyways may be a waste of funds. Stayers who do not mitigate may need more fundamental changes in their belief systems through effective risk communication. To check for the existence of stayers in a future study, one might test the assumption that stayers would be less sensitive to different starting levels of income than non-stayers. Assuming stayer decision-making exists, one would expect the distribution of movers and stayers to remain relatively constant, while movers would adjust mean uptake due to the difference in income.

Other Potential Improvements

There are some improvements which could be made to this experimental design which are recommended to any researchers considering implementing a similar tool. Firstly, the order of the design effects (changes in income, flood events) should be randomized among participants to account for any confounding effect on decisions based on the timing of the effect as opposed to the effect itself. Additionally, anytime a list is used in terms of offering choices to participants, the order of the options should be randomized to avoid order effects (Hanemann 1994). Also, we did not formally account for response effects (Hanemann 1994) which could occur due to misinterpretation of our communication within the game or the survey questions[6]. In the future, one could run a pilot version of the experiment (as done by Bubeck et al. (2013)) with follow up questions designed to identify difficult-to-understand questions and to test their understanding of communication within the experiment. Alternatively, one could vary the way that questions are asked or that information is delivered to see if the different versions caused significant differences in responses.

[6] Informally, friends and colleagues pointed out unclear questions while testing the tool

Finally, assuming that pricing is based on hypothetical values, the price of purchases could be varied randomly around a mean value between participants to ensure that findings are robust to differences in price.

Future Applications

The use of serious game role-play experiments has applications which could address gaps in the literature on decision-making under flood risk. Furthering the discussion of validation, it is possible that the type of experiment outlined in this paper could be used to validate sociohydrological models like agent-based models (ABMs). Haer et al. (2016) calibrate an ABM to explore how risk mitigation behaviour impacts flood risk in a community. The researchers calibrate the behaviour of their agents using inputs derived from a logistic model that predicts mitigation using individual characteristics. The model is relatively similar in structure to the one used in this study, but the data come from a survey of participants on the River Rhine, which among other factors, asks about their history of mitigation, individual characteristics, attitudes, and geographical contexts (Bubeck et al. 2013). Haer et al. (2016) argue that basing their agent rules off of empirical data validates their model but note the lack of empirical data for determining which adaptive responses are used in the specific context of changing flood risk in their study area. The researchers remark that opportunities to obtain these kinds of data are limited given the low probabilistic nature of flooding. Using a role-play experiment designed to simulate a specific setting, such as the River Rhine, could provide a unique opportunity to generate empirical data, such as responses to a flood, where real data do not exist or are unfeasible to gather.

Furthermore, serious games have the potential for multiplayer interactivity which could provide opportunities for unique study designs on social networks and decision-making. For example, consider a game in which people could exchange goods and information in a hypothetical community. One could examine whether others in the community experiencing a flood would have a similar effect on decisions as experiencing a flood themselves.

Another potential application of this research tool is in comparing different forms of policy tools. For example, suppose that an educational campaign is being proposed in a given municipality to encourage flood-mitigation behaviour. Some research suggests that the content of risk communication strategies is important for eliciting a mitigation response (Bubeck et al. 2013). The research tool could be used to investigate which messaging is most effective in encouraging mitigative action before funds are used on the campaign. As a further illustration of the comparative use of the tool, consider various versions of the same scenario with different incentive structures for mitigation options. For example, income-based subsidies, subsidies contingent on having flood insurance, or flood insurance contingent on implementing physical mitigation could all be compared in terms of their relative uptake of mitigation options.

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CHAPTER 2

Application of the Decision Game Model: A Case Study of Calgary Alberta

Introduction and Background

1.1 Introduction

This research is a case study of the Decision Game (DG) model developed in Chapter One. Decision-making in the context of natural disasters is subject to biases and heuristics which make predicting mitigation behaviour difficult (Kunreuther et al. 2013). Efforts have previously been made to understand and model flood risk mitigation decisions and demand based on factors such as household socioeconomic characteristics, situational factors and psychometrics such as income, flood experience, and risk perception (Yiannakoulias et al. 2018; Bubeck et al. 2013; Dubbelboer et al. 2017; Brouwer and Schaafsma 2013; Botzen et al. 2009). The DG model predicts mitigation uptake likelihood based on results of a role-play experiment, which separates it from typical stated preference methods of data collection. In this chapter, we apply the DG model to Calgary, Alberta, and compare results to a meta-analysis based model of insurance uptake developed by Yiannakoulias et al. (2018). We use census data to provide input data for the model and investigate the uptake of mitigation under initial conditions, after a flood event, and after a floodproof subsidy.

We also analyze and map the geographic variability of outcomes of household flood mitigation likelihood under the different scenarios. Being able to understand the range of potential outcomes after floods and policy interventions can help to optimize the use of household mitigation in flood risk management policy portfolios.

1.2 Insurance

One dimension of effective flood risk management highlighted in the literature is resilience, which is a measure of the ability of a municipality to return to its initial conditions after a flood (Bhattacharya-Mis and Lamond 2014; Soetanto et al. 2008). Insurance can be an important part of improving community resilience, as it lowers the financial burden of experiencing a flood, ultimately allowing people to return to their normal lives with less inconvenience. Insurance can help to internalize the cost of flooding, help ration and prioritize public flood management measures, and cover losses that could not be prevented short of moving out of the floodplain (Yiannakoulias et al. 2018; Chivers and Flores 2002). Some have questioned whether resilience is appropriate to strive for in cities where equilibrium conditions are overexposed to flood risk (Capano and Woo 2017). Flood insurance has also been criticized for causing moral hazard, wherein more risk-taking behaviour is taken in floodplains when insured. However, some research has shown insurance and other mitigation efforts to be complements as opposed to substitutes (Botzen et al. 2017; Osberghaus 2014). Insurance is often suggested to be coupled with incentives or requirements for structural mitigation (Sandink et al. 2016). Notwithstanding potential criticisms, flood insurance can be an important component of a flood risk management portfolio which is desirable to planners and governments to help manage risk.

1.3 Household Structural Mitigation

Structural private household mitigation includes measures like temporary flood shields, backflow valves, sump-pumps, and sealants (FEMA 2014). Household structural mitigation is being increasingly recognized as an important component of an integrated flood risk management portfolio (Babcicky and Seebauer 2017; Bubeck et al. 2012). There is also a view that private households should be expected to contribute to reducing losses before government aid is allowed after a flood event (Kreibich et al. 2011; Sandink et al. 2016). While structural household mitigation methods are often encouraged, they are often assumed to be cost-beneficial with little research to support the assumption. Cost-benefit analysis has been done outside of Canada and it has been found that measures are not universally recommended, often being context specific with different methods suggested for different risk levels (Kreibich et al. 2015). Canadian examples of cost-benefit analysis for floodproofing measures are limited, emphasizing the need for research into this area. Nevertheless, private household structural measures are a beneficial component of a flood risk management portfolio and efforts to optimize their implementation are well advised.

1.4 Social Vulnerability

There has been growing interest and recognition of social vulnerability as a priority for management of flood risk. Social vulnerability partly encompasses the idea that some social groups can have more severe losses due to floods than others. Vulnerable populations have attributes that make them more likely to be negatively affected by and less likely to recover from a flood. This includes factors like being elderly or very young, low-income, or living in a rural area. Social vulnerability can be influenced by private household physical mitigation and insurance. Innovative efforts have been made to identify how to influence Canadian households to engage in mitigation efforts (Henstra and Thistlethwaite 2017), but these types of policy recommendations tend to not take into account differences in social groups or geographic variation of those groups. Exploring how variation in social characteristics influences the geography of mitigation behaviour can further optimize implementation of household mitigation. Additionally, mapping geographic variability of household mitigation is important to recognize patterns which can ultimately optimize implementation of interventions, and mitigate negative outcomes of flooding or of unintended consequences of policies.

1.5 Optimizing Mitigation-Influencing Policies

Different populations could be affected with varying types of flood interventions aimed at increasing flood mitigation. For example, lower-income people might be more impacted by a subsidy, and higher-income or older people might be more impacted by convenience-increasing measures. Moreover, from a risk reduction efficiency perspective, having the highest risk areas be the most encouraged to mitigate is well-advised. Conversely, some interventions might encourage mitigation in social groups that are at lower objective flood risk, potentially resulting in economic inefficiencies. Understanding geographic variability of mitigation outcomes can help to tweak incentives or programs to optimize household mitigation interventions.

1.6 Optimizing Policy Tools for Household Mitigation

Henstra and Thistlethwaite (2017) have noted that economic policy tools for influencing mitigation behaviour are underutilized in some Canadian cities. Visualization of policy outcomes may be helpful for practitioners to understand the benefits of their policy and may be able to gain institutional support for potential interventions if their benefits can be made clear. Analyzing patterns of mitigation spatially may also help prioritize and understand management options. For example, certain policies may result in concentrated uptake in certain areas while some would be expected to have a more widespread modest increase. As an example, (Dubbelboer et al. 2017) use an ABM to model the outcomes of the Flood Re insurance scheme in London. Part of their study compares the geographic distribution of investment in risk reduction between government and households, showing that government investment would be more targeted to high-risk areas than household investment. This study exemplifies building an understanding of the spatial impacts of a policy, which may ultimately increase support for the insurance scheme.

Methods

2.1 Overview

In this study, we generate predictions of proportions of household flood insurance and floodproofing at the dissemination area level in Calgary, Alberta. We employ the Decision Game (DG) models developed in Chapter One to generate these predictions. We use a combination of census data and Chapter One survey data as inputs to the DG models. Furthermore, we explore the effects of a flood event and a subsidy on mitigation outcomes in the city, and compare results of the insurance analysis to meta-analysis based predictions of insurance demand developed by Yiannakoulias et al. (2018).

2.2 Data analysis

1) $$y_k = h(-4.1698 - 1.8447x_1 + 1.5446x_2 + 2.4329x_3 + 5.6766x_4 - 2.1455x_5 + 0.6533x_6 + 2.8059\gamma_1 + 6.4629\gamma_2)$$

2) $$y_k = h(-5.4371 + 1.2395x_1 + 1.4642x_2 + 1.3342x_3 + 3.4505x_4 - 0.5376x_5 + 0.7616x_6 + 2.4267\gamma_1 + 3.5316\gamma_2)$$

(1) (Insurance) and (2) (Floodproofing) specify the equations that we use to generate predictions of the likelihood of mitigation, where: y_k represents the

probability of insuring or floodproofing for a given dissemination area *k;* h represents the inverse of the logit link function of the form $\frac{e^{(\cdot)}}{1+e^{(\cdot)}}$; the x and γ represent fixed and design effects which explained in Table 1. The coefficients were determined from the generalized linear mixed models developed in Chapter One of this thesis. The x and γ values represent the proportion of households in a dissemination area which are part of the comparison categories. Dissemination areas are typically the smallest geographic areas available for obtaining data from the Canadian census; in Calgary, these dissemination areas have a few hundred households. Dwelling counts and the proportion of households with $50 000 or above income levels in each dissemination area were drawn from the 2010 National Household Survey (Statistics Canada, 2011). Objective risk in each dissemination area was calculated using distance to water calculated using Euclidean distance to dissemination area centroids. The rest of the values were taken from proportions of survey responses from Chapter One, presented in Table 1. γ_x variables were design effects estimated in Chapter One.

Table 1 - *Description of Model Components*

Fixed or Design Effect	Description	Reference Category	Comparison Category	Proportion of Comparison category Households
(x_1) Income	Proportion of households with above $50 000 annual income.	0-$49 999	$50 000+	Dependent on 2010 National Household Survey
(x_2) Flood risk perception	Assessment of the severity of and vulnerability to flooding	None to Low Risk	Medium to Very High Risk	0.3000
(x_3) Coping appraisal	Perceived effectiveness of potential interventions against flooding	No or unknown perceived effectiveness	Positive perceived effectiveness	0.2195
(x_4) Personal measures	Having previously implemented a flood mitigation measure	No previous implementation	One or more previous implemented methods	0.2683
(x_5) Flood Experience	Having previously experienced a flood	No experience	One or more experienced flood	0.4146
(x_6) Flood risk	Living in a high-risk area in-game - high-risk areas in-game are being treated as hazard levels 4 or 5 in the methodology of (Yiannakoulias et al. (2018).	Low to Medium Risk (1-3 as per Yiannakoulias et al. 2018))	High Risk (4-5 as per Yiannakoulias et al. 2018))	This value was binary, every household in the dissemination area was considered to have the same flood risk
(γ_1) Purchasing Power (In-game Income Raise)	The effect of having $10 000 more in-game income compared to initial conditions of $50 000. For this analysis we have interpreted this as an increase in the purchasing power of a household, similar to a real-life income	Initial Conditions (Lower Purchasing Power)	Higher Income (Higher Purchasing Power)	For the initial conditions, the purchase power took on the same value as income
(γ_2) Flood Event	The effect of experiencing a flood in-game.	Initial Conditions	Post-Flood	For the initial conditions, the flood event value was considered to be 0

2.3 Scenario Analysis

We generate predictions for initial conditions, with the input values equal to the rightmost column in Table 1. We generate scenarios based on manipulation of design effect variables in (1) and (2). Firstly, we simulate the effect that a flood would have on the likelihood of insurance purchase and floodproofing. For the flood event scenario, in dissemination areas that had experienced evacuation in the 2010 National Household Survey (Statistics Canada 2011), we set the flood event design effect to 1 and generate predictions. We also generate a subsidy scenario for floodproofing. In the initial conditions, the purchase power value is set to be the same as income. After the subsidy, while income remains the same, purchase power increases according to the following logic: in a given dissemination area, if the proportion of households at or above $50 000 is in the bottom fifth percentile, increase the proportion by 6%, if in the second bottom fifth, increase by 4.5%, if in the middle fifth, increase by 3%, if in the second highest fifth, increase by 1.5%, and if in the highest fifth, stay the same. This graded change is meant to represent that lower income dissemination areas would be more impacted by a monetary subsidy.

