ADAPTING TO EXTREME EVENTS:
HOUSEHOLD RESPONSE TO FLOODS IN URBAN AREAS

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ABSTRACT

Maura Connolly Allaire: Adapting to Extreme Events: Household Response to Floods in Urban Areas
(Under the direction of Dale Whittington)

This dissertation is an economic study of household-level decisions related to flood risk mitigation. It is composed of four chapters that focus on the 2011 Thailand flood, the world's most costly flood event in the past 30 years. The first chapter examines the magnitude and composition of economic costs that households in Bangkok bore during the 2011 flood. Two rounds of surveys with 469 Bangkok households collected detailed information on a broad set of flood costs. Results indicate that total flood cost was substantial. The median cost was equivalent to half of annual household spending. However, structural damage to homes was surprisingly low, given the depth and duration of the flood.

The second chapter assesses how online information can enable households to reduce flood losses. Propensity score matching is used to test for evidence of a relationship between social media use and flood loss. Results indicate that social media use enabled households to reduce mean losses by 37%. Social media offered information that was not available from other sources, such as localized and nearly real-time updates of flood location and depth. With knowledge of current flood conditions, households could move belongings to higher ground before floodwaters arrived.

The third chapter shifts focus to longer-term mitigation actions. It presents results from a randomized experiment that tests the effect of information on household uptake of flood

insurance and home retrofits. A sample of 364 flood-prone households in Bangkok was randomly split into treatment and control groups. The treatment group received practical details on home retrofits and subsidized flood insurance as well as social norm information regarding insurance purchase decisions of peers. Results indicate that the information intervention increased insurance purchases by about four percent, while no effect was detected for home retrofits.

The fourth chapter evaluates the social benefits of the information intervention presented in the third chapter. Results suggest that the intervention raises welfare of households, but not society. Furthermore, greater benefits are associated with better informing households that have high insurance demand, compared to using social pressure to persuade those with low demand.

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LIST OF ABBREVIATIONS

BCA	Benefit-Cost Analysis
GDP	Gross Domestic Product
NPV	Net Present Value
THB	Thai Baht
US$	United States Dollars

INTRODUCTION

The costs of natural disasters have increased dramatically around the world in recent decades (Munich Re Group, 2005; Miller et al., 2008; IPCC, 2012). Multi-billion-dollar disasters are becoming common. While flood-related mortality has declined due to improved early warning, property costs continue to rise (White, Kates, & Burton, 2001). Increased disaster costs are largely driven by greater concentrations of people and assets in disaster-prone areas. In particular, coastal cities around the world face rising flood exposure due to growing population, greater asset values, land subsidence, and sea-level rise (De Sherbinin et al., 2007; Dixon et al. 2006; Hanson et al., 2011). The world's population is urbanizing and moving to these vulnerable areas, nearly two-thirds of the global population is expected to live in cities by 2050 (United Nations, 2015). In addition, more severe and frequent precipitation events due to climate change could further increase flood frequency and intensity (World Bank, 2010).

As the prospect for more frequent and severe weather-related disasters gains scientific support, many nations are weighing options for risk mitigation and adaptation. Several notable challenges confront planners and decision makers as they seek to manage the consequences of flood events. The magnitude and composition of flood costs must be known so that interventions can be targeted at cost categories that can readily be reduced. In addition, effective strategies must be identified for mitigation of flood costs, both through short-term prevention and longer-term adaptation actions.

Mitigating losses of life and property in vulnerable areas is a growing policy concern. However, limited knowledge of disaster costs and household mitigation behavior make informed public policy challenging. There is a worldwide lack of accurate, disaggregated, and comparable estimates of the economic costs of disasters. This limits analysis of disaster risk. Flood risk analysis has major two components – a hydrological assessment of the flood hazard (probability and physical intensity) and estimation of economic consequences (Mileti, 1999). While hydrological hazard models are well developed in the engineering literature, economic damage models are not and could be greatly improved (Wind, Nierop, de Blois, & de Kok, 1999). A major barrier to the improvement of damage models is a lack of reliable and disaggregate flood cost data. International datasets on disaster damage underestimate indirect and production interruption cost. Furthermore, these datasets do not include non-financial costs or costs to the informal economy. Most engineering studies focus only on property and contents damage, while economics studies typically seek to find evidence of changes in macroeconomic indicators, such as gross domestic product (GDP).

Full costs of disasters extend beyond property damage and include impacts on health, the environment, and interruption of business and public services. Worldwide, there is a great need for comprehensive disaster cost data and improved understanding of factors that affect types and magnitude of damage. A lack of comprehensive loss data means that most economic assessments do not include a full picture of mitigation costs and benefits. Improved data and understanding are crucial for selecting and prioritizing flood risk mitigation policies.

Once disaster costs are better understood, the challenge for policymakers is to identify interventions that reduce expected costs. Historically, within the field of water management, flood control and structural defense measures have been the focus of flood management efforts.

The focus has been on decreasing the probability of a flood and intensity. Under a more modern approach, flood control structures are assumed not to be fail-safe and communities are prepared for the possibility of inundation. This risk management approach considers the extent to which a given intervention can reduce those costs (Messner et al., 2007). A wide variety of mitigation strategies, both public and private, are conceivable under this modern approach and are not limited to publically-funded flood control structures. Private mitigation actions could play a role in reducing flood impacts. However, even after disasters, households often do not take risk mitigation actions and therefore remain vulnerable to future events (Burby et al., 1988; Kunreuther et al., 2009). Furthermore, little is known about how households prepare for, respond to, and recover from disasters (e.g. Bruneau et al., 2003; de Bruijn, 2004; Zhou, Wang, Wan, & Jia, 2010).

Household flood risk mitigation decisions tend not to be privately, let alone socially, optimal. For example, despite mandates and possible benefits, uptake of insurance against floods and other natural disasters tends to be low globally (Dixon et al., 2006). In U.S., only half of households in flood-prone areas are insured against flooding (Kriesel and Landry, 2004; Dixon et al., 2006). The failure of households to take mitigation actions is partly due to the fact that individuals rely on heuristics to assess hazards with low probability and can treat low-probability events as having zero probability (Kunreuther et al., 2002). Other reasons for household inaction include (i) lack of awareness of cost-effective mitigation actions, (ii) financial cost as well as time and inconvenience costs, and (iii) reliance on disaster relief. Understanding adaptation barriers is crucial for managing the economic cost of disasters. Household inaction creates a burden on taxpayers who bear the cost of disaster response and recovery. The Thai government spent nearly US$ 757 million for disaster response due to the 2011 flood, of which

US$ 97 million was cash transfers to compensate flood-affected households (DDPM, 2013). Therefore, as assets become more concentrated in coastal cities, both households and taxpayers bear costs.

My dissertation addresses how the economic cost of climatic disasters among households can be reduced. A particular focus is placed on how information can improve household decision-making. In four chapters, I examine the types of costs households bore during the 2011 Bangkok flood, how online information allowed households to reduce flood costs, and how households can be encouraged to take flood loss mitigation actions. In all four dissertation chapters the 2011 Bangkok flood is used as an illustrative example in all four dissertation chapters. Bangkok is a highly relevant field site for issues regarding the economic costs of flooding and household decision-making. The 2011 flood ranks as the world's most costly flooding disaster in the past 30 years (A.M. Best, 2012; Orie and Stahel, 2013).

Information provision could improve household decisions related to flood risk mitigation since there is often a lack of complete information. My dissertation addresses the role of information in improving flood mitigation decisions. One chapter examines how online information can inform short-term loss prevention actions, while another investigates if information campaigns can encourage households to take longer-term adaptation actions.

In order to take effective short-term prevention measures immediately before a flood, households require accurate and timely forecasts of expected conditions and recommended actions. When confronted with natural disasters, individuals around the world increasingly utilize online resources. During the 2011 Bangkok flood, most households had access to multiple information sources and faced a challenge of assessing the quality and accuracy of conflicting messages. As floodwaters progressed, government sources could not predict the path and timing of the flood through the urban environment with much precision or lead time. Online sources, especially social media, may have offered households different types of information not provided by government or other traditional information sources. Online sources can be used as a tool to improve household preparedness and address new challenges presented by urban flood management.

When deciding to take longer-term flood mitigation measures, households evaluate information on flood loss (both magnitude and likelihood) as well as the cost of the action. Yet, even when measures are privately beneficial, households might fail to take action due to lack of awareness or incomplete information, inconvenience costs, or reliance on disaster relief. Mitigation actions could be encouraged via practical information on flood risk and mitigation options as well as social messages that convey the actions of others. Increasingly, practical and social messages are used in policy interventions to influence individual decisions. Experimental research has begun to investigate the effects of information on household behavior. The effectiveness of practical information has been demonstrated in research on environmental hazards (e.g. Smith et al., 1995; Hamoudi et al., 2012). Meanwhile, the impacts of social norms on household behavior has been assessed within the realm of electricity and water conservation (e.g. Ferraro and Price, 2013; Allcott, 2011). In these water and electricity conservation studies, households are informed of peer use of services and how their behavior compares. There is evidence that information on social norms might be able to produce similar size effects on the quantity purchased as price incentives (Allcott and Mullainathan, 2010; Allcott, 2011).

Bangkok is susceptible to flooding due to its location on a river delta, flat topography, and subsiding land surface. In addition, flood risk in Bangkok has increased over the past several decades due to rapid urban growth. Therefore, the Bangkok case provides insight into how flood impacts can be mitigated and managed in the face of urbanization and climate change. Low-lying megacities, such as Bangkok, present new challenges for disaster risk mitigation. In these productive urban centers, neither massive evacuations nor limits on concentrations of people and assets are desirable. Rather than encourage relocation of people and assets, risk mitigation strategies in megacities must focus on how to reduced expected losses. Information could play a vital role in allowing individuals to take effective actions to reduce flood losses.

The 2011 Bangkok flood is an especially interesting case study because it offers a window on the flood management challenges facing millions of people around. It represents one of the first major floods in a megacity in the twenty-first century. Asian megacities in particular are expected to face higher flood losses due to rapidly growing populations, climate change, and vulnerable low-income communities (Hallegatte et al., 2013; Shah, 2011). Slum populations face relatively high disaster losses since they tend to be located in hazard prone areas with poorly constructed dwellings. More than half of the world's slum population lives in East and Southeast Asia (Shah, 2011). Risk mitigation measures could reduce vulnerability and expected disaster losses.

Overall, the four chapters offer insight into the role of information in mitigating the risk of natural disasters. The first chapter examines the magnitude and composition of economic costs that households bore during the 2011 Bangkok flood. The second chapter assesses how online information can enable households to reduce flood losses. The third presents results from a randomized experiment that tests the effect of information on household uptake of flood insurance and home retrofits. The fourth and final chapter evaluates the social benefits of this information campaign. Brief overviews of each of these chapters are provided below.

Chapter 1 assesses the magnitude and types of economic costs borne by households during the historic 2011 Bangkok flood. This chapter presents the first estimates of flood costs based on in-person interviews and modern nonmarket valuation techniques. It contributes to the literature by demonstrating how household-level data on the economic costs of flooding can be collected and analyzed in order to inform decision making. A worldwide lack of comprehensive cost data means that most economic assessments do not include a full picture of mitigation costs and benefits. Some countries are beginning to address this knowledge gap in order to inform flood risk mitigation policies. For example, the U.S. Army Corps of Engineers is actively exploring improved methods to estimate flood costs.

Cost estimates analyzed in this study represent a broad set of adverse consequences that extend beyond property damage. These costs include preventative costs, evacuation expenditures, increased travel time, property damage, health costs, and foregone income. Two rounds of surveys were conducted with 469 Bangkok households. Households were first interviewed immediately after floodwaters receded and were asked about preventative actions, expenses to repair and replace property, health care costs, and time lost from work. The second interview was conducted one year later to collect additional expenses incurred to repair and replace property damaged in the flood. This chapter presents summary statistics of economic costs as well as multivariate analysis that examines factors associated with these costs, such as characteristics of the respondent, household, and neighborhood.

The second chapter examines how online information can enable households to reduce disaster impacts. Individuals around the world are rapidly gaining online access and joining social networks. This paper is the first to investigate the role of online information and social media in enabling households to reduce natural disaster losses. The historic 2011 Bangkok flood was one of the first major disasters to affect an urban area with a substantial population connected to social media. To explore the role of online information in mitigation of flood loss, a mixed methods approach was employed, making use of both quantitative (propensity score matching and multivariate regression analysis) and qualitative (in-depth interviews) techniques. Regression analysis of survey responses identifies associations between online activity and flood losses as well as before flood mitigation actions. Propensity score matching is used to test for evidence of a causal relationship between social media use and flood losses. The study relies on two data sources – survey responses from 469 Bangkok households (also used in Chapter 1) and in-depth interviews with twenty-three internet users who are a subset of the survey participants. Understanding the effect of social media information on flood losses would have broad implications for incorporating online applications into disaster preparedness and response efforts. For example, the U.S. Federal Emergency Management Agency is testing the use of social media for distributing emergency updates.

The third chapter shifts attention to loss mitigation actions and how households can be encouraged to take action. Private mitigation actions could play a prominent role in reducing flood impacts. Yet, even after disasters, households often fail to mitigate future losses. This chapter presents a field experiment that tests the effect of information on household uptake of flood insurance and home retrofits. A sample of 364 flood-prone households in Bangkok was randomly split into treatment and control groups. All participants were homeowners who did not have catastrophe insurance at the time of the baseline interview. The treatment group received practical details on home retrofits and subsidized flood insurance as well as social information regarding insurance purchase decisions of households in their district. The control group received no information. A baseline survey collected background characteristics of participating households. Six months later, a follow-up survey recorded experiment outcomes such as insurance purchase, home retrofits, information gathering, and risk perception.

This study is the first randomized experiment to address household flood loss mitigation actions, such as home retrofits and flood insurance. Generally, experimental evaluation designs are rare in the environmental policy field (Ferraro and Hanauer, 2014). Yet, such designs are important since they are less prone to bias than observational designs. This chapter also makes a contribution to understanding flood insurance demand. Little empirical work has been done on household demand for flood insurance, especially in developing countries (Akter et al., 2011; Landry and Jahan-Parvar, 2011; Kunreuther et al., 2013). Households tend to lack perfect information regarding flood risk and the costs and benefits associated with flood insurance and home retrofits. Information could influence perceptions of flood probability, losses, and costs of insurance and home retrofits. This study tests the hypothesis that household inaction is in part due to incomplete and insufficient information.

The fourth chapter evaluates the social benefits of the information campaign presented in the previous chapter. This study presents the first benefit-cost analysis (BCA) of a practical and social norm information intervention. No previous information experiment has assessed social welfare implications of the tested intervention.   However, the value of analyzing welfare implications of information treatments and other behavioral nudges has been acknowledged in the economics literature (Allcott, 2011; Bernedo et al., 2014). Without a full accounting of economic costs and benefits across all stakeholders, it is unclear if these types of strategies are beneficial to society. Disaster management could especially benefit from rigorous evaluation of policy alternatives, given the large amounts of government resources at stake.

A key question that this BCA addresses is whether or not the information campaign is preferable to the status quo of government compensation for flood losses. The BCA accounts for the distribution of costs and benefits across stakeholders including new insurance policyholders, insurance providers, and the general taxpayer. Taxpayers bear the cost of the information campaign, annual expected subsidized claims and administrative costs. Insured households benefit from insurance claims, limited flood aid, and consumer surplus, but must pay subsidized premiums. The net social benefit to society is equal to the consumer surplus, less the cost of the information campaign, administrative cost of flood aid and insurance, and deadweight loss. Parameter values for the BCA are derived from datasets compiled in two previous chapters. The first is from the randomized experiment that tested the effect of the information campaign (Chapter 3), while the second is from the household survey of costs incurred due to the 2011 flood (Chapter 1). Sensitivity analysis is conducted for all key parameters, with particular attention given to level of government flood compensation, persistence of information treatment effect, and household demand for insurance.

Combined, these four dissertation chapters advance understanding of the economic cost of extreme events and household decision making regarding flood risk. As communities consider risk mitigation and adaptation options, greater knowledge of disaster impacts and household response can inform crucial policy decisions.

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CHAPTER 1: ECONOMIC COSTS INCURRED BY HOUSEHOLDS IN THE 2011 GREATER BANGKOK FLOOD [1]

1.1 Introduction

1.1.1 Overview

This paper presents the first comprehensive estimates of the economic costs experienced by households in the 2011 Greater Bangkok flood. More generally, it contributes to the literature by presenting the first estimates of flood costs based on primary data collected from respondents of flooded homes using in-person interviews. Two rounds of interviews were conducted with 469 households in three of the most heavily affected districts of greater Bangkok. The estimates of economic costs include preventative costs, *ex post* losses, compensation received, and any new income generated during the flood. Median household economic costs were US$3089, equivalent to about half of annual household expenditures (mean costs were US$5261).

Perhaps surprisingly given the depth and duration of the flood, most houses incurred little structural damage (although furniture, appliances, and cars were damaged). Median economic costs to poor and non-poor households were similar as a percentage of annual household expenditures (53% and 48%, respectively). Compensation payments received from government did little to reduce the total economic losses of the vast majority of households. Two flood-related deaths were reported in our sample—both in low-income neighborhoods.

[1]This chapter previously appeared as an article in Water Resources Research. The original citation is as follows: Nabangchang, O., Allaire, M., Leangcharoen, P., Jarungrattanapong, R., and Whittington, D. (2015). Economic costs incurred by households in the 2011 Greater Bangkok flood. Water Resour. Res., 51(1) 58–77.

Overall, *ex post* damage was the largest component of flood costs (66% of total). These findings are new, important inputs for the evaluation of flood control mitigation and preventive measures that are now under consideration by the Government of Thailand. The paper also illustrates how detailed microeconomic data on household costs can be collected and summarized for policy purposes.

1.1.2 Motivation

Climate change is increasing the risks populations face from hydrological uncertainty. Water resource planners are devoting more and more attention to the development of planning protocols and procedures that can better incorporate these new uncertainties surrounding the magnitude and consequences of extreme hydrological events such as floods. A common element in all methods for addressing the implications of climate change for water resources planning is the need for better estimates of the economic costs that hydrological risks impose on households and businesses. Decision makers need accurate estimates of these economic costs in order to design and choose improved, cost-effective risk management and adaptation strategies.

Surprisingly, the methodology for estimating the economic costs to households from flood events has not advanced much over the last several decades. Although there have been major theoretical and methodological advances in nonmarket valuation techniques in the environmental and resource economics field, these have not made their way to research on the economic costs to households of major flood events. There are several reasons for this peculiar state of affairs.

First, by definition the precise timing of flood events are unknown in advance and researchers must act quickly after a flood to try to measure the consequences to households while they are fresh in people's minds. Funding for most research is not sufficiently flexible to respond in a timely manner to study the economic costs of unpredictable flood events. Second, dealing with the humanitarian crisis created by major flood events naturally takes precedence over longer-term research objectives. Simply put, researchers have an ethical obligation not to get in the way of relief efforts.

Third, research on flood damages usually has been conducted by teams of engineers, planners, financial analysts, and infrastructure economists, and is largely focused on estimating the financial losses to buildings and contents, for both households and businesses. This is perhaps understandable when the purpose of the study is to determine financial compensation to be paid by government and insurance companies. But the resulting cost estimates will be incomplete measures of the welfare costs imposed by the risk of floods that are needed for improved decision making.

There are no published studies of costs households incur from floods in either industrialized countries or developing countries in which the researchers' findings are based on data collected from affected households using in-person interviews and modern nonmarket valuation techniques. Because the microeconomic literature on estimating the economic costs to households is thin, and because much of the existing research has been conducted by noneconomists, the terminology used in the literature to describe and categorize different types of household costs due to floods is inconsistent and confusing. This study addresses these gaps in the literature on the economic costs households incur from extreme hydrological events such as floods.

In-person interviews were conducted with households in greater Bangkok affected by the 2011 Thailand flood. The 2011 flood in Thailand is an especially interesting case study because it offers a window on the flood management challenges facing millions of people around the world and for their governments in a time of climate change. There are seven megacities in South and Southeast Asia with over 10 million people located near the coast that are experiencing rapid population growth and must confront the combined threats of land subsistence, increased extreme rainfall and storm events, and rising sea levels (Mumbai, Dhaka, Kolkata, Karachi, Manila, Jakarta, and Bangkok).

In this case study, we examine the magnitude and composition of the economic losses experienced by 469 households from the 2011 flood in three of the most affected neighborhoods of the Greater Bangkok Metropolitan area. We first interviewed individuals in these households in January and February 2012, while their memories of the flood were fresh. A second round of interviews was conducted a year later to measure additional recovery costs incurred between January 2012 and January 2013. The attrition rate between the first and second round surveys was 20%; 589 households participated in the first survey. In the first round survey, respondents were asked about the actions they took before the flood arrived to try to reduce the direct and indirect costs incurred as a result of the flood, and the financial expenses they expected in order to repair and replace their property after the flood waters receded. Questions to estimate both health-related and nonhealth-related costs were included in the survey instrument. In the second round survey, we were able to collect data on the actual expenses incurred to repair and replace property damaged in the flood, as well as time lost from work.

The paper is organized as follows. The next, Section 1.2 of the paper provides background on the 2011 Thailand flood. Section 1.3 describes the study sites and fieldwork protocol. Section 1.4 describes how the different components of households' economic costs were estimated and the modeling strategy used to examine the factors associated with these costs. Section 1.5 presents the results, and section 1.6 offers some concluding observations.

1.2 Background—The 2011 Thailand Flood

The Chao Phraya River Basin drains about 30% of the surface area of Thailand. Four main rivers—Ping, Wang, Yom, and Nan—merge in Nakhon Sawan province (in Thailand's Upper Central Region) to form the Chao Phraya River. The river begins in the northern, mountainous region of Thailand, and then flows south through the flat central plains. Greater Bangkok is located at the southern, downstream end of the Chao Phraya River Basin in the Chao Phraya river delta near the coast.

In late 2011, Thailand was hit with the worst floods experienced in 50 years (since the floods in 1942). The 2011 flood, which eventually inundated much of greater Bangkok, had three distinct phases. The first phase was from March to April when heavy rainfall caused widespread flooding in southern Thailand, resulted in 61 deaths, damaged 600,000 homes, and caused extensive damage to businesses and transportation infrastructure. Rainfall in March 2011 was over 3 times the average for the past 30 years. Land became saturated and further infiltration was limited even before the summer monsoon rains arrived. Eight provinces in Thailand were declared disaster zones.

The second phase was from June to the middle of October when the remnants of five tropical storms hit Thailand. Rainfall in June was 128% of the average. In July and August, rainfall was 150% of the average. During August and September, monsoon rains were heavier and lasted longer than usual perhaps due to the presence of La Niña. Rainfall in September was 135% of the average and in October 116% of average (AON, 2012). Rainfall in 2011 was considerably greater than rainfall that preceded the last major flood to reach Bangkok in 1995. Total rain in northern Thailand for July to September was 1156 mm, the highest amount recorded since records began in 1901. World Bank (2012) estimated the annual probability of such high rainfall to be 1 in 250 years.

Month after month of heavy rains led to widespread flooding in the northern, northeastern, and central portions of Thailand. Major dams filled to capacity and 10 major flood control structures experienced breaches from mid-September to early October. Flash flooding and landslides occurred in central and northern Thailand. This long period of heavy rainfall also caused very high flows in the northern sections of the Chao Phraya River, and these floodwaters spread southward. By mid-September, many provinces in the central part of the basin were affected by the flood. The agricultural lands in the central plain initially served as water retention areas and slowed the southward flow of the floodwaters toward Bangkok.

The third phase of the flood started in mid-October and lasted through December 2011. By mid-October, major industrial estates in the Central Region were flooded. The floods in Ayutthaya, north of Bangkok, peaked in October, and flood barriers around seven industrial estates failed. These industrial estates flooded for the first time in their history, disrupting supply chains throughout the world (e.g., cars, disk drives, and other electronic components). Some industrial estates were under as much as 3 m of water. By late October, over 5.5% of Thailand was under water, and floodwaters entered greater Bangkok. By mid-November, 5.3 million people were affected, over 8% of the total population of Thailand (World Bank, 2012). Efforts to protect the central business district were successful, but districts in northern Bangkok and the provinces of Nonthaburi and Pathum Thani in the greater Bangkok metropolitan area were hit especially hard. Transportation networks were severely affected; several main highways and the city's secondary airport were forced to close. In many districts of greater Bangkok, floodwaters rose to a maximum of 2–3 m and remained for 2–3 months. In an attempt to drain their neighborhoods, frustrated residents tore down flood barriers, sending floodwaters into other parts of the city. By late November and early December, the floodwaters had receded in many areas, but some places remained flooded until mid-January 2012.

The inability of the two major dams in the Chao Phraya basin, Bhumibol and Sirikit, to mitigate the severity of the 2011 flood has been the subject of much public discussion and debate in Thailand. Some argued that the dams had been mismanaged since a large quantity of water was stored at the beginning of the monsoon, resulting in large subsequent releases after the heavy rains occurred in the late summer and fall. Early in the 2011 monsoon season, these dams held large amounts of water in storage. During the 2010 monsoon season, rainfall had been low, and dam levels were at record lows in June 2010 (Asian Correspondent, 2011a). The Bhumibol Dam was filled to capacity in only 3 months, from August to October 2011 (Asian Correspondent, 2011b). Once the Bhumibol Dam reached capacity, heavy rains continued and releases from the dam had to be increased. Of course, had the monsoon rains in 2011 again been low as in 2010, the opposite situation would have occurred. Reservoir managers would have been criticized if they had released too much water early in the season to minimize flood control risks, and then had too little water in storage to meet irrigation needs.

Based on flood property loss data from 1950 to 2010, Thailand has had the highest average annual property losses from floods of any country in Southeast Asia and ranks 34th in the world (EM-DAT, 2011). In Thailand, expected annual property losses from floods are US$ 2.74 per capita, compared to US$ 1.62 per capita in Malaysia and less than US$ 0.11 per capita in Singapore. However, Thailand's flood mortality risk (0.11 deaths per 100,000 population per year) is below the world average of 0.86 deaths per 100,000 population per year.

Thailand's relatively low flood mortality risk is partly because residents in flood-prone areas of the Chao Phraya River Basin and other parts of the country have coped with regular flooding for centuries. People expect floods and have adapted to reoccurring flood events. Historically, people in flood-prone areas have constructed their homes on stilts and built two-story housing so that they can move their possessions and themselves up to the second floor during floods. Although the rural areas in the northern Chao Phraya basin are especially used to regular flooding, severe flooding in Bangkok is more infrequent. Large parts of Bangkok were inundated for 2 months in 1942 and for 5 months in 1983. Before the 2011 flood hit the Greater Bangkok Metropolitan Area, the last severe flood was in 1995. However, in 2006, other parts of Thailand experienced severe flooding. Bangkok was not affected because local rainfall was not excessive, and the city's flood protection system of canals, embankments, and pumps was able to contain the floodwaters. In 2011, many Bangkok residents (mistakenly) used the 1995 flood as a benchmark of the worst that could happen in their neighborhood.

A combination of factors has led to increasing flood risks in Thailand. Increased agricultural cultivation in the upstream portions of the Chao Phraya Basin has caused deforestation, which has resulted in a decrease in flood retention areas. Urban growth in the lower Chao Phraya basin has reduced the ability to disperse floodwaters over agricultural lands in a flooding emergency. Many canals in and around Bangkok have low gradients and are filled with silt and debris, reducing the ability of the drainage system to remove floodwaters. Moreover, the greater Bangkok area is one of the locations in Southeast Asia most vulnerable to climate change (Yusuf and Francisco, 2010). A 30% increase in flood-prone area is expected in greater Bangkok by 2050 due to increased precipitation and land subsidence of 5–30 cm (Panya

Consultants, 2009). Most of the increase in flood-prone area is expected in western Bangkok, where flood control infrastructure is especially inadequate.

During the 2011 flood, more than 680 people were killed nationwide, and 6 million hectares (nearly 12% of the surface area of the country) were flooded over the 4 month period from September to December (A.M. Best, 2012). The 2011 Thailand flood was the fifth most costly insured loss event worldwide in the last 30 years (A.M. Best, 2012). The World Bank estimated economic losses and damages at THB1.4 trillion (US$ 47 billion, or about US$ 700 per capita) (World Bank, 2012). Thailand's annual GDP growth in 2011 declined from midyear estimates of 4.0% to 2.9%.

In the past, a major focus of flood damage mitigation has been on early warning systems to alert people of the imminent risk of flood events, and the hope has been that people could act effectively on this information before the flood arrives to reduce the costs they are likely to incur. The 2011 Bangkok flood was the first major flooding disaster to hit a population center in South or Southeast Asia in which many people were connected to the web with smart phones and other types of internet access. The flood unfolded slowly, and most households in greater Bangkok had access to information from multiple sources—television, radio, internet, friends and neighborhood leaders, and local and national governments (television was the most important information source for the majority of households). The problem for most households was not lack of early warning, but rather how to assess the quality and accuracy of conflicting information from different sources. This is a relatively new flood management problem, but one that will grow in importance, especially for urban residents connected to global media channels.

The ways in which households could act effectively on the information they received in order to reduce flood losses were limited. Some households in Bangkok managed to move their automobiles to higher ground (e.g., elevated motorways), and some of their possessions to the second story or roof of their dwellings. The current transportation infrastructure will not support a mass exodus, and there are few places for this many people to go. Moreover, as in many types of disasters, some people will not want to leave their homes, due in part from a desire to protect their possessions from theft.