For each scenario, we generate the mean and variance of predicted probabilities of mitigation across all dissemination areas and calculate the total number of predicted insured or floodproofed households by multiplying the predicted probabilities by the number of dwellings in each dissemination area. We also conduct the same analysis for the meta-analysis based model predictions. For the insurance scenarios, we compare the distribution of predicted insured households across hazard levels between the initial conditions, post-flood conditions, and the meta-analysis based predictions. We conduct a chi-square test of independence between the distributions of the initial condition scenario and meta-analysis based predictions to compare the two models. We also compare the distribution of floodproofed households across hazard levels between the initial conditions, and after the flood and subsidy events. Moreover, we also compare the proportion of the total growth in floodproofed households in each hazard level between the flood and subsidy scenarios. Furthermore, we map the flooded dissemination areas to show areas of post-flood increases in insurance and floodproofing. Finally, the change in predicted probabilities of floodproofing in each dissemination area after the subsidy introduction are mapped.

Results

3.1 Summary Statistics

In order to understand uptake of flood insurance and floodproofing under multiple scenarios, we use the DecisionGame (DG) model to generate predictions of the likelihood of mitigation at the dissemination area in Calgary. Summary statistics of the predicted probabilities are presented in Table 2. The total number of predicted households in each scenario is also included. For comparison purposes, the meta-analysis based model developed by Yiannakoulias et al. (2018) is included.

Table 2 - *Summary statistics*

	Mean Dissemination Area Predicted Probability (%)	Variance of Predicted Probabilities (%)	Total Predicted Number of Insured/Floodproofed Households
Insurance Initial Conditions	9.879058	6.209683	42228
Meta-Analysis Based Model of Insurance	10.83031	147.2399	41589
Insurance Post-Flood	15.33199	477.1467	68974
Floodproofing Initial Conditions	3.356438	1.029915	14381
Floodproofing Post-Flood	6.912824	203.1887	32337
Floodproofing Post-Subsidy	3.586053	1.032847	15305

3.2 Insurance Scenario Comparisons

In Table 3, we compare the number of predicted insured households in each flood hazard level between the DG insurance scenarios and the meta-analysis based model. We also report the expected values of each category from the chi-square test of independence between the initial conditions DG model and the meta-analysis based model in parentheses below each value. The chi-square test of independence had a chi-square statistic of 708.36 on 4 degrees of freedom. This yielded a p-value of virtually 0, for which we can consider the distributions to be statistically significantly independent of each other at the <0.01 level. In order to more easily compare the post-flood distribution of insured households to the initial conditions, the square bracketed numbers are the number of households insured multiplied by a constant such that the total number of households insured is equal to the amount in the initial conditions.

Table 3 - *Insurance Scenario Comparisons*

Hazard Level	Model: Meta-Analysis Model	Model: Decision Game Model Initial Conditions	Model: Decision Game Model Post-Flood
1	28601 *(30063.55)*	31988 *(30525.45)*	38017 [23275]
2	1157 *(1003.29)*	865 *(1018.71)*	2826 [1730]
3	3166 *(2516.17)*	1905 *(2554.83)*	5999 [3673]
4	4109 *(4058.32)*	4070 *(4120.68)*	10312 [6313]
5	4557 *(3948.67)*	3401 *(4009.33)*	11821 [7237]

3.3 Floodproofing Scenario Comparisons

In Table 4, we compare the number of floodproofed households in each hazard level between each scenario. For more intuitive comparison, we present in parentheses the proportion of the growth of floodproofed households in each hazard level.

Table 4 - *Floodproofing Scenario Comparisons*

	Model		
Hazard Level	**Initial Conditions**	**Post Flood**	**Post Subsidy**
1	10589	13871 *(18%)*	11299 *(77%)*
2	286	1315 *(6%)*	305 *(2%)*
3	634	2881 *(13%)*	681 *(5%)*
4	1570	6408 *(27%)*	1661 *(10%)*
5	1303	7861 *(37%)*	1358 *(6%)*

3.4 Mapped Analysis

Below, we present maps to enhance interpretation of our results. We show the flooded dissemination areas which experience increases in insurance and floodproofing probabilities. And, we map the increase in predicted probabilities of floodproofing at the dissemination area level after a subsidy is introduced, with the larger increases being darker on the greyscale. Dissemination areas which are missing data are in white.

Figure 1 – *Flooded Dissemination Areas*

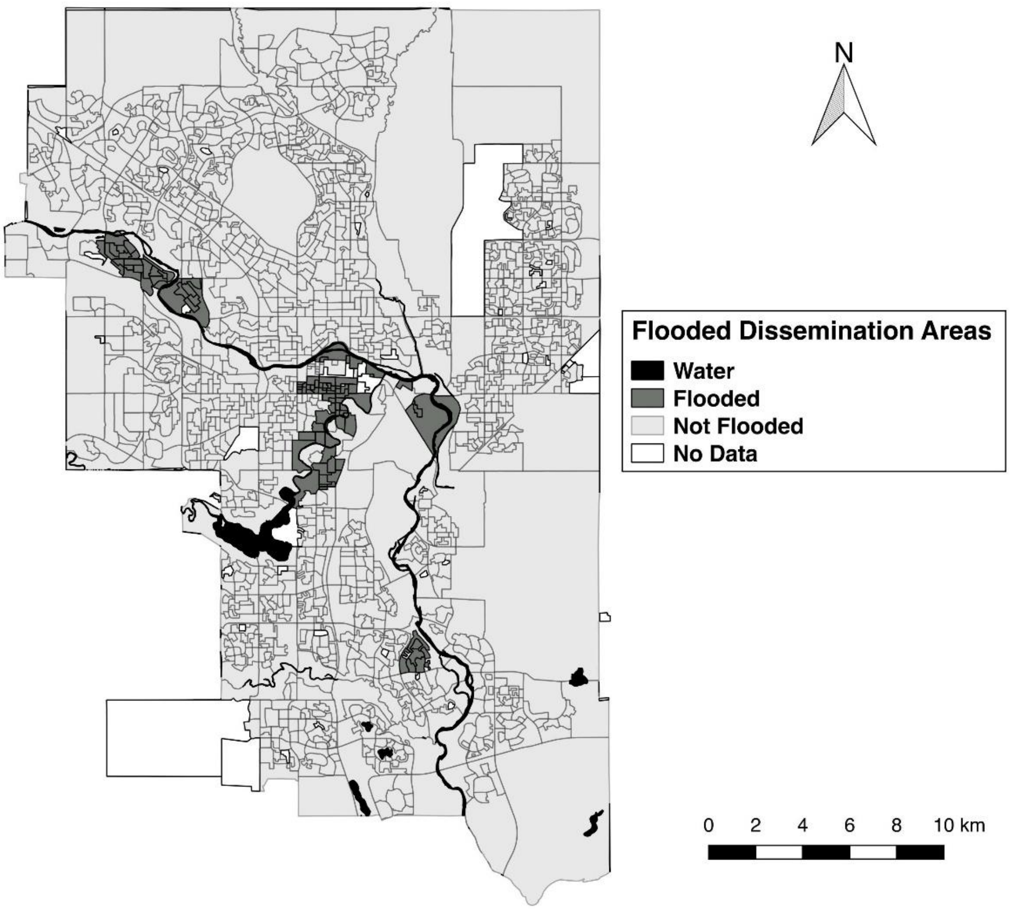
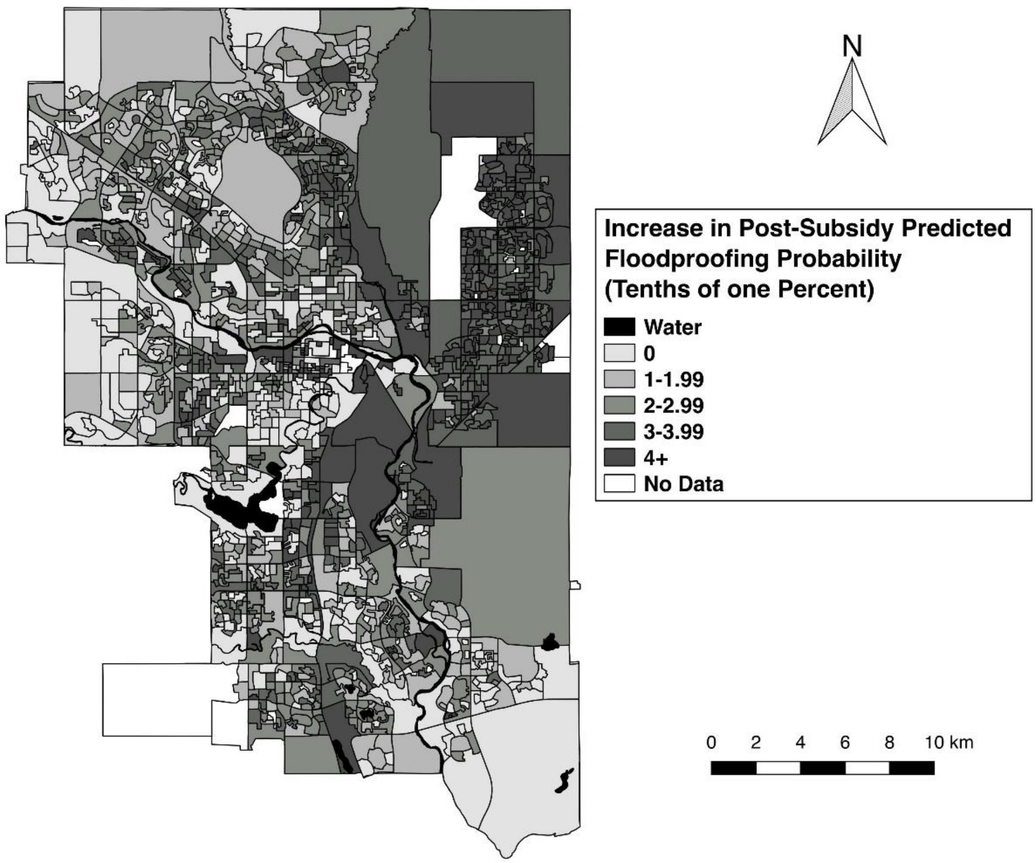


Figure 2 – *Post-Subsidy Changes in Floodproofing Probability at the Dissemination Area Level*[7]



[7] Note that there were no values between 0 and 1

Discussion

4.1 Summary Statistics of the Predicted Number of Insured Households

We observe similar levels of predicted probabilities between the initial conditions of the Decision Game (DG) model and the meta-analysis based model. However, the variance of predicted probabilities is larger in the meta-analysis based model. The lower variability in the DG model is due to most of the values of the model variables being held constant. Note that we assume that most of the of the DG model variables like risk perception and coping appraisal do not have systematic geographical patterns independent of variables included in our analysis, namely income and flood risk. In both the post-flood insurance and floodproofing scenarios, the variance increases considerably. Experiencing a flood has a large effect size in the DG model, which creates a large separation in probabilities between flooded and non-flooded dissemination areas, driving up the variance in these scenarios. In the floodproofing post-subsidy scenario, we do not observe a notable increase in variance compared to the initial conditions. This is due to the subsidy raising the probability of lower-income dissemination areas more than already higher-probability higher-income dissemination areas, effectively squeezing dissemination probabilities closer together.

4.2 Comparing Insurance Scenarios

The meta-analysis based model is derived from the factors the literature suggests should contribute to insurance demand, while the DG model is based on observed experimental behaviour. The ability to contrast between the two models offers a unique opportunity to better understand and contextualize the results. We see from the results of the chi-square test of independence that the two distributions are different from one another in terms of the number of insured households in each hazard level. Compared to the meta-analysis based model, the DG model predicts more uptake of insurance in the lowest hazard level area and predicts fewer insured households in other hazard levels, particularly in the highest hazard level area. This could potentially be beneficial for insurance companies who may try to cross-subsidize premiums from low-risk areas to high-risk areas, allowing them to offer coverage for high-risk areas and limit reputational costs. However, from the consumer perspective, over-insurance in low risk areas may not be desirable. In the post-flood scenario, we observe an increase in insurance for all hazard levels. When we normalize the total number of households to be equal to the initial conditions number, we observe that the distribution among hazard levels inverts, with the lowest hazard level having fewer predicted insured households and the higher levels having more predicted insured households. This is perhaps to be expected given the clustering of flooded dissemination areas around the higher hazard level dissemination areas near the rivers, observable in Figure 1. These higher hazard level dissemination areas experienced more evacuations, and subsequently had higher predicted probabilities after experiencing the flood. Even so, the increase in the total number of insured households is comparable between the lowest and highest risk levels (about 6000 and 8500 respectively). This suggests that insurance cross-subsidization could still be reasonably maintained after a flood event.