1.3 Description of the Study Sites, Sampling, and Fieldwork

The study was conducted in three provinces of the Greater Bangkok Metropolitan Area: Nonthaburi, Pathum Thani, and Bangkok. We purposively selected three districts, one in each province, that were among the hardest hit by the 2011 flood: Bang Bua Thong District (Nonthaburi); Klong Luang District (Pathum Thani); and Don Mueang District (northern Bangkok). Within each of these three districts, we purposively selected two middle-income neighborhoods and two low-income neighborhoods, for a total of 12 neighborhoods.

The depth of the floodwaters at its highest level (about 2 m) was comparable for the study areas in the three districts (Table 1.1). The duration of flood (about 2 months) for the three study areas was also similar. The three districts differed, however, with respect to the speed with which the floodwater rose. In Bang Bua Thong (Nonthaburi), the floodwaters rose to their maximum level within 24 h. In Klong Luang (Pathum Thani), the floodwaters rose more gradually, 0.5 m in 1 week. The Don Mueang District of Bangkok flooded before the other two study sites and water rose at a moderate pace (0.8 m within 24 h).

Table 1.1 Profile of the Study Area

	Bang Bua Thong, Nonthaburi	Don Mueang, Bangkok	Klong Luang, PathumThani
History of flooding	Major flood in 1995	Did not flood in 1995	Flooded in 1995
When flood arrived	Mid-October	Late October	Mid- October
Speed of rising water	Fast (nearly 2 meters within 24 hours)	Moderate (80 cm within 24 hours)	Slow (50 cm within 1 week)
Median depth of flood (on road)	1.5 meters (range: 0.5 to 3 m)	1.5 meters (range: 0.5 to 3 m)	0.6 meters (range: 0.5 to 2 m)
Population of study area districts [1]	201,254	166,951	120,766
Distance from Central Business District	39 km	30 km	45 km
Elevation(meters above sea level)	0 meter	0.5 to 1 meter	2.30 meters
Number of districts flooded	4 out of 6	36 out of 50	7 out of 7

Note: [1] Population of Nonthaburi province =1,135,299; Bangkok = 5,668,502 ; and Pathum Thani =1,026,934.
Source: Department of Provincial Administration

In each of the three districts, we tried to interview 200 respondents; the total target sample size was thus 600 respondents. Within each of the 12 residential areas, we set a quota of 50 respondents to be interviewed. To the extent practicable, we tried to distribute the 50 respondents in each residential area across the entire spatial area of the neighborhood. For example, for one of the two middle-income neighborhoods in Bang Bua Thong (Nonthaburi), we selected the Chollada Housing Estate and the Pattaraniwetr neighborhood. The former is a large housing estate with more than 1000 households. The low-income neighborhoods in all three districts were much smaller. In these neighborhoods, we had to interview almost everyone we could find in order to meet our quota of 50 households. In this paper, neighborhoods are classified as “low income” or “middle income” depending on the socioeconomic status of the majority of the households living there (including the characteristics of their housing). The terms “poor” and “non-poor” are used to refer to specific households. Survey data collected from households in the sample are used to designate individual households as “poor” or “non-poor.”

Not all households living in a “low-income” neighborhood are poor. In fact, only about half of the households in low-income neighborhoods were classified as poor.

In all three districts, during the first round of the survey the response rates were higher in low-income neighborhoods than in middle-income neighborhoods. For the low-income neighborhoods in Bang Bua Thong District (Nonthaburi), the response rate was 93% compared to 68% in the middle-income neighborhoods (Chollada and Pattaraniwetr). In the Klong Luang District (Pathum Thani), the response rate was of 97% and 61% for the low-income and middle-income neighborhoods, respectively. For Don Mueang District (Bangkok), response rate was 91% for the low-income group and 61% for the middle-income group. The locations of all the households interviewed were geocoded. We do not claim that our final sample is representative of households either in greater Bangkok or within the three provinces. We do believe, however, that sample households span a wide range of socioeconomic and housing conditions in some of the most severely flooded neighborhoods in different parts of the city.

To assist with question selection and design, six pilot interviews were conducted during which respondents were told to “think out loud” as they answered the questions. This helped us to better understand the respondents' experience with the flood and how they interpreted the questions. Before the first round of the survey was implemented, the survey instrument was pretested with 36 respondents. During the actual first-round survey implementation four field staff supervised 18 enumerators. All of the first-round interviews were conducted during January and February 2012, soon after the floodwaters had receded from respondents' houses. On average, interviews lasted 40–45 min. Informed consent was received from all respondents. Before the second round of interviews was conducted in January 2013, the questionnaire underwent further pretesting and refinement.

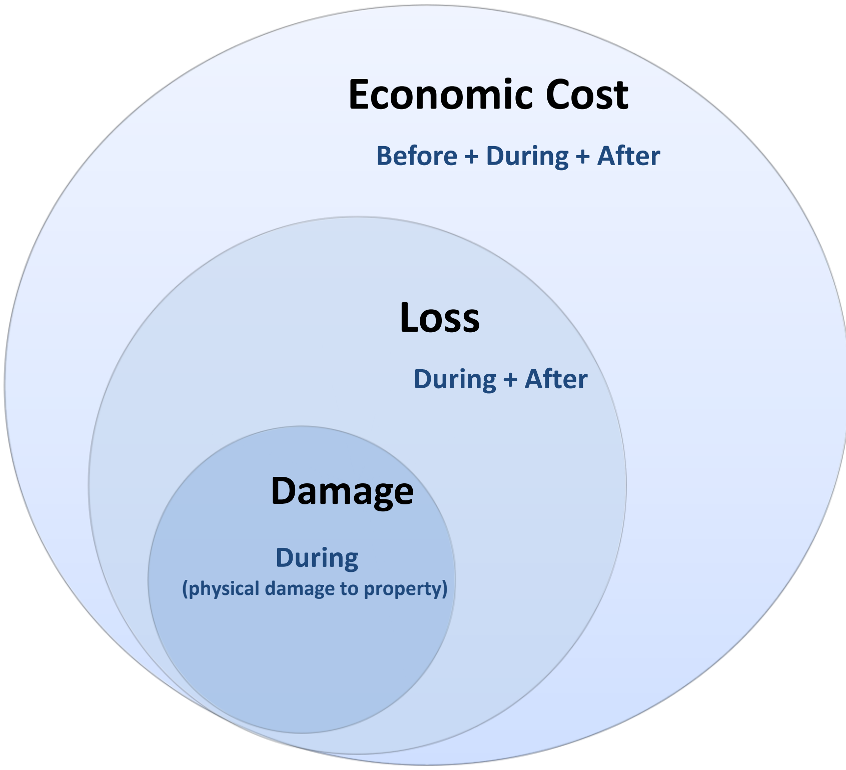
1.4 Definitions, Calculations of Economic Costs Incurred by Households, and Modeling Strategy

1.4.1 Terminology

There is no standardized methodology to estimate the economic costs of floods (White et al., 2001). Nor is there a standardized terminology used to describe the adverse consequences of floods. When estimating the economic consequences of a flood event, one should consider the effects on households' well-being in three time periods, or stages of the event—(1) before the flood arrives; (2) during the flood, (3) after the floodwaters recede. We use the term "economic costs" as inclusive of the negative consequences of a flood in all three of these stages. We refer to the costs incurred before the flood arrives (stage 1) as *ex ante* costs; and costs incurred after the flood hits as *ex post* costs during the flooding event and after the floodwater recede, (stages 2 and 3, respectively).

We use the terms "damages" and "losses" to refer to the *ex post* economic costs of floods. We follow Krutilla (1966) and use the term "damages" to refer to the physical impairment of structures and other property. We use the term "losses" to refer to all *ex post* economic costs. "Damages" are thus a subset of "losses," and "losses" are a subset of "economic costs" (Figure 1.1).

Figure 1.1 Economic cost, loss, and damage categories



Households make financial expenditures before the flood to reduce economic losses after the flood arrives. They also make financial expenditures after the flood has hit in order to deal with the economic losses they have suffered. Both types of financial expenditures are components of the total economic costs of the flood event. Preventative (*ex ante*) expenditures made before the flood arrives are real costs to the household, but are not best conceptualized as "damages" or "losses." Expenditures made after the flood hits to deal with the consequences are one monetary measure of the magnitude of the losses incurred by the household, but such expenditures are not a comprehensive or complete measure of the *ex post* loss incurred because residual losses may remain even after financial expenditures have been made to reduce the losses (damages).

Some of the engineering literature on the costs of floods separates *ex post* costs incurred into tangible and intangible components based on the extent to which the consequences of the flood can be expressed in monetary terms Dutta et al. (2003); (Smith and Ward, 1998; Thieken et al., 2005). Tangible losses include damages to property, buildings, and business interruptions that can be expressed in financial terms. Intangible losses are more challenging to monetize and include, for example, mortality and psychological suffering. However, over the past few decades, nonmarket valuation techniques (both revealed and stated preference methods) have experienced continual methodological improvements, and losses that once were considered impossible to quantify in monetary terms (and thus “intangible”) may now be counted as “tangible” and expressed in monetary, welfare-theoretic terms (Hanemann, 1992; Smith, 2004). For example, in the past, some studies of flood losses considered mortality and morbidity losses to be intangible, but such health effects are now often expressed in monetary terms Dutta et al. (2003).

Another distinction sometimes made is between direct and indirect economic costs. Direct economic costs often refer to easily monetized costs; often they can be approximated by the financial expenditures households make to deal with the negative consequences of the flood, such as repair and rehabilitation of a flooded house. Indirect economic costs may include the time spent on preventative and clean-up activities. Often indirect costs can be expressed in monetary terms, but market prices are not readily available for their estimation. Direct tangible economic losses would include damage to buildings and property, while indirect tangible losses would include disruptions in trade and business activity. Direct damages may be considered to involve physical contact of floodwater with people and property. Much of the flood loss literature focuses on direct tangible damages to property (Merz and Thieken, 2004). Many studies, as well as insurance claims for flood losses, do not include indirect tangible losses such as depreciated property and business values (White et al., 2001). For households with insurance coverage, insurance claims can sometimes be used as a measure of some components of property damages.

In this study, we classify economic costs using three distinctions:

(i) Timing: before the flood arrives (*ex ante*); during the flood (*ex post*), and after the floodwaters recede (*ex post*),

(ii) Direct and indirect,

(iii) Health-related and nonhealth-related.

We do not attempt to classify economic costs as "tangible" versus "intangible" costs. Nor do we report damages separately from losses, although we do use both these two terms (as defined above). Finally, we do not report "financial expenditures" separately; but these are closely associated with our category of "direct costs."

1.4.2 Calculation of Household Economic Costs

We used the data obtained from the first and second rounds of the household survey described above and other data obtained from secondary sources to estimate the economic costs that sample households incurred as a result of the 2011 Thailand flood. Our estimates of the economic costs include both *ex ante* (pre-flood) expenditures and other costs incurred to reduce *ex post* economic losses (e.g., damages to property, health, and forgone income incurred during and after the flood). We do not include residual damages, i.e., property damages that households do not plan to repair after the flood event, or any property damages that remain after repairs and rehabilitation efforts are complete.

We report estimates for five categories of flood-related economic costs: (1) *ex ante* preventative costs; (2) *ex post* nonhealth-related losses during the flood; (3) *ex post* nonhealth-related losses after the flood, (4) *ex post* health-related losses both during and after the flood; and (5) household contributions to community (both *ex ante* and *ex post*). We further report the direct and indirect costs associated with each of these five components. In addition, some households received compensation from government and other sources, which is a transfer payment to the household that reduces the total household costs. A very small number of sample households may have received payments from insurance companies for the property damages they incurred.

We did not collect this information in the surveys because (1) very few households had coverage; and (2) these payments would be transfers (i.e., our estimates of property losses represent the real resource costs). Table 1.2 presents the various items included in the cost estimates for the direct and indirect costs for each of these five categories. Direct costs were comprised of expenditures for hired labor and materials to prepare, cope, and recover from the flood. Indirect costs included own labor, volunteer labor, and opportunity cost of time due to missed work, increased travel time, and caring for sick household members. For the survey respondent, indirect costs were calculated as the product of a monetary value of lost productivity, days of work missed, and increased travel time to work and home. The value of lost productivity was estimated based on the respondent's self-reported income. For all other household members, we assumed that the value of lost time was the minimum daily wage rate in Thailand (THB 300, US$ 9.7).

Table 1.2 Components of Total Economic Costs Incurred by Households

Cost Component	Equation
Total Economic Cost	**= A+B+C+D+E**
A. Preventative Costs (Ex ante)	
Direct	
Hired labor	= # of days * minimum daily wage of THB 300
Materials & Activities	
Parking car in alternate location	
Preventative materials (sandbags, pumps, etc.)	= total preventative materials cost/ 2
Indirect	
Own labor	= # of days * monthly income/ 22 days
Volunteer labor	= # of days * THB 300 per day
B. During-Flood Economic Loss (Non-health related)	
Direct	
Preparation expenditures	
Alternate accommodation (shelter)	
Kitchenware, food supplies, boats, clothing	
Other (sandbags, pumps, construction materials)	= total preventative materials cost / 2
Increased work commute costs	= Δ work commute costs * # flooded days
Increased cost to travel home	= Δ home travel costs * # of trips home
Increased food cost	= Δ weekly food costs * flood duration
Indirect	
Increased travel time to work	= Δ commute time * (flood duration*(5/7) –holiday – work days missed)* (monthly income/22 days)
Increased travel time to house	= Δ time to travel home * # trips * opp. cost of time [a]
Foregone income	
C. After-Flood Economic Loss (Non-health related)	
Direct	
Car Repairs	
Housing and belongings damage	
Hired labor for moving + repair	= # of days * THB 300 per day
Cost to repair, clean, replace	
Indirect	
Housing and belongings damage	
Own labor for moving + repair	= # of days * monthly income/ 22 days
Volunteer labor for moving + repair	= # of days * THB 300 per day
D. Health-related Cost	
Direct: Doctor visits; medicine	
Indirect: Foregone income of patient [c] and care taker	= # of days * opp cost of time [b]
E. Household contributions to community	
Direct: Cash contribution and volunteer time	=contribution + (# of days * THB 300 per day)
Cash contribution	

[a] Opportunity cost of time for respondent is income, otherwise THB 300 per day is assumed

Preventative costs comprised *ex ante* expenditures and self-supplied labor to prepare for the arrival of the floods and hopefully mitigate losses. Households parked cars in alternate locations and purchased goods to prepare for the flood such as construction materials, sandbags, and small boats. Nonhealth related economic costs during the flood included expenditures for alternative shelter, materials to cope with flooding, emergency food and drinking water, and increased travel costs. Foregone income due to days of worked missed was also included for respondents who were wage workers, self-employed, or business owners. Direct nonhealth-related losses during the flood included coping costs (shelter, supplies, etc.), increased expenses to commute to work and home, and increased food expenditure. Indirect nonhealth-related losses during the flood included increased travel time to work and home as well as foregone income due to not being able to commute to work.

Ex post nonhealth-related economic losses included expenditures for car repairs and to repair, clean, and replace housing and other property damage. *Ex post* health-related costs were based on the information reported by survey respondents about flood-related diseases experienced by household members. Expenditures on medicine and doctor visits were included in direct costs, while indirect costs were comprised of foregone income of the patient and caretakers. As for indirect nonhealth-related losses, respondent's time was valued based on self-reported income, and for sick household members other than the survey respondent, time was valued at the minimum daily wage rate of THB 300 (US$ 9.7).

In addition, some households contributed to community flood efforts, either through cash contributions or volunteer time. These contributions are included in total household costs. Most households received government compensation for flood damage. This compensation is a transfer from government to households, and is reported separately from total household costs.

Some households were able to generate new income during the flood, by offering needed goods and services such as prepared food and boat transport. The net economic costs experienced by a household are the total costs minus any compensation received or new income generated.

In summary, our estimates of the costs incurred by households in the 2011 Bangkok flood go far beyond the typical engineering estimates of financial damages to households' dwellings and contents. Notably, they include:

(i) Not only *ex post* costs, but also *ex ante* expenditures;

(ii) Health-related costs;

(iii) Productivity losses due to lost work and illness; and

(iv) Households' coping costs for alternative shelter and supplies when they were forced to leave their homes.

Households' payments for flood insurance can be considered one measure of the perceived *ex ante* costs of flooding risks. We have not included these payments because (1) few households (less than 1%) in Bangkok had flood insurance at the time of the 2011 flood (Orie and Stahel, 2013); (2) the policies were subsidized, and thus not a good measures for estimating expected real costs; (3) information was not collected on insurance company payments for property damage. Including insurance payments to households as a cost component would result in double counting real resource costs.

Our household cost estimates from the 2011 Bangkok flood can be used to estimate the benefits of flood mitigation strategies when such interventions will reduce such costs. These measures of potential “avoided costs” are conceptually similar to the use of “coping costs avoided” as welfare-theoretic benefits from water and sanitation investments (Pattanayak et al., 2005), and avoided cost-of-illness estimates as measures of the benefits of health interventions in the public health field (Poulos et al., 2011). Of course, the costs borne by households are not the total economic costs of the flood event. For example, they do not include foregone production or property damages in the flooded industrial districts of Bangkok.

1.4.3 Modeling Strategy: Factors Associated With Preventative Costs and Household Economic Losses

We used regression analysis to estimate the association between preventative costs and whether the household received a provincial-level flood warning, and respondent, household, and neighborhood characteristics. Our model specification was:

$$PreventCost = \beta_0 + \beta_1\, warning + \gamma_j X_j + \mu_k H_k + \omega_m V_m \qquad (1.1)$$

where PreventCost = total preventative costs incurred by household

warning = household received a district-level flood warning or not

X_j = personal characteristic j (e.g. education level)

H_k = household characteristic k (e.g. annual expenditure, number of cars owned)

V_m = neighborhood controls

We expected information in the form of provincial-level flood warnings to increase the magnitude and effectiveness of preventative actions. However, in addition to being aware of the flood risk, households can only take carefully considered preventative actions if they are informed about the cost and effectiveness of measures to mitigate flood losses (Thieken et al., 2005; Grothmann and Reusswig, 2006). Perceived flood risk is not only influenced by flood warnings, but also the frequency of past events, how recent the previous flood was, and personal risk tolerance. Such variables are not considered in our model. Nor did we include variables related to previous flood experience due to correlation with household income and neighborhood. Higher-income households tended to have shorter residence periods in their current homes and therefore tended to have less previous flood experience. The household decision to undertake flood mitigation measures is also influenced by expectations regarding responsibility for flood control and response, i.e., whether these responsibilities lie more with individual households or the government.

In order to determine which factors were associated with losses incurred during and after flooding, *ex post* household economic losses were regressed on characteristics of the respondent, the household, and the neighborhood. We also included depth of flood and whether the household received a provincial-level flood warning. Our model specification was:

$$Flood\ Loss = \beta_0 + \beta_1\, warning + \beta_2 flood\ depth + \gamma_j \mathrm{X}_j + \mu_k \mathrm{H}_k + \omega_m \mathrm{V}_m + \varepsilon \quad (1.2)$$

where Flood Loss = total *ex post* flood loss (costs incurred during and after the flood)

warning = district-level flood warning received

flood depth = Depth of flood water (first floor of house)

X_j = personal characteristic j (e.g. education)

H_k = household characteristic k (e.g. annual expenditure, number of cars owned)

V_m = neighborhood controls

The association between receiving a provincial-level flood warning and *ex post* losses was expected to be negative since informed households should be better able to prepare and cope with the flood. A household's ability to respond to a provincial-level flood warning will be constrained by its income. A similar model was specified for total flood costs (preventative costs plus flood loss):

$$Total\ Flood\ Cost = \beta_0 + \beta_1\, warning + \gamma_j X_j + \mu_k H_k + \omega_m V_m + \varepsilon \tag{1.3}$$

Table 1.3 provides definitions and summary statistics for all variables included in the preventative expenditure, *ex post* flood loss, and total flood cost models (i.e., equations 1.1 to 1.3). Preventative costs were excluded from the *ex post* loss model (equation 1.2) due to endogeneity concerns. We do not have good, household-specific measures of either the objective or perceived flood risk. Therefore, there is the possibility that households with higher preventative costs knew that they were at greater risk, especially in Klong Luang, and thus spent more *ex ante* on mitigation strategies. Since preventative costs are a function of flood risk, and people act on perceived flood risk, establishing a causal relationship between preventative expenditures and *ex post* losses is challenging. This is a common problem in flood cost estimation studies, and we do not claim to have a compelling identification strategy. Nevertheless, we believe that the association between preventative expenditures and *ex post* losses is still of interest.

Table 1.3 Summary Statistics of Regression Variables (Obs = 469)

	Definition	Mean	Std Dev	Min	Max
Preventative Cost	Expenditures on preventative measures (in THB)	8,235	14,904	0	180,773
Ex Post Losses	Total household losses during and after the flood (in THB)	151,499	187,530	400	1,511,432
Total Flood Losses	Total costs, before, during, and after flood (in THB)	162,050	192,084	1,423	1,519,323
Annual Household expenditures	Total household expenditures per year (in THB)	261,381	192,006	30,600	1,200,000
Cars owned	Number of cars owned	0.9	1	0	5
Education Level					
Elementary or less	Dummy variable=1, if respondent had elementary school education or less	0.38	0.49	0	1
High School or Vocational	Dummy variable=1, if respondent had high school or vocational education	0.33	0.47	0	1
College or more	Dummy variable=1, if respondent had college education or more	0.29	0.45	0	1
Flood warning (district-specific)	Dummy variable=1, if household received province-specific flood information	0.83	0.37	0	1
Flood depth (first floor)	Flood depth on first floor of house (in cm)	107	57	0	300

1.5 Results

1.5.1 Socioeconomic Profile of Respondents

Respondents were located in both middle-income neighborhoods (220 households) and low-income neighborhoods (249 households). The 220 respondents living in middle-income neighborhoods were mostly self-employed or employed by businesses in the private sector. The average monthly expenditure of middle-income households (estimated using data from the second-round of the survey) ranged from THB 50,843 in Klong Luang to THB 82,053 in Bang Bua Thong to THB 156,391 in Don Mueang.

Most respondents in low-income neighborhoods were wage workers; about a quarter were self-employed. The average monthly expenditure of households in low-income neighborhoods of Bang Bua Thong and Don Mueang (THB 11,643 and THB 12,412, respectively) were significantly lower than in Klong Luang district (THB 15,238). The years of education and household expenditures of the respondents in middle-income neighborhoods were significantly higher than of respondents in low-income neighborhoods.

Almost all respondents in lower-income neighborhoods lived in one-story houses. In general, households in low-income neighborhoods have lived longer in their homes than households in the middle-income neighborhoods. The average length of stay for households in low-income neighborhoods was over 25 years. The average length of stay in middle-income neighborhoods ranged from 7 years in Don Mueang and Klong Luang to 15 years in Bang Bua Thong. Self-reported house values for households in middle-income neighborhoods range from THB 1.5 million (US$ 50,000) in Klong Luang to THB 3.5 million (US$ 113,000) in Bang Bua Thong and THB 4.7 million (US$ 151,000 US$) in Don Mueang. For households in low-income neighborhoods, house values in Klong Luang and in Don Mueang averaged about THB 295,000

(US$ 9590) and THB 317,000 (US$ 10,280), respectively. Average house values for Bang Bua Thong were slightly higher (THB 368,000; US$ 11,946).

1.5.2 Total Economic Costs from the 2011 Flood

Median total household costs were about THB 95,138 (US$ 3089) for the 469 households included in the sample for whom both rounds of interviews were completed (Table 1.4). Nearly 14% of households had economic costs in excess of THB 300,000, although less than 5% of households had over THB 600,000. The cumulative frequency distribution of total household costs (Figure 1.2) shows how total economic costs varied dramatically across households—even in these neighborhoods most severely affected by the 2011 Bangkok flood. About 22% of households had economic costs over THB 200,000. Households with losses over THB 200,000 tended to have more property at risk (e.g., more cars and more valuable homes) and to have higher monthly expenditures. These households were also more likely to live in middle class neighborhoods in Bang Bua Thong (Nonthaburi), where floodwaters rose quickly.

Table 1.4 Summary Statistics of Economic Cost Components, by poverty status

		Above 150% Poverty Line	Below 150% Poverty Line	Total
Cost Component	Obs	359	110	469
A. Preventative Costs (Ex-ante)	Median	5,273	1,893	3,409
	Mean	9,756	3,272	8,235
	Std Dev	16,553	4,610	14,904
	Max.	180,773	30,395	180,773
B. During-Flood Economic Loss	Median	26,761	19,304	25,343
	Mean	48,714	27,113	43,647
	Std Dev	81,101	26,565	72,661
	Max.	817,932	152,500	817,932
C. After-Flood Economic Loss	Median	69,652	21,920	51,709
	Mean	131,018	30,774	107,507
	Std Dev	165,756	29,480	151,749
	Max.	1,051,100	155,800	1,051,100
D. Health-related loss [a]	Median	0	0	0
	Mean	336	372	345
	Std Dev	2,633	2,105	2,517
	Max.	42,630	17,000	42,630
E. Household contributions to community	Median	0	0	0
	Mean	2,432	1,939	2,316
	Std Dev	6,100	5,099	5,879
	Max.	53,700	36,900	53,700
Total Economic Cost	Median	121,896	52,123	95,138
	Mean	192,256	63,470	162,050
	Std Dev	209,018	45,987	192,084
	Max.	1,519,323	247,691	1,519,323

Table 1.4 (Continued)

		Above 150% Poverty Line	Below 150% Poverty Line	Total
Total Economic Cost (continued)				
Direct	Median	80,200	30,807	59,000
	Mean	139,874	37,822	115,939
	Std Dev	169,797	33,501	155,530
	Max.	1,088,700	176,800	1,088,700
Indirect	Median	27,158	18,178	24,545
	Mean	52,382	25,648	46,112
	Std Dev	83,724	25,207	75,091
	Max.	807,023	167,159	807,023
Total Economic Cost (% annual expenditures)	Median	0.48	0.53	0.48
	Mean	0.65	0.60	0.64
	Std Dev	0.5	0.4	0.5
	Max.	2.8	2.6	2.8
Total Economic Cost (% annual income)	Median	0.27	0.25	0.26
	Mean	0.35	0.31	0.34
	Std Dev	0.3	0.2	0.3
	Max.	3.0	1.4	3.0
Dwelling-Related Cost (% of house value)	Obs	323	95	418
	Median	0.02	0.05	0.02
	Mean	0.06	0.12	0.08
	Std Dev	0.12	0.20	0.14
	Max.	0.9	1.1	1.1

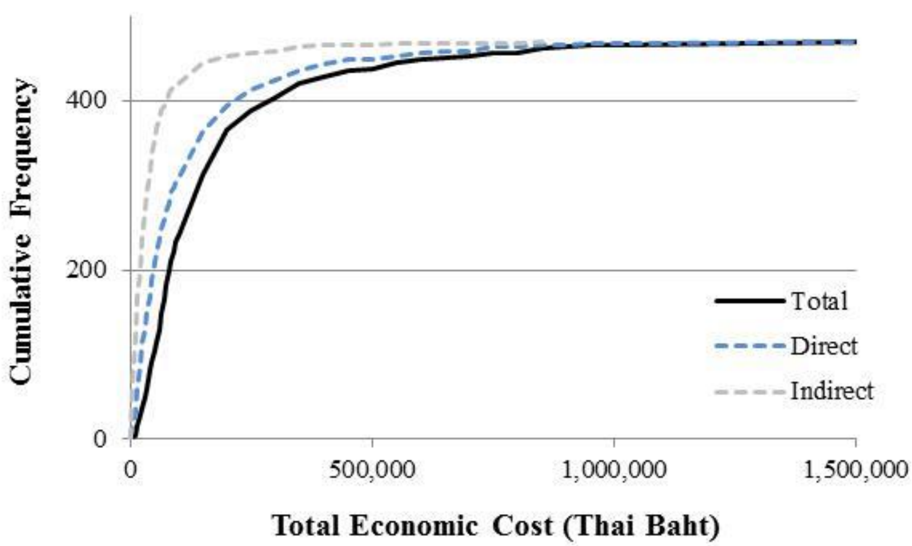
Table 1.4 (Continued)

		Above 150% Poverty Line	Below 150% Poverty Line	Total
F. Compensation	Median	25,000	24,250	25,000
	Mean	22,973	21,450	22,616
	Std Dev	9,536	6,279	8,897
	Max.	125,000	35,000	125,000
New Income During Flood	Median	0	0	0
	Mean	739	326	642
	Std Dev	5,623	2,895	5,116
	Max.	80,000	30,000	80,000
Net Economic Cost	Median	93,987	31,711	71,789
	Mean	166,004	41,395	136,778
	Std Dev	206,113	46,154	189,174
	Min	(33,347)	(26,138)	(33,347)
	Max.	1,496,323	222,691	1,496,323

[a] Note: In addition, two deaths were reported. Although not included in total loss estimates, using VSL, this loss amount is estimated to be between US$ 2.2 to $2.8 million (2012 US$) (Vassanadumrongdee and Matsuoka, 2005)

For most households, direct costs were greater than indirect costs (Figure 1.2). As a proportion of annual household expenditure, median costs were 48% of annual expenditure. As a percentage of annual household income, median costs were 26%. A considerable number of households incurred high costs relative to annual expenditure (Figure 1.3). About 18% of households had costs that were equivalent to or greater than their annual expenditure, while only 2% of households had costs that were equivalent to or greater than twice their annual expenditure. The cost of house repairs was surprisingly low given the depth and duration of the floods (Tables 1.4 and 1.5). Median house repair costs as a percent of house value were 2% (mean of 8%). Most houses incurred little structural damage.

Figure 1.2 Frequency of total, direct, and indirect costs

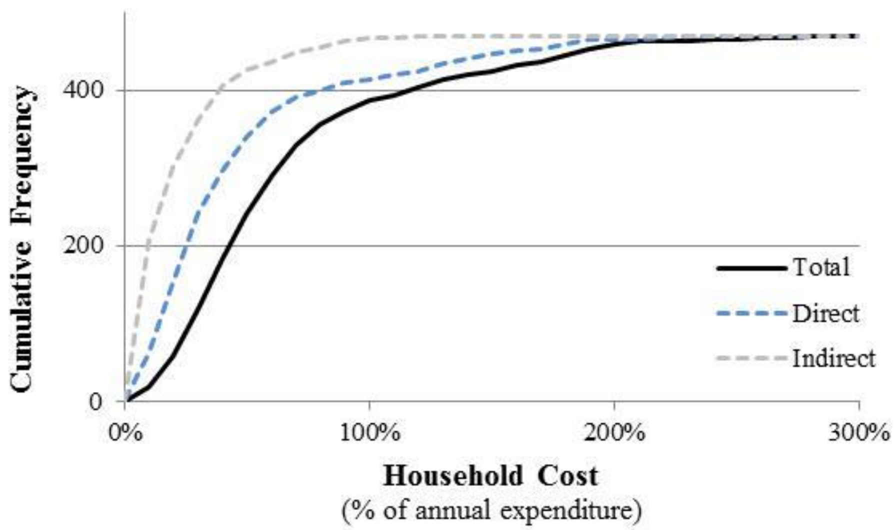


1.5.3 Composition of Economic Costs

The total household economic cost was subdivided into five components: (1) *ex ante* preventative costs; (2) *ex post* nonhealth-related losses during the flood; (3) *ex post* nonhealth-related losses after the flood; (4) *ex post* health-related losses both during and after the flood; and

(5) household contributions to community (both *ex ante* and *ex post*). The largest component was the *ex post* nonhealth-related losses after the flood, which accounted for 66% of mean household total cost, followed by nonhealth losses during the flood (27% of mean total cost) (Figure 1.4, Panel A).

Figure 1.3 Frequency of total, direct, and indirect costs as a percentage of annual expenditure

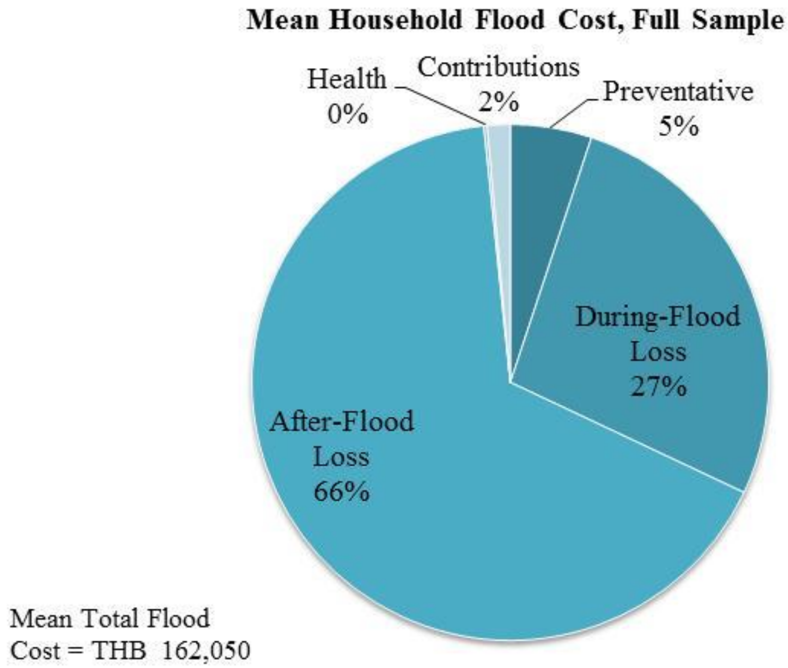


Median nonhealth-related losses after the flood were about THB 51,700 (US$ 1680). Damage to homes and belongings was by far the largest component of *ex post* economic loss. Particularly high losses were incurred for replacement of furniture, cleaning of home, and replacement of electrical appliances.

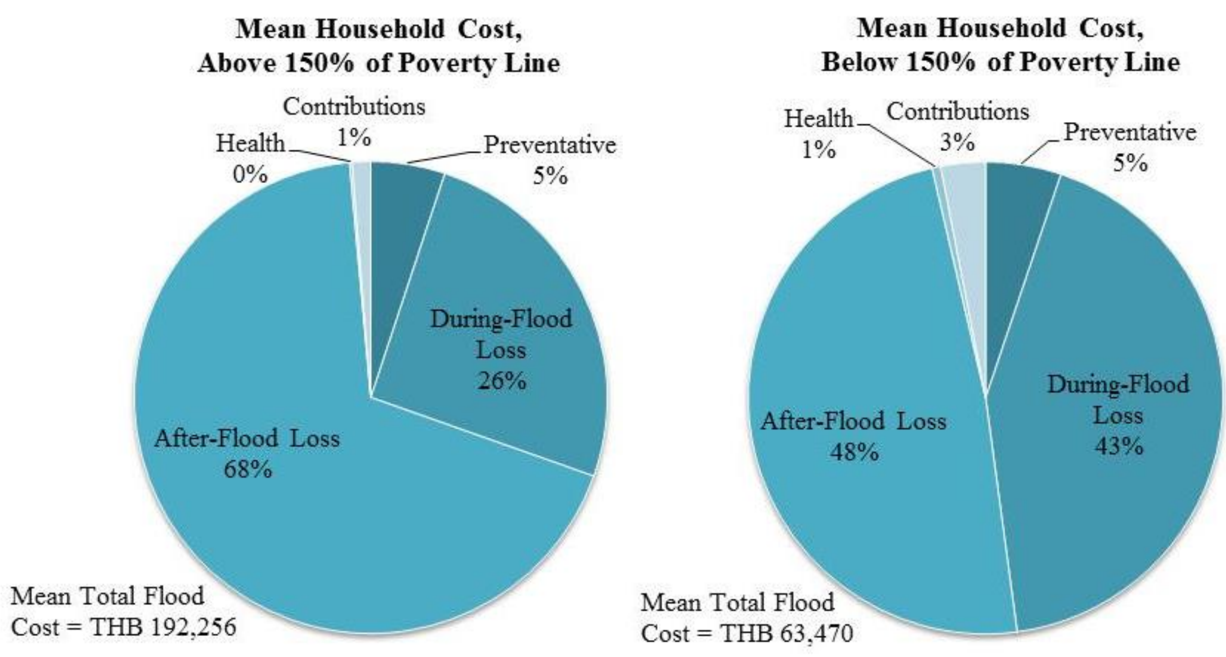
Ex post nonhealth-related losses during the flood was the second-highest cost category. Median nonhealth-related losses during the flood were about THB 25,343. Foregone income was the largest component of nonhealth-related losses incurred by households during the flood (mean of THB 27,276), followed by coping costs for alternative shelter and supplies (mean of about THB 10,160), and increased food expenses (mean of about THB 3463). About half of the

Figure 1.4 Composition of mean household costs

Panel A. Full sample



Panel B. By poverty category



Note: About 23% of the sample (110 households) had annual expenditures less than 150% of the poverty line.

households had no foregone income during the flood largely because salaried employees were able to collect their salary even when they missed work due to the flood. It is therefore the organizations that employed salaried workers that bore these losses. Only 5% of households were estimated to have foregone income over THB 100,000.

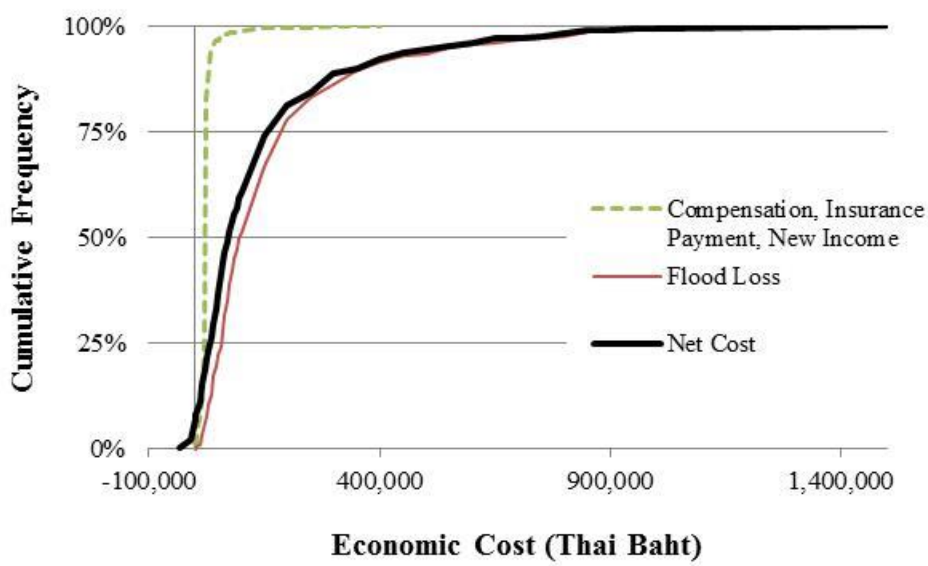
Few households experienced health-related losses. Only 52 households (11% of the sample) had at least one member who suffered from an illness or accident that the respondent attributed to the flood. In total, 62 disease episodes or accidents were reported and attributed to flood-related causes. Of these, 36 households (58%) reported incurring health costs. The majority of reported episodes were due to one of two causes: (1) Tinea pedis, a contagious skin infection caused by ringworm fungus, (23 cases), or (2) accidents (13 cases). In addition, rheumatism and muscular pain, common colds, and diarrhea were reported by several households, but it is difficult to know the proportion of these cases that were actually due to the flood. Two flood-related deaths were reported. One was due to electrocution and the other due to cramps that resulted in drowning. Both cases involved the death of the head of household and were in the poor neighborhoods of Bang Bua Thong in Nonthaburi. We have not adjusted our estimates of household economic losses using the value of a statistical life (VSL) in Bangkok (Vassanadumrongdee and Matsuoka, 2005) to include these two deaths. Had we done so, the total economic losses experienced by the households in our sample would have been much higher (roughly double).

The majority of health-related losses were borne by only a few households. Most households in which a member was ill incurred very modest health losses—median heath loss was THB 600. About 29% of households with a sick or injured member bore no health loss. However, health costs varied widely across households, from zero to THB 42,630. The magnitude of indirect health losses was much greater than direct health losses. In addition, only 12 households (representing 23% of households with a sick or injured member) incurred indirect health losses due to foregone wages (as a result of a sick or injured individual missing work or due to a caregiver missing work).

Preventative costs incurred by households before the flood amounted to a relatively small proportion of total household cost (Figure 1.4, Panel A). *Ex ante* preparation costs included supplies and labor to mitigate losses and prepare for flooding. Households parked cars in alternate locations and purchased goods to prepare for the flood such as construction materials, sandbags, and water pumps. Median preventative costs were about THB 3409 (US$ 111). However, costs range from zero to over THB 180,770. Less than 6% of households had preventative costs in excess of THB 30,000. Indirect expenditures (own labor and volunteer labor to take preventative actions) tended to be much greater (median of THB 2500) than direct expenditures on supplies and hired labor (median of zero).

Nearly all households received disaster compensation, which was provided from various sources including the national government, employers, and aid organizations. The median value of disaster compensation received was THB 25,000 (about US$800). Few households generated additional income during the flood (4% of our sample). Most of these households created new income sources such as selling food and drinks or providing boat transportation. By including compensation and income from new sources, the median value of net flood losses was THB 71,789. Seven percent of the sample households had zero or negative net flood losses (i.e., some households benefited) after accounting for compensation and income from new sources. Figure 1.5 presents the cumulative frequency distribution total household costs, compensation received and net costs. As illustrated, compensation paid made a relatively small reduction in the total economic losses of the vast majority of households.

Figure 1.5 Cumulative frequency distributions of economic costs

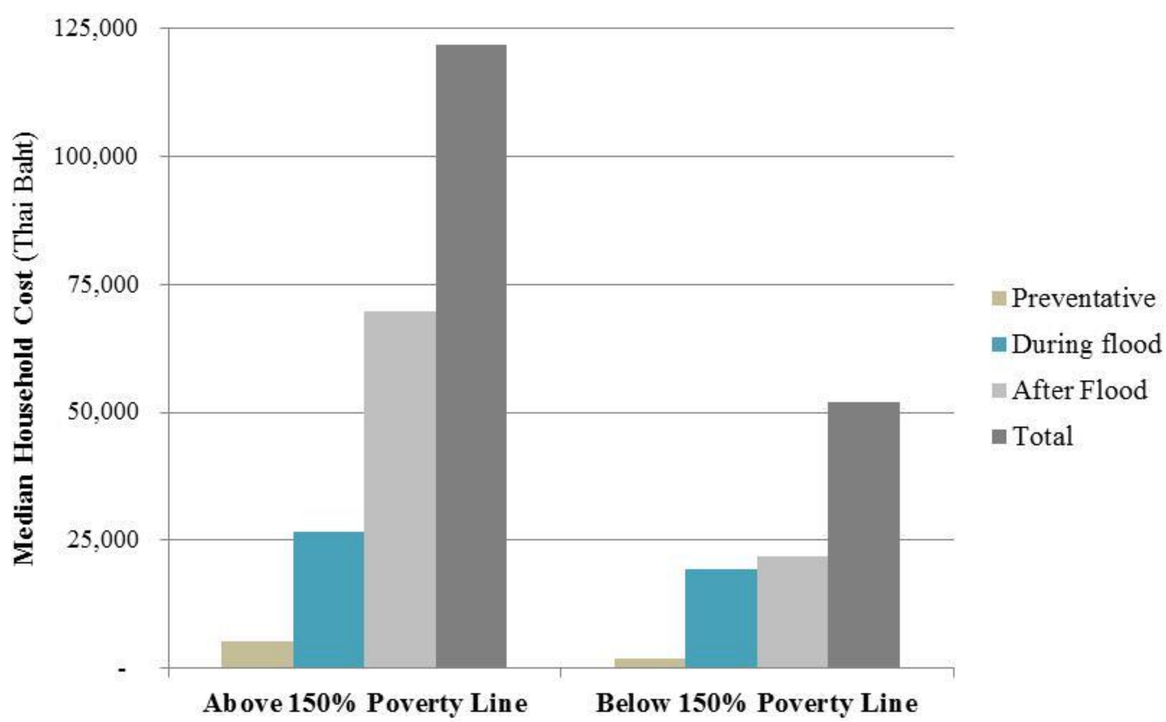


1.5.4 Distribution of Economic Costs Across Income Groups

Economic costs also varied considerably across poor and non-poor households. Poor households were defined as having expenditures below 150% of the national poverty line. The national poverty line was expenditures of THB 1443 per person per month in 2007 (United Nations Development Program (UNDP), 2010). Adjusting for inflation, this is equivalent to THB 1618 per person per month in 2011. Households with expenditures under THB 2427 per person per month were considered to be poor. In our sample of 469 households, 110 households (23%) were defined as poor.

Poor households incurred much lower total costs than non-poor households, both in terms of direct and indirect costs. Median total costs for non-poor households (THB 121,896) were more than twice as large as median total costs for poor households (THB 52,123). For both income groups, after flood losses were by far the largest category, followed by losses incurred during the flood (Figure 1.6). Median losses during the flood (stage 2) were comparable for the non-poor (THB 26,761) and poor (THB 19,304) households. In addition, preventative costs were relatively low for both non-poor and poor households (median of THB 5273 and THB 1893, respectively). The biggest difference in losses between non-poor and poor households was for after flood (stage 3) losses (median values of THB 69,652 and THB 21,920, respectively). This large difference in *ex post* losses was due to wealthier households owning more property that was at risk and that was subsequently damaged.

Figure 1.6 Median household costs, by loss type and income group



Nonhealth losses during the flood were a much larger share of poor household total costs (43% of mean total costs) than of non-poor households (26%) (Figure 1.4, Panel B). In contrast, non-poor households had a larger share of costs accounted for by *ex post* loss (68%) than poor households (48%). This is due, in part, to poor households being more likely to forego wages when missing work. The ratio of preventative costs to total costs was approximately the same for non-poor and poor households (5%). Non-poor households were slightly more likely to evacuate from their homes—77% of non-poor households had at least some members evacuate compared to 65% of poor households.

In terms of after flood losses, poor households tended to have relatively greater repair and rehabilitation costs as a percentage of housing value (median of 5% of house value, for poor households), compared to non-poor households (median of 2% of house value). About 6% of poor households (six households) had repair costs that were more than 50% of house value, compared to 3% of non-poor households (nine households). One poor household reported repair costs that exceeded the self-reported market value of their house.

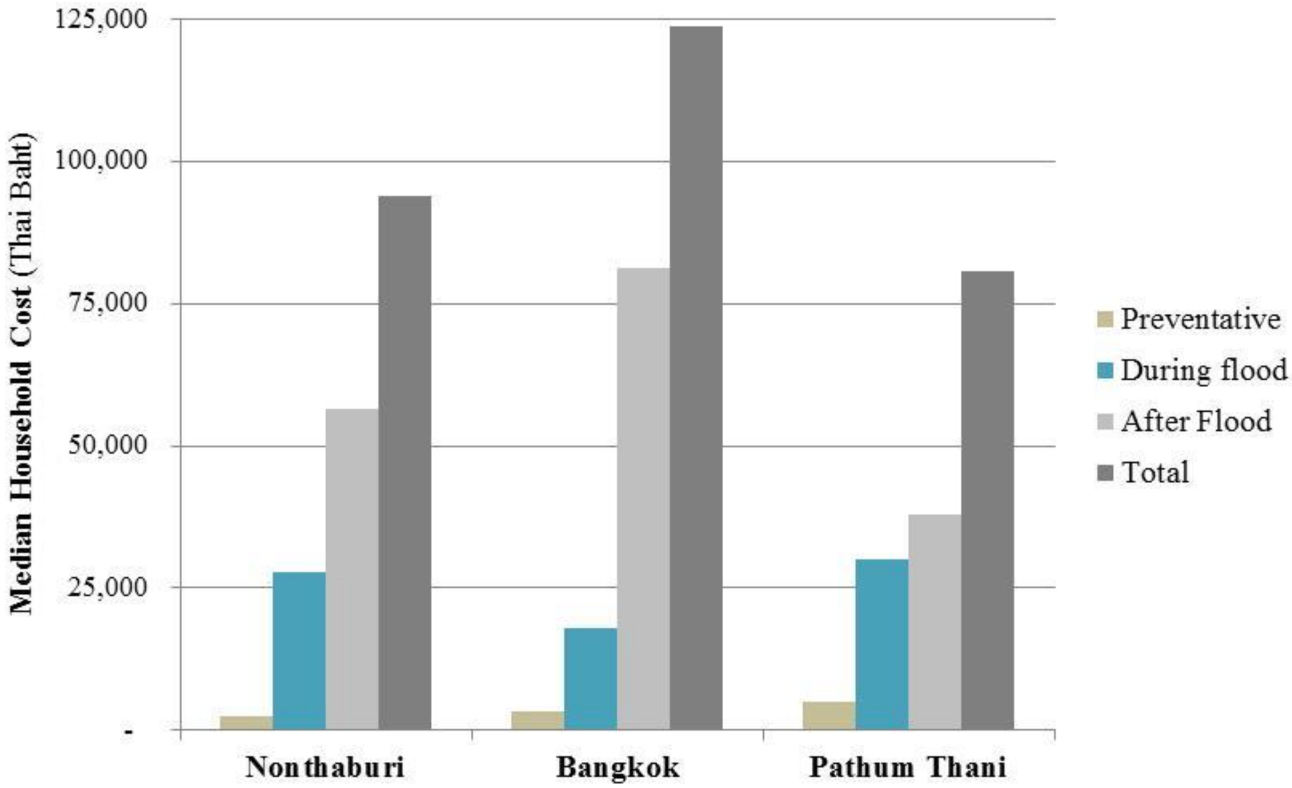
The difference between the incidence of flood-related health cases in poor and non-poor households was not statistically significant. In addition, incidence of flood-related health cases was similar across low-income and middle-income neighborhoods. Neighborhoods are grouped into low-income and middle-income categories. Each of the three provinces has one category of low-income neighborhoods and one category of middle-income neighborhoods. So, if health cases were evenly distributed, the income category within each province would have 16% of health cases. Five of these categories (Don Mueang low-income, Nonthaburi low- and middle-income, Pathum Thani low- and middle-income) have between 16 and 21% of the cases. However, the Don Mueang middle-income neighborhoods only have 3% of the health cases.

Poor and non-poor households with at least one sick or injured member had similar total health losses (median of THB 750 and 500, respectively).

Non-poor households had higher preventative costs (median THB 5273) than poor households (median of THB 1893) because they have more property at risk and are more able to afford such preventative measures. However, the vast majority of households in both income groups took some preventative measures. A slightly smaller percentage of poor households (90%) took preventative action than non-poor households (94%). The proportion of poor and non-poor households that moved belongings to higher ground or the second floor were comparable, but slightly more poor households built scaffolding structures within the house as temporary living or storage space. Poor households were more likely to resort to scaffolding because a greater proportion of poor households lived in one-story dwellings. In addition, poor households were less likely to build concrete block or sandbag flood barriers.

Poor and non-poor households tended to bear similar burdens in terms of costs as a percentage of annual expenditure. About 14% of poor households and 19% of non-poor households had losses that were equivalent to or greater than their annual expenditure. Households in Bang Bua Thong and Don Mueang tended to have greater losses as a percentage of annual expenditure than households in Klong Luang (Figure 1.7). In our sample, Bang Bua Thong and Don Mueang also had larger shares of poor households. About 22% of households in Don Mueang (Bangkok) and Klong Luang (Pathum Thani) were poor, compared 27% in Bang Bua Thong (Nonthaburi).

Figure 1.7 Median household costs, by province



1.5.5 Results of Multivariate Analyses

The regression model (equation 1.1) used to examine the factors associated with household preventative costs (i.e., before the flood) explained little of the variation in the data (adjusted R^2 =0.17). Households that owned cars and had a college education spent somewhat more on preventative costs (Table 1.5). Whether the household received a flood warning at the district level was not statistically significant. Before the 2011 flood arrived in the greater Bangkok metropolitan area, most households in the study areas knew it was coming, and almost everyone incurred preventative costs to mitigate the expected losses. The majority of households received provincial-level flood warnings in Don Mueang and Klong Luang and Bang Bua Thong. After controlling for socioeconomic factors and provincial-level flood warning, there were few neighborhood-specific effects on the magnitude of preventative costs that households incurred, with the exception of one neighborhood.

Table 1.5 OLS Regression Results for Preventative Costs

	Preventative Expenditure					
	(1)			**(2)**		
	Coeff.		Std. Err.	Coeff.		Std. Err.
Annual household expenditures	0.007	**	0	0		0
Cars owned	2,626	***	770	2,569	***	801
Education Level						
High School or Vocational	2,106		1,532	1,704		1,620
College or more	7,223	***	1,829	7,244	***	2,270
Flood warning (province-specific)	1,582		1,732	-214		1,876
Neighborhood						
YaJai (low-income)				1,024		3,063
FangNean (low-income)				-727		2,978
Chollada (middle-income)				-1,834		3,574
Pattaranivate (middle-income)				-2,471		3,504
Ruamjairuk (low-income)				2,597		3,230
Promsumrit (low-income)				1,859		2,959
Saraneepark (middle-income)				6,335	*	3,329
Chudapa (middle-income)				-2,448		5,715
Suksombun (low-income)				1,083		2,903
PhinicPark (middle-income)				4,277		3,055
Phapinjad (middle-income)				4,229		3,302
Constant	51		1,909	1,068		2,805
R^2	0.138			0.167		
Adj R^2	0.129			0.138		
Obs	469			469		

Table 1.6 presents the results of the regression models (equations 1.2 and 1.3) that examined factors associated with variation in the *ex post* household losses (i.e., during and after the flood) and total flood costs. These models explain more of the variation in *ex post* household losses (adjusted $R^2 = 0.43$) and total costs (adjusted $R^2 = 0.44$). Since *ex post* household losses tend to comprise the majority of total costs, the results of both models are similar. Three groups of variables stand out as associated with *ex post* household losses and total household costs. First, households with higher annual expenditures and more cars incurred more losses because they had more property at risk. Households with a college education or higher also suffered higher losses, which we interpret as an additional indicator for more property at risk.

Second, even after controlling for socioeconomic factors, neighborhood effects were large and statistically significant. Specifically, household losses in middle-income neighborhoods Bang Bua Thong and Don Mueang were higher than in Klong Luang. This is expected because the floodwaters were deeper in Bang Bua Thong and arrived with much less advanced warning than in Klong Luang.

Third, provincial-level flood warnings were not significant in any of the *ex post* loss model specifications that controlled for neighborhood effects. Such warnings may have been less useful during the 2011 greater Bangkok flood than in flood events that unfold more quickly. The amount of time households had to prepare before the arrival of the flood appears to be an important factor for flood loss mitigation. Longer lead times are usually associated with lower damages and lower death rates [Parker et al., 2009]. During slow moving flood events, such as the 2011 Thailand flood, more people are informed in advance about the event. By the time floodwaters reached greater Bangkok, most households were aware the flood was coming, but these warnings might not have conveyed sufficient information about appropriate mitigation actions or the depth of floodwater that households could expect.

Table 1.6 OLS Regression Results for Ex Post Flood Losses, and Total Costs

	***Ex Post* Flood Losses**					
	(1)			**(2)**		
	Coeff.		Std. Err.	Coeff.		Std. Err.
Annual household expenditures	0.22	***	0.05	0.22	***	0.05
Cars owned	45,713	***	8,326	47,927	***	8,434
Education Level						
High School or Vocational	-13,702		16,999	-8,347		17,056
College or more	46,769	**	23,639	58,195	**	23,904
Flood warning (province-specific)	-9,535		19,530	-10,085		19,752
Flood depth (first floor)	209		146			
Neighborhood						
YaJai (low-income)	15,690		33,058	27,719		32,255
FangNean (low-income)	3,299		31,039	7,394		31,358
Chollada (middle-income)	150,169	***	37,147	146,512	***	37,639
Pattaranivate (middle-income)	67,382	*	36,423	62,957	*	36,901
Ruamjairuk (low-income)	15,008		35,232	31,602		34,020
Promsumrit (low-income)	-841		32,287	14,176		31,160
Saraneepark (middle-income)	109,814	***	34,794	109,661	***	35,061
Chudapa (middle-income)	58,885		59,555	49,067		60,176
Suksombun (low-income)	-1,047		30,878	11,359		30,572
PhinicPark (middle-income)	-22,283		32,059	-10,978		32,168
Phapinjad (middle-income)	33		34,626	-812		34,773
Constant	-1,470		31,819	18,451		29,540
R^2		0.433			0.444	
Adj R^2		0.412			0.424	
Obs		469			469	

1.6 Discussion

The estimates of household economic losses presented in this paper are valuable as one of many inputs needed to undertake an integrated water resources assessment of flood control strategies for Bangkok. The estimates themselves are not sufficient grounds on which to base policy recommendations. However, our results do suggest some policy alternatives should be the focus of more serious analysis.

First, from the household's perspective, the top priority of the State should be to save lives. This is true not only on moral grounds, but on economic grounds as well. Two people in our sample households lost their lives in the flood. If we had assigned a monetary value to these two deaths using an estimate of the value of a statistical life estimated for Bangkok, the economic value of this mortality loss would be more than the estimated total household costs for the entire sample of 469 households. Saving more lives would also appear to be relatively straightforward and cheap (cutting off electricity to flooded areas more quickly). This finding also suggests that it might be useful to design an insurance product that offered protection against both against loss of life and property losses.

Second, also from a flood insurance perspective, there would appear to be a greater need for catastrophic insurance than for insurance against the smaller losses experienced by most households in our sample. Our results show that many households even in the most severely flooded parts of Bangkok suffered what are best described as moderate, but not catastrophic losses. Based on these results, catastrophic insurance should be relatively cheap because even in such a severe event as the 2011 flood, few people suffered catastrophic losses. Insurance providers that offer households products to insure against such catastrophic losses would have to carefully protect themselves against the moral hazard that households would not take sufficient care *ex ante* to minimize losses if they had catastrophic insurance. However, this is a well-understood problem for the insurance industry, and copayments and coverage caps should provide adequate protection.

The findings also bring into sharper focus other important policy questions that we cannot yet answer based solely on the estimates of household economic losses. For example, if the policy focus is on protecting residential areas, should the Government of Thailand put more emphasis on structural or nonstructural flood control strategies? Conventional wisdom holds that flood-warning systems are among the most cost-effective nonstructural options to reduce flood losses. Having more time to react to the evolving flood situation probably would have helped some households reduce their economic losses, but receiving the information contained in a provincial-level flood warning did not seem to matter much to the households in our sample.