4.3 Comparing Floodproofing Scenarios

For the floodproofing scenarios, we can observe the effects of two different events—a flood, and a subsidy for floodproofing. It is important to note that the flood event was associated with a much higher increase in the number of floodproofed households. However, this difference has a limited interpretation because of the arbitrary nature of the subsidy effect on purchase power. It is perhaps more valuable to compare the proportions of predicted floodproofed households in each hazard level. In the flood scenario, the majority of the growth in floodproofed households occurs in hazard levels four and five, which is to be expected given the clustering of dark zones around the rivers (see Figure 1). In the post-flood scenario, the majority of the increase in predicted floodproofing occurs in hazard level one, due to more lower-income households being located in this hazard level. This can be seen in the post-subsidy map (see Figure 2), where higher-increase darker areas are more evenly distributed throughout the city and are not clustered around the rivers, noting several darker dissemination areas in the northeastern section of the map. It can be argued that from a floodproofing uptake perspective, the flood event results in a more desirable situation than the subsidy because the floodproofing is more concentrated in higher risk areas. This highlights the value of ensuring that households are aware of mitigation options they may have after a flood event to capitalize on the increased likelihood of floodproofing. However, it is likely that policy-makers want a more proactive solution to increase floodproofing than waiting for a flood. While they may be an attractive option, we see from these results that floodproofing subsidies must be used with caution. Under the assumption that lower-income households are more likely to increase uptake after a subsidy than higher-income households, we observe that increased floodproofing would increase mostly in the lower risk areas in Calgary. This would likely not be cost-beneficial to these households and government resources could be better spent elsewhere. These results suggest that subsidies should be restricted to high risk areas for cities in which lower-income households are overrepresented in lower-risk areas.

Limitations

Several factors place limitations on our interpretation of the findings from this chapter. Many limitations stem from the DG model which was used to generate predicted probabilities. The model was developed with a sample size of 123. This sample size contributed to standard errors of the effect estimates of the DG model which were often of similar magnitude to the estimates themselves, meaning there is uncertainty associated with the equation coefficients which are not considered in this chapter. The design effect sizes of the DG model were also likely overstated for floodproofing. This is because Decision Game allowed purchasing floodproofing with a drop-down selection box; the game did not include transaction costs associated with floodproofing like time or inconvenience. The way that purchasing power was used in this case study was also a limitation. The subsidy caused an increase in the proportion of households who had the income increase design effect activated. An in-game design effect that better matched a case-study policy would be better for the future. Furthermore, the DG model was not validated against a real-life revealed preference experiment. While the insurance DG model was compared to the meta-analysis based model, no rigorous validation method was used in this chapter either.

Conclusion

In this chapter, we applied the DG model developed in Chapter One in a case study of Calgary, Alberta. We looked to analyze the geographic variability of outcomes of insurance and floodproofing uptake under several different scenarios. The initial conditions of insurance uptake in Calgary were comparable to the meta-analysis based model (Yiannakoulias et al., 2018). A flood event resulted in an over 50% increase in the number of insured households. We found that even though proportionally more households switched to purchasing insurance after the flood event, enough low hazard level households bought insurance to suggest favourable conditions for cross-subsidization of insurance. In the floodproofing scenarios, we found that the subsidy resulted in over 75% of new floodproofed houses being in the lowest hazard level, whereas in the post-flood scenario this was only 18%, with about a third of new floodproofed households being in the highest hazard area. These results suggested that policymakers should be cautious when using subsidies to ensure that funds are spent on higher hazard areas to avoid economic inefficiencies.

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Conclusion

In the first chapter of this thesis, we looked to answer the question of which individual and contextual factors contribute to the decision to mitigate against floods. We logged decisions made in a serious game role-playing experiment to generate data to make a model of floodproofing and insurance decisions to address this question. Among other findings, we found that experiencing a flood was perhaps unsurprisingly the most important predictor of flood mitigation behaviour in the models. We also found that previous real-world flood experience did not have a notable positive effect. Moreover, having more income in real-life did not have a strong positive effect in both models, while increasing in-game income did have a relatively large positive effect on decisions to mitigate. Objective in-game flood risk had a small, statistically significant positive effect in both models. Our key observation is that incentivizing flood risk mitigation should be done quickly following a flood event, given that the effect of flood experience may decay over time. Moreover, we found that low-income individuals were no less likely to implement mitigation measures than their higher-income counterparts, suggesting that subsidies to address an income barrier may be an effective method of encouraging low-income household mitigation. Furthermore, communicating objective risk information may not be enough to encourage mitigation uptake. These results must be taken with caution since there was large error associated with model estimates, and the random effects were explaining more of the variability in the data than the fixed and design effects in which we were interested. In the future, a larger sample size and a wider range of model parameters may be able to improve the reliability of the model.

We applied the Decision Game model to Calgary, Alberta, finding that the insurance market could maintain a good degree of cross-subsidization after a flood to make insuring higher risk areas more feasible. Moreover, we found that Calgarian policymakers should be encouraged to limit subsidy coverage to high-risk areas to avoid inefficient use of funds in low-risk areas which were projected to have the clear majority of program uptake.

Overall, the digital serious game role-playing experiment shows great promise as a research tool, mainly through being able to operate in the space in between stated and revealed preference methods. The tool observes decisions as opposed to asking more abstract hypothetical questions, but also allows for complete control over experimental conditions, unlike natural experiments. While acknowledging the limitations of this study, the possibilities for this type of research tool are exciting. We hope that the serious gaming approach to understanding flood risk mitigation decision-making can be further developed in the future. A first logical step for this research would be to create an experiment which more closely mimics a real-life scenario to compare outcomes and validate the method. Other potential applications involve introducing events to test and compare policy options, such as risk communication tools. The father of behavioural economics, Richard Thaler, once said that "we can't do evidence-based policy without evidence." In the flood risk context, serious games can offer a data-driven approach to understanding decision-making, ultimately contributing to an evidence-based optimization of household-level mitigation measures.

Appendix

Appendix 1 - *Table of Potential Independent Variables*

Factor	Description	Question[8]	Possible Answers	Examples from the literature on the variable's Relationship with Mitigation and Insurance Purchase Decisions
Age	The age of the participant.	"How old are you?"	18-20 21-25 26-30 31-35 36-40 41-45 46-50 51-55 56-60	• Brody et al. (2017 b) and Atreya et al. (2015) found that individuals over the age of 45 tended to be more likely to have purchased flood insurance. • Shah et al. (2017) found mixed results of age on mitigation depending on the particular strategy employed. • Bubeck et al. (2012) find in a review that age has a small or no effect on likelihood of mitigation.

[8] Questions were used and adapted from the questionnaire developed by Sobiech (2013)

			61-65 65-69 70+	
Income	The Income level of the participant.	"What is your income Bracket?"	0-24999 25000-49999 50000-74999 75000-99999 100000-124999 125000-149999 150000+	• People with higher value homes, arguably linked to income, are more likely to undertake structural measures to protect against flooding Brody et al. (2017). • Income effect on mitigation found to be insignificant or positive (Osberghaus 2014; (Bubeck et al. 2012; Grothmann and Reusswig 2006; Botzen et al. 2009; Botzen and Van Den Bergh 2012).
Education Level	The highest level of education achieved by the participant.	"What is your highest level of education achieved?"	No Education Elementary High School College/University	• Brody et al. (2017 b) found a link between higher education levels and the likelihood of purchasing flood insurance. • Bubeck et al. (2012) find in a review that education has a small or no effect on mitigation decisions. • Atreya et al. (2015) find that insurance policy purchase likelihood increases with the percentage of high school graduates in a given county.
Risk Perception	The extent to which the respondent perceives flooding as a risk to the	"How would you evaluate the risk of flooding/a storm surge in your community?"	Very High High Medium	• Risk perception has been found to have a positive relationship with flood preparedness (Fuchs et al. 2017; Miceli et al. 2008; Grothmann and Reusswig 2006). • Some studies show mixed results when comparing risk perception to mitigation efforts Brody et al. (2017), and some find no relationship between risk perception and flood preparedness (Siegrist and Gutscher 2008;

	community.		Low Very Low Not at all	Steinführer and Kuhlicke 2007; Bradford et al. 2012; Bubeck et al. 2013).
Perception of personal Exposure	The extent to which floods/storm surges are viewed as a personal risk.	"Do you live in a flood prone area, i.e. an area that could be flooded in case of extreme weather conditions?"	Yes Don't Know No	• This relationship is similar to risk perception. However, the individual's perception of exposure may be different than the perceived exposure of their community.
Flood Experience	The participant's past experience with flooding.	"Have you personally experienced impacts of a flooding event/storm surge?"	Yes, More than once Yes, once No	• Brody et al. (2017 b) found that, consistent with the literature, a flooding experience raises insurance purchases for three years, after which the effect fades. • Siegrist and Gutscher (2008) reported that people who had not experienced a flood underestimated the negative effects of a flood compared to people in the same area who had experienced a flood. • Osberghaus (2017) detail results which show a causal relationship between insured flood damage and private flood mitigation, as well as a correlation of mitigation with self-reported flood experience. • Tobin and Montz (1994) note that rare flood events are associated with a drop in housing price, followed by a recovery once repairs are complete. • Atreya et al. (2013) find using hedonistic price analysis that 4-7 years after a 1 in 100-year flood, the price of flood-prone houses returned to pre-flood levels.
Level of Information	Knowledge and Information	"Do you feel sufficiently informed on the	Yes	• Allaire (2016) found evidence from Bangkok that insurance purchases increased after an information

	level of respondents regarding flood-related protection/pre vention measures	occurrence of flooding/storm surges and possible prevention measures?”	Don’t know No	intervention, but home retrofits did not change significantly. • The perception of information, specifically with respect to risk, is argued to be necessary for influencing protective behaviour (Bradford et al. 2012; Terpstra 2010)
Sources of Information (Including Social Network)	Where they obtained that information.	“Where did you learn how to protect yourself against flooding/storm surging?”	Don’t Know How to Own Experience Talking to others affected Media Coverage Public Information Events Social Media Government information sources (indicate municipal/provincial/fede ral) Other - Please Describe	
Measures	State of already having applied preventative or protective measures.	“Have you personally taken measures against flooding/storm surges?”	Yes No	• Botzen et al. (2017) find evidence that past insurance purchases are associated with an increase in likelihood of future mitigation measures. • Richert et al. (2017) find that people who had previously taken precautionary measures had lower risk perception than those who had not. • Poussin et al. (2013) note that households that had previously mitigated are perhaps less likely to mitigate in the future if those mitigation efforts were effective after a flood event.
Type of measures		“Have you personally applied one or more of these measures?”	Structural measures - For example, sealing wiring/electrical conduits against water seepage, using water-resistant building materials, backflow valves, relocating electrical panels	

			out of basement -Please Describe: Behavioural measures - For example, moving furniture out of the basement; preparing a flooding emergency kit with insurance documents; having a family emergency plan Please describe: Purchased Flood Insurance None Other - Please Describe	
Assets (Owner or Renter)	Does the respondent own their place of dwelling?	"Are you the owner or the tenant of the house/apartment you live in currently?"	Owner Tenant	• Longer house ownership has been found to increase likelihood of using structural measures Brody et al. (2017). • Shah et al. (2017) find a positive relationship between home ownership and a number of household mitigation options
Coping Appraisal	Attitude towards self-protective measures, or more	"Do you think that you are capable of lessening the impacts of flooding/storm surges?"	Yes Don't know No	• Coping appraisal has been found to be an important factor in influencing mitigation and preparation behaviour (Bubeck et al. 2012; Poussin et al. 2014). • Risk perception has been found to not be a straightforward indicator of protective action (Scolobig

	specifically the belief that one can influence their vulnerability to a hazard.			et al. 2012), but is mediated by factors including coping appraisal (Bubeck et al. 2013).
Expectations	Does the respondent believe that flood risk will increase in the future?	"Do you think that losses due to flooding/storm surges will increase in the future for you?"	Yes Don't Know No	• Osberghaus (2015) found evidence from Germany which suggest that propensity to mitigate against floods increases with expectations of future damage increases due to climate change. • Bichard and Kazmierczak (2012) find that climate change awareness is coupled with low flood risk perception.
Trust	The extent that the respondent has trust in preventative measures of their community.	"Assuming that the risk of flooding/storm surges increases in the future, to what extent do you agree with the following statement? 'Due to the flood protection measures in the community, no further measures of self-protection are necessary.'"	Yes, strongly agree Yes, somewhat agree No, somewhat disagree No, do not agree Don't know	• Bichard and Kazmierczak (2012) find that that homeowners in England and Wales were less likely to be willing to pay for flood mitigation if they believed the authorities were responsible for mitigating against floods. • Buchecker et al. (2016) found that the level of trust in government authorities predicted support for non-structural measures, including individual prevention measures.

Appendix 2 - *Frequency Table of Independent Variables with Reference Categories*

Response	Frequency	Reference Category for Modelling
Owner or Renter of Home		N/A
Owner	60	
Renter	63	
Flood Risk Perception		No Risk to Low
No Risk	17	
Very Low	32	
Low	44	
Medium	21	
High	6	
Very High	3	
Personal Flood Exposure Perception		N/A
No	62	
Yes	33	
Don't Know	28	
Flood Experience		No
No	72	
Yes, Once	8	
Yes, More than Once	43	
Sufficiently Informed about Flood Information		N/A

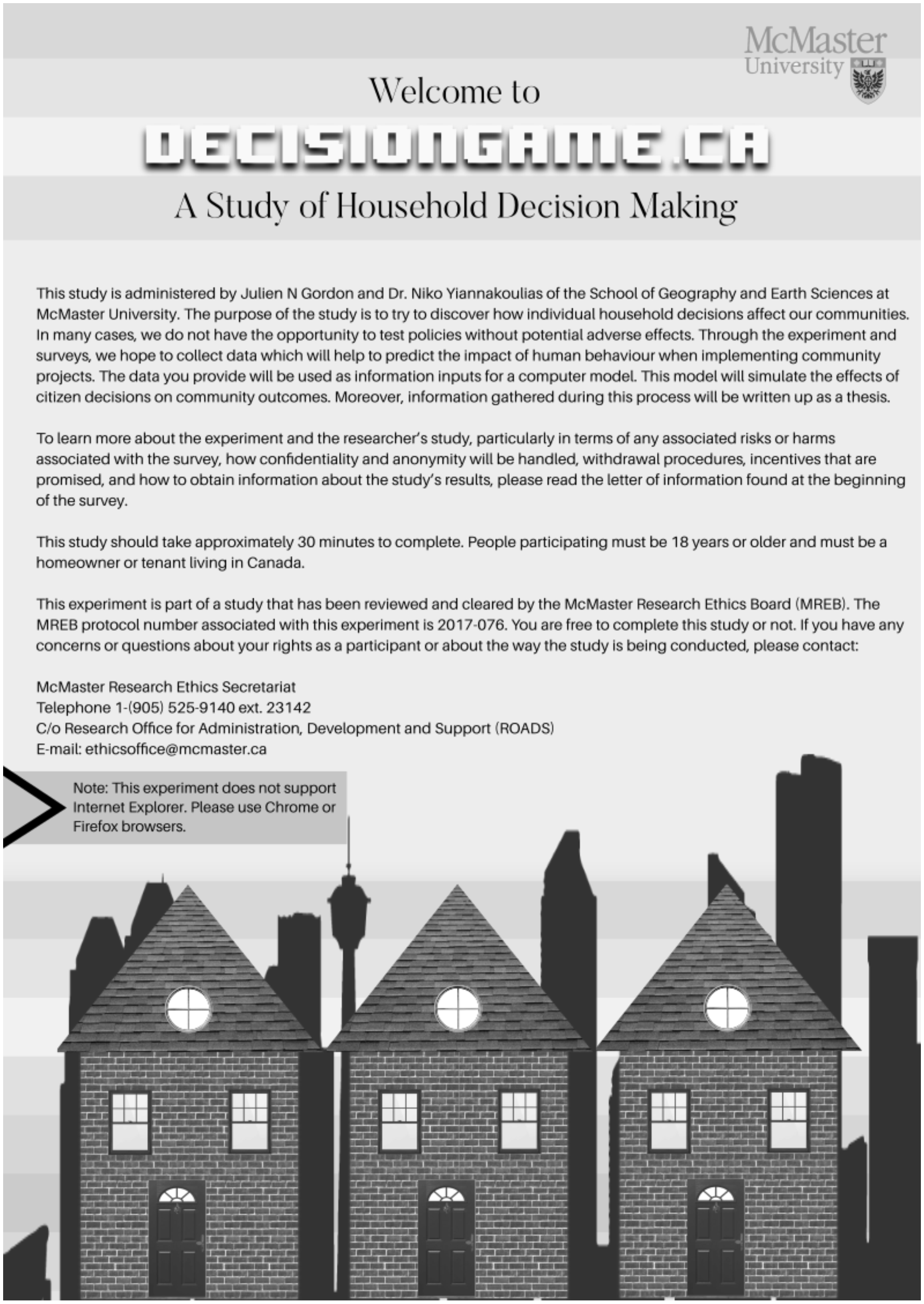
No	50	
Yes	58	
Don't Know	15	
Personal Measures Against Flooding		No
No	90	
Yes	33	
Coping Appraisal (Ability to Influence Flood Impact)		No or Don't Know
No	57	
Yes	27	
Don't Know	39	
Future Loss Increase Perception		N/A
No	31	
Yes	40	
Don't Know	52	
Trust in Community Measures Against Flooding		N/A
Strongly Disagree	24	
Somewhat Disagree	27	
Neutral	22	
Somewhat Agree	23	
Strongly Agree	16	
Don't Know	11	
Age		N/A

18-20	11	
21-30	42	
31-40	35	
41-50	21	
51-60	7	
61-70	7	
71+	0	
Education		N/A
None	1	
Elementary	1	
High School	21	
College/Uni	101	
Income ($1000)		0-49
0-24	30	
25-49	26	
50-74	22	
75-99	14	
100+	31	

Appendix 3 – *Results of Chi Square Test of Independence Results: P value Matrix*

	Age	Education	Income	Owner or Renter of Home	Flood Risk Perception	Personal Flood Exposure Perception	Sufficiently Informed about Flood Information	Personal Measures Against Flooding	Coping Appraisal	Future Loss Increase Perception	Trust in Community Measures Against Flooding	Flood Experience
Age		4.23E-03	3.22E-05	3.54E-05	1.46E-01	1.68E-01	4.52E-02	5.24E-02	0.7275	0.751	2.37E-02	5.86E-01
Education	4.23E-03		6.12E-05	3.36E-03	1.16E-01	0.5836	0.9526	0.4564	*0.994*	3.44E-01	9.94E-02	2.56E-01
Income	3.22E-05	6.12E-05		1.01E-08	1.83E-01	3.22E-04	3.22E-02	1.50E-01	0.4238	0.724	9.23E-02	3.18E-01
Owner or Renter of Home	3.54E-05	3.36E-03	1.01E-08		1	3.81E-03	5.99E-02	6.24E-04	5.72E-02	4.48E-02	7.00E-03	2.16E-01
Flood Risk Perception	1.46E-01	1.16E-01	1.83E-01	1		7.88E-12	7.53E-03	3.49E-02	8.65E-01	1.71E-02	7.54E-01	3.10E-02
Personal Flood Exposure Perception	1.68E-01	*0.5836*	3.22E-04	3.81E-03	7.88E-12		1.73E-02	1.13E-04	2.20E-01	5.30E-04	5.06E-02	1.77E-03
Sufficiently Informed about Flood Information	4.52E-02	0.9526	3.22E-02	5.99E-02	7.53E-03	1.73E-02		4.41E-02	2.93E-01	3.30E-01	2.07E-03	2.06E-01
Personal Measures Against Flooding	5.24E-02	0.4564	1.50E-01	6.24E-04	3.49E-02	1.13E-04	4.41E-02		5.49E-02	0.9871	3.59E-02	4.66E-02
Coping Appraisal	0.7275	*0.994*	0.4238	5.72E-02	8.65E-01	2.20E-01	2.93E-01	5.49E-02		1.40E-01	5.32E-01	2.54E-01
Future Loss Increase Perception	0.751	3.44E-01	0.724	4.48E-02	1.71E-02	5.30E-04	3.30E-01	0.9871	1.40E-01		7.78E-04	4.11E-01
Trust in Community Measures Against Flooding	2.37E-02	9.94E-02	9.23E-02	7.00E-03	7.54E-01	5.06E-02	2.07E-03	3.59E-02	5.32E-01	7.78E-04		4.67E-01
Flood Experience	5.86E-01	2.56E-01	3.18E-01	2.16E-01	3.10E-02	1.77E-03	2.06E-01	4.66E-02	2.54E-01	4.11E-01	4.67E-01	

Appendix 4.1 - *Welcome Page*



McMaster University

Welcome to

DECISIONGAME.CA

A Study of Household Decision Making

This study is administered by Julien N Gordon and Dr. Niko Yiannakoulias of the School of Geography and Earth Sciences at McMaster University. The purpose of the study is to try to discover how individual household decisions affect our communities. In many cases, we do not have the opportunity to test policies without potential adverse effects. Through the experiment and surveys, we hope to collect data which will help to predict the impact of human behaviour when implementing community projects. The data you provide will be used as information inputs for a computer model. This model will simulate the effects of citizen decisions on community outcomes. Moreover, information gathered during this process will be written up as a thesis.

To learn more about the experiment and the researcher's study, particularly in terms of any associated risks or harms associated with the survey, how confidentiality and anonymity will be handled, withdrawal procedures, incentives that are promised, and how to obtain information about the study's results, please read the letter of information found at the beginning of the survey.

This study should take approximately 30 minutes to complete. People participating must be 18 years or older and must be a homeowner or tenant living in Canada.

This experiment is part of a study that has been reviewed and cleared by the McMaster Research Ethics Board (MREB). The MREB protocol number associated with this experiment is 2017-076. You are free to complete this study or not. If you have any concerns or questions about your rights as a participant or about the way the study is being conducted, please contact:

McMaster Research Ethics Secretariat
Telephone 1-(905) 525-9140 ext. 23142
C/o Research Office for Administration, Development and Support (ROADS)
E-mail: ethicsoffice@mcmaster.ca

Note: This experiment does not support Internet Explorer. Please use Chrome or Firefox browsers.

Appendix 4.2 - *Intro Survey*

Section 1 of 6

A Study of Household Decision Making: Background Information

Letter of Information

Student Investigator:

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(905) 525-9140 ext. 28611
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Principal Investigator:

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Research Sponsor: Natural Sciences and Engineering Research Council (NSERC)

Purpose of the Study:

We are trying to discover how individual household decisions affect municipal communities over time. Human behaviour is a

Purpose of the Study:

We are trying to discover how individual household decisions affect municipal communities over time. Human behaviour is a crucial factor to understand when estimating the effects of social policies. In many cases, we do not have the opportunity to test policies without potential adverse effects. Through this experiment and survey, we hope to collect data which will help to predict the impact of human behaviour when implementing community projects.

You are invited to take part in this study on household decision making. The data you provide will be used as information inputs for a computer model. This model will simulate the effects of human behaviour on community outcomes.

Procedures involved in the Research:

You will be asked to provide some basic demographic information. You will take on the role of someone living in the community of Hamilton or Calgary. You will be given an income within the experiment, and provided with some basic information about the neighbourhoods. You will be asked to indicate where you would choose to live, and how much money you would spend on different categories. You will make these choices ten times, with each set of decisions representing a year in the experiment. Finally, you will be asked to complete a survey about your decisions and habits in your real life. Note that there are no "correct" answers, we rather want to gather information about your individual choices.

The experiment is expected to require about 30 minutes of your time. This can be completed at any computer with an internet connection, or on one of our designated laptops. If you are participating online, you may also choose to quit and resume the experiment at a later time if you wish.

Are there any risks to doing this study?

The risks involved in participating in this study are minimal. You may feel uncomfortable or experience stress with some of the spending decisions that you will make. You may also feel distressed when considering some of the scenarios, including low income levels, presented within the game.

While we do not collect names, email addresses can be personally identifying. Survey responses could be linked to your email address in the event of a security breach. Thus, there is a privacy risk associated with participating, however this risk is minimal.

Potential Benefits

The research will not likely benefit you directly. You may find it helpful to have undergone a budgeting exercise within the game to make you more financially aware of your spending habits. Your community may benefit in the long term through policy-making which takes into account how the people in your neighbourhood would react.

Payment or Reimbursement

If you complete the experiment, you will be entered in a draw for a $500 Amazon.ca gift certificate.

Confidentiality

The information you submit for this study will be kept confidential. I will not use your name or any information that would allow you to be identified. No one but Dr. Niko Yiannakoulias, my supervisor, and I will know whether you participated in the study unless you choose to tell us. If submitting paper responses in person, your information will be stored in a locked cabinet as soon as possible.

If completed online, your email, consent information and survey responses will be stored in a password-protected file for distributing prizes and study results. After approximately September 2018, when I expect to submit my thesis, this database will be destroyed.

Participation and Withdrawal:

Your participation in this study is voluntary. If you decide to be part of the study, you can stop (withdraw) from the experiment for any reason, even after signing the consent form up until December 2017. The experiment will have a quit button on every page, enabling you to withdraw. If you decide to withdraw, there will be no consequences to you. In cases of withdrawal, any data you have provided will be destroyed unless you indicate otherwise.

How do I find out what was learned in this study?

I expect to have this study completed by approximately September, 2018. If you would like a brief summary of the results, we will share it with you via email.

Questions about the Study:

If you have questions or need more information about the study itself, please contact me at: gordonjn@mcmaster.ca

Section 2 of 6

Consent to participate

This study has been reviewed by the McMaster University Research Ethics Board and received ethics clearance. If you have concerns or questions about your rights as a participant or about the way the study is conducted, please contact:

McMaster Research Ethics Secretariat

Telephone: (905) 525-9140 ext. 23142
C/o Research Office for Administrative Development and Support
E-mail: ethicsoffice@mcmaster.ca

I have read the information presented in the information letter about a study being conducted by Julien N Gordon and Dr. Niko Yiannakoulias, of McMaster University.

I have had the opportunity to ask questions about my involvement in this study and to receive additional details I requested.

I understand that if I agree to participate in this study, I may withdraw from the study at any time or up until December 2017

I agree to participate in the study.

I am 18 years of age or older

Do you wish to continue with the study? *

- ◯ Yes, I agree to participate
- ◯ No, I do not agree to participate

Section 3 of 6

Survey Questions

Please answer the following questions. You must enter a valid email address to participate in this study.

What is your email address? *

Short answer text

How old are you?

- 18-20
- 21-30
- 31-40
- 41-50
- 51-60
- 61-70
- 71+

What is your income bracket?

- $0 - $24,999
- $25,000 - $49,999
- $50,000 - $74,999
- $75,000 - $99,999
- $100,000 - $124,999
- $125,000 - $149,999
- $150,000+

What is your highest level of education achieved?

- ○ None
- ○ Elementary school
- ○ High school
- ○ College/university

Section 5 of 6

Final study results

Would you link to receive a summary of the study results via email?