Although almost everyone in Bangkok knew the flood was coming, it was challenging for people to assess the conflicting information coming from different sources and to determine what the likely consequences of the flood would be for them. Despite the massive news coverage, many people in the neighborhoods we studied were still caught off guard by the severity of the flood in their own neighborhood. This was partially due to the content of the information obtained from the media, which often was not of much practical value. For example, instead of being informed about the volume of water coming, households could have benefited more from information about expected water depth, which would have enabled households to better decide whether to move cars and belongings. With better information about the depth of floodwaters to be expected, households might not have placed as much emphasis on building barriers to prevent water from coming into the house. Households could have devoted more effort to moving their belongings to higher ground.

Almost all the households in our study took preventative actions to mitigate flood losses—such as moving possessions higher—to a second story, roof, or higher ground (86%), moving vehicles (46%), and sandbagging (35%). Many of these preventative actions proved to be ineffective, and it is unclear how much households knew about the likely effectiveness of various loss prevention measures. For the few households that did not take preventative measures, some did not take action either because they did not believe their houses would be affected, or they wanted to wait and see the progression of the flood. Some people who took preventative actions did not receive explicit flood warnings at the province level. They acted based on the news coverage and common knowledge that the flood was progressing toward greater Bangkok. But even for those who did receive province-level warnings, this information did not make much difference because it turned out that there was not much they could do to reduce property losses, with the exception of those who moved their cars out of the area and moved their possession to higher grounds.

Even though members of many households evacuated their homes, our findings show that many people did not do so immediately after the floodwaters arrived. Thus, these members were at risk of electrocution and other flood-related accidents and diseases. Even after people evacuated, many returned often to their homes before the floodwaters receded to check on their belongings. Short animations broadcast on television tended to fill information gaps left by government sources. These animated service announcements provided instruction on how to keep safe, to lower health risk, and how to cope with flood waters if people did not want to evacuate.

For residents in our study areas who survived, the 2011 flood was a traumatic event, one that people will remember all their lives. But for the vast majority of these households, the economic losses they incurred should not be characterized as “catastrophic.” Our findings from three of the most severely affected neighborhoods of greater Bangkok show that median household economic losses were about THB 95,138 (US$3089). Economic costs were higher for middle-income households than for poor households because they had more property at risk, and somewhat higher for residents in Bang Bua Thong where people had little warning before the floodwaters rose rapidly in their neighborhood and were especially deep. However, economic costs as a percentage of annual household expenditures were similar between poor and non-poor households (53% and 48%, respectively).

The median household economic cost was equal to about 6 months of self-reported household expenditures (and about 3 months of self-reported household income), a large loss to be sure, but probably not a life-changing economic event. For most households, recovery efforts began quickly. Households had to pay for cleaning their homes and making minor repairs, but most homes were constructed of concrete or simple wood frames, neither of which suffered permanent structural damage. Repair and rehabilitation costs to houses were about 2% of the self-reported market value of the house. Very few households experienced morbidity losses, and for those that did, the economic value of the losses was very low (less than 1% of median household economic costs).

Our findings of household economic losses are approximately 2–5 times higher than the estimates of the World Bank (2012), depending on the province (Table 1.7). This is largely due to two reasons. First, our estimates included cost components that were not included in the World Bank study. The World Bank conducted a rapid assessment of all sectors that did not make use of household surveys. The World Bank team estimated housing damage based on the number of dwellings that were likely inundated, based on flood maps. To estimate cost of damage to buildings, representative costs were determined by type of housing (based on construction materials, number of floors). On the other hand, our estimates included both direct and indirect costs before, during, and after the flood. We also captured more recovery costs by conducting the second-round, follow-up survey 1 year after the floodwater receded. Second, our study focused on households in three of the most severely affected areas of the Greater Bangkok Metropolitan area where losses were clearly higher.

Table 1.7 Mean Household Damages, Comparison of Study Results to World Bank (2012) Estimates

	Housing Damage	Content Damage	Shelter	Prevention	Other (e.g. repair time, foregone income, health cost)	Total (THB)	Total (US$)
World Bank Estimates							
Bangkok	2,565	19,486	17,276	N/A	N/A	40,336	1,310
Nonthaburi	3,240	19,686	19,455	N/A	N/A	43,399	1,409
Pathum Thani	4,701	19,448	22,023	N/A	N/A	47,179	1,532
EEPSEA Estimates							
Bangkok (Don Muang)	136,387		3,770	11,441	37,120	203,222	6,598
Nonthaburi (Bang Bua Thong)	99,704		3,780	5,861	47,733	182,864	5,937
Pathum Thani (Klong Luang)	41,342		731	7,707	45,392	108,753	3,531

Our analysis of the composition of the total household economic costs revealed that about 5% of the total household economic costs were incurred before the flood, 27% during the flood, and 66% after the flood. This does not necessarily mean that preventative expenditures were too low; indeed, as noted, many of the preventative expenditures undertaken seem to have been ineffective. But it does point to the need for government policy to focus on the importance of evaluating alternative policies to reduce households' *ex post* economic costs. Very few households in our sample had any kind of flood insurance. Despite the difficulty of assessing risks of future flooding and the moral hazards of encouraging development in flood-prone areas, there would seem to be an important role for government to facilitate the development a market for catastrophic flood insurance for households.

Finally, this paper demonstrates that it is practical and feasible to collect microeconomic data from households affected by floods using in-person interviews. Such microlevel data yield a much clearer and comprehensive picture of household floods costs.

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CHAPTER 2: INFORMING MITIGATION OF DISASTER LOSS THROUGH SOCIAL MEDIA: EVIDENCE FROM THAILAND [2]

2.1 Introduction

2.1.1 Overview

This paper is the first to investigate the role of online information and social media in enabling households to reduce natural disaster losses. The historic 2011 Bangkok flood is utilized as a case study to assess how internet use allowed households to mitigate flood losses. This event was one of the first major disasters to affect an urban area with a substantial population connected to social media. The role of online information is investigated with a mixed methods approach, using both quantitative (propensity score matching and multivariate regression analysis) and qualitative (in-depth interviews) techniques. The study relies on two data sources – survey responses from 469 Bangkok households and in-depth interviews with twenty-three internet users who are a subset of the survey participants.

Propensity score matching indicates that social media use enabled households to reduce mean total losses by 37%, using a nearest neighbor estimator. Average loss reductions amounted to US$ 3,708 to US$ 4,886, depending on the matching estimator. These reductions are in relation to comparable households (i.e. those who are well-educated, higher-income, and have multi-story houses), rather than the general population. In addition, regression analysis suggests

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that social media use is associated with lower flood losses (average reduction of US$ 2,743). These reductions are notable when considering that total flood losses in 2011 averaged US$ 4,903. Social media offered information that was not available from other sources, such as localized and nearly real-time updates of flood location and depth. With knowledge of current flood conditions, Bangkok households could move belongings to higher ground before floodwaters arrived. These findings suggest that utilizing social media users as sensors could better inform populations during natural disasters, particularly in locations that lack real-time, accurate flood monitoring networks. Therefore, expanded access to the internet and social media could especially be useful in developing countries, ungauged basins, and highly complex urban environments. Overall, the study reveals that online information can enable effective disaster preparedness and reduce flood losses.

2.1.2 Motivation

When confronted with natural disasters, individuals around the world increasingly use online resources to inform themselves of forecasted conditions and advisable actions. In particular, websites that facilitate interaction among users are becoming common sources of disaster information. The emergence of Web 2.0 applications, such as social media, has fundamentally altered how the internet is used globally. Social media sites enable users to create and share content. Through social media, users can access information that is continuously updated and interactive. However, ensuring accuracy remains a challenge.

This paper uses the historic 2011 Bangkok flood as a case study to assess how internet activity allowed households to mitigate losses. This event represents one of the first major floods in the 21st century to affect a megacity with an online population. Low-lying megacities present new challenges for flood control since massive evacuations are practically impossible with present transportation infrastructure. While evacuations of entire megacities are infeasible, information can play a vital role in allowing people to take effective actions to reduce flood losses. Social media is a key focus of this study and the 2011 Bangkok flood is one of the first major disasters to affect a substantial population connected to social media. Nearly one-quarter of the Thailand's population had internet access in 2011 and 61% of internet users actively used Facebook (World Bank, 2014; We Are Social, 2012). When Hurricane Katrina struck New Orleans in 2005, Facebook was not available to the general public and Twitter was undergoing beta testing. Therefore, the case of Bangkok represents an important research opportunity to identify if and how online activity can inform disaster preparation and recovery.

The 2011 flood event unfolded slowly, taking several weeks to reach its maximum extent in the Bangkok Metropolitan Area. As the flood progressed, government sources could not predict the path and timing of the flood through the urban environment with much precision or lead time. A complex network of canals and dikes winds through the Bangkok Metropolitan Area, making predictions about the precise timing of floodwaters in specific neighborhoods difficult. Social media offered households different types of information not provided by government or other traditional information sources. For example, social media offers the ability to communicate and share information with one's extended social circle. This information may have allowed households to understand the progression of the flood through the metropolitan area. In addition, households would have the ability to share ideas and advice for mitigation actions via social media, which may have allowed households to better prepare.

No previous study has investigated the role of online information in reducing natural disaster losses. Yet, social media may offer enormous potential to improve disaster communication, save lives, and reduce disaster losses. Worldwide, social media has an immense presence with over one billion users on Facebook and 500 million users on Twitter (WebCertain, 2012). Disaster management agencies are beginning to establish a presence on these networks. Understanding the effect of social media information on flood losses could allow governments to better select channels to disseminate disaster messages. For example, the U.S. Federal Emergency Management Agency is testing the use of social media for distributing emergency updates.

This study assesses if and how online information can enable households to reduce losses due to flooding. The types of flood losses that are the focus of this study are those borne during and after flooding, rather than costs of preventative actions. Insights into whether online information, particularly social media, can allow households to reduce flood losses would have broad implications for incorporating Web 2.0 applications into disaster management efforts.

To explore the role of online information in mitigation of flood loss, a mixed methods approach was employed, making use of both quantitative (propensity score matching and multivariate regression analysis) and qualitative (in-depth interviews) techniques. The study relies on two data sources – survey responses from 469 Bangkok households and in-depth interviews with 23 internet users who are a subset of the survey participants. Propensity score matching (PSM) is used to test for evidence of a causal relationship between social media and flood losses. Regression analysis of survey responses identifies possible associations between online activity and flood losses as well as before flood mitigation actions. In-depth, qualitative interviews complement the quantitative analysis, and provide explanations for statistical associations. In-depth interview responses provide further understanding of how households used online information before, during, and after the flood

The paper is organized into the following sections. The next, second section of the paper provides background on internet use in Thailand and the 2011 flood. The third section presents a description of study sites and fieldwork procedures, followed by the analysis strategy in the fourth section. The fifth section presents results and the sixth section offers concluding observations.

2.2 Background

2.2.1 Natural Disasters and Web 2.0

During natural disasters, information on the Web 2.0 may offer advantages over long-established information sources such as television, radio, and print media. Advantages include (i) search functions, (ii) real-time updates and ability to establish chronological records of information, and (iii) self-publishing capability and widespread distribution through social media. One key feature of online information is its ability to be searched. Internet searches allow users to quickly find relevant information. In contrast, traditional media such as television, radio, and newspaper require recipients to sift through a considerable amount of information that is not necessarily relevant for them. Search capabilities exist both within social media sites and for the World Wide Web. During natural disasters, search capabilities may allow users to find relevant information necessary to make informed decisions regarding mitigation and evacuation decisions.

Social media offers advantages beyond conventional uses of internet. A key advantage of social media is the ability to self-publish and rapidly distribute information through established social networks. Social media sites offer information that might not be available elsewhere since users can collectively create and share content among their networks. In addition, these sites offer a powerful way for messages to reach large audiences in a short timeframe. In some cases, social media can distribute news updates faster than traditional media or government sources (Guan and Chen, 2014). For example, social media users can report earthquakes faster than current U.S. Geological Survey procedures are able to, which was illustrated during the 2008 earthquakes in China (Earle et al., 2010). Furthermore, social network sites can facilitate widespread reach of messages through vast networks of users. This is possible since messages travel via electronic word-of-mouth (Betsch et al., 2012). A notable feature of social media sites is that users receive messages from those who they know and trust. Therefore, messages distributed via these sites may have a larger impact than information from traditional news sources since known and trusted sources are more likely to influence beliefs and behavior (Betsch et al., 2012).

Social media also offers content that would be difficult to obtain from other sources. This content includes first-hand accounts from laypeople, which can provide highly localized and timely information. In a disaster situation, reports from users across a geographical area can present a dynamic view of real-time disaster conditions. For example, during the 2007 California wildfires, social media users were able to gather and share localized information about affected areas, which was not adequately provided by traditional news sources (Sutton et al., 2008). Social media allows individuals and organizations to self-publish and therefore bypass traditional gatekeepers of information.

Drawbacks to user-generated content on Web 2.0 application include the possibility of inaccurate or incomplete information (Witteman and Zikmund-Fischer, 2012). Users can easily share information without the oversight of an information gatekeeper. Substantial misinformation abounds on the internet. A challenge for Web 2.0 applications is ensuring accuracy. During natural disasters, reliance on online information could be a drawback due to the vulnerability of internet connections to outages (Laituri and Kodrich, 2008). However, this could change with the spread of mobile devices. Unlike internet service provided via cable or fixed telephone lines, mobile devices can access the internet even during electricity outages if they are able to charge their batteries in advance.[3] Thus, mobile internet access could offer an opportunity to improve natural disaster communication and relief efforts.

Most of the past literature on natural disasters and Web 2.0 applications is limited to descriptions of online activity during an event. Numerous studies have described the types of online information sought and/or the popularity of disaster-related internet searches. Descriptive studies of social media use during disasters have been conducted for floods (Kongthon et al., 2012; Vieweg et al., 2010), earthquakes (Earle et al., 2010), wildfires (Vieweg et al., 2010), hurricanes and typhoons (Chan and Schofer, 2014; Hughes and Palen, 2009; Marcias et al., 2009), and tsunamis (Acar and Muraki, 2011). In other contexts, more rigorous studies have observed how online activity responds to air quality forecasts (Aldy and Bind, 2014) and cigarette taxes (Ayers et al., 2011).

A growing literature has also assessed whether information on social media during an event can reliably describe disaster impacts (Guan and Chen, 2014; Hughes and Palen, 2009). If the post-disaster situation can be accurately assessed via social media content, then this could inform disaster and recovery efforts. The role of Web 2.0 in disaster relief and recovery has also been described in case studies on the Haiti earthquake (Holguıín-Veras et al., 2012; Harvard Humanitarian Initiative, 2011; Zook et al., 2010), Deepwater Horizon oil spill (Sutton et al., 2013), and 2010 Taiwan typhoon (Huang et al., 2010).

[3]Many mobile phone stations have backup power (e.g. battery or generator) or service providers can deploy moveable, temporary stations in disaster situations (Reardon, 2011).

No studies have addressed how online information may influence natural disaster mitigation actions and losses. Within the public health literature, studies have also analyzed how online information might influence individual decisions, such as preparedness for the 2001 anthrax scare (Kittler et al., 2004) and vaccinations (Betsch et al., 2012; McRee et al., 2012). In the case of vaccinations, social media appears to have facilitated the wide distribution of anti-vaccination messages (Betsch et al., 2012). No study collected behavior or action outcomes from individuals, with the exception of Kittler et al. (2004).[4] This current study represents the first to use a rich dataset of household-level observations to understand the effect of online information on flood losses. It is an improvement over past studies because it goes beyond a description of online activity during the 2011 Bangkok flood and utilizes in-person interviews.

2.2.2 Overview of 2011Thailand Flood

The historic Thailand flood in 2011 is the world's most costly flooding disaster in terms of insured losses (Orie and Stahel 2013). More than four months of flooding claimed over 680 lives and caused massive disruptions to industry. The disastrous flood was largely caused by extremely high rainfall. In the three months before the flood, Thailand had its highest amount recorded since records began in 1901 (World Bank, 2012). The flood began in northern Thailand, in the upper reaches of the Chao Phraya River basin and eventually reached Bangkok. The Chao Phraya River basin is the major river system of Thailand, draining nearly a third of the country's land surface. Bangkok is located at the end of the Chao Phraya River, before it empties into the Gulf of Thailand. Bangkok is a megacity built on top of a river delta, has flat topography, and the land surface is subsiding. Thus, the greater metropolitan area is susceptible

[4]This study on the 2001 anthrax scare conducted a mail survey (n=209) and found that many of the respondents who sought anthrax-related information online (n=44) reported to handle mail differently (n=26) and wash hands more often (n=29). Kittler et al (2004) did not address social media sites since they were not widespread in 2001.

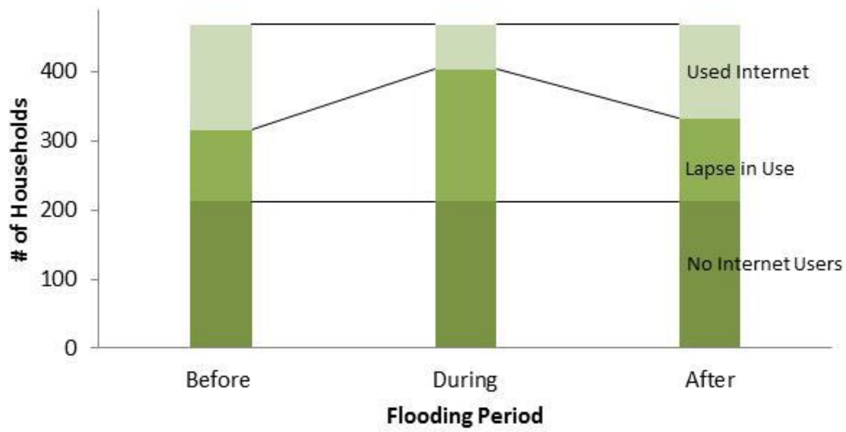
to flooding. In the future, flood risk is expected to rise due to land subsidence and increased precipitation resulting from climate change (Shah, 2011).

2.2.3 Internet Use during the 2011 Thailand Flood

Thailand's population is well-connected to the internet and social media, given the country's level of development. At the time of the 2011 flood, nearly one-quarter of Thailand's population had access to the internet (World Bank, 2014). The rapid rise of mobile-broadband (i.e. smartphones) offers a large possibility of bringing even more individuals online. While few Thais had smartphones in 2011, subscriptions dramatically rose to 35 million in 2013, covering over half the country's population (Webcertain, 2014). In addition, social media is popular in Thailand, with 61% of internet users in 2011 being active Facebook users, i.e. accessing Facebook in the past month (We Are Social, 2012).

Social media allowed Bangkok households to share updates regarding progression of floodwaters through the city and to share advice on how to prepare, cope, and recover from flooding. Nearly 40% of flood-related messages on Twitter during the 2011 flood were related to updates of flood conditions including water level, road conditions, and warnings (Kongthon et al., 2012). Social media was an alternative to official government or media sources. Over the course of the flood, internet usage changed considerably among study households, as shown in Figure 2.1. Internet use was highest before floodwaters arrived to a respondent's neighborhood, with 33% of study households using the internet. Once floodwaters inundated a household's neighborhood, internet use decreased dramatically and only 14% of households accessed the internet at this time. After floodwater receded, internet use recovered to nearly pre-flood levels (29%).

Figure 2.1 Household internet use, by period of flooding



2.3 Description of Study Site and Fieldwork

The study includes three provinces located in the Bangkok Metropolitan Area – Nonthaburi, Pathum Thani, and Bangkok. One district within each of the three provinces was purposively selected – Bang Bua Thong District (Nonthaburi), Klong Luang District (Pathum Thani), and Don Mueang District (Bangkok). These districts were among the most severely affected during the 2011 flood. Within each of the three districts, two middle-income and two low-income neighborhoods were purposively selected.

Information regarding internet use during the 2011 Thailand flood was collected by a household survey and in-depth interviews with internet users. A summary of the study design is presented in Figure 2.2. All interviews were conducted at respondents' homes. The survey involved two rounds of questionnaires with 469 households. The survey inquired about economic costs incurred during the 2011 flood, socioeconomic status, and flood-related online activity. During the second round, respondents were asked about their general internet use and flood-related online activity in 2011. Questions were related to specific information that respondents found online before, during, and after the flood. Questions were selected and designed based on in-depth interviews with internet users and pilot interviews. One member from each household provided survey responses.[5] A full description of fieldwork procedures for the two survey rounds can be found in Nabangchang et al. (2015). Informed consent was obtained from all respondents and survey protocols were approved by the institutional review board of the University of North Carolina at Chapel Hill.

In addition to the two rounds of household surveys, in-depth qualitative interviews were conducted with 23 households who were *social media* households (12 respondents) or *conventional internet* households (11 respondents). These 23 households are a subset of the full survey sample of 469 households. In-depth interview respondents were selected to represent a broad range of wealth and age groups. In-depth interviews were conducted in person during December 2012, just before the second round household survey. Interviews of approximately 30-35 minutes were conducted with a household member over the age of 18 years who sought online information related to the 2011 flood. The purpose of the in-depth interviews was to explore alternative explanations for how internet use may have influenced household decisions and actions during various stages of flooding. During these interviews, respondents described what types of information they sought online before, during, and after the flooding event. Respondents also discussed whether the information was useful for taking preventative measures, coping with the flood, or post-flood recovery and repairs. Interviews were semi-structured, with several open-ended questions designed to guide discussion.

[5]The household member interviewed may or may not have been an internet user. Detailed questions were asked about all internet users in the household, including the user's age and typical time spent online. If a household had at least one internet user over the age of 15 years, but this was not the respondent, the household was categorized as having at least one internet user. During a flooding event, it is conceivable that actions are decided with input from multiple household members since preparation, coping, and recovery actions would affect the entire household. Therefore, responses discussed in this study describe household information seeking behavior during the course of the 2011 flood.

Figure 2.2 Summary of Study Design

2.4 Analysis and Modeling Strategy

A mixed methods approach is used to assess the role of online information in mitigation of flood loss. Both quantitative (propensity score matching and multivariate regression analysis) and qualitative (in-depth interviews) techniques are employed. These analyses test the hypothesis that online activity allowed households to reduce flood losses by informing mitigation decisions before the flood.

Regression analysis of household survey data can indicate if a statistically significant association exists between flood losses and social media and/or conventional internet use. Regressions are also used to assess possible associations between online activity and the likelihood of taking mitigation actions before the flood. Both the regression analysis and PSM focus on online information sought before flooding occurred. This allows temporal precedence of online information to be established. If the analyses included losses during and after flooding, then endogeneity concerns would arise. In this case, it could be conceivable that online activity was influenced by the extent to which a household was affected by flooding. Households who are less affected by the flood could conceivably be more likely to have stable internet access or have more time to seek online information during and after the flood. This study also address endogeneity by focusing on online activity specifically related to the 2011 flood. The analysis does not simply relate general online activity to flood losses.

Propensity score matching is used to test whether the relationship between online activity and flood losses is causal. PSM assesses the influence of social media on flood losses. PSM allows households that followed flood information on social media to be matched with households without flood-related social media use. This matching is done in such in a way that balances observable characteristics between these two groups. Differences in flood losses between households with social media use and the matched comparison group will represent the effect of social media use.

In-depth interviews complement the quantitative analysis. Responses from internet users allow possible explanations to be identified for any statistically significant associations found in the regression analysis and any significant treatment effects found with PSM techniques.

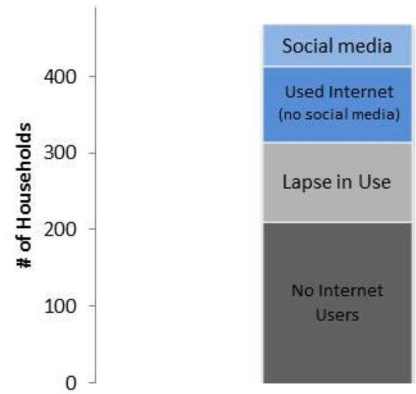
2.4.1 Definitions of Flood Information Sources

Before floodwaters entered the Bangkok Metropolitan Area, households sought information from a variety of sources. This study focuses on two sources of information – social media and other types of online information. Households that followed flood information on social media are referred to as *social media* households. Meanwhile, those who found online information on sites other than social media are referred to as *conventional internet* households. These categories are based on the characteristics of the household and not the individual respondent. For example, if a household member (not necessarily the respondent) followed flood information on social media, such a household would be categorized as a *social media* household. About 12% of the sample (55 households) followed flood-related information on social media such as Facebook and Twitter. Meanwhile, 21% of surveyed households found information from conventional internet sources, as presented in Table 2.1. Internet use was quite prevalent among sample households – about 55% had at least one internet user. Households without an internet user are categorized as a sub-category of offline information, *no internet users in household*.

The vast majority of households in this study (67%) relied on offline sources of information before the flood, such as television, government announcements, and neighborhood committees. Households relying on offline sources of information were not necessary unfamiliar with the internet. Nearly one-third of households relying on offline information sources before the flood had at least one internet user. However, since there was a lapse in internet use and no online flood information was sought before the flood, these households are categorized as relying on offline sources.

Table 2.1 Categories of Flood Information Source (Before flood)

	# of households	% of sample
Social media	55	12%
Conventional internet (no social media)	98	21%
Offline information only	316	67%
Internet users in household (lapse in internet use before flood)	*105*	*22%*
No internet users in household	*211*	*45%*



2.4.2 Definitions of Flood Losses

In this study, the term 'losses' includes all economic costs incurred during the flooding event and after floodwaters recede. During a flood, households incur a variety of losses related to emergency supplies, evacuation, travel, foregone income, and health. In order to cope with the flood situation and continue living in a house that is partially flooded, a household can make expenditures on emergency supplies such as water storage, food preparation, boats, and plastic boots. A household may choose to evacuate and thus incur the cost of alternate accommodation. In order to travel within a flooded city, households incur additional travel expenditures and time, particularly where inundated streets require boat transport. During exposure to floodwaters, flood-related illness could cause some household members to seek medical care and/or require time away from work for care takers. Households could also lose income if flooding prevents them from working.

After flood waters recede, households bear losses as they clean, repair, and replace property. These *ex post* losses are incurred in the form of expenditures and time. Motor vehicles damaged by flooding may need to be repaired or scrapped. In addition, housing structure (e.g.

house exterior and interior, utilities) and contents (e.g. furniture and appliances) may require cleaning, repair, or replacement. In this study, the loss categories of particular interest are (i) total flood loss, (ii) during flood loss, and (iii) *ex post* flood loss. The analysis does not focus on costs of preventative actions. Excluding preventative costs allows the analysis to establish the online information was sought before the household incurred flood-related costs (i.e. temporal precedence).[6]

2.4.3 Propensity Score Matching

Propensity score matching is used to determine if a causal relationship exists between social media and flood loss reduction. PSM addresses the issue of non-random assignment by identifying a suitable subset of untreated households to be compared with those who received treatment. PSM provides a useful alternative to an experimental research design, particularly for settings such as a post-disaster situation where experiments would be not be feasible and/or ethical to implement.

With estimated propensity score values, a comparison group is selected among households that did not use social media to follow flood-related information (*n=414*). A key assumption of PSM is selection on observables (i.e. outcomes are independent of treatment conditional on a set of observable characteristics). Therefore, from the possible pool of 414 households that did not use social media prior to the flood, PSM will be used to select a comparison group that has a similar distribution of observed variables as the distribution in the

[6]If preventative costs were to be included, it would be unclear which event occurred first – online information seeking or preventative actions. The survey inquired about household actions during three broad phases of the flood event – before, during, and after flooding. Information on exact calendar dates of specific preventative actions and online activity was not collected.

treated group.[7] With an appropriate matched comparison group, an average treatment effect can be estimated.

One limitation of the PSM methodology in this study is that a binary indicator is used for treatment. Households are either defined as using social media before the flood or not. Characteristics of use are not accounted for, such as time spent on social media, specific sites used, and number of contacts. Usefulness may vary across sites, although nearly all social media users in this study relied on Facebook. Overall, the treatment likely is not uniform across *social media* households.

PSM Methodology

Estimation of the average treatment effect on the treated (ATT) is done in three steps. First, the probability of using social media prior to the flood is estimated, which produces balancing scores for each household. Second, these balancing scores are used to identify a suitable comparison group from the 414 households that did not use social media to follow flood-related information prior to flooding. The mean differences in flood losses are compared between *social media* households and the comparison group. Third, regression of flood losses on key covariates is done to estimate treatment effects, using the matched sample.

Estimation of Balancing Score

A logit regression model estimates balancing scores that represent the probability of using social media prior to flooding. Balancing scores are used to identify a region of common support in which score values overlap between *social media* and comparison households. The

[7]Possible limitations of the study concern selection bias associated with the decision to use social media. A strength of applying PSM methodology to the context of a natural disaster is that the treatment period is relatively short, therefore the concern is relatively low for selection bias attributable to attrition. In the case of the 2011 Bangkok flood, households tended to access online information only days to several weeks before floodwaters inundated their communities.

model estimates the probability of a household using social media before the flood, *P(T)*, as a function of control variables (X_i) that include annual household expenditure, number of cars owned, number of household members, size of property, indicator for one-story building, indicator for low-income neighborhood, and characteristics of survey respondent (age, education level, marriage status). The model is run with standard errors clustered by neighborhood.

$$Prob(T = 1|x) = \frac{1}{1 + e^{-(\beta_0 + \beta_i X_i)}} \tag{2.1}$$

Matching Techniques

Matching methods use balancing scores to identify suitable comparison households. Once a comparison group is established, mean differences in flood losses are compared between treatment and control groups. The ATT is estimated using the matched sample to run post-PSM regression of the outcome on covariates. In this study, several matching methods are used – nearest neighbor and kernel matching. The nearest neighbor estimator (without replacement) matches one comparison household to one treatment household. If there is no match for a given treatment or comparison household, then that household is excluded from the analysis. The kernel method matches treated households to a weighted average of comparison households. This study uses a normal kernel weight, so all comparison households with balancing scores inside the common support region are used.