Would you like to receive a summary of results? *

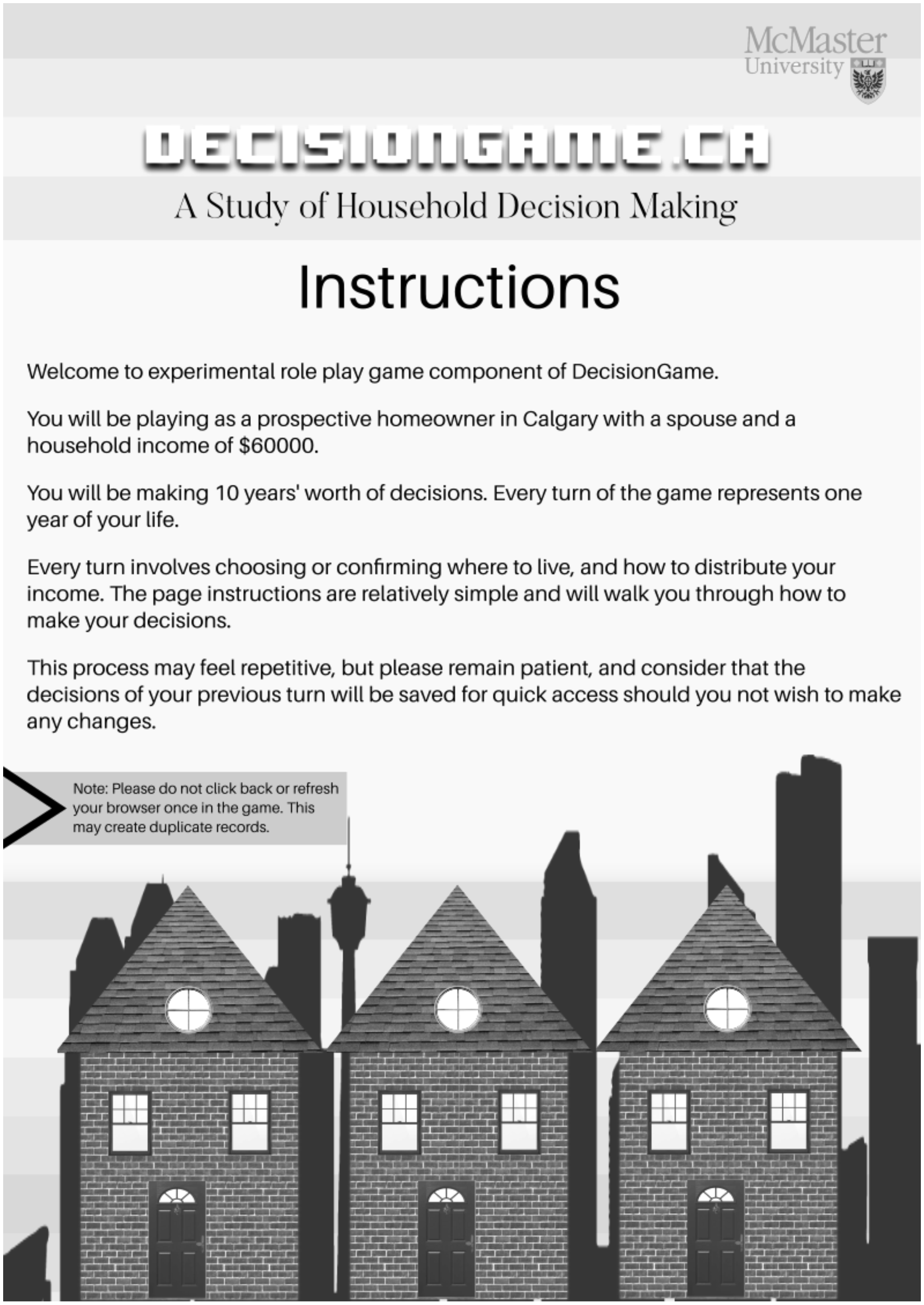
- ○ Yes
- ○ No

Section 6 of 6

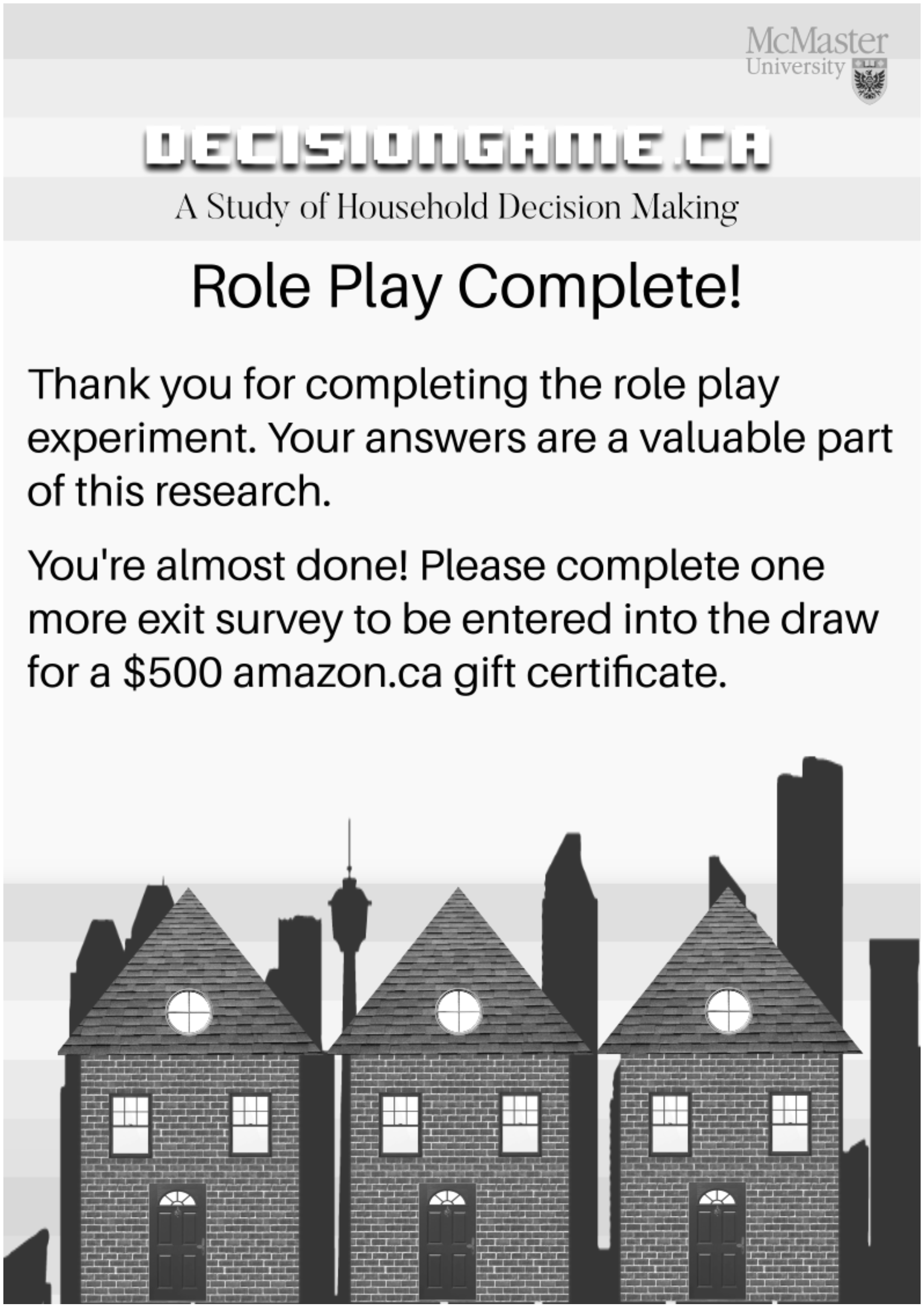
Thank you

Click the SUBMIT button below to complete this part of the study. Following this, you will be sent an email (from thedecisiongame@gmail.com) containing a web link to the study. Check your spam folder if you do not receive the email initially.

Appendix 4.3 - *Instruction Page*



Appendix 4.4 - *Exit page*



Appendix 5 - *Exit Survey*

Section 1 of 10

A Study of Household Decision Making: Survey #2

Thank you for completing the decision game! Now, we wish to ask you a few specific questions about your personal circumstances, attitudes and opinions about flood risk in the environment in which you actually live.

Section 2 of 10

Email address

Description (optional)

First, please verify your email address *

Short answer text

Section 3 of 10

Where you live

Description (optional)

What is the name of the neighbourhood within your city or town if applicable? E.g. Kensington, East End, Midtown, Riverdale

Short answer text

What are the first three digits of your postal code?

Short answer text

Are you an owner or a renter of your current home?

- ○ Owner
- ○ Renter

Section 4 of 10

Risk, risk perception and experience

Description (optional)

How would you evaluate the risk of flooding in your community?

- ◯ Very high
- ◯ High
- ◯ Medium
- ◯ Low
- ◯ Very low
- ◯ No risk

Do you live in an area that could be flooded in the case of extreme weather conditions?

- ◯ Yes
- ◯ No
- ◯ Don't know

Have you personally experienced the impacts of flooding?

- ◯ Yes, more than once
- ◯ Yes, once
- ◯ No

Section 5 of 10

Information about flooding and flood prevention

Description (optional)

Do you feel sufficiently informed about the occurrence of flooding and possible prevention measures?

- Yes
- No
- Don't know

Where did you learn how to protect yourself against flooding? (select all that apply)

- [ ] Don't have any information/don't know
- [ ] Personal experience
- [ ] Talking to others affected
- [ ] Media coverage (e.g., television, newspapers, radio, internet news sources)
- [ ] Public information events
- [ ] Social media
- [ ] Government information sources (municipal, provincial or federal)
- [ ] Other

If you answered 'other' to the above question, please specify

Short answer text

Section 6 of 10

Flood prevention measures

Description (optional)

Have you personally taken measures to protect against flooding?

- Yes
- No

Section 7 of 10

Flood prevention measures

Description (optional)

Have you personally applied structural measures? For example, have you sealed wiring/electrical conduits against water seepage, used water resistant building materials, installed backflow prevention valves, or relocated electrical panels? Please describe.

Short answer text

Have you personally applied any non-structural changes to your household environment? For example, have you moved furniture out of basement, prepared a flooding emergency kit that includes essential documents or made an emergency evacuation plan in the event of a flood? Please describe.

Short answer text

Have you purchased any form of flood insurance?

- Yes
- No
- Don't know/unsure

Section 8 of 10

Attitudes and expectations

Description (optional)

Do you think that you are capable of reducing the impacts of flooding?

- Yes
- No
- Don't know

Do you think that your losses due to flooding will increase in the future?

- Yes
- No
- Don't know

Assuming that the risk of flooding increases in the future, to what extent do you agree with the following statement? "Due to the flood protection measures in my community, no further measures are needed to protect my home from floods."

- Strongly agree
- Somewhat agree
- Neutral
- Somewhat disagree
- Strongly disagree
- Don't know

Section 9 of 10

Study information

If you know of anyone who may want to participate in this study, please consider inviting them. By including their emails here, we will send them an invitation to participate on your behalf. You are not required to complete this section.

Invitation 1

Short answer text

Invitation 2

Short answer text

Invitation 3

Short answer text

How did you find out about this research?

- I was recruited in person
- Through my social network (Twitter, Facebook, etc.)
- I saw a poster or pamphlet
- From a web page
- Other...

Section 10 of 10

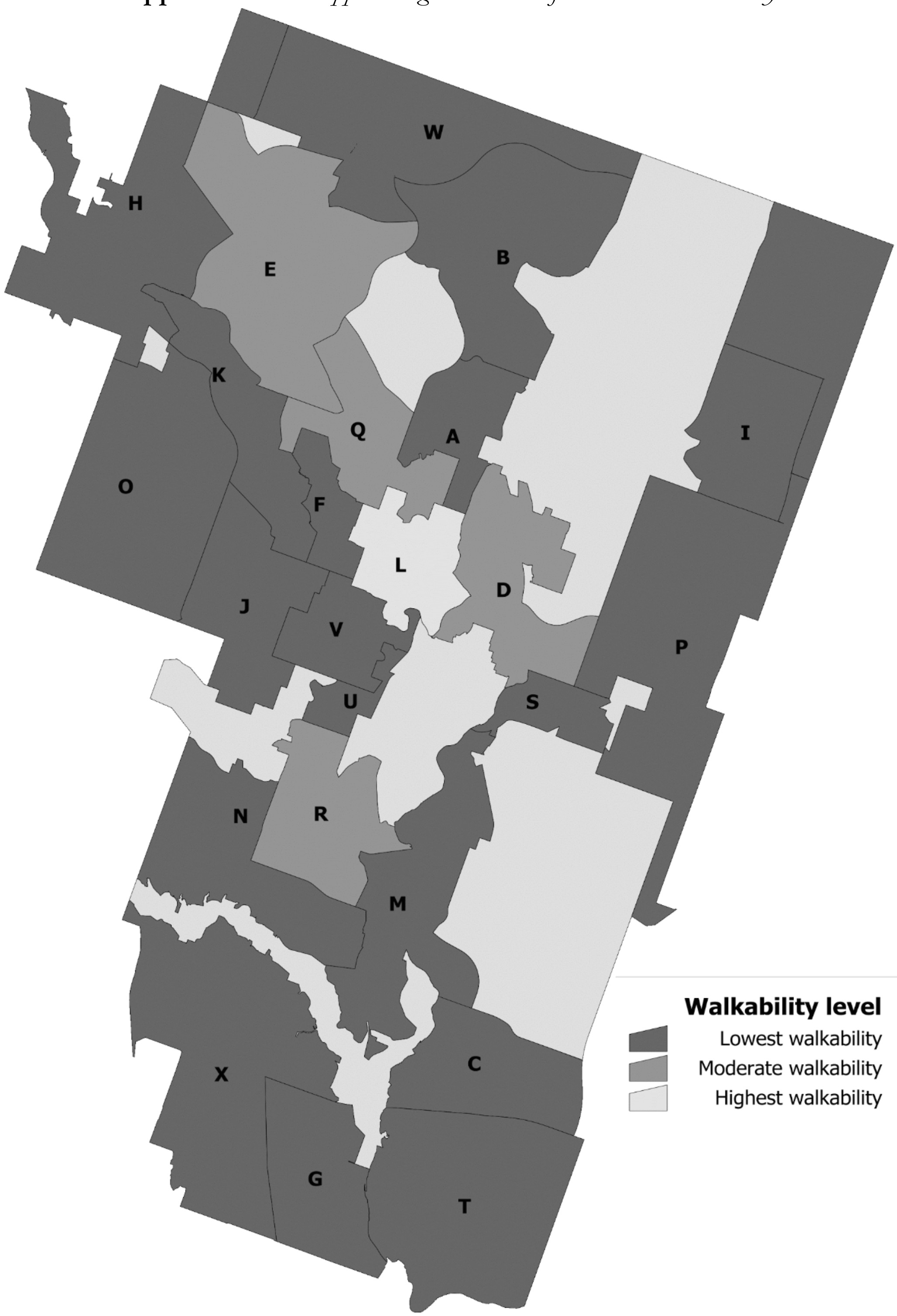
Thank You for Completing the Study

Your participation is much appreciated. Your answers are a valuable part of this research.
Please click the SUBMIT button to complete this survey.

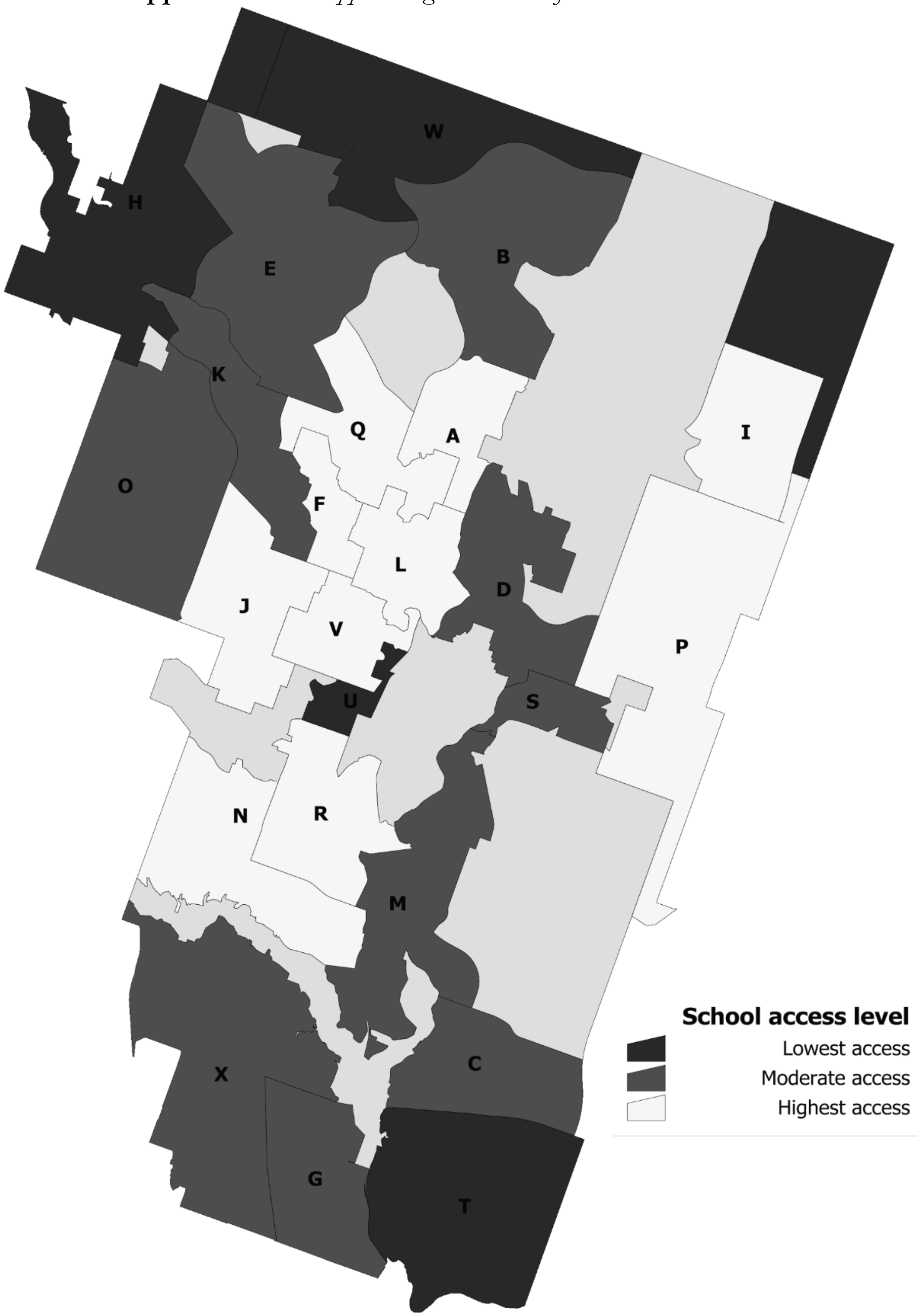
As a thank you for participating in this study, we would like to offer you a chance to enter a draw to win a 500 dollar gift certificate to amazon.ca. Would you like to be included in the draw? You will be informed of the draw results at the end of the data collection period (September 2017).

- ○ I would like to be included in the draw
- ○ I do not wish to be considered for the draw

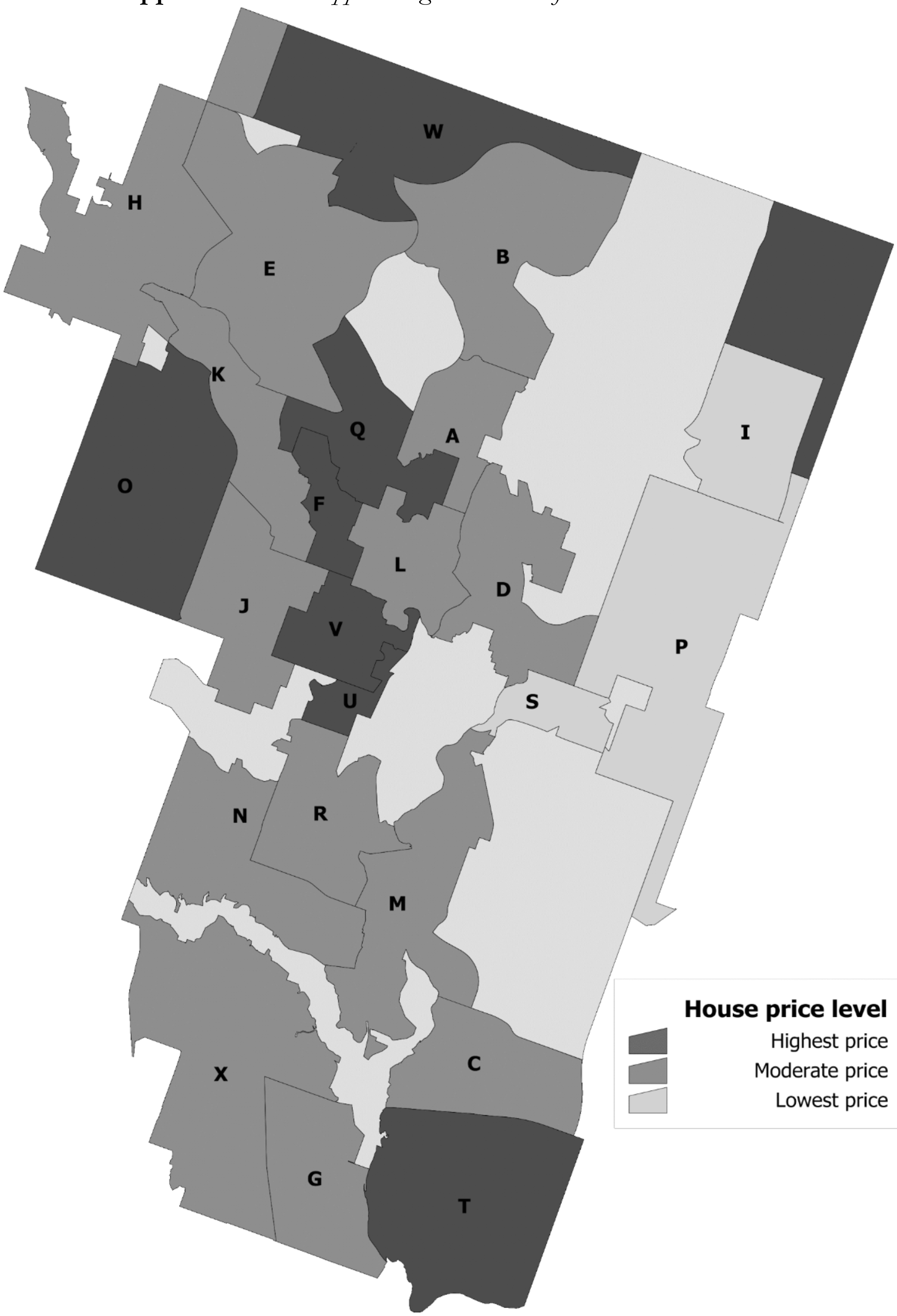
Appendix 6.1 - *Mapped Neighbourhood Information - Walkability*



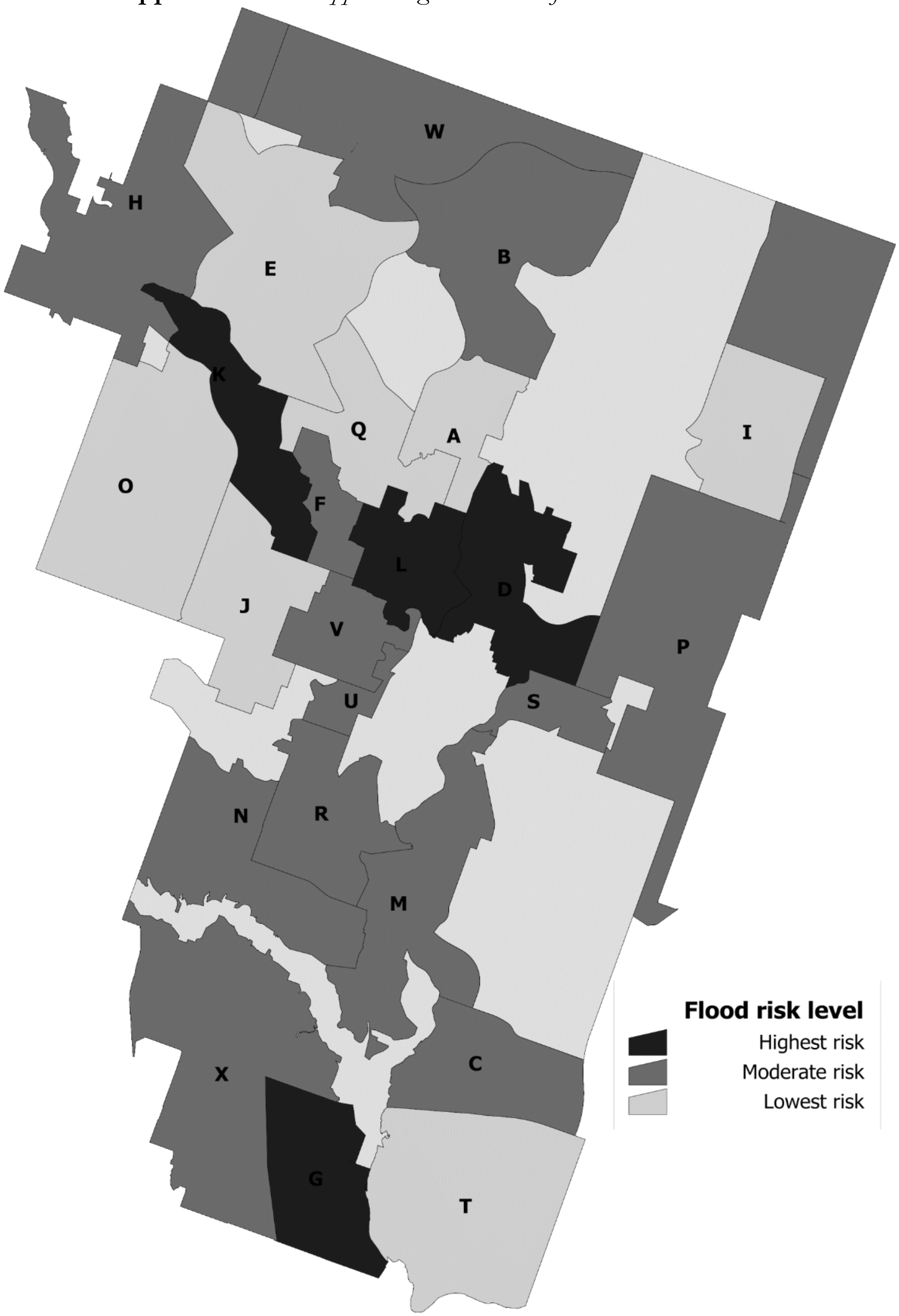
Appendix 6.2 - *Mapped Neighbourhood Information – School Access*