Post-PSM Regression to Estimate Treatment Effect

Lastly, the ATT is estimated using the matched sample to run post-PSM regression of the outcome on covariates. This approach further controls for differences in covariates between treatment and comparison groups that are associated with flood losses, but not necessarily the likelihood of using social media. The linear regression model is specified as:

$$Total\ flood\ loss = \beta_0 + \beta_1\, social + \beta_2 depth + \gamma_k X_k + \omega_m V_m + \varepsilon \tag{2.2}$$

where $Total\ flood\ loss$ = Total flood loss, incurred during and after the flood
$social$ = dummy variable equal to 1 if household followed flood-related information on social media prior to flooding
depth = depth of flood water (on street in front of house)
X_k = household or personal characteristic k (e.g. annual expenditure, number of cars owned, education, age)
V_m = neighborhood controls

Probability weights (equal to the inverse of the probability that a household is selected into the matched sample) are included in the post-PSM regression with the matched sample identified via the kernel estimator.

2.4.4 Regression Analysis: Flood Losses and Online Information

Modeling Strategy: Types of online information associated with flood losses

Regression analysis is used to estimate the association between flood losses and the source of information households relied on before the 2011 flood. Information sources are defined as media, conventional internet sites, and offline. The full sample of 469 households is included and the analysis focuses on two types of flood-related information – social media and conventional online information. In order to assess the association between flood losses and the source of flood-related information, the following OLS model was specified:

$$Flood\ loss_i = \beta_0 + \beta_j\, info\ source_j + \beta_2 depth + \gamma_k X_k + \omega_m V_m + \varepsilon \tag{2.3}$$

where $Flood\ loss_i$ = flood loss, category *i* (e.g. total loss; house and contents)
$info\ source_j$ = flood information source *j* (e.g. social media, conventional internet, or offline source)
depth = depth of flood water (on street in front of house)
X_k = household or personal characteristic k (e.g. annual expenditure, cars owned, age composition of household members, education, one-story house)
V_m = neighborhood controls

Three models are specified using the above equation. One model (Model 3a) is used to estimate the association between total flood losses and information source (i.e. social media, conventional internet, or offline). By estimating separate associations for social media and conventional internet, the analysis can assess whether households benefit from each of these two information sources. The other two (Models 3b,3c) focus on the association of social media and a variety of flood loss categories, compared to any other source of information (i.e. conventional internet or offline). The association between flood losses and online activity (both social media and conventional internet use) is expected to be negative. More informed households should be better able to prepare and cope with the flood.

Modeling Strategy: Types of online information associated with mitigation actions

Additional regression analysis examines how online flood information may have been useful for households. A binary maximum likelihood estimation model is specified in order to determine if online information is associated with a greater likelihood of moving belongings to upper floors. The model is limited to the 317 households that had multi-story houses and controls for information source and other covariates:

$$Prob\left(Move_{up} = 1 \middle| x\right) = \frac{1}{1 + e^{-(\beta_0 + \beta_j info\ source_j + \gamma_k X_k + \varepsilon)}} \tag{2.4}$$

where $Move_{up}$ = Moved contents to upper floors (dummy)
$info\ source_j$ = flood information source *j* (e.g. social media, conventional internet, or offline source)
X_k = household or personal characteristic *k* (e.g. annual expenditure, cars owned, age composition of household members, education)

The key independent variable of interest, information source, uses offline information as the referent category. It is anticipated that both social media and conventional internet will be associated with a greater likelihood of taking action (compared to offline information).

2.4.5 In-depth Interviews

In-depth interviews with s*ocial media* and *conventional internet* households complement the quantitative analysis. This mixed methods approach allows the experiences of flood-affected households to be examined in greater detail by exploring underlying processes through which internet use and flood losses are related. Interviews are analyzed with an explanation building approach, which relies on establishing initial propositions and then testing these propositions against evidence obtained from interview discussions. The initial proposition is that a relationship existed between internet use and flood losses, and that online information may have informed households regarding mitigation decisions. Evidence for and against rival explanations is compiled using summary statistics as well as tabulation of qualitative responses (both for the sample of 23 households and by type of online information source).

In this way, the qualitative analysis can determine the types of online information found, which loss-mitigating actions were informed by online information, and which mitigation actions were effective in reducing cost (as perceived by the respondent). The role that social media played in providing flood-related information to households is also examined. Detailed interview responses include the types of information that households searched for online before, during, and after the flooding event. In addition, responses contained considerable information regarding how online content was useful for taking preventative measures, coping with the flood, or post-flood recovery and repairs.

In order to ensure the validity of responses, in-depth interview responses were cross-checked against survey answers (each household that participated in the in-depth interview was also a respondent in the larger household survey). For example, if an in-depth interview respondent indicated that they took a mitigation action, this was checked against the recorded answer in the household survey. Overall, these interviews allow for a deeper understanding of the types of information that internet users found as well as household perception of the usefulness of online information.

2.5 Results

2.5.1 Summary Statistics

Socioeconomic profile of households

Household annual expenditures varied widely across households, ranging from the equivalent of US$ 990 to US$ 38,835, with a mean of US$ 8,459, as shown in Table 2.2. *Social media* households had significantly higher annual spending (mean: US$ 14,214) compared to both *conventional internet* households (mean: US$ 11,777) and offline households (mean: US$ 6,428), as shown in Table 2.3. The number of cars owned by a household is an additional measure of wealth. Both *social media* and *conventional internet* households owned more cars, on average, than offline households.

Respondents (the household member that provided survey responses) tended to be well-educated, with 33% completing either vocational or high school and 29% holding a university degree or higher. Respondents from *social media* and *conventional internet* households were considerably more educated than respondents from offline households. The difference in respondents with a university education is not statistically significant between *social media* (64%) and *conventional internet* households (56%). Yet, respondents from these households are much more highly educated than respondents from offline households, 14% of whom have a bachelor's degree or greater.

While wealth and education differed considerably between offline households and those who relied on online flood information (social media and conventional internet), the age distribution of household members did not. The age distribution of a household is estimated by estimating the percentage of household members that are within specified age brackets. Within the full sample, on average, 18% of household members were under the age of 18 years.[8]

[8]This proportion did not differ significantly across flood information sources. The only age category to slightly differ between sources was the bracket representing members 55 years or older. Offline households had a greater proportion of members 55 years or older (23%) than households relying on online information (18%). Yet, offline households did not have a greater proportion of members in this age bracket when compared to *social media* or *conventional internet* households separately.

Table 2.2 Summary Statistics of Regression Variables, Full Sample (n=469)

Variable	**Definition**	**Mean**	**Std Dev**	**Min**	**Max**
Total Flood Loss: During + *Ex Post*	Total losses, during and after flood (in US$)	4,903	6,069	13	48,914
During Loss	Losses incurred during flood (in US$)	1,424	2,352	0	26,470
Ex Post Loss	Losses incurred after flood (in US$)	3,479	4,911	0	34,016
Ex Post: House + Contents	House and contents losses (in US$)	3,148	4,635	0	34,016
Flood Information Source, before flood					
Social media	Dummy variable=1, if household relied on social media for flood information	0.12	0.32	0	1
Conventional internet (No Social Media)	Dummy variable=1, if household relied on online information, but not social media	0.21	0.41	0	1
Offline information only	Dummy variable=1, if household relied on offline flood information	0.67	0.47	0	1
Household Characteristics					
Annual household expenditures	Total household expenditures per year (in US$)	8,459	6,214	990	38,835
Cars owned	Number of cars owned	0.9	1.0	0	5
Age distribution of household members					
<18 years	Percentage of household members less than 18 years old	0.18	0.18	0	0.67
18-34 years	Percentage of household members 18-34 years old	0.23	0.22	0	1
35-54 years (Middle age)	Percentage of household members 35-54 years old	0.37	0.27	0	1
55+ years	Percentage of household members 55+ years old	0.21	0.25	0	1
Education Level of Respondent					
Elementary or less	Dummy variable=1, if respondent had elementary school education or less	0.38	0.49	0	1
High School or Vocational	Dummy variable=1, if respondent had high school or vocational education	0.33	0.47	0	1
College or more	Dummy variable=1, if respondent had college education or more	0.29	0.45	0	1
One-story house	Dummy variable=1, if house consists of one story	0.32	0.47	0	1
Flood depth	Maximum flood depth on street in front of house (meters)	1.5	0.4	0	3.0
Flood Loss Mitigation					
Moved contents to higher location	Dummy variable=1, if household moved contents higher	0.87	0.34	0	1
Moved contents to upper floors	Dummy variable=1, if household moved contents to upper floors or roof	0.55	0.50	0	1
Moved contents on top of furniture	Dummy variable=1, if household moved contents on top of furniture	0.32	0.47	0	1
Built barrier	Dummy variable=1, if household built a flood barrier	0.43	0.50	0	1

Table 2.3 Summary Statistics of Regression Variables, by information source category

	Social Media (n=55)					**Conventional Internet Use (n=98)**					**Offline Information (n=316)**				
Variable	**Mean**	**Std Dev**	**Min**	**Max**		**Mean**	**Std Dev**	**Min**	**Max**		**Mean**	**Std Dev**	**Min**	**Max**	
Total Flood Loss: During + *Ex Post*	6,665	6,244	780	29,180	†	8,770	9,063	413	48,419	†	3,397	3,909	13	29,463	† * ^
During Loss	1,593	3,071	16	17,240		2,270	3,768	0	26,470	†	1,132	1,385	0	12,001	† ^
Ex Post Loss	5,073	4,890	285	27,197	†	6,500	7,097	190	34,016	†	2,265	3,385	0	25,916	† * ^
Ex Post: House + Contents	4,502	3,872	0	14,576	†	5,927	6,897	60	34,016	†	2,051	3,282	0	25,916	† * ^
Household Characteristics															
Annual household expenditures	14,214	8,073	2,990	38,835	†	11,777	6,246	3,068	30,126	† *	6,428	4,564	990	36,112	† * ^
Cars owned	1.5	1.1	0	5	†	1.4	0.9	0	4	†	0.6	0.9	0	5	† * ^
Age distribution of household members															
<18 years	0.17	0.18	0	0.67		0.19	0.20	0	0.60		0.18	0.18	0	0.67	
18-34 years	0.22	0.23	0	0.67		0.23	0.21	0	1		0.24	0.22	0	1	
35-54 years (Middle age)	0.42	0.30	0	1		0.39	0.25	0	1		0.36	0.27	0	1	
55+ years	0.18	0.23	0	1		0.18	0.22	0	1		0.23	0.26	0	1	†
Education Level of Respondent															
Elementary or less	0.16	0.37	0	1	†	0.16	0.37	0	1	†	0.49	0.50	0	1	† * ^
High School or Vocational	0.20	0.40	0	1	†	0.28	0.45	0	1		0.37	0.48	0	1	† *
College or more	0.64	0.49	0	1	†	0.56	0.50	0	1	†	0.14	0.35	0	1	† * ^
One-story house	0.07	0.26	0	1	†	0.16	0.37	0	1	†	0.42	0.49	0	1	† * ^
Flood depth	1.4	0.2	0.9	2.0		1.5	0.3	0.9	2.0		1.6	0.5	0	3.0	†
Flood Loss Mitigation															
Moved contents: to higher location	0.91	0.29	0	1		0.87	0.34	0	1		0.86	0.35	0	1	
to upper floors	0.82	0.39	0	1	†	0.63	0.48	0	1	*	0.47	0.50	0	1	† * ^
on top of furniture	0.09	0.29	0	1	†	0.23	0.43	0	1	† *	0.39	0.49	0	1	† * ^
Built barrier	0.56	0.50	0	1	†	0.59	0.49	0	1	†	0.36	0.48	0	1	† * ^

Significant difference (at 5% level) between selected information category and: † full sample; * social media sample; ^ conventional internet sample

Household flood experience in 2011

Mean total flood losses amounted to THB 151,499 (US$ 4,903) for all 469 households in the survey sample.[9] Losses varied considerably across households – ranging from US$ 13 to more than US$ 48,900. *Ex post* losses (mean of US$ 3,479) tended to be greater than losses incurred during the three month duration of the flood (mean of US$ 1,424). *Ex post* losses include expenditures and value of time to clean, repair, and replace housing structure, contents, and vehicles. For the average household, *ex post* losses accounted for 71% of total losses, while during flood loses account for 29%.

Social media and *conventional internet* households experienced higher flood losses than those relying on offline sources of information. This is largely attributable to wealth – households that relied on online information had more property at risk. *Conventional internet* households have significantly higher losses for every loss category, compared to the full sample. *Social media* households have significantly higher losses compared to the full sample, with the exception of during flood losses and *ex post* vehicle losses. When comparing *social media* and *conventional internet* households, none of the loss categories differ significantly. Depth of floodwater on the street in front of a household's residence ranged from 0 to 3 meters, with a mean of 1.5 m. Neither s*ocial media* nor *conventional internet* households experienced flood depths that significantly differed from the full sample.

Mitigation actions

The majority of households took some type of mitigation action before floodwater entered their neighborhood. Moving contents to higher ground was a particularly common action, with 87% of households moving belongings to upper floors. In addition, about 50% of

[9]In October, 2012, US$ 1 = 30.9 Thai baht.

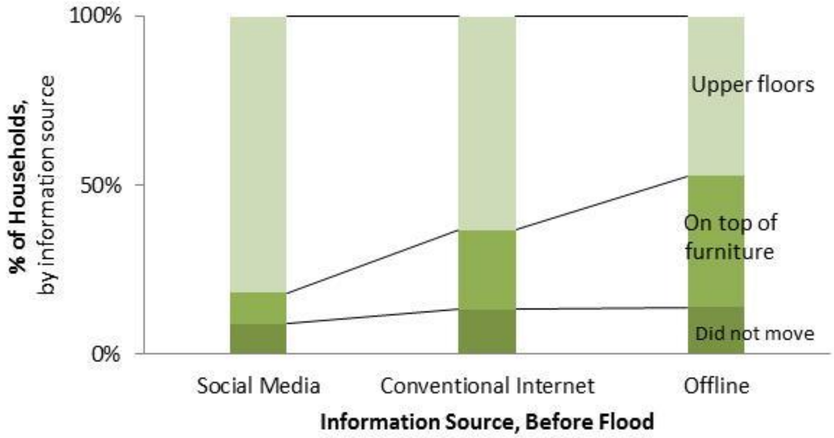
households with a car or motorcycle moved these vehicles to higher locations.[10] Constructing barriers to prevent floodwater from entering the home was a less prevalent action, with 43% of households undertaking this mitigation measure. The most common flood barrier action was sandbagging (35% of households), follow by constructing a concrete block wall (22%). Very few households (14%) believed that they built a successful barrier. A successful action is identified based on a household's survey response regarding perceived success

The types of moving contents actions that households undertook differed drastically across information sources, as shown in Figure 2.3, Panel A. Moving contents to upper floors was significantly more prevalent among *social media* households. Nearly 82% of *social media* households moved belongings to upper floors, compared to 63% of *conventional internet* households and 47% of offline households. Moving contents was perceived to be a more effective mitigation strategy by Bangkok households than building flood barriers. This seems conceivable in the case of the 2011 flood since flood barriers can fail if not properly constructed or flood depth accurately anticipated.

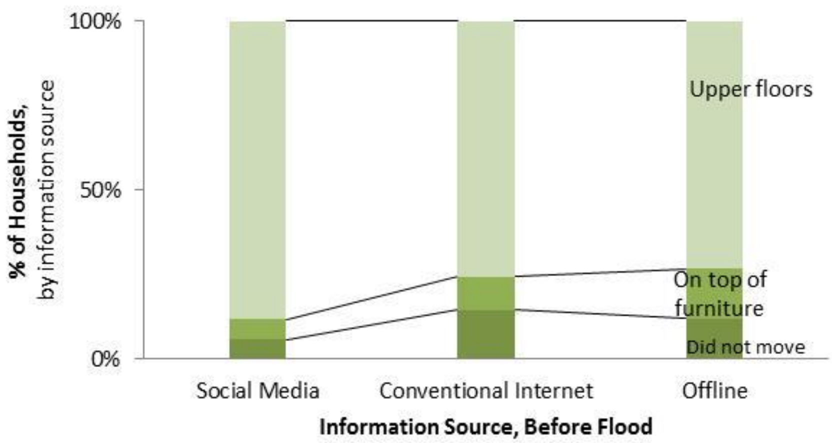
[10]*Social media* households were more likely to state that their efforts to move vehicles were successful than all other households. However, the proportion of *social media* households that incurred any vehicle loss (33% of the 54 vehicle-owning *social media* households) is not significantly different than the proportion of other households (40%). The magnitude of vehicle losses also is not significantly lower for *social media* households. Therefore, this study does not find evidence that social media use reduced vehicle losses.

Figure 2.3 Types of Moving Contents Actions, by information source

A. Full Sample



B. Households with Multi-Story Houses



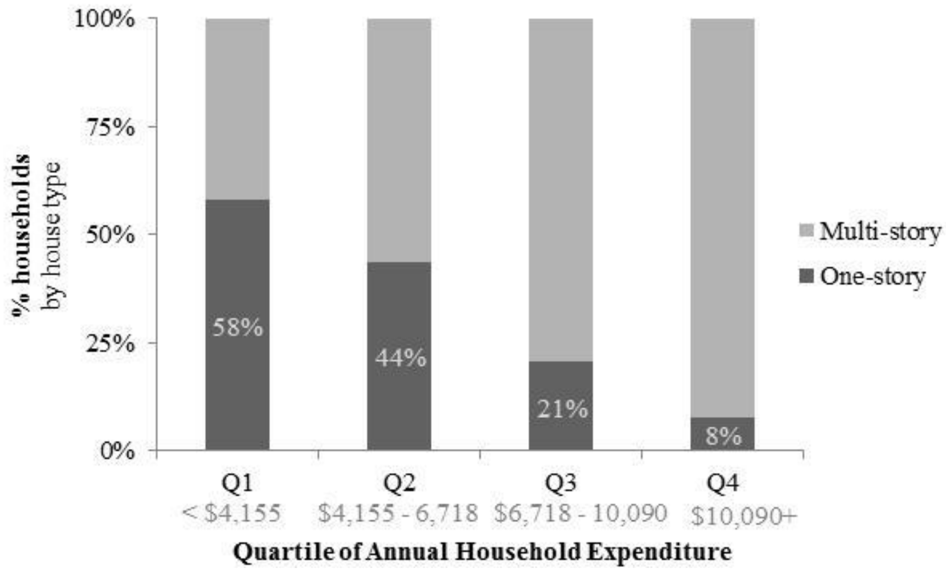
Dwelling characteristics largely determined the type of moving actions that were available to households. For example, moving contents to upper floors was only possible for those with multi-story houses. The number of floors within a house varies considerably across information source and wealth level. The proportion of one-story houses among *social media* households (7%) and *conventional internet* households (16%) is not statistically significant. However, the proportion of *offline* households with one-story houses (42%) is much greater (Figure 2.3, Panel

B). When comparing moving contents actions among households with multi-story houses, it appears that social media offered a possible advantage over offline information, while conventional internet did not. Moving contents to upper floors (given that a household had a multi-story house) was significantly more prevalent among *social media* households (88%) than of *offline* households (73%). No significant difference exists for between *conventional internet* (76%) and *offline* households (73%).[11]

Since dwelling characteristics are associated with household wealth, the types of moving actions available to households will also be partly influenced by annual expenditure. Figure 2.4 presents the proportion of households with one-story and multi-story houses by quartile of annual expenditure. As expenditure increases, so does the proportion of households with a multi-story dwelling. This suggests that wealthier households have a greater ability to mitigate flood losses by moving contents to upper floors. Therefore, if evidence is found that social media informed decisions regarding moving contents, then this result would be most relevant for wealthier households.

[11]Furthermore, only a weakly significant difference (10% confidence level) exists between *social media* with multi-story houses that moved contents to upper floors (88%) and *conventional internet* (76%).

Figure 2.4 Number of stories in dwelling, by expenditure quartile



Internet users in household

Internet use is more prevalent among sample households than in Thailand as a whole. About 55% of sample households (257 out of 469 total households) had at least one internet user, compared to about 30% of the total Thai population (WebCertain, 2012). Many households had multiple internet users and overall, there were 499 internet users in the sample over the age of 15 years. Before the 2011 flood, 33% of survey households found flood-related information online (12% of survey households used social media, while 21% relied on conventional internet sources). Online flood information was considered useful by many households. About 24% of households considered online flood information to be useful. This means that 74% of households that sought online flood information considered it to be useful. A significantly greater proportion of *social media* households (87%) considered online information to be useful, compared to conventional internet households (66%). This suggests that social media sites many have offered actionable information not available on conventional internet sites, which is examined in the quantitative and qualitative analysis.

2.5.2 Results of Propensity Score Matching

Mean Characteristics of Sample

Summary statistics of the covariates used in the logit regression to estimate balancing scores are presented in Appendix A (Table A1). Covariates are summarized for the full sample (n=469), treatment households (n=55), and all potential comparison households (n=414). Treatment households and all potential comparison households are unbalanced in every covariate. Yet, all covariates are balanced between treatment groups in the nearest neighbor matched sample (Table 2.4). Households in the matched sample have significantly higher flood losses, household expenditure, car ownership, and education than the full sample. This is to be expected since *social media* households have higher values of all these variables compared to the full sample. Thus, in order to match *social media* households with comparable control households, the matched sample will have higher values of these covariates. Table 2.4 indicates that *social media* households incurred significantly lower mean flood losses (US$ 6,594) than comparison households identified using the nearest neighbor estimator (US$ 9,961).

Key differences in household characteristics between the matched and full samples have implications for the generalizability of results. For example, one-story houses were more prevalent among the full sample (32%) than the matched sample (7%). Households in one-story dwellings were unable to move belongings to upper floors. Therefore, if social media informed actions to move contents to upper floors, then this finding would only be relevant for those with multi-story dwellings. Since one-story houses are most prevalent among households at lower quartiles of annual expenditure (Figure 2.4), this suggests that social media would not be as useful for poor households.

Table 2.4 Descriptive Statistics for Propensity Score Matching, Matched Sample

	Matched sample (N=96)				Social Media Households (N=48)				Households without social media (N=48)			
Variable	Mean	Std Dev	Min	Max	Mean	Std Dev	Min	Max	Mean	Std Dev	Min	Max
Outcome Variable												
Total Flood Losses (US$)	8,278	8,066	413	40,330	6,594	6,591	780	29,180	9,961	9,071	413	40,330 †
Household Characteristics												
Annual Household Expenditure (US$)	13,122	7,471	2,990	36,112	12,976	7,245	2,990	33,126	13,269	7,765	3,305	36,112
Cars owned (number)	1.3	1.0	0	5	1.3	1.0	0	5	1.3	1.0	0	4
Household members (number)	3.9	1.7	1	9	3.9	1.7	1	9	4.0	1.8	1	8
Size of property (sq. m)	327	177	40	880	332	190	120	880	323	165	40	800
One-story building	0.1	0.3	0	1	0.1	0.3	0	1	0.1	0.2	0	1
Low-income neighborhood	0.2	0.4	0	1	0.1	0.4	0	1	0.2	0.4	0	1
Survey Respondent Characteristics												
Age of Respondent	42.5	9.8	19	70	43.2	10.0	19	70	41.8	9.8	24	69
Married	0.8	0.4	0	1	0.8	0.4	0	1	0.8	0.4	0	1
Education level												
High School or Vocational	0.28	0.45	0	1	0.23	0.42	0	1	0.33	0.48	0	1
College or higher	0.54	0.50	0	1	0.60	0.49	0	1	0.48	0.50	0	1

† denotes significant difference at the 5% level between households with and without social media use
Matched sample is created using nearest neighbor without replacement and common support.

Balancing Score

Results of the logit model to estimate the probability of using social media before the flood are reported in Appendix A (Table A2). Covariates that are significant at the 5% confidence level are household expenditure, number of cars owned, number of household members, respondent age, and marriage status. Each coefficient has the anticipated sign. Household expenditure and number of cars owned are positively associated with using social media, while age and number of household members have a negative association.

The balancing score (the log odds ratio) is estimated from the predicted values of the logit model. Summary statistics of the balancing score are presented in Appendix A (Table A3). The area of common support is defined as below the maximum of minimum values (-4.99) and above the minimum of the maximum values (0.65) of the balancing score. Households with balancing scores outside the region of common support are not included in the matching analysis. Seven *social media* households are outside the region of common support, while 69 potential comparison households are outside. Therefore, 87% of the treatment group and 83% of the comparison group satisfy the comment support criteria.

Matched Samples and Post-Matching Regression

Each matching method used in this study allows suitable comparison households to be identified, based on the balancing scores. The two matching methods – nearest neighbor and kernel matching – select different comparison groups and result in different ATT estimates.

Nearest Neighbor Matching

Average characteristics for the sample of households matched on the balancing score estimated with nearest-neighbor matching are summarized in Table 2.4. Compared to the full sample of 469 households, the matched sample (48 *social media*, 48 comparison) has significantly higher flood losses, household expenditure, car ownership, and education. In addition, the mean age of the survey respondent in the matched sample is significantly lower than in the full sample. The mean difference in total flood losses between the 48 *social media* households and 48 comparison households is US$ 3,367. Mean total losses for *social media* households are US$ 6,594 compared to US$ 9,961 for comparison households (Table 2.5). The bootstrapped standard error indicates that this mean difference is significant at the 5% level. This mean difference is large, considering that total losses for the overall matched sample (n=96) have a mean of US$ 8,278.

A regression of total flood losses on a social media dummy and other covariates is used to estimate the ATT of social media use. This regression is restricted to the matched sample of 96 households. The ATT estimated using regression analysis is less than the mean difference calculated in the PSM analysis. This difference is attributable to the regression controlling for additional covariates, such as flood depth and neighborhood controls, which influence flood losses but not the probability of using social media. The ATT of social media use is estimated to be US$ 3,708 in the matched sample identified with the nearest-neighbor estimator. Post-PSM regression results are presented in Table 2.6.

Kernel Matching

Kernel matching produces a larger matched sample (48 *social media*, 345 comparison) than the nearest neighbor estimator. This is to be expected since the kernel matching estimator makes use of all comparison households with balancing scores inside the common support region. Treated households are matched to a weighted average of comparison households. The weighted average mean difference in total flood losses between the 48 *social media* households and 345 comparison households is US$ 4,501. This is comparable to the mean difference found with the nearest-neighbor estimator and is significant at the 5% level (*p-value*=0.031). Post-PSM regression analysis indicates that the ATT of social media is US$ 4,886 in the matched sample identified with the kernel estimator.

This estimate of ATT is lower than the estimate obtained using the nearest-neighbor matched sample. The kernel matched sample is much larger (n=393) since it includes all households that meet the common support criteria. This means that a greater variety of comparison households are included in the sample that might have lower annual expenditures, wealth, and education. Although such comparison households would receive lower weights, they are present in the matched sample.

Table 2.5 Mean Differences in Total Flood Loss (in US$), Matched Samples

	Nearest-Neighbor			**Kernel Matching**		
	N	Mean	Bootstrapped Std Error	N	Mean	Bootstrapped Std Error
Treatment	48	6,594		48	6,594	
Comparison	48	9,961		345	11,095	
Difference		-3,367	1,626		-4,501	2,074
Significance level		*5%*			*5%*	

Table 2.6 Estimation of Average Treatment Effect on the Treated (ATT): Using regression analysis and PSM Matched Samples

	Nearest-Neighbor			Kernel Matching		
	Coeff.		Robust Std Error	Coeff.		Robust Std Error
Social media (dummy)	-114,589	**	50,242	-150,966	**	58,886
Annual Household Expenditure (Thai baht)	-0.03		0.11	-0.06		0.11
Cars owned (number)	65,860	***	20,500	93,645	***	22,688
Household members (number)	56,626		60,516	88,952	*	47,492
Household members, squared	-3,288		6,377	-6,201		3,877
Size of property (sq. wah)	254		536	286		441
One-story building	91,367		101,184	154,632	**	72,066
Low-income neighborhood	-148,681		115,805	-139,027		89,521
Age of Respondent	-399		2,737	-2,880		3,116
Married	25,203		72,311	79,678		65,783
Education Level of Respondent						
High School or Vocational	27,196		59,462	-22,043		60,388
College or more	122,110	*	67,806	93,561		74,386
Flood depth (on street in front of house)	2,998	***	739	1,922	***	667
Constant	-443,784		181,357	-320,226	**	159,239
Neighborhood controls (V_m)	yes			yes		
R^2	0.474			0.508		
Obs	96			393		

* Statistically significant at the 10% level. ** Statistically significant at the 5% level. *** Statistically significant at the 1% level

Causal Relationship between Social Media and Flood Losses

The significant ATT values estimated in the PSM analysis suggest a causal relationship between social media use and reduced flood losses. Flood-related social media use enabled households to reduce flood loss by an average of US$ 3,708 (as indicated by the nearest neighbor estimator) or US$ 4,886 (kernel estimator). It should be noted that these reductions are in relation to comparable households (i.e. those who are well-educated, higher-income, and have multi-story houses), rather than the general population. In particular, findings are likely not generalizable to the many low-income households that have one-story houses. Since households residing in one-story dwellings are unable to move belongings to upper floors, this suggests that social media would not be as useful for poor households.

Balancing tests indicate that all covariates in the nearest neighbor matched sample are similar between *social media* and comparison households. The balancing tests include all variables used to estimate propensity scores (e.g. household expenditure, cars owned, respondent age and education) as well as additional observed characteristics (e.g. depth of floodwater, age distribution of household members). Balance is achieved both in the overall matched sample and within each quintile of the balancing score. Therefore, the selected comparison groups appear to be suitable. This suggests that the ATT estimates provide a credible measure of the causal effect that social media use had on flood losses.

A possible alternative explanation for social media being associated with reduced flood losses is that *social media* household may have been younger and thus had fewer assets at risk. Several pieces of evidence suggest that this alternative explanation does not hold. First, the matched sample in the PSM analysis was balanced both on respondent age and household wealth. Second, the age distribution of household members does not differ between those who did and did not rely on social media. Third, within the full sample (n=469), *social media* households tend to own assets of greater value than other households.[12]

[12] *Social media* households tend to own homes of higher value and a greater number of cars than other households. Reported home values of *social media* households (mean: US$ 96,173) were much higher than all other households (mean: US$ 49,673). Yet, when only compared with *conventional internet* households, there is no significant difference in home value.

2.5.3 Results of Regression Models

Flood Loss Model Results

The regression model used to assess the association between flood losses and online information use (Model 3a) explains much of the variation in flood losses (Table 2.7). Social media use is significantly associated with lower flood losses, while conventional internet is not. This suggests that social media offered households information that was not available to either households relying on conventional internet or offline sources. This association might be attributable to social media offering the ability to communicate and share information with one's extended social circle (i.e. connections that are secondary, tertiary, and beyond). This information could have allowed households to better understand the progression of the flood through the Bangkok Metropolitan Area.

Two additional models (Model 3b and 3c) examine the association between losses and social media, relative to any other information source (i.e. conventional internet or offline source). In Model 3b, using social media is associated with a THB 84,772 (US$ 2,743) reduction in total losses compared to relying on information from any other source. Model 3c focuses on the flood loss category of house and contents loss. There is a particularly significant association between house and contents loss and social media. Households that used social media had an average reduction in house and content loss of THB 58,271 (US$ 1,886).[13] This suggests that if social media were to be causally-related to flood loss, then this might be due to social media providing information that allowed households either to prevent loss or reduce recovery costs. Before the flood, losses could be prevented via effective mitigation actions.

[13]The additional analysis not presented in this paper, significant relationships (at the 5% level) could not be found between online information and either vehicle or during flood losses.

Social media may have allowed households to make more informed mitigation decisions, especially regarding when and how to act.

Mitigation Action Model Results

The vast majority of households took mitigation actions prior to the 2011 flood. Moving house contents to higher locations was by far the most prevalent. When moving contents located on the flood-prone ground floor, households could either move items to upper floors or place them on top of furniture or scaffolding. Moving contents to upper floors would be expected to be more effective in preventing losses than keeping items on the ground floor on top of furniture. Floodwaters were quite high (mean of 1.5 meters), which could inundate the tops of tables and counters. Upper floors would be expected to provide a more secure location for contents compared to the tops of furniture located on the ground floor.

Model 4 investigates the association between moving contents to upper floors and flood information source (Table 2.7). Results indicate that while social media use is significantly associated with a greater likelihood of moving contents (compared to offline information), conventional internet is not. *Social media* households were 19 percentage points more likely to move contents to upper floors, compared to offline households. This suggests that information on social media may have led to households deciding to move items to upper floors, if they had a second floor.

Table 2.7 Regression results for flood losses – sources of flood information

	3a			3b			3c			4		
(Dependent variable)	(Total Losses, Thai baht)			(Total Losses, Thai baht)			(House +Content Losses, Thai baht)			(Moved contents to upper floors): *Exclude One-Story Houses*		
	Coeff.		Robust Std Error	Coeff.		Robust Std Error	Coeff.		Robust Std Error	ME		Delta Std Err.
Flood Information Source [a]												
Social Media	-66,298	**	28,698	-84,772	***	29,836	-58,271	***	20,548	0.19	**	0.09
Conventional Internet (No Social Media)	38,250	*	22,885							0.03		0.05
Moved contents to upper floors												
Annual Household Expenditure (Thai baht)	0.24	***	0.07	0.25	***	0.07	0.11	**	0.06	9.1E-8		1.2E-7
Cars owned	46,364	***	11,616	47,241	***	11,814	27,631	***	8,374	-0.03		0.02
Middle age (% of household members 35-55 years old)	12,957		26,845	13,366		26,438	13,480		20,465	0.03		0.06
Education Level of Respondent												
High School or Vocational	-10,946		12,984	-9,298		12,770	1,791		7,766	0.05		0.05
College or more	49,321		31,135	56,256	*	30,516	49,495	**	20,820	0.02		0.06
Flood depth (on street in front of house)	192		140	171		137	252	*	139			
One-story house	22,223	*	12,052	20,783	*	11,923	16,771		11,314			
Constant	-50,843	*	28,194	-42,562		27,587	-58,355	*	27,180	0.76	***	0.05
Neighborhood controls (V_m)	yes			yes			yes			no		
R^2 or psuedo R^2	0.457			0.453			0.458			0.024		
Obs	469			469			469			317		

[a] Comparison group for model 3a and model 4 is offline information. The comparison group for models 3b and 3c is an information source other than social media (e.g. internet without social media, television, government announcements, neighborhood committee).

Notes: In model 4, marginal effects (ME) reported and standard errors clustered by neighborhood.

* Statistically significant at the 10% level. ** Statistically significant at the 5% level. *** Statistically significant at the 1% level

2. 5.4 Results of In-Depth Interviews

Description of Respondents and Online Activity during 2011 Flood

The twenty-three households that participated in the in-depth interviews were *social media* households (12 respondents) and *conventional internet* households (11 respondents). As expected, these households were more highly educated and wealthier than the full sample of 469 households. About 78% of the 23 in-depth interview respondents had a university degree or higher (Appendix B), compared to 29% in the full sample. In addition, average annual household expenditures for in-depth interview respondents (US$ 12,663) were nearly 50% larger than expenditures of the full sample (US$ 8,459).

During the in-depth interviews, the vast majority of respondents reported that that online information helped them to reduce flood losses (70%). Among *social media* households, 75% reported that the internet helped them to reduce losses, while 64% of *conventional internet* households stated this. Respondents who stated that information on the internet allowed them to reduce their losses appear to have found information that was relevant for their household and thus allowed them to prepare, cope, or recover from the flood. The most important types of online information that allowed households to reduce flood losses were information regarding flood progression (65% of respondents stated that this was useful in reducing losses), mitigation actions (39%), and transportation during the flood such as options for boat transport and road closures (22%). Other helpful information included repair or cleaning (13%) as well as housing and transport for evacuation (9%).

Households that sought flood information online were able to find content that was more relevant to them. During the 2011 Bangkok flood, many of the 469 households in the full survey sample spent considerable time watching television, waiting to catch the information that was relevant to their area. The internet offered the ability to search for any type of information desired by the household. The vast majority of in-depth interview respondents (70%) relied on a mix of television and internet. Some first found information online and then confirmed its credibility via television or direct observation, particularly concerning updates of water levels. Others first watched television before using the internet to search for further information. While online information did not allow every household to make more effective decisions, a majority of in-depth interview respondents perceived that the information was useful and may have allowed flood losses to be reduced.

Online information: Before the flood

Respondents tended to feel that internet use was most useful before the flood. Before flood waters arrived, internet users could follow the flood situation and locate information on mitigation actions. Social media in particular appears to have been a useful source for flood progression information. About half of in-depth interview respondents stated that they used social media to seek flood-related information. In-depth interview respondents stated that flood progression information included first-hand reports from their extended social network of where floodwaters were moving. These first-hand reports represent information that social media users had access to that other households did not. If a friend's home was flooded, social media users could be updated on the location, timing, and flood depth as floodwaters flowed through the metropolitan area. They could also determine if and to what extent flooding would occur in their neighborhood.

Respondents emphasized that information on social media was useful for knowing when and how they should prepare for the flood. Official government predictions of flood path and timing were not accurate for several areas in Greater Bangkok. For example, in study areas near

Bangkok's domestic airport, respondents mentioned that official predictions indicated that their neighborhoods would not flood, yet they eventually were inundated.

As a result of social media updates, households were able to successfully move their belongings in time. Furthermore, social media respondents had a better sense of how deep floodwaters would be. While many other households used the depth of the previous 1995 flood as a reference, social media households tended to know that the 2011 would be more severe. Two social media respondents explicitly stated that knowledge of deeper floodwater led to their decision to move contents to upper floors. An additional social media respondent stated that they were prompted to move belongings to the second floor based on recommendations on a community Facebook group.

In addition to flood progression information, both *social media* and *conventional internet* respondents found advice regarding which flood mitigation actions to take and how to carry out those actions. Some respondents found advice for moving belongings to upper floors of their home, while others learned how to protect large, heavy items that are difficult to move (e.g. refrigerator, other major appliances). In addition, households found online information regarding how to construct sandbag and concrete block barriers as well as where to buy materials for these barriers.

Online information: During and After the Flood

While in-depth interview respondents tended to think that online information was most useful before the flood, several found useful information during and after the flood. During the flood, the internet allowed 22% of the in-depth interview respondents to be aware of transportation options, both for work commutes and daily activities. Households also searched for evacuation transport and housing options. For example, several respondents browsed for condo rental availability and prices.

A useful feature of social media during the flood was neighborhood Facebook groups. Several neighborhoods included in the study established Facebook groups to suggest mitigation actions and to update evacuated households about the condition of their house. One respondent stated that because the neighborhood Facebook group provided updates on the condition of her home while evacuated, she did not need to make visits to check-up on the house. Conceivably, Facebook groups could help households prepare for flooding and reduce travel costs during the flood.

After the flood, online information aided 13% of the in-depth interview respondents. Three respondents found information that was useful for repair and recovery efforts including how to fix damaged belongings, when and how to turn the electricity safely back on, and how to cope with mold. In addition, cleaning advice and comparing the services and prices of professional cleaners was also useful for several respondents.

2.6 Discussion

Social media use allowed households to reduce losses during the 2011 flood in Bangkok. Propensity score matching indicates that social media enabled households to reduce flood loss by an average of US$ 3,708 (as indicated by the nearest neighbor estimator) or US$ 4,886 (kernel estimator). This reduction is massive when considering that total flood losses for the full sample averaged US$ 4,903. Social media use appears to be associated with a 37% reduction in mean flood losses, when *social media* households compared to similar households using nearest neighbor matching.[14] These reductions are in relation to comparable households (i.e. those who are well-educated, higher-income, and have multi-story houses), rather than the general population. In addition, regression analysis suggests that social media use is associated with lower total flood losses (an average of US$ 2,743).

Social media likely offered information that was not available from traditional media to the 12% of the study sample that used online social networks. Social media offered information that was not available from other sources, such as updates on the location, timing, and depth of floodwater at the homes of those in their social network. Such a dynamic view of localized conditions was not available from other sources. The vast majority of *social media* households (80%) stated that they followed flood progression information. User updates may have been more useful than government flood predictions in some areas. Government predictions were inaccurate in some neighborhoods and only reported expected volume of water, which did not clearly convey how severe the flooding would be. Flood depth would have been a more understandable indicator and social media users had access to this information.

With knowledge of current flood conditions, *social media* households could prepare effectively for the flood. In particular, in-depth interview responses suggest that social media users were able to successfully move belongings in time and thus reduce *ex post* losses. Furthermore, social media respondents had a better sense of the depth of floodwater to expect. While many other households used the depth of the previous 1995 flood as a reference, social media households tended to know that the 2011 event would be more severe. In-depth interviews indicate that reductions in flood loss were driven by the greater likelihood of *social*

[14]Nearest neighbor matching finds that the ATT of social media on flood losses is US$ 3,708. Mean losses among the 48 matched households were US$ 9,961. This suggests an average reduction of 37% is attributable to social media use. In the nearest neighbor matched sample, the 48 *social media* households had mean total losses of US$ 6,594 and median losses of US$ 4,261 compared to the 48 matched households with mean and median losses of US$ 9,961 and 6,229 respectively.

media households to move contents to upper floors. High prevalence of moving contents to upper floors among *social media* households could be due to greater expected flood depth or mitigation advice found on social media.[15] It appears that *social media* households focused their *ex ante* mitigation efforts on moving belongings as high as possible.

Social media appears to have offered advantages over conventional internet sites as well as offline sources, particularly in terms of mitigation actions before flooding. However, the benefits of social media during the 2011 Thailand flood largely did not reach lower-income households since these households are less likely to access the internet. Only 15% of *social media* households resided in low-income neighborhoods compared to 58% of all other households.[16] Whether social media could help poor households as much as it helped wealthier households is an open question. Findings of this study cannot be generalized to lower-income households due to key differences in household characteristics between the matched and full samples. In particular, poor households in Bangkok are much more likely to live in a one-story dwelling and therefore are unable to move contents to upper floors. Yet, social media could offer possible benefits to the 42% of households in the lowest quartile of annual expenditures and 56% of households in the second-lowest quartile. Possible benefits could be achieved as disparities in social media use are likely to decrease in the near future due to rapid uptake of smartphones. During the 2011 flood, less than one million smartphone subscriptions existed in Thailand. Subscriptions dramatically rose to 35 million in 2013, covering over half the country's

[15]Among the 317 households with multi-story houses, *social media* households had the highest prevalence of moving contents to upper floors (88%), compared to *conventional internet* (76%) and *offline* households (73%).

[16]In addition, *social media* households have much greater annual spending and income than all other households (Table 2.3). Only 3% of *social media* households are in the lowest quartile of annual expenditure, while 60% are in the highest quartile.

population (Webcertain, 2014). Government interventions could hasten expansion of internet access and ensure that low-income populations are served.

These findings have three major implications for future policies designed to reduce household flood losses. One is that flood disaster communication should emphasize the urgency and effectiveness of moving belongings to higher locations. In the case of the 2011 flood in Bangkok, moving contents appears to have been a more effective strategy than attempting to build flood barriers that can be overtopped. Yet, households might delay or fail to move belongings high enough if they do not have accurate information regarding flood depth and timing. Households must devote time and effort to moving contents and therefore might not take action until it is perceived to be absolutely necessary. Furthermore, households would either need live in a multi-story house or construct scaffolding to move their contents beyond the level of floodwaters.

Second, social media could be a useful technology for natural disaster management. There is an enormous opportunity for government disaster communication to move online. Social media could be a highly effective means of disseminating crucial information related to flood conditions, evacuation warnings, and mitigation actions. In the U.S., the Federal Emergency Management Agency is testing the use of distributing disaster information on social media. In developing countries, expanded access to broadband and mobile networks could be justified on the grounds of a better prepared populous.

Third, in locations that lack sufficient monitoring networks, social media provides an inexpensive way to track flood progression and map affected areas. Using people as sensors offers immense possibilities for improved early warning and flooding predictions, particularly in developing countries, ungauged basins, and highly complex urban environments. User updates could be more reliable and useful if cross-checked and then aggregated into user-generated flood maps. User reporting could also revolutionize flood response and recovery efforts. Social media offers an opportunity for disaster response agencies to quickly obtain a first-cut overview of damage and what assistance is needed and where, although on-the-ground reconnaissance would remain crucial. Efforts by the private and public sectors to develop web-based applications that can aggregate user updates posted on social media sites could be immensely useful for disaster preparedness, response, and recovery.

Overall, this study demonstrates the potential of social media for effective flood preparation. Disaster preparedness requires accurate, timely, and readily accessible information to guide household decisions. Social media sites have the potential to provide crucial information that could reduce loss of life and property damage, particularly for slow-onset events such as the 2011 Bangkok flood. In developing urban areas with rapidly growing internet user bases, social media could offer the opportunity to ensure that residents receive timely disaster information. Expanding the reach and functionality of Web 2.0 applications can offer promising opportunities to save lives and reduce impacts of future disasters.

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CHAPTER 3: USING INFORMATION TO INFLUENCE FLOOD MITIGATION BEHAVIOR: EVIDENCE FROM A FIELD EXPERIMENT [17]

3.1 Introduction

3.1.1 Overview

As the prospect for more frequent and severe extreme weather events gains scientific support, many nations are evaluating mitigation options. Insurance and home retrofits could play a prominent role in reducing household welfare losses due to flood events. Yet, even after disasters, households often fail to take risk mitigation actions. This paper presents results of the first field experiment that tests the effect of information provision on household uptake of flood insurance and home retrofits.

A sample of 364 flood-prone households in Bangkok was randomly split into treatment and control groups. The treatment group received practical details on home retrofits and subsidized flood insurance as well as social information regarding insurance purchase decisions of peers. Results indicate that the information intervention increased insurance purchases by about four percent, while no effect was detected for home retrofits. If scaled up to include all uninsured, flood-prone households in Bangkok, nearly 60,000 additional households could be insured. The results suggest that well-designed information interventions could increase household uptake of flood insurance, without additional premium subsidies or mandates.

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3.1.2 Motivation

Increasingly, information interventions seek to promote climate mitigation by influencing individual behavior (e.g. Allcott, 2011; Ayres et al., 2013; Costa and Kahn, 2013). Such persuasive appeals could also be used to encourage adaptation and risk mitigation behavior related to extreme events. This study is the first randomized experiment to address flood loss mitigation decisions. Experimental evaluation designs are rare in the environmental policy field (Ferraro and Hanauer, 2014). Yet, such designs are important since they are less prone to bias than observational designs. This study tested the effect of practical and social information on the uptake of flood insurance and home retrofits.[18] Results indicate that the information intervention increased insurance purchases about four percent, while no effect was detected for home retrofits. This effect is nearly equal to the increase in uptake that the national insurance program in Thailand has achieved through all other means since its establishment in 2012. Overall, this study demonstrates that information can promote voluntary flood insurance purchases and thus play a role in reducing flood losses for households.

Coastal cities around the world face rising flood exposure due to growing population, greater asset values, land subsidence, sea-level rise, and other climate change impacts (Dixon et al., 2006; De Sherbinin et al., 2007; Hanson et al., 2011). The costs of weather-related disasters have increased dramatically in recent decades (Munich Re Group, 2005; Miller et al., 2008; IPCC, 2012). This increase is largely driven by greater concentrations of people and assets in disaster-prone areas. In particular, the world's population is urbanizing and moving to vulnerable coastal cities (United Nations, 2015). At the same time, climate change and other factors could further increase flood frequency and intensity (World Bank, 2010).

[18]Social information conveys description of the behavior, attitudes, and beliefs of a particular group.

Many nations are assessing options for mitigation of damage and adaptation to extreme events. Household mitigation actions could play a prominent role in reducing flood impacts. However, even after disasters, households often do not take risk mitigation actions and therefore remain vulnerable to future events (Burby et al., 1988; Kunreuther et al., 2009). Furthermore, little is known about how households prepare for, respond to, and recover from disasters (e.g. Bruneau et al., 2003; de Bruijn, 2004; Zhou et al., 2010). Information provision could improve household decisions related to flood risk mitigation. Households often lack accurate information regarding flood risk and the costs and benefits associated with insurance and home retrofits to reduce flood losses. This study presents a field experiment that tests the effect of information provision on household uptake of flood insurance and home retrofits. The central hypothesis is that household inaction is in part due to incomplete and insufficient information.

3.2 Background

Low Uptake of Flood Insurance and Home Retrofits

Household flood risk mitigation decisions tend not to be privately, let alone socially, optimal. For example, despite mandates and possible benefits, uptake of insurance against floods and other disasters tends to be low globally (Dixon et al., 2006). The failure to take mitigation actions is partly due to the fact that individuals rely on heuristics to assess hazards with low probability and can treat low-probability events as having zero probability (Kunreuther et al., 2002). It is challenging for individuals to assess the probability and losses associated with low-frequency, high-loss events, such as large floods. Other reasons for household inaction include (i) lack of awareness of cost-effective mitigation actions, (ii) financial cost as well as time and inconvenience costs, and (iii) reliance on government disaster compensation.

Understanding adaptation barriers is crucial for managing the economic cost of disasters. Household inaction creates a burden on taxpayers who bear the cost of disaster response and recovery. The Thai government spent nearly US$ 757 million for disaster response due to the 2011 flood, of which US$ 97 million was cash transfers to compensate flood-affected households (DDPM, 2013). As assets become more concentrated in coastal cities, both flood-affected households and taxpayers bear costs.

Benefits of Flood Insurance and Home Retrofits

Flood insurance and home retrofits could reduce the cost of flooding events for households. Home retrofits can decrease expected property damage, while insurance reduces the variance in household wealth between periods with and without flooding. Home retrofit investments can either prevent a property from being flooded or reduce magnitude of loss if a property floods (Ehrlich and Becker, 1972; Shogren and Crocker, 1991). Retrofits to reduce the probability of floodwater entering property include flood barriers, lifting the house, and sealing cracks in structure. Meanwhile, should a property flood, loss reductions can be achieved through flood adapted use (e.g. locating difficult to move and costly items on higher floors; avoiding built-in furniture on lower floors, and flood resistant materials).

Home retrofits by urban residents have been found to reduce flood damage by 50 to 80% (ICPR, 2002; Kreibich et al., 2005; Bubeck et al., 2012). Insurance reduces variance in household wealth and could decrease the amount of government funds allocated for post-disaster compensation programs.[19] In the U.S., the National Flood Insurance Program estimates that every US$3 paid in flood insurance claims decreases federal flood assistance by US$1 (Kousky, 2011).

[19]The ability of insurance to reduce government disaster spending will depend on the size of the premium subsidies and level of insurance uptake.

Information Interventions to Influence Household Behavior

Providing information to households could increase demand for flood insurance and home retrofits. Increasingly, practical and social messages are used in policy interventions to influence individual decisions. Experimental research has begun to investigate the effects of information on household behavior. The effectiveness of practical information has been demonstrated in research on environmental hazards (e.g. Smith et al., 1995; Chen et al., 2007; Madajewicz et al., 2007; Scott et al., 2007; Jalan and Somanathan, 2008; Poulos et al., 2009; Somanathan, 2010; Davis et al., 2011; Hamoudi et al., 2012; Bennear et al., 2013). These experimental studies typically provide participants with information regarding their risk level and recommended actions. Treatment effects in environmental hazard studies have varied widely. For example, Hamoudi et al. (2012) finds a 5.3% effect for treatment households purchasing water from private providers. A large average treatment effect of 21% was found for latrine construction due to a total sanitation program in India (Pattanayak et al., 2009).

The effects on household behavior of providing information about social norms has been investigated in the electricity and water sectors (e.g. Allcott, 2011; Ferraro et al., 2011; Ayres et al., 2013; Costa and Kahn, 2013; Ferraro and Price, 2013). Social norms are behaviors, attitudes, and beliefs that are considered appropriate within a particular group. In these utility conservation studies, households are informed of peer use of services and how their behavior compares. There is evidence that information on social norms might be able to produce similar size effects on amount of services used as price incentives and conventional utility-run conservation programs (Allcott and Mullainathan, 2010; Allcott, 2011).[20] Non-monetary

[20]In Allcott (2011), average electricity consumption decreased by 2%, which is equivalent to a short-run price increase of 11 -20%. Allcott and Mullainathan (2010) find that providing social information can be comparable or less costly from the perspective of utility providers (2.5 cents per kilowatt-hour saved) than the average cost of other

incentives to alter household behavior are attractive due to their low cost and greater political feasibility in comparison to increased utility rates. [21]

No experimental studies have been published regarding flood insurance or home retrofits to reduce flood losses. Some parallels could be drawn between information interventions for flood insurance and rainfall index insurance. Several rainfall index insurance experiments have been conducted in developing countries (e.g. Cole et al., 2013; Hill et al., 2013; Mobarak and Rosenzweig, 2013; Berhane et al., 2014; Gunnsteinsson, 2014; Karlan et al., 2014). Gaurav et al. (2011) assessed the effect of financial education courses on uptake of rainfall insurance in rural India. While treatment effects were quite large, 8% to 16% increase in insurance uptake, the intervention involved a relatively large cost of $63 per policy sold. This current study on flood insurance seeks to evaluate a much lower cost information treatment (US$ 1 per treated household and about US$25 per policy sold). Furthermore, this study makes a contribution to understanding flood insurance demand. Little empirical work has been done on household demand for flood insurance, especially in developing countries (Akter et al., 2011; Landry and Jahan-Parvar, 2011; Kunreuther et al., 2013).

Household Uptake of Flood Insurance and Home Retrofits in Bangkok

Bangkok is a highly relevant field site for an experiment focused on flood insurance and home retrofits. Prior to the study, the city was struck by a devastating flood in 2011, which ranks as the world's most costly flooding disaster in the past 30 years (A.M. Best, 2012; Orie and Stahel, 2013). The Bangkok Metropolitan Area is susceptible to flooding due to its location on a river delta, flat topography, and subsiding land surface. In the future, flood risk is expected to

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utility energy efficiency programs. These traditional programs range in cost from 1.6 to 3.3 (Friedrich et al., 2009) and 5.5 to 6.4 cents per kilowatt-hour (Arimura et al., 2012).

[21] Changes in net welfare due to these policy interventions would need to be carefully estimated.

rise due to land subsidence and increased precipitation resulting from climate change (Shah, 2011).

In the aftermath of the 2011 flood, few Bangkok households have taken mitigation actions to prepare for future floods (Nabangchang et al., 2015). In addition, uptake of flood insurance remains low. Prior to the 2011 flood, less than 1% of households in Thailand had flood insurance (Orie and Stahel, 2013). After 2011, the national insurance market was severely disrupted as Thailand's flood risk was re-assessed. Premiums soared and coverage levels were capped.

The National Catastrophe Insurance Fund (NCIF) was created in January 2012 to stabilize insurance markets and make affordable policies available to households. Under the NCIF, households can purchase policies to cover losses from natural hazards, including floods, through private companies at subsidized premiums. The Thai Government serves as the insurer of last resort for these policies. Coverage levels up to US$ 3,247 receive subsidized annual premiums of 0.5% of total coverage. In locations highly prone to flooding, such as much of Greater Bangkok Area, NCIF premiums are likely lower than market-based premiums and, in some areas, below actuarially-fair rates (Threemingmid, 2013). In order for households to file claims, a catastrophe must be declared by the Thai Government and claims are determined by the maximum level of flood water.[22] To encourage uptake of flood insurance, the NCIF created a mandatory purchase requirement for households with active mortgages from a bank. Yet, insurance coverage by 2013 amounted to only 6% of households countrywide, or 1.3 million households (Prayoonsin, 2013).[23]

[22]The flood levels in house and maximum payouts are the following: (i) water reaches ground floor of house: up to 30% of coverage, (ii) 50 cm: 50%, (iii) 75cm: 75%, (iv) 100 cm: 100%

[23]In the Greater Bangkok Area, about 15% of households have flood insurance, based on data from NCIF (2013).

Expected Effects of Information Treatment

The information treatment used in this study was expected to address the information failure regarding flood risk mitigation strategies and influence households in three ways. First, it raises awareness of flood insurance and home retrofit options. Raising awareness of the existence of the subsidized flood insurance program might be an effective strategy in encouraging action, given that only 60% of study participants at baseline were aware of it. Second, the information provides useful inputs into a household risk mitigation decision such as the flood risk faced by households in Bangkok, costs of possible actions, and how to undertake actions. Last, the social information can enable social learning regarding optimal level of insurance coverage. Households are often influenced by actions of their neighbors, even when they are not aware of the motivations underlying those actions (Somanathan, 2010). Through the provision of social information, households may update their perceptions of flood risk and the welfare gain from mitigation actions. The conceptual framework that underlies these expected effects is presented in Appendix B.

3.3 Research Design, Hypotheses, & Modeling Strategy

Experimental design

A sample of 364 flood-prone households in Bangkok was randomly split into treatment and control groups. All participants were homeowners who did not have flood insurance at the time of the baseline interview. The treatment group (n=185) received practical details on home retrofits and subsidized flood insurance as well as social information regarding insurance purchase decisions of households in their district. The control group (n=179) received no information. Power calculations suggested that a sample of this size (n=364) would be sufficient to detect treatment effects of 4% or greater, while achieving at least 80% Power for a 1-tailed test.[24] Informed consent was obtained from all respondents and survey protocols were approved by the institutional review board of the University of North Carolina.

The information intervention included both practical and social information. A summary of the experimental design and timeline of activities is provided in Figure 3.1. The practical information was delivered during the baseline interview in October and November, 2013. Treatment households were presented with an informational pamphlet that enumerators read and a short video (2 minutes) about flood risk in Bangkok and how to purchase insurance and undertake home retrofits. The pamphlet also provided a contact list of insurance companies and compared damage costs that a household might face with and without insurance. An excerpt from the practical information pamphlet is presented in Figure 3.2.

Two weeks after the baseline interview and the delivery of the practical information, treatment households were provided with social information, which was delivered as a brochure hung on the front gate of their house. The social information conveyed a description of average household losses from the 2011 Bangkok flood and prevalence of flood insurance uptake by households within a respondent's district.[25] The social information was intended to have households perceive that flood insurance is not a rarity in Bangkok. Information spillovers between treatment and control households were accounted for in the follow-up survey, as described in Appendix C.