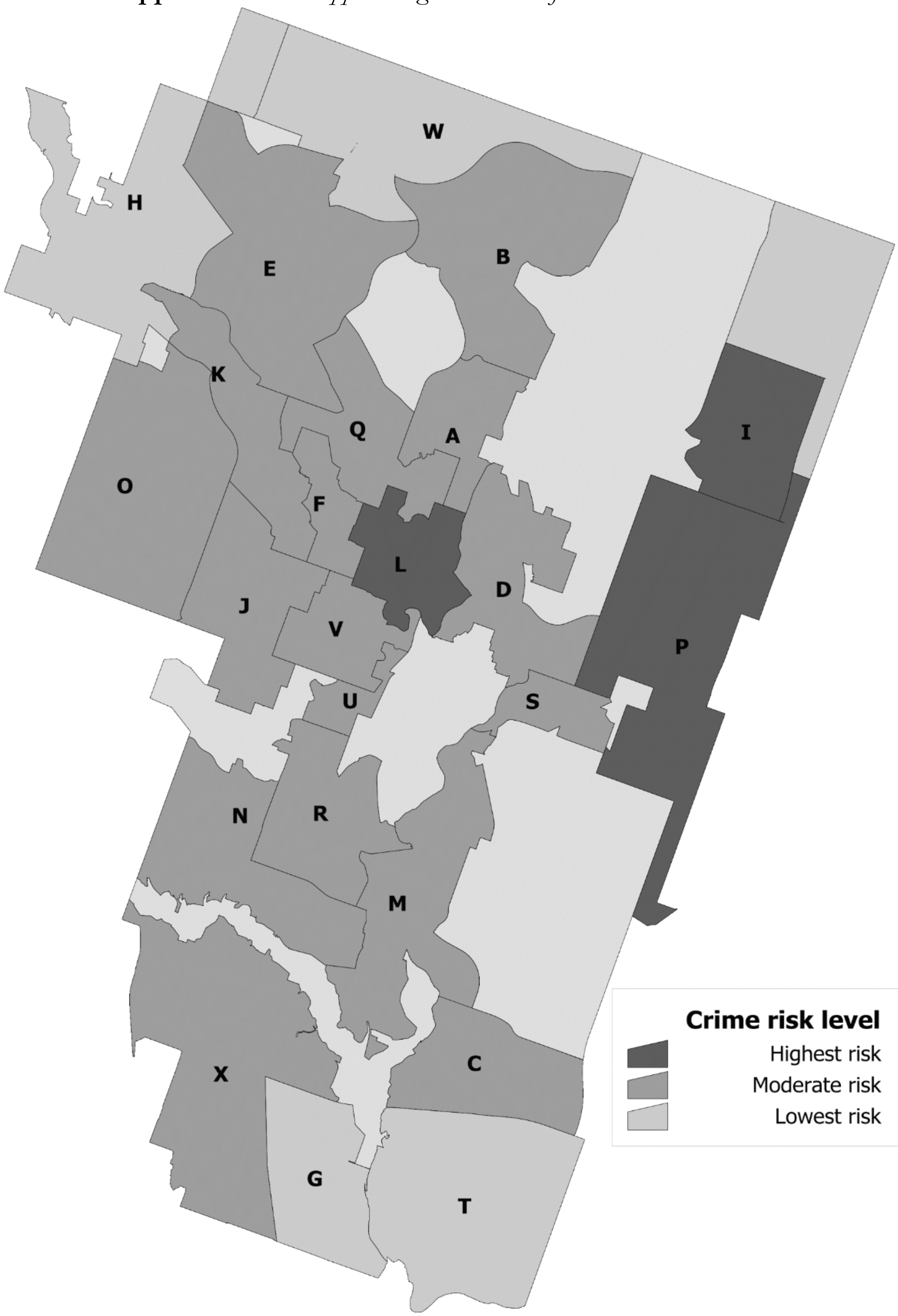
Appendix 6.3 - *Mapped Neighbourhood Information – House Price*



Appendix 6.4 - *Mapped Neighbourhood Information – Flood Risk*



Appendix 6.5 - *Mapped Neighbourhood Information – Crime Risk*



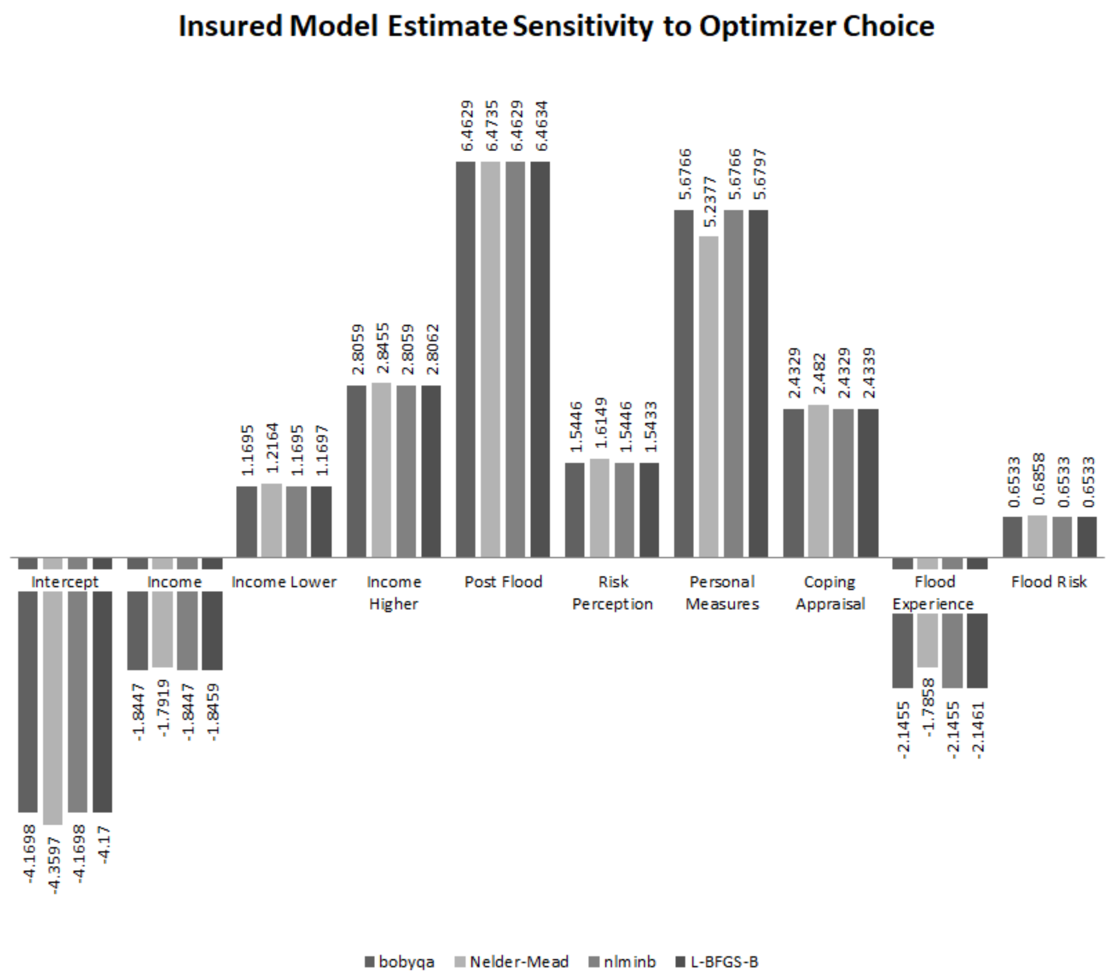
Appendix 7.1 - *Complete Glmer Model Results - Insurance*

```
Generalized linear mixed model fit by maximum likelihood (Laplace Approximation)
['glmerMod']
 Family: binomial ( logit )
Formula: Insured ~ Income + TurnId + Risk_Eval_Community + Personal_Measures +
    Coping_Appraisal + Flood_Experience + FloodRisk + (1 | id)
   Data: data
Control: glmerControl(check.conv.grad = .makeCC("warning", tol = 0.001, relTol = NULL),
optimizer = "bobyqa")

     AIC      BIC   logLik deviance df.resid
   661.1    717.4   -319.6    639.1     1219

Scaled residuals:
    Min      1Q  Median      3Q     Max
-8.8505 -0.1094 -0.0068  0.0863 11.6782

Random effects:
 Groups Name        Variance Std.Dev.
 id     (Intercept) 64.82    8.051

Number of obs: 1230, groups:  id, 123

Fixed effects:
                                   Estimate Std. Error z value Pr(>|z|)
(Intercept)                         -4.1698     1.7752  -2.349   0.0188 *
Income$50,000+                      -1.8447     1.8719  -0.985   0.3244
TurnId3-5_Income_Lower               1.1695     0.4863   2.405   0.0162 *
TurnId6-7_Income_Higher              2.8059     0.5546   5.059 4.21e-07 ***
TurnId8-10_PostFlood                 6.4629     0.6928   9.328  < 2e-16 ***
Risk_Eval_CommunityMedium_to_VHigh   1.5446     2.1652   0.713   0.4756
Personal_MeasuresYes                 5.6766     2.6914   2.109   0.0349 *
Coping_AppraisalYes                  2.4329     1.9404   1.254   0.2099
Flood_ExperienceYes_Once_or_more    -2.1455     1.9915  -1.077   0.2813
FloodRiskHigh                        0.6533     0.5645   1.157   0.2471
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:
            (Intr) I$50,0 TI3-5_ TI6-7_ TI8-10 R_E_CM Prs_MY Cpn_AY F_EY_O
Inc$50,000+ -0.415
TrnI3-5_I_L -0.225 -0.026
TrnI6-7_I_H -0.223 -0.044  0.630
TrnI8-10_PF -0.263 -0.068  0.550  0.697
Rs_E_CM__VH -0.190 -0.059  0.013  0.020  0.043
Prsnl_MsrsY -0.042 -0.096  0.057  0.129  0.208 -0.231
Cpng_ApprsY -0.390 -0.127  0.029  0.062  0.105  0.034 -0.110
Fld_ExY_O__ -0.294 -0.026 -0.026 -0.070 -0.106 -0.107 -0.289 -0.068
FloodRskHgh -0.184 -0.002  0.261  0.078  0.056  0.019 -0.054 -0.012  0.066
```

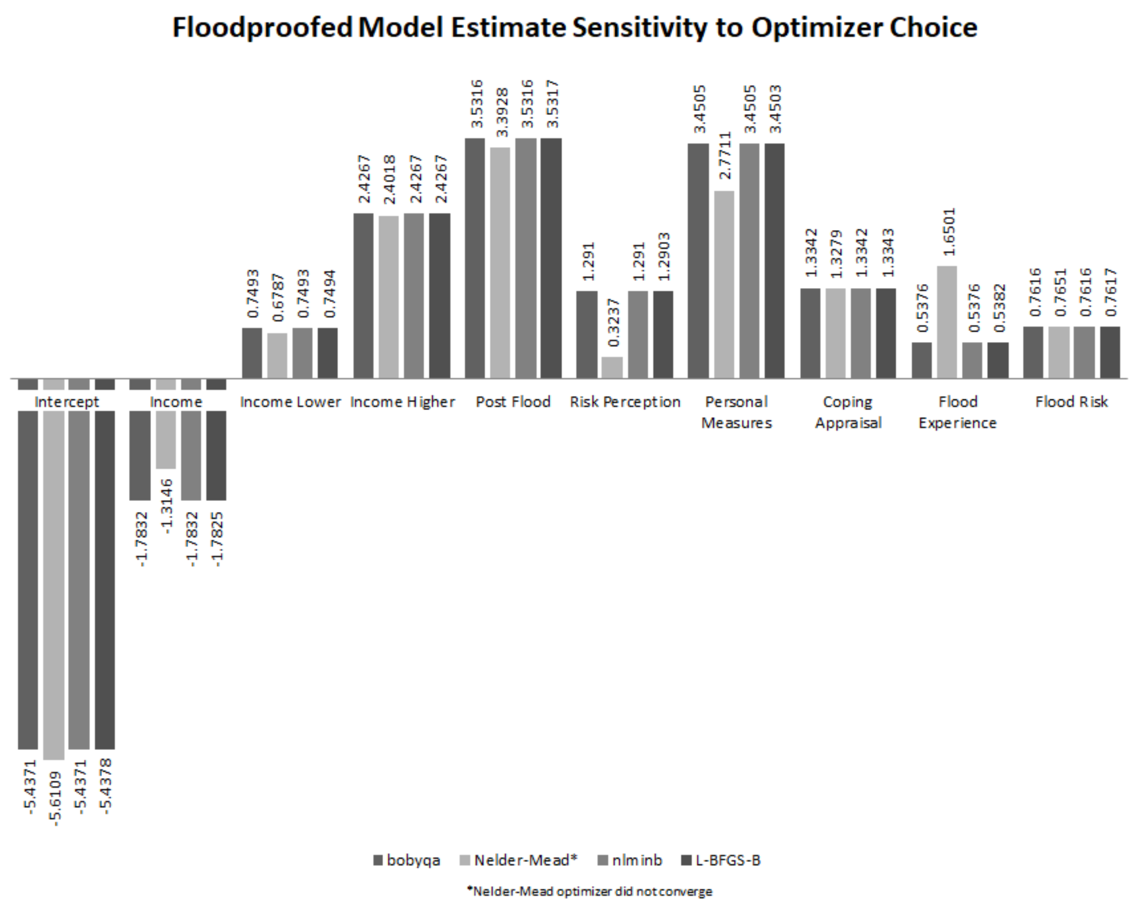
Appendix 7.2 - *Complete Glmer Model Results – Floodproofed*

```
Generalized linear mixed model fit by maximum likelihood (Laplace Approximation)
['glmerMod']
 Family: binomial  ( logit )
Formula: Floodproofed ~ Income + TurnId + Risk_Eval_Community + Personal_Measures +
    Coping_Appraisal + Flood_Experience + FloodRisk + (1 | id)
   Data: data
Control: glmerControl(check.conv.grad = .makeCC("warning", tol = 0.001,      relTol =
NULL), optimizer = "bobyqa")

     AIC      BIC   logLik deviance df.resid
   788.2    844.5   -383.1    766.2     1219

Scaled residuals:
    Min      1Q  Median      3Q     Max
-3.2168 -0.1542 -0.0342  0.1520 10.3434

Random effects:
 Groups Name        Variance Std.Dev.
 id     (Intercept) 28.55    5.343

Number of obs: 1230, groups:  id, 123

Fixed effects:
                                   Estimate Std. Error z value Pr(>|z|)
(Intercept)                         -5.4371     1.2859  -4.228 2.35e-05 ***
Income$50,000+                      -1.7832     1.2395  -1.439   0.1503
TurnId3-5_Income_Lower               0.7493     0.3529   2.123   0.0337 *
TurnId6-7_Income_Higher              2.4267     0.4014   6.045 1.49e-09 ***
TurnId8-10_PostFlood                 3.5316     0.4109   8.594  < 2e-16 ***
Risk_Eval_CommunityMedium_to_VHigh   1.2910     1.4642   0.882   0.3779
Personal_MeasuresYes                 3.4505     1.4575   2.367   0.0179 *
Coping_AppraisalYes                  1.3342     1.2194   1.094   0.2739
Flood_ExperienceYes_Once_or_more     0.5376     1.2395   0.434   0.6645
FloodRiskHigh                        0.7616     0.4505   1.691   0.0909 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:
            (Intr) I$50,0 TI3-5_ TI6-7_ TI8-10 R_E_CM Prs_MY Cpn_AY F_EY_O
Inc$50,000+ -0.300
TrnI3-5_I_L -0.227 -0.023
TrnI6-7_I_H -0.265 -0.055  0.578
TrnI8-10_PF -0.331 -0.082  0.585  0.661
Rs_E_CM__VH -0.178 -0.147  0.011  0.030  0.044
Prsnl_MsrsY -0.175 -0.219  0.027  0.079  0.119 -0.123
Cpng_ApprsY -0.428 -0.063  0.011  0.036  0.056  0.162 -0.127
Fld_ExY_O__ -0.315 -0.023  0.009  0.014  0.026 -0.208 -0.128 -0.076
FloodRskHgh -0.170 -0.026  0.182  0.074  0.108 -0.004 -0.009 -0.012  0.032
```