An in-person, baseline survey collected background characteristics of participating households. Six months later, a follow-up survey recorded experiment outcomes, including insurance purchases, home retrofits, information gathering, and risk perceptions. This follow-up

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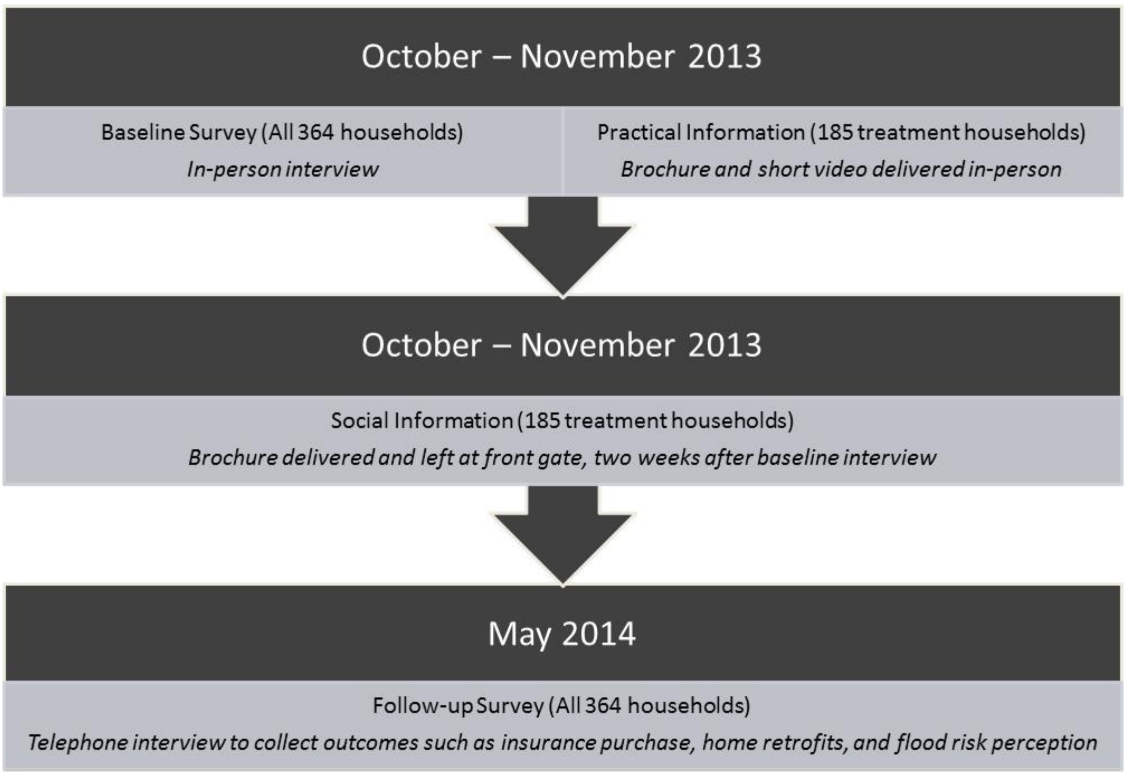
[24]Power calculations were estimated with a Chi-squared test on proportions (2x2 test for independent samples) using the statistical software *Power and Precision*.

[25]A district in Thailand is a local government unit that is below a province. Districts are analogous to a county in the United States.

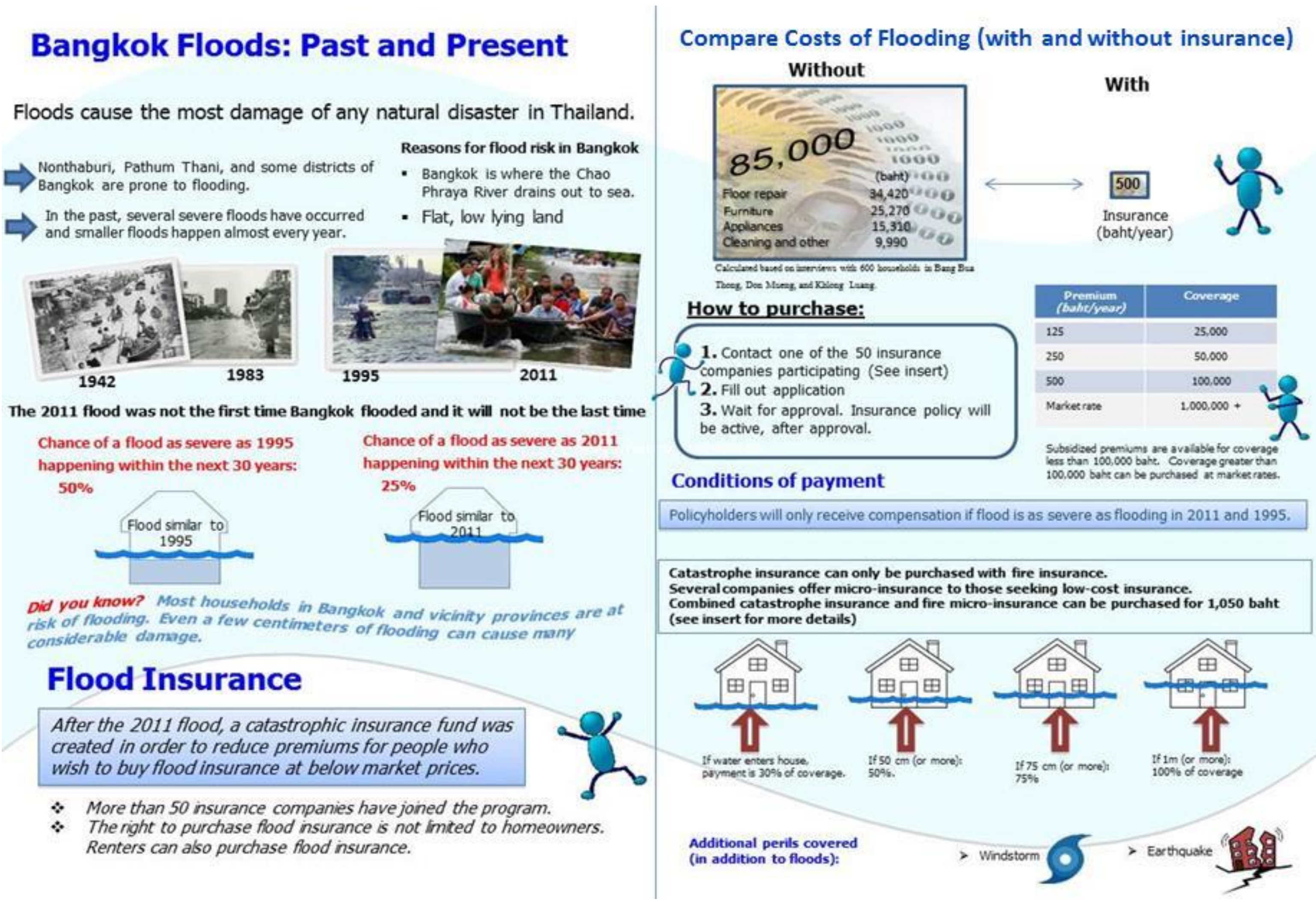
survey was administered in May 2014 by enumerators who used Skype to call respondents' telephones.[26]

Figure 3.1 Summary of Experimental Design



[26]The follow-up survey utilized several types of telephonic devices. Enumerators used laptops equipped with Skype (an online telecommunications application) to call respondents' mobile phones and landline telephones. Skype accounts were configured with Bangkok-area cell phone numbers so that calls to respondents would appear as local numbers.

Figure 3.2 Excerpt from Practical Information Brochure, English Translation



Modeling Strategy

First, a difference in proportions between treatment and control groups is used to estimate the effect of the information intervention on three outcomes – 1) insurance purchase, 2) decision progress regarding insurance purchase, and 3) household information seeking regarding flood risk, protection against flood damage, and insurance.

Next, a difference in differences (DiD) estimator is used to measure the effect of the information intervention on outcome variables collected at both baseline and follow-up. The DiD estimator is estimated using the following linear regression:

$$y_{it} = \beta_0 + \beta_1 \cdot T_i + \beta_2 \cdot P_{it} + \beta_3 \cdot T_i \cdot P_{it} \tag{3.1}$$

where *y* is the outcome variable, *T* is the treatment assignment, and *P* is a dummy variable that is equal to 1 for the follow-up survey and 0 for the baseline. Ordinary least squares is used to estimate Equation 1 for perceived probability of future flooding, a continuous variable. Linear probability regression models are applied for three binary outcome variables, which include 1) insurance awareness, 2) awareness that Bangkok is generally a flood prone area, and 3) completion of any of nine home retrofits.

Description of Study Site

This study was conducted in the Bangkok Metropolitan Area, within two purposively selected districts (Don Mueang and Bang Bua Thong) that were among the most severely affected areas during the 2011 flood. Within these two districts, a total of fourteen neighborhoods (7 low-income and 7 middle-income) were randomly selected. Middle-income neighborhoods tend to be gated communities with neighbors of similar socioeconomic class and housing characteristics. Low-income neighborhoods include both slums and low-income townhouse communities. The poorest communities are often located on marginal land along canals and many homes in these areas are constructed on stilts due to frequent, minor floods.

Sampling procedure

Participant households were selected using a multistage cluster sampling procedure, which included three stages – (1) sub-district, (2) community, and (3) household. Sub-districts and communities were randomly sampled with probability proportional to size, while households within a community were sampled via a 'random walk'. Each community was visited twice and households that were not at home during the first visit were re-visited. Full details on the sampling procedure and other methods are provided in Appendix C.

3.4 Results

Baseline Household Characteristics

The quality of randomization process is assessed by comparing key household characteristics between treatment and control groups. A total of 37 baseline characteristics were examined for statistically significant differences, using t-tests for continuous variables and χ^2 tests for categorical variables. Most household characteristics prior to the interventions are balanced between the treatment and control groups (Tables 3.1 and 3.2). This suggests that the randomization procedure resulted in comparable groups. Treatment and control households were not statistically different in 35 of 37 characteristics, at the 5% confidence level. Respondents in the treatment group were slightly more likely to be married. In addition, the control group received slightly higher *ex post* compensation for flood losses from government after the 2011 flood. However, this difference is largely driven by five extreme values in the control group. When these extreme observations are dropped, the difference is no longer significant.

Table 3.1 Household characteristics in the baseline

Household Characteristic	Definition	Control	Treatment	Difference (95% CI)	*p* value
Monthly household income	Total household income per month (in US$)	1,346	1,367	-21 (-247, 205)	0.86
Age	Age of respondent	54.2	55	-0.802 (–3.48, 1.88)	0.56
Male	Dummy variable=1, if respondent is male	0.39	0.43	-0.038 (–0.141, 0.064)	0.46
Marriage status				χ^2 test, *p*=	0.03
Single	Dummy variable=1, if respondent is single	0.11	0.12	-0.013 (-0.079, 0.052)	0.69
Married	Dummy variable=1, if respondent is married	0.75	0.82	-0.072 (-0.158, 0.013)	0.09
Divorced, separated, or widowed	Dummy variable=1, if respondent is divorced, separated, or widowed	0.15	0.06	0.086** (0.024, 0.148)	0.01
Awareness of Catastrophe Insurance	Dummy variable=1, if respondent is aware of catastrophe insurance	0.61	0.59	0.020 (–0.081, 0.121)	0.70
Perceived probability of future flooding	Perceived probability of a flood similar in magnitude as 2011 event within the next five years. Scale of 0 (will not occur) to 10 (will certainly occur).	4.8	5.1	-0.289 (–0.842, 0.265)	0.31
House loss in 2011 flood	House and contents losses (in US$)	2,107	1,574	534 (-999, 2066)	0.49
Compensation received after flood [a]	Compensation received after 2011 flood (in US$)	693	642	51* (4, 97)	0.03
N		179	185		

Rows with values greater than 1 represent mean values in treatment and control households. All other rows represent a binary variable and therefore values are the percentage of households who have that particular characteristic.

Significant at the *p < 0.05 level and **p < 0.01 level.

[a] Compensation is significantly higher in control group due to five outliers. When these outliers are dropped, the difference is no longer significant (*p*=0.15)

Table 3.2 Household retrofit behavior in the baseline

Household Characteristic	Definition	Control	Treatment	Difference (95% CI)	*p* value
Home Retrofits [b]					
Avoiding built-in furniture	Dummy variable=1, if built-in furniture (i.e. custom shelves and counters attached to interior walls) on the ground flood was avoided.	0.11	0.12	-0.013 (–0.079, -0.053)	0.70
Use of flood-resistant materials	Dummy variable=1, if flood-resistant materials used (e.g. tile, cement)	0.14	0.23	-0.093* (–0.174, -0.013)	0.02
Move heavy items to upper floors	Dummy variable=1, if heavy items moved to upper floors	0.42	0.48	-0.062 (–0.165, 0.041)	0.23
Move utilities higher	Dummy variable=1, if utilities, such as AC compressor, moved higher	0.12	0.2	-0.072 (–0.148, 0.0036)	0.06
Permanent flood barrier	Dummy variable=1, if permanent flood barrier constructed	0.11	0.14	-0.029 (–0.098, 0.040)	0.41
Lifting house	Dummy variable=1, if house structure was lifted	0.06	0.06	-0.004 (–0.052, 0.045)	0.88
Sealing cracks in structure	Dummy variable=1, if cracks in housing structure were sealed	0.16	0.17	-0.011 (–0.089, 0.067)	0.78
Build shelving for storage	Dummy variable=1, if shelving built for additional storage during flood	0.15	0.21	-0.060 (–0.139, 0.018)	0.13
Create additional living space	Dummy variable=1, if additional space created for living on upper floors during flood (e.g. lifted roof tiles)	0.07	0.04	0.029 (–0.017, 0.076)	0.21
N		179	185		

Rows with values greater than 1 represent mean values in treatment and control households. All other rows represent a binary variable and therefore values are the percentage of households who have that particular characteristic.

Significant at the *$p < 0.05$ level and **$p < 0.01$ level.

[b] Home retrofits at baseline are those that household made before the baseline survey

Outcome Variables

Estimated impacts represent an average treatment effect (ATE). Tables 3.3 and 3.4 summarize the impact of the information intervention on insurance purchase, home retrofits, information seeking, and risk perceptions. For flood insurance purchase, a 4.3% average treatment effect was found, $p<0.05$. Less than 1% of control households purchased insurance, compared to nearly 5% of treatment households. Thus, the provided information appears to have persuaded some treatment households to purchase insurance. The magnitude of this treatment effect is similar to those in information experiments related to water and electricity use (e.g. Allcott, 2011; Ferraro et al., 2011; Ayers et al., 2013) and rainfall index insurance (e.g. Costa and Kahn, 2013; Hill et al., 2013).

In addition, several households indicated that they had decided to purchase insurance but had not purchased a policy as of May 2014. If this group of households is combined with the households that purchased insurance, the treatment effect of information reaches 7.5%.[27]

A significant treatment effect for insurance uptake was found despite the risk of information spillover from treatment to control households within neighborhoods. Only 6% of control households reported that they received insurance information from neighbors so the risk of information spillover is low. Moreover, it is not known whether the information received by these control households was (i) from treatment households,[28] or (ii) derived from the information intervention materials. If the information that some control households received was derived from materials provided to the treatment group, then this would lead to downward bias of the treatment effect. Alternatively, if the information received by controls was not from

[27]Two control and eight treatment households indicated that they had decided to purchase insurance but had not purchased a policy as of May 2014. When re-calculating the average treatment effect, both these households and the ten that actually purchased insurance are included.

[28]In order to confirm if information was received from treatment households, the names of neighbors that provided the information would need to be stated, raising privacy concerns.

treatment materials, then this represents a confounding factor, which is controlled through randomization.

The most commonly stated reason for purchasing insurance was to receive compensation in the event of a future flood. Two newly insured treatment households also stated that the price was lower than they had originally thought, prior to the baseline interview. Households were also asked about the usefulness of the provided information in assisting their purchase decision. Overwhelmingly, treatment households indicated that the information was useful because they learned that flood insurance was available (6 households) and how to purchase it (5 households). Thus, households acknowledge that the provided information was part of their decision to purchase insurance.

For households that did not purchase insurance, the most common reason was that the respondent did not believe that a flood would occur again (88 households). Others stated that policies were too expensive (57 households), lack of sufficient information about insurance (57 households), and had confidence in their ability to self-protect (43 households). The only reason that had a statistical difference between control and treatment groups was perceived eligibility, $p<0.05$. More control households (11) than treatment households (3) incorrectly believed that they were ineligible for flood insurance. This difference in perceived eligibility suggests that the information treatment increased familiarity about insurance policy terms and eligibility criteria. Expectation of disaster compensation may have also dissuaded some households from purchasing insurance. About 60% of households expect to receive some level of compensation after a future flood. However, expected compensation levels are a relatively small portion of expected losses.[29,30]

[29]About 82% of the 202 households that expect compensation believe that it will cover less than half of their losses.

For home retrofits, the information intervention does not appear to have motivated households to take action. The only significant treatment effect appears to be for creating additional living space. Additional space on upper floors was created to serve as additional living quarters during a future flood. However, only one treatment household took this action after the information treatment. The significant DiD estimate is driven by the fact that no control households undertook this home retrofit after the information intervention. The DiD estimator indicates that this action was more prevalent among treatment households, $p<0.01$. The DiD estimates also suggest that control households were more likely to have used flood-resistant materials. However, this estimate is driven by treatment households undertaking this retrofit before, rather than after, the baseline interview. Therefore, there is no evidence that the information treatment motivated households to undertake home retrofits, with the possible exception of creating additional upstairs living space.

Possible reasons that a significant treatment effort was not be found for retrofits include (i) the information provided did not motivate households to take action, and (ii) awareness of insurance might led treatment households to forego retrofits. Among the ten households that purchased insurance, it does not appear that insurance decreased the likelihood of undertaking home retrofits. In fact, insurance buyers were more likely to undertake new mitigation actions. While 30% (3 out of 10 households) of insurance purchasers undertook a home retrofit action after the baseline interview, less than 6% of non-buyers did (20 out of 354), $p<0.01$.

[30]Households that purchase flood insurance in Thailand are only eligible for automatic flood aid, which amounted to US$ 160 in 2012 (Threemingmid, 2015). However, insured households are not able to apply for additional aid (up to US$ 960 in 2012) that might become available.

Table 3.3 Difference in insurance purchase and information seeking between control and treatment households at follow-up

	Control	Treatment	Difference (95% CI)	*p* value	Obs
Purchased insurance	0.01	0.05	0.043* (0.010, 0.077)	0.01	364
Purchased or Decided to buy but have not yet	0.02	0.09	0.075** (0.029, 0.12)	0.00	364
Decision progress for insurance purchase			χ^2 test, *p*=	0.01	364
Have not thought about it	0.50	0.38	-0.11* (-0.22, -0.011)	0.03	
Decided not to purchase	0.34	0.31	-0.027 (-0.12, 0.069)	0.58	
Have not decided yet	0.15	0.22	0.065 (-0.014, 0.15)	0.11	
Decided to buy but have not yet	0.01	0.04	0.032[†] (0.002, 0.066)	0.06	
Purchased	0.01	0.05	0.043* (0.010, 0.077)	0.01	
Information seeking [a]					
Flood risk in local area	0.24	0.28	0.043 (-0.049, 0.13)	0.36	361
How to protect property from floods	0.21	0.23	0.020 (-0.066, 0.11)	0.65	362
Catastrophe insurance	0.03	0.09	0.053* (0.004, 0.10)	0.03	362
Contacted insurance company (after baseline interview)	0.03	0.06	0.032 (-0.011, 0.074)	0.14	362

All rows represent a binary variable and therefore values are the percentage of households who undertook a given action.
Significant at the [†] $p<0.10$, *$p < 0.05$ level and **$p < 0.01$ level.

[a] Respondent was asked if they attempted to seek information on any of the three listed items, in the period between the baseline and follow-up interview. For example, in the case of catastrophe insurance, both treatment and control households were asked if they sought information regarding catastrophe insurance during the period after the baseline interview.

Table 3.4 Difference in risk perception and home retrofits between control and treatment households at baseline and follow-up

	Difference between groups (% treatment - % control)				
	At baseline	At follow-up	DiD	Average at baseline	Obs
Awareness of Catastrophe Insurance	-0.083 (-0.50, 0.34)	0.48* (0.05, 0.92)	0.57† (-0.04, 1.17)	0.60	364
Awareness of General Flood Risk in Bangkok	0.12 (-0.41, 0.65)	0.004 (-0.58, 0.59)	-0.21 (-0.99, 0.57)	0.80	344
Perceived probability of future flooding	0.31 (-0.25, 0.86)	-0.009 (-0.58, 0.57)	-0.30 (-1.09, 0.50)	5	358
Perceived damages from future flooding [a]	-0.012 (-0.11, 0.083)	-0.035 (-0.11, 0.037)	-0.06 (-0.18, 0.06)	2	338
Home Retrofit					
Avoiding built-in furniture on ground floor	0.19 (-0.47, 0.85)	0.19 (-1.14, 1.53)	0.07 (-1.42, 1.55)	0.11	362
Use of flood-resistant materials	0.62* (0.08, 1.17)	-1.67 (-3.83, 0.49)	-2.29* (-4.52, -0.06)	0.19	362
Move heavy items to upper floors	0.23 (-0.19, 0.65)	-0.03 (-1.29, 1.22)	-0.26 (-1.59, 1.06)	0.45	362
Move utilities higher	0.54† (-0.032, 1.12)	-0.61 (-1.86, 0.64)	-1.16† (-2.53, 0.22)	0.16	362
Permanent flood barrier (e.g. cement wall)	0.32 (-0.31, 0.95)	-0.03 (-2.01, 1.94)	-0.30 (-2.36, 1.77)	0.12	362
Lifting house	0.065 (-0.82, 0.95)	-0.03 (-2.01, 1.94)	-0.10 (-2.26, 2.06)	0.06	362
Sealing cracks in structure	0.12 (-0.43, 0.66)	-0.03 (-2.81, 2.75)	-0.15 (-2.98, 2.69)	0.17	362
Protecting against sewerage backflow	0.56 (-0.13, 1.26)	1.08 (-1.20, 3.35)	0.52 (-1.87, 2.89)	0.10	362
Build shelving for storage	0.23 (-0.07, 0.54)	0.24 (-0.62, 1.10)	0.01 (-0.91, 0.92)	0.18	362
Create additional living space	-0.51 (-1.48, 0.46)	[b]	3.42** (2.60, 4.23)[c]	0.05	362

Each row represents a separate linear probability regression, with the exception of perceived damages from future flooding, which represents a multinomial regression. Coefficients and 95% CI limits (shown in parentheses) represent marginal effects. Significant at the $^{\dagger}p<0.10$, $*p < 0.05$ level and $**p < 0.01$ level.

Notes:
[a] Multinomial model used to estimate DiD for perceived damages from future flooding, which is a categorical variable.
[b] No control households undertook this home retrofit.
[c] Only one treatment households created additional living space after the information treatment.

3.5 Discussion

As risk mitigation of extreme events becomes a growing policy priority, it is crucial to understand how households respond to disasters and how to encourage actions to reduce future losses. This study demonstrates that practical and social information can encourage flood insurance purchases and thus reduce costs of flooding for households. Results indicate that the information intervention increased insurance purchases by about four percent, while no effect was detected for home retrofits. Providing information achieves about the same increase in uptake as the national insurance program in Thailand has been able to achieve through all other means since its establishment in 2012.[31] If this intervention were scaled up to include all uninsured, flood-prone households in the Bangkok Metropolitan Area, nearly 60,000 additional households could be insured.[32]

The findings of this study raise several questions for future research. The magnitude of the treatment effect might depend on socioeconomic and other characteristics of participants. Knowing how the effectiveness of information varies across background characteristics could lead to improved targeting of the intervention. Future work could capture longer-term treatment effects and insurance policy retention rates. In addition, testing less costly interventions, such as mass media campaigns, could also be useful to determine how the information delivery mode affects response to treatment. More generally, expanding field experiments to other types of disaster mitigation and adaptation actions could produce valuable lessons for public policy.

Results from this experiment have relevance for flood prone areas around the world. In particular, the study provides insight into how household losses due to floods can be mitigated in

[31]Flood insurance uptake in Thailand rose from less than 1% of households before the 2011 flood to 6% by 2013 (Orie and Stahel, 2013; Prayoonsin, 2013).

[32]About 1,686,346 households live in districts flooded in 2011. Approximately 299,899 households in these districts are already insured against floods. If an information campaign was targeted to all uninsured households (1,386,447), then 59,617 households would purchase insurance policies, assuming a treatment effect of 4.3%.

the face of urbanization and climate change. Low-lying megacities, such as Bangkok, present new challenges for disaster risk mitigation. In these productive urban centers, neither massive evacuations nor limits on concentrations of people and assets are likely desirable. Therefore, risk mitigation strategies must focus on how to reduced expected losses when people and assets remain in place. Information could play a vital role in motivating households to take voluntary actions to reduce the economic impacts of extreme events. Overall, this study demonstrates well-designed information interventions could further increase household uptake of flood insurance, without additional mandates or increases in premium subsidies.

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CHAPTER 4: BENEFIT-COST ANALYSIS: INFORMATION CAMPAIGN FOR FLOOD INSURANCE [33]

4.1 Introduction

4.1.1 Overview

This paper presents a benefit-cost analysis (BCA) of an information campaign to encourage flood insurance uptake among households in Bangkok. Households in neighborhoods severely affected by the 2011 Bangkok flood were provided practical details about a subsidized insurance program currently available in Thailand as well as social norms regarding purchase decisions of households in their district. The BCA accounts for the distribution of costs and benefits across stakeholders including new policyholders, insurance providers, and the general taxpayer. Transfer payments (premiums, claims) as well as efficiency gains and losses (consumer surplus, deadweight loss) are accounted for in the analysis.

Results suggest that the information campaign does not deliver social benefits relative to the status quo flood aid program. Furthermore, the campaign increases taxpayer burden and delivers subsidies to higher income households. Greater benefits are associated with better informing households that have high insurance demand, compared to using social pressure to persuade those with low demand. Overall, findings suggest that *ex post* flood aid could be a reasonable policy in cases where the alternative is an information campaign to promote a subsidized insurance program.

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4.1.2 Motivation

The costs of natural disasters have increased dramatically around the world in recent decades (Munich Re Group, 2005; Miller et al., 2008; IPCC, 2012). Multi-billion-dollar disasters are becoming common. Seven of the ten costliest events since 1980 occurred in the past ten years (Munich Re Group, 2015). This increasing cost is largely driven by greater concentrations of people and assets in disaster-prone areas, such as floodplains. At present, global flood losses are about US$ 6 billion per year for the 136 largest coastal cities, combined. This is expected to rise to US$52 billion by 2050 due to socioeconomic growth alone (Hallegatte et al., 2013). Global flood losses are expected to become increasingly concentrated in developing countries, especially Asian megacities.

Understanding how households can be encouraged to insure against disasters is of interest to scholars and policymakers concerned with reducing the social costs of extreme events. This study assesses the economic benefits and costs of an information campaign to encourage uptake of subsidized flood insurance in Bangkok. Flood insurance can increase private welfare by allowing households to smooth consumption. Yet, uptake of flood insurance remains low globally, even in countries where such insurance is mandated and subsidized (Dixon et al., 2006). Less than 1% of households were insured during the 2011 Thailand flood, the world's most costly flooding event in the past 30 years (A.M. Best, 2012; Orie and Stahel, 2013; Munich Re Group, 2015).

This study presents a benefit-cost analysis (BCA) of an information intervention designed to deliver both practical and social norm information about a subsidized flood insurance program. While past field experiments have assessed the effectiveness of information interventions in influencing behavior, none have evaluated the social welfare implications of the intervention. Without a full accounting of economic costs and benefits across all stakeholders, it is unclear if this type of information campaign produces net benefits for society. Disaster management could especially benefit from evaluation of policy alternatives, given the large amounts of government resources at stake.

A key question that this BCA addresses is whether or not the information campaign is preferable to the status quo in which households receive government compensation for flood losses. *Ex post* flood aid and subsidized insurance are two widely-applied strategies to cope with household disaster losses. In the analysis presented in this paper, the distribution of costs and benefits are accounted for across stakeholders including new policyholders, private insurers, and taxpayers. A limitation of the analysis is that no data exists for household demand for subsidized flood insurance in Bangkok. Therefore, the study makes illustrative calculations based on assumed demand curves for a typology of households. Important insights can be drawn from applying BCA with these demand assumptions. For example, interactions between government aid programs and insurance can be better understood in terms of benefits to households and costs for taxpayers. In addition, insights can be gained regarding the distribution of costs and benefits across taxpayers, insurers, and households of various income levels.

Key parameter values for the BCA are derived from two household surveys in Bangkok reported elsewhere (Chapter 3; Nabangchang et al., 2015). I found an average treatment effect of the information intervention to be approximately 4%, nearly equal to the increase in uptake that the national subsidized insurance program has achieved through all other means since its establishment (Chapter 3). Responses are from 397 uninsured households in severely flood-affected areas of Bangkok. The second data source is a household survey of the economic costs incurred by households due to the 2011 flood. The 469 households in this survey are also located in areas of Bangkok severely affected by the 2011 flood (Nabangchang et al., 2015).