Appendix 8.1 - *Sensitivity Analysis: Model Estimates with Different Optimizers - Insurance*



Appendix 8.2 - *Sensitivity Analysis: Model Estimated with Different Optimizers - Floodproofing*



Appendix 9.1 - *SabreR Model Results with Endpoints – Insurance*

(Random Effects Model)

Parameter	Estimate	Std. Err.	Z-score
(intercept)	-7.1945	1.3176	-5.4602
income50,000+	1.7851	0.85823	2.0800
turnid3-5_income_low	1.4985	0.59318	2.5262
turnid6-7_income_hig	3.2886	0.65414	5.0273
turnid8-10_postflood	6.7744	0.78125	8.6711
risk_eval_communitym	0.80749	0.87329	0.92465
personal_measuresyes	0.42306E-01	1.1738	0.36040E-01
coping_appraisalyes	-0.43477	0.94622	-0.45948
flood_experienceyes_	1.7104	1.0459	1.6353
floodriskhigh	0.30305	0.52283	0.57963
scale	2.7281	0.55158	4.9460
			PROBABILITY
endpoint 0	0.61202	0.16100	0.25875
endpoint 1	0.75330	0.16884	0.31848

Univariate model
Standard logit
Gaussian random effects, with endpoints

Number of observations = 1230
Number of cases = 123

X-var df = 10
Scale df = 1
Endpoint df = 2

Log likelihood = -313.50126 on 1217 residual degrees of freedom

Appendix 9.2 - *SabreR Model Results without Endpoints – Insurance*

(Random Effects Model)

Parameter	Estimate	Std. Err.	Z-score
(intercept)	-3.7355	0.60319	-6.1929
income50,000+	-2.7132	0.56674	-4.7875
turnid3-5_income_low	1.3033	0.47459	2.7461
turnid6-7_income_hig	3.0155	0.55611	5.4225
turnid8-10_postflood	7.0595	0.74851	9.4314
risk_eval_communitym	2.3694	0.46740	5.0693
personal_measuresyes	2.6275	0.51884	5.0641
coping_appraisalyes	3.6614	0.54699	6.6936
flood_experienceyes_	-3.2207	0.48838	-6.5947
floodriskhigh	1.2081	0.47195	2.5597
scale	6.1233	0.49158	12.456

Univariate model
Standard logit
Gaussian random effects

Number of observations = 1230
Number of cases = 123

X-var df = 10
Scale df = 1

Log likelihood = -313.45508 on 1219 residual degrees of freedom

Appendix 9.3 - *SabreR Model Results with Endpoints – Floodproofed*

```
(Random Effects Model)

    Parameter                      Estimate        Std. Err.       Z-score
    ______________________________________________________________________________
    (intercept)                    -4.0283          1.2731         -3.1641
    income50,000+                  -1.5427         0.97127         -1.5883
    turnid3-5_income_low           0.77661         0.36455          2.1303
    turnid6-7_income_hig            2.4668         0.40905          6.0306
    turnid8-10_postflood            3.6011         0.42047          8.5645
    risk_eval_communitym            1.1405          1.1531         0.98904
    personal_measuresyes            3.0517          1.1543          2.6436
    coping_appraisalyes             1.4339         0.92649          1.5477
    flood_experienceyes_           0.17600E-01     0.97218         0.18103E-01
    floodriskhigh                  0.65580         0.44016          1.4899
    scale                           2.6249         0.61014          4.3020
                                                                  PROBABILITY
                                                                  ___________
    endpoint 0                     0.45880         0.21431         0.27311
    endpoint 1                     0.22109         0.88275E-01     0.13161

    Univariate model
    Standard logit
    Gaussian random effects, with endpoints

    Number of observations            =    1230
    Number of cases                   =     123

    X-var df          =    10
    Scale df          =     1
    Endpoint df       =     2

    Log likelihood =     -376.10036     on    1217 residual degrees of freedom
```

Appendix 9.4 - *SabreR Model Results without Endpoints – Floodproofed*

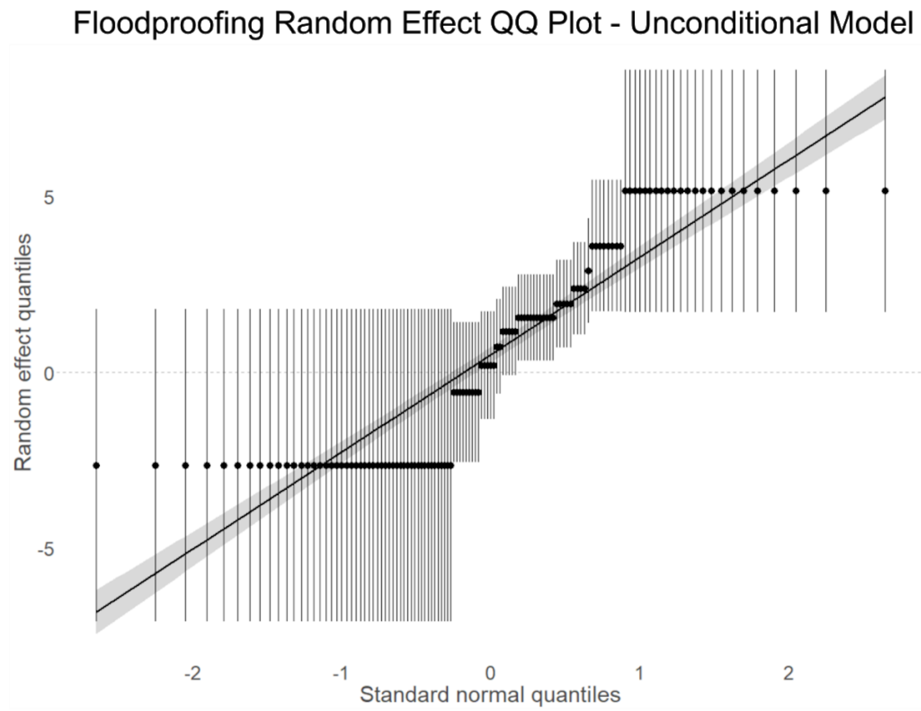
(Random Effects Model)

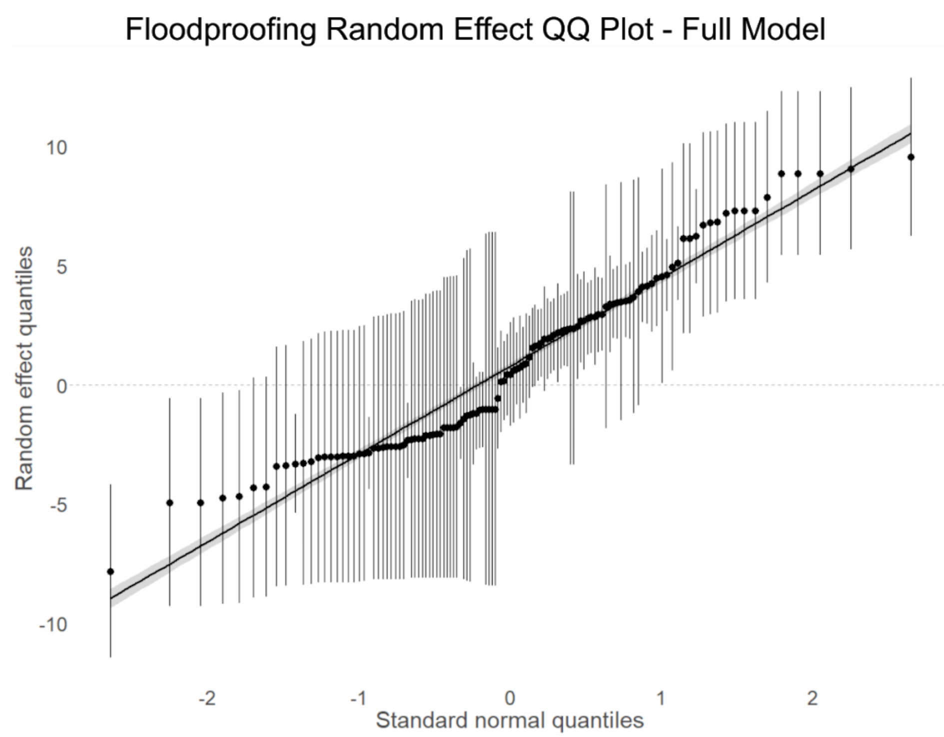
Parameter	Estimate	Std. Err.	Z-score
(intercept)	-4.3602	0.58490	-7.4547
income50,000+	-1.6707	0.32423	-5.1529
turnid3-5_income_low	0.75396	0.33928	2.2222
turnid6-7_income_hig	2.4137	0.39131	6.1682
turnid8-10_postflood	3.6187	0.40986	8.8290
risk_eval_communitym	0.21785	0.35944	0.60608
personal_measuresyes	2.5156	0.35423	7.1017
coping_appraisalyes	1.2517	0.39218	3.1917
flood_experienceyes_	0.58274	0.35797	1.6279
floodriskhigh	1.0318	0.31211	3.3060
scale	4.9759	0.39712	12.530

```
Univariate model
Standard logit
Gaussian random effects

Number of observations           =    1230
Number of cases                  =     123

X-var df           =    10
Scale df           =     1
```

Log likelihood = -370.33150 on 1219 residual degrees of freedom

Appendix 10 – *Visualizing Floodproofing Model Random Effects*





Appendix 11.1 – *Testing associations with Mover/Stayer Behaviour (Insurance)*

	P-Value of Test		
Variable Tested	2-category (Mover/Stayer) Chi-Square test of Independence	3 category (Stayer/Mover/Stayer) Chi-Square test of Independence	3 category Ordinal Linear-by-Linear test of Association
Age	0.1542	0.09773	0.174
Education	0.6591	0.742	0.7397
Income	1	0.6854	0.3892
Risk Eval. Community	0.4789	0.3168	0.633
Owns Home	0.2293	0.6267	0.7402
Perceived Flood Possibility	0.4023	0.6985	0.6032
Sufficiently Informed Perception	0.6745	0.7859	0.7541
Coping Appraisal	0.9244	0.3967	0.1894
Trust in Community Measures	0.8342[9]	0.739	0.5211
Flood Experience	0.08453	0.1478	0.628

[9] Trust is currently split into two categories: don't know, neutral or disagree; and agree. When using three categories, splitting neutral or disagree into its own category, p<0.1.

Appendix 11.2 – *Testing associations with Mover/Stayer Behaviour (Floodproofing)*

	P-Value of Test		
Variable Tested	2-category (Mover/Stayer) Chi-Square test of Independence	3 category (Stayer/Mover/Stayer) Chi-Square test of Independence	3 category Ordinal Linear-by-Linear test of Association
Age	0.19	0.1587	0.1261
Education	0.26	0.3857	0.8358
Income	1	0.7579	0.4865
Risk Eval. Community	0.9793	0.6343	0.342
Owns Home	0.8899	0.9198	0.8675
Perceived Flood Possibility	0.9665	0.5373	0.08685[10]
Sufficiently Informed Perception	0.1932	0.3315	0.6704
Coping Appraisal	0.7506	0.5876	0.3214
Trust in Community Measures	0.5581	0.4123	0.2194
Flood Experience	0.04672	0.09263	0.4907

[10] This significance is likely due to having a small number problem using the three categories. When combining no and don't know into one category, p=0.25.