The paper is organized as follows. The next, second section of the paper provides background on flood insurance in Bangkok and the information campaign to be evaluated. The third section presents the conceptual framework. The fourth section describes the study sites and fieldwork, while the fifth section discusses results from the benefit-cost analysis of the information campaign. The sixth section offers concluding remarks.

4.2 Background

In 2011, Bangkok experienced the world's most costly flooding disaster in the past 30 years (A.M. Best, 2012; Orie and Stahel, 2013). The Greater Bangkok Metropolitan area is susceptible to flooding due to its location on a river delta, flat topography, and subsiding land surface. In the future, flood risk is expected to rise due to continued land subsidence and development, as well as increased precipitation and sea-level rise resulting from climate change (Shah, 2011).

4.2.1 Flood compensation

In the aftermath of the 2011 flood, the Thai government distributed flood compensation to households in order to offset some of the costs of flooding. Flood compensation in this study is defined as reimbursement for losses incurred due to flooding, rather than emergency response. As floodwaters receded, all households residing in government-declared flood-affected areas received a cash transfer of US$160 (equivalent to 11% of median insurable losses and 5% of median total flood costs).[34] Many flood-affected households were not satisfied with the US$160 transfer and applied pressure on their municipal and national representatives in order to obtain greater *ex post* compensation. As a result, a second round of cash transfers was made available. During the second round, households had to submit an application that documented flood damage in order to receive compensation up to US$ 960, depending on the estimated value of damage.

Flood compensation programs shift the burden of disaster losses from households in flood-prone areas to taxpayers. After disasters, there is typically an outpouring of assistance for affected households. Yet, the availability of flood aid can reduce the incentive for homeowners to take risk mitigation actions or insure against flooding.

If households treat government compensation as a substitute for insurance, then *ex post* flood compensation might lead households to underinsure or to forgo insurance altogether (Kelly and Kleffner, 2003).[35] In Thailand, *ex post* aid and insurance appear to be good substitutes since the conditions that trigger payments are similar. Therefore, *ex post* flood aid may hinder households' uptake of flood insurance, since aid functions as zero-premium insurance policy. In order to reduce the incentive for households' to under-protect and underinsure, some suggest that flood aid either be limited to low levels or be provided in the form of loans (Michel-Kerjan and Kunreuther, 2011).

Yet denying disaster compensation to households or communities that do not take adequate mitigation action or fail to insure is generally viewed as politically infeasible. Thus,

[34]Insurable losses are out-of-pocket expenses to repair and replace house structure, contents, and motor vehicles. These losses do not include foregone income or the value of household time devoted to repair, recovery, or greater travel time.

[35]In the U.S., evidence suggests that flood compensation decreases average coverage levels selected by households, but does not reduce insurance uptake (Kousky et al., 2013).

governments have often tried to institute mandatory, and typically subsidized, flood insurance programs in an attempt to reduce the liability of the general taxpayer to pay for *ex post* flood compensation. However, these programs require new expenditures by taxpayers, such as subsidies to make the insurance attractive to households, and the administrative costs for program operation and advertisement.

4.2.2 Flood insurance

Prior to the 2011 flood, less than 1% of households in Thailand had flood insurance (Orie and Stahel, 2013). During this flood disaster, the national insurance market was severely disrupted as Thailand's flood risk was re-assessed. As a result, the government-sponsored National Catastrophe Insurance Fund (NCIF) was created in 2012 in order to stabilize insurance markets and make affordable policies available to households. Under the NCIF, the Thai Government serves as the "insurer of last resort" for flood insurance policies. Insurance payouts only occur after flood events that are declared a catastrophe by the Thai Government. Households can purchase policies with coverage levels up to THB 100,000 (US$ 3,200) at premium rates of 0.5% of coverage. This coverage limit is comparable to median losses due to the 2011 flood, US$3,089 (Nabangchang et al., 2015). In areas highly prone to flooding, such as most of the Greater Bangkok Area, the NCIF premiums are lower than market-based premiums (Threemingmid, 2013).

The NCIF premiums are not calculated based on estimates of actual flood risk. Flood risk maps are not publically available in Thailand that would allow for risk-based pricing. Flood claim payouts are based on the maximum level of flood water in a dwelling and not damage verified by a claims adjuster. This means that water must enter a dwelling in order for a claim to be made. This requirement may provide a disincentive to take preventive measures to stop water from entering.

Despite the establishment of NCIF, insurance coverage by 2013 amounted to only 6% of households countrywide, or 1.3 million households (Prayoonsin, 2013). In the Greater Bangkok Area (Bangkok, Nonthaburi, and Pathum Thani provinces), insurance coverage is higher than the national average (15%) (based on data from (NCIF, 2013). Most locations in the Greater Bangkok metropolitan area are considered by the NCIF to be highly prone to flooding.

Low uptake of flood insurance is an issue in many countries. In U.S., only half of households in flood prone areas have flood insurance despite federal mandates and publically-available flood risk maps (Kriesel and Landry, 2004; Dixon et al., 2006).[36] Scholars believe that flood insurance take-up in the U.S. is low relative to the social optimum (Kriesel and Landry, 2004; Kunreuther et al., 2013). Major reasons why households fail to purchase flood insurance include (i) low risk perception, (ii) lack of awareness of insurance, (iii) lack of understanding of insurance, (iv) price, and (v) reliance on government aid. Lack of understanding and awareness of flood insurance are the focus of the information intervention in this study. In Bangkok, only 60% of participants in the information campaign field experiment were aware of the Government's flood insurance program prior to the intervention. Yet, the randomized experiment that tested the use of the information campaign evaluated in this BCA study found a relatively small treatment effect (4%) (Chapter 3). Therefore, even after receiving information, few households purchased the subsidized insurance. Possible explanations include low risk perception and the non-monetary costs of time and effort to purchase insurance.

[36]In the U.S., about 20% of flood insurance policies are intentionally subsidized. On average, premiums are a less than half of actuarially fair levels (Beider, 2009).

Low risk perception regarding the probability and consequences of an event is particularly relevant for floods, which are low frequency, high consequence events. Many individuals can treat low probability events as zero probability (Kahneman and Tversky, 1979; Kunreuther et al., 2002). Systematic underestimation of flood risk is a well-documented barrier to flood insurance purchase. Even after a major disaster or after receiving risk information, individuals might be overly optimistic about their risk level (Camerer and Kunreuther, 1989; Kunreuther et al., 2013). In addition, non-monetary costs of adopting an action, such as time and effort, can also pose a barrier to insurance purchase. Within the field of energy efficiency, non-monetary costs are gaining increasing attention as an explanation for low uptake of privately beneficial interventions (Sallee, 2014; Fowlie et al., 2015). In the case of flood insurance, households would need to incur inconvenience costs, time costs, and cognitive effort in order to purchase a policy. These processing costs of implementing an action are typically not accounted for in cost-benefit analyses and are not included in this study.

4.2.3 Information Campaign to Increase Insurance Uptake

An intervention to increase household uptake of subsidized flood insurance could potentially enhance household and social welfare. The information campaign provided households with practical details about a subsidized insurance available in Thailand as well as social norms regarding purchase decisions of households in their district. Practical information about flood risk in Bangkok and how to purchase insurance was delivered via an in-home visit in the form of a pamphlet and short video. Social information was provided two weeks later in the form of a front gate hanger. The social information conveys a description of average household losses from the 2011 Bangkok flood and prevalence of catastrophe insurance uptake by households within a respondent's district. A full description of the campaign is provided in Chapter 3.

4.3 Theoretical Approach to Estimate Welfare Effects of Information Intervention

4.3.1 Household Perspective

In order to conceptualize a household's insurance decision and how an information campaign might influence decision making, I use a modified version of the classic expected utility (EU) framework presented in Smith (1968). Chapter 3 provides a more detailed description of this framework. Consider a utility-maximizing household with wealth *W* that is making a decision on the level of flood insurance coverage (*I*) to purchase. The household faces two states of the world, that a flood occurs or not, with annual probabilities of p and *1-p* of these two states. The cost of insurance per unit of coverage is *c*. If the house is flooded, the household will incur a cost of flooding (L) and receive an insurance claim of I. Any coverage level can be selected up to the lesser value of L or coverage limit. The household may receive government disaster compensation (G). When deciding to purchase insurance, a household will bear costs of searching for information (F).

The household is assumed to be risk averse, with strictly increasing and concave utility function. The von Neumann-Morgenstern expected utility for an insured household can be determined by the sum of the utilities in each state, weighted by the probability of each state. The optimal amount of insurance can be determined by maximizing expected utility:

$$\underset{I}{max} = E[U(W)] = p \cdot U[W - L + I - cI - F + G] + (1 - p) \cdot U[W - L - cI - F] \qquad (4.1)$$

The optimal level of I will be influenced by L, F, G, and the relative magnitudes of p and c. In order to determine the optimal coverage level (I^*), the household's expected utility is maximized over I. A household will select insurance coverage up to the point where marginal utility in the state with flooding is equal to the marginal utility in the state without flooding (as shown in Appendix B). Full insurance coverage ($I^*=L$) will be selected if several conditions hold: (i) insurance is actuarially fair ($c=p$), (ii) search costs are zero, (iii) household's perceived probability of loss equals the insurer's estimate, (iv) household is risk averse, (v) no compensation is anticipated, and (vi) coverage limit imposed by insurer is not less than L.

EU theory is an appropriate framework if it is assumed that low flood insurance demand can be explained by a lack of complete information (e.g. flood probability and magnitude of loss) and individuals use heuristics to make decisions. Therefore, with full information and no time constraints, individuals would not need to rely on these mental shortcuts. An information campaign could be justified depending on its costs and the value of providing information regarding insurance and flood probability in order to improve decisions. Observed insurance behavior could move closer to that described by EU theory.

Consider a rational household that is deciding between the status quo (relying on *ex post* government flood aid) and purchasing subsidized insurance, as shown in Figure 4.1. This household is aware that subsidized insurance is available. However, prior to an information intervention, the household is not willing to pay subsidized or actuarially fair premiums. It is assumed that insured households must forgo most flood aid, as is the case in many countries. Therefore, households face a tradeoff and must weigh the relative net benefits of aid and subsidized insurance. Both aid and subsidized insurance are assumed to provide limited compensation for flood losses. The maximum level of *ex post* flood aid (*Aid*) is assumed to be less than the subsidized insurance coverage limit (I_{limit}) and wealth at risk (I_{wealth}).

Flood aid is treated in this analysis as an insurance policy with a zero-premium. The annual expected amount of flood aid received by a household is equal to the product of *ex post* compensation and the flood probability (*p*). Yet, from the perspective of the household, the value of aid is equal to the area under the demand curve ($B_1 + E_1$).

Alternatively, the household can purchase subsidized insurance. Any amount of coverage can be selected, up to the coverage limit (I_{limit}) at a subsidized premium of *s*.[37] If the premium rate was zero, the household would purchase coverage for the total value of wealth at risk, equal to I_{wealth}. This household has relatively low demand for flood insurance and the choke price is equal to the actuarially fair premium rate. This household will not purchase insurance prior to the information campaign since the net benefit of insurance (B_2) is less than that of aid (E_1).

The information campaign is expected to increase household demand for coverage. Benefits of the information campaign, at the household level, can be measured as the change in area of consumer surplus between the values of *Aid* and I_{limit} (Figure 4.1). For this household, the intervention causes an outward shift in demand due to reduced search costs, increased awareness about insurance, and changed flood risk perceptions. It is assumed that the campaign causes demand to shift just enough such that households are willing to pay subsidized premiums ($\Delta A_2 + B_2 + \Delta B_2 + \Delta C_1 > E_1$). The net benefit of the information campaign for this household is equal to $\Delta A_2 + B_2 + \Delta B_2 + \Delta C_1 - E_1$. Part of the net benefit of insurance is attributable to consumer surplus above the actuarially fair price (area A_2), which implies that some households

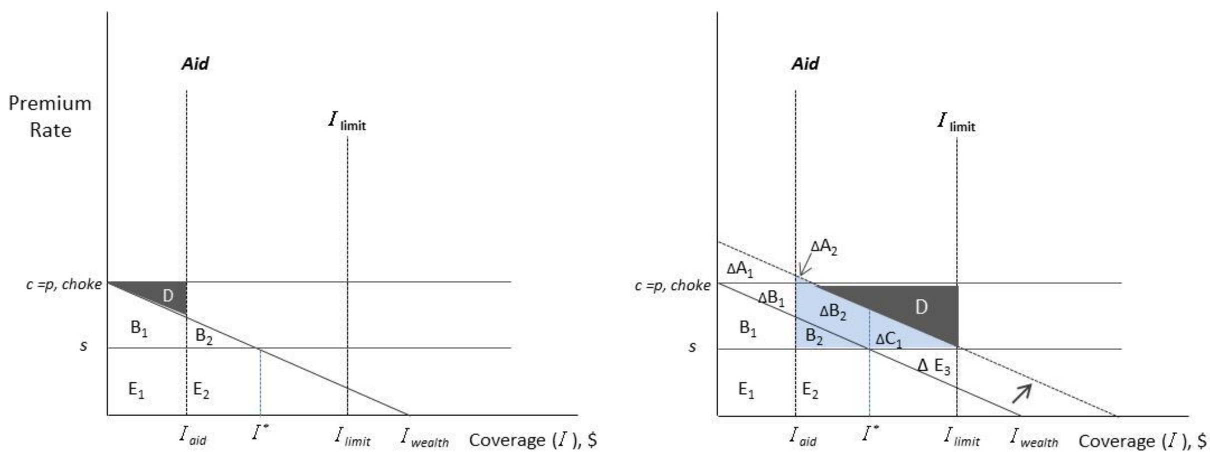
[37]Subsidized insurance allows households to purchase coverage at a premium rate below the actuarially fair level. In Thailand, insurance is offered at a fixed premium rate of 0.5%, which in high-risk areas is below the actuarially fair rate.

value insurance beyond the amount of expected annual claims. However, as Figure 4.1 is drawn, most of the benefit is attributable to consumer surplus due to subsidized premiums (areas B_2, ΔB_2, and ΔC_1). This benefit to households attributable to subsidized premiums is a transfer payment from taxpayers.

Figure 4.1 Household insurance demand, Type 3 household

Before Information Campaign

Post-Information Campaign



The household described above represents one of several possible types of households. A typology of households is developed based on awareness of insurance (unaware or aware), baseline willingness to pay for insurance (actuarially fair rate, subsidized rate, or less than subsidized rate), and insurance purchase decision after the information campaign. No data exist for household demand for subsidized flood insurance in Bangkok. Therefore, illustrative calculations are made, based on assumed demand curves for a typology of households. In addition, assumptions are made regarding the number of households categorized as each type in the typology so that costs and benefits can be aggregated to a population total.

Table 4.1 presents a total of six possible household types. However, only four types of households would be targeted by an information provision campaign. Households that are aware of insurance and willing to pay either actuarially fair or subsidized premiums would have purchased insurance prior to the campaign. Since the campaign targets uninsured households, these types of households are not considered in this BCA study since they would have already purchased insurance. Furthermore, households that do not purchase insurance after the information campaign (Type 4) are only included in the BCA in terms of their information campaign costs. These households are assumed to receive zero benefits from the campaign.

Table 4.1 Types of households, by awareness of insurance and demand

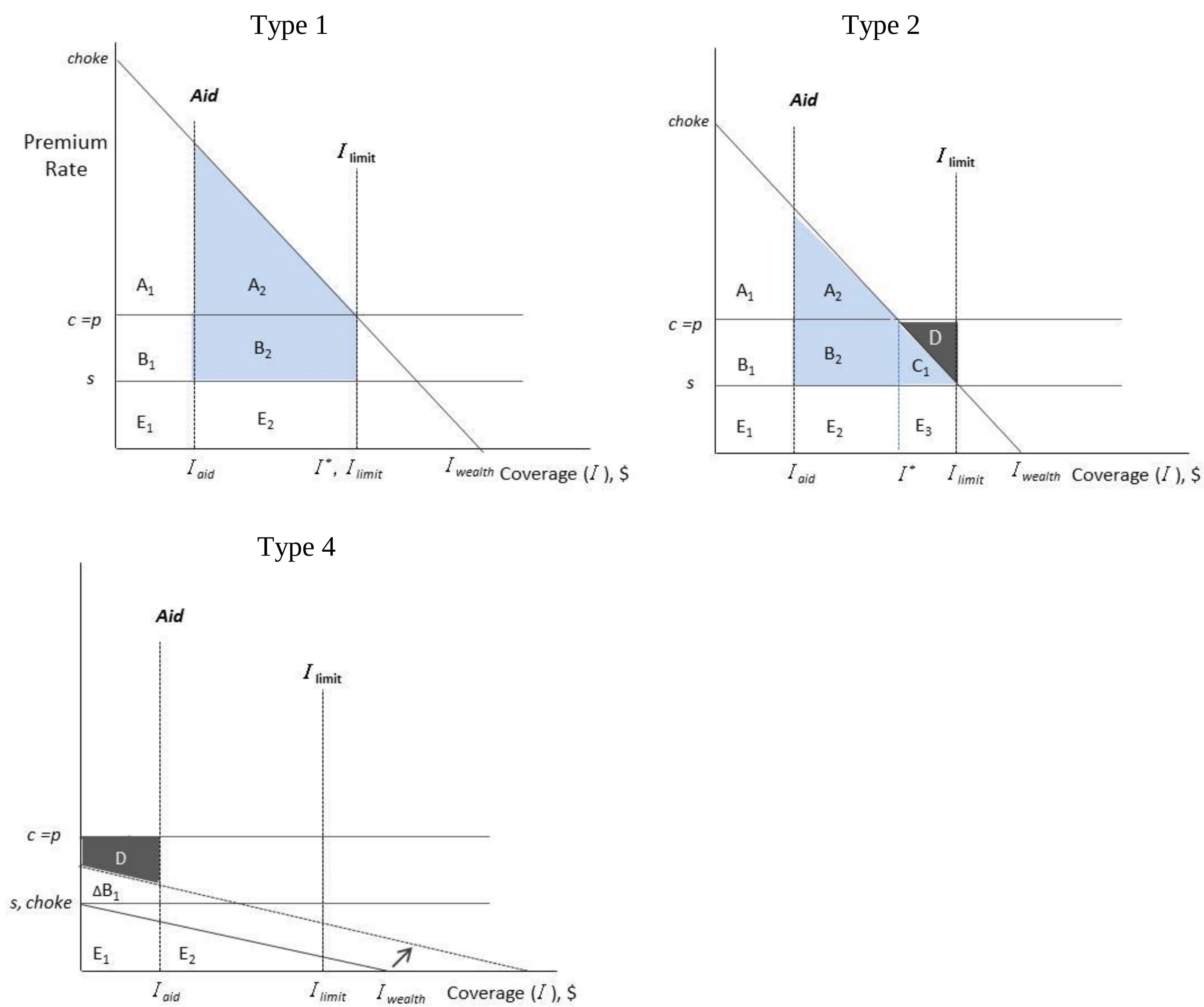
<table>
<tr><th></th><th colspan="4">Willingness to Pay (baseline)</th></tr>
<tr><th></th><th>Actuarially fair</th><th>Subsidized</th><th colspan="2">< Subsidized</th></tr>
<tr><td>Post-treatment insurance decision:</td><td>Purchased</td><td>Purchased</td><td>Purchased</td><td>Didn't purchase</td></tr>
<tr><td>Unaware
(at baseline)</td><td>Type 1</td><td>Type 2</td><td rowspan="2">Type 3</td><td rowspan="2">Type 4</td></tr>
<tr><td>Aware
(at baseline)</td><td>-</td><td>-</td></tr>
</table>

Benefits will vary across households, largely influenced by baseline awareness of the insurance program and the extent to which the intervention increased insurance demand. In addition to the household describe above (a Type 3 household), there are three other household types that would be targeted by the information campaign, as depicted in Figure 4.2. For all household types, it is assumed that I_{limit} is greater than *Aid*, but less than I_{wealth}. Type 1 and 2 households are assumed to have a relatively high demand for coverage, with the choke price exceeding the actuarially fair premium rate ($c=p$). Type 1 would purchase coverage equal to I_{limit} at the actuarially fair premium, while Type 2 would purchase I_{limit} at subsidized premiums. The total benefit of aid to Type 1 and 2 households is equal to the area under the demand curve (A_1+ B_1 + E_1). The portion of the benefit above the actuarially fair price of coverage ($c=p$) is represented by A_1, while B_1 + E_1represents the amount of aid transferred from taxpayers to flood-affected households. Therefore, the net social benefit of aid is equal to A_1, which is the difference between household benefits (A_1+ B_1 + E_1) and taxpayer cost (B_1 + E_1).

The net benefit of subsidized insurance to households is equivalent to the annual expected claim, less the annual premium and loss of flood aid (compared to the status quo). Prior to the information campaign, the net benefit of insurance for Type 1 and 2 households (A_2 + B_2 + C_1) exceeds that of aid (E_1). Part of the net benefit of insurance is attributable to consumer surplus above the actuarially fair price (area A_2), which implies that some households value insurance beyond the amount of expected annual claims.[38] Households also benefit from subsidized premium payments (B_2 + C_1), which represent a transfer payment from taxpayers to flood-affected households. Yet, Type 1 and 2 households are not insured at baseline due to lack of awareness of the insurance program and/or incomplete information regarding flood aid and insurance. It should also be noted that Type 1 households would have bought the same amount of insurance coverage without the subsidy. The net social benefit of aid is equal to the benefit that households receive (A_2 + B_2 + C_1), less the cost of subsidized premiums that taxpayers bear (B_2 + C_1).

[38]These additional benefits of insurance include consumption smoothing and risk reduction and emotional goals (Krantz and Kunreuther, 2007).

Figure 4.2 Household insurance demand (Post-Information Campaign), by household type



In contrast, Type 3 and 4 households have relatively low demand and are not willing to pay the subsidized insurance premium. The choke prices for households of Type 3 and 4 are equal to the actuarially fair rate and subsidized rate, respectively. For these households, the net benefit of insurance at baseline (B_2) is less than that of aid (E_1). Therefore, had Type 3 and 4 households known about insurance, they would not have purchased it prior to the information campaign.

The information campaign is expected to cause demand curves to be generated for households that are unaware of insurance. Total benefits of purchasing insurance are summarized in Table 4.2 for each household type. Type 1 households will have a benefit of $A_2 + B_2 + E_2 - E_1$, while Type 2 households have a benefit equal to $A_2 + B_2 + C_1 + E_2 + E_3 - E_1$. For households of Types 3 and 4, the demand curve will shift. After the information campaign, the benefit of a Type 3 purchasing insurance will be $\Delta A_2 + B_2 + \Delta B_2 + C_1 + E_2 + E_3 - E_1$. For a household of Type 4, the shift in demand is not large enough for insurance to be preferred over flood aid. Benefits will vary across households, largely influenced by baseline awareness of the insurance program and the extent to which the intervention increased insurance demand.

Benefits can be aggregated across all households. An aggregate benefit measure is equal to the change in area of consumer surplus between the values of *Aid* and I_{limit} (Figure 4.3). This magnitude of this area is influenced by the extent to which households with high demand lack information about insurance at baseline.

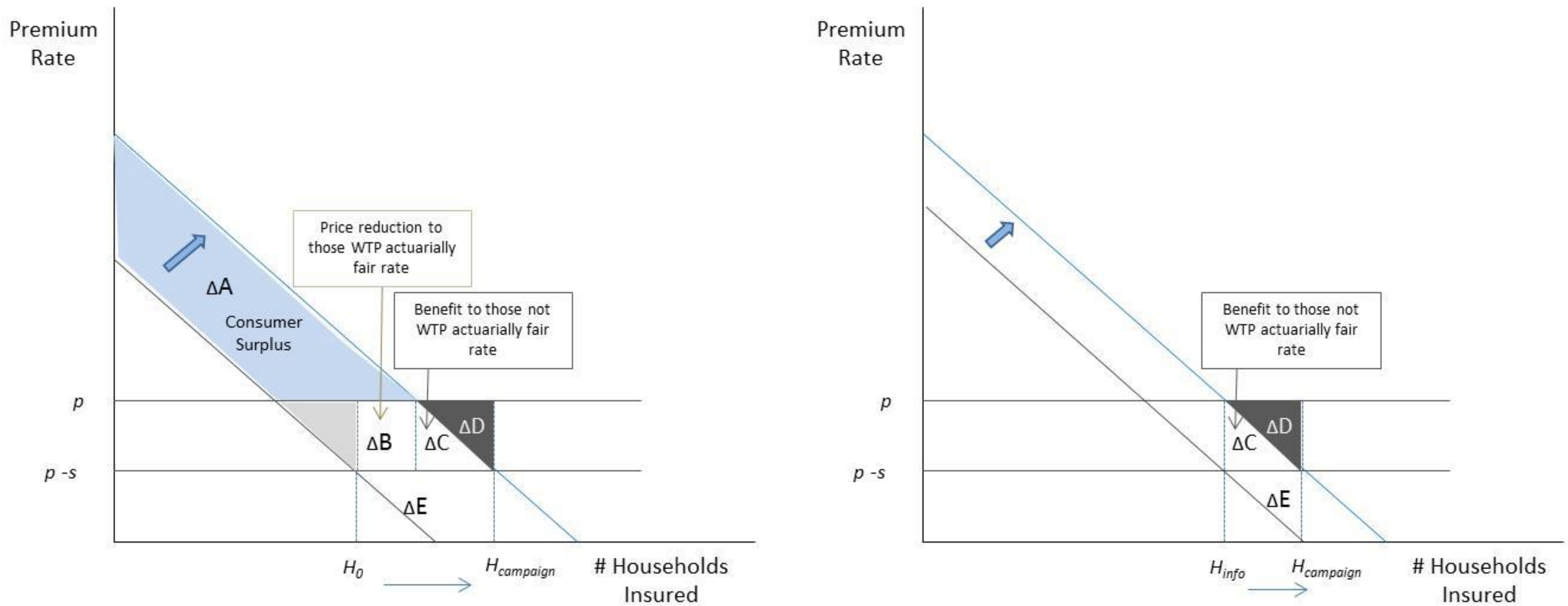
Table 4.2 Summary of Demand for Insurance Coverage, by household type

	Type 1	Type 2	Type 3		Type 4	
			Pre-intervention	**Post-intervention**	**Pre-intervention**	**Post-intervention**
Household demand						
Choke price	> *c=p*	> *c=p*	*c=p*	> *c=p*	s	< *c=p*
WTP for I_{limit}	*c=p*	*s*	-	*s*	-	-
Total Benefit						
Aid	$A_1 + B_1 + E_1$	$A_1 + B_1 + E_1$	$B_1 + E_1$	$B_1 + E_1 + \Delta B_1 + \Delta A_1$	$B_1 + E_1$	$E_1 + \Delta E_1 + \Delta B_1$
Insurance	$A_2 + B_2 + E_2 - E_1$	$A_2 + B_2 + E_2 + C_1 + E_3 - E_1$	-	$\Delta A_2 + B_2 + \Delta B_2 + C_1 + E_2 + E_3 - E_1$	-	-
Consumer Surplus (above actuarially fair)						
Aid	A_1	A_1	-	-	-	-
Insurance	A_2	A_2	-	-	-	-
Deadweight Loss						
Aid	-	-	D	D	D	D
Insurance	-	D	-	D	-	D

Figure 4.3 Market Demand for insurance, after information campaign

Panel A. Assumption: lack of insurance awareness at baseline

Panel B. Assumption: full information regarding insurance at baseline



4.3.2 Societal Perspective

Other key stakeholders include insurance providers and taxpayers. Insurers are assumed to not earn economic rents. Their costs include claims paid and administrative costs, and normal returns to capital at risk, all of which are assumed to be covered by premium payments and/or government subsidies. For insurance providers, the net benefit of an information campaign will be equal to premium payments, both those paid by households (m_{pay}) and subsidized by government (m_{sub}), less claims paid (I), multiplied by the number of new policyholders (*n*):

$$Net\ Benefit_{Insurers} = \left[\left(m_{sub} + m_{pay}\right) - I\right] \cdot n \;\; = \;\; 0 \qquad (4.2)$$

Taxpayers bear costs under both an *ex post* aid and flood insurance program. Aid represents a transfer payment between taxpayers and households. Households receive the annual expected flood aid payment, while taxpayers incur the cost of the transfer plus any associated administrative costs. Flood aid that is displaced due to increased insurance uptake is a gain for the taxpayer, but a loss for insured households. Under an information campaign to increase insurance uptake, taxpayers bear the cost of the campaign (*info*) in addition to the portion of insurance payments that are subsidized (m_{sub}) and administration costs of insurance ($Admin_I$). Yet, taxpayers will have reduced costs of an *ex post* aid (*aid*) and associated administrative costs ($Admin_{aid}$). Taxpayer burden increases with campaign costs and size of subsidizes for insurance payments. The net benefit of the campaign for taxpayers, relative to the status quo, is equal to:

$$Net\ Benefit_{Taxpayers} = \left[\left[\Delta Aid + \Delta Admin_{aid} - Admin_I - Info - m_{sub}\right] \cdot n\right] \; - Info \qquad (4.3)$$

From the perspective of households, the net benefit of the campaign, relative to the status quo, is equal to the change in consumer surplus above the actuarially fair premium (CS_{act}), plus claims, and less insurance premiums paid (m_{pay}) and change in *ex post* aid (*aid*). The values of CS_{act} are aggregated across all households of type *i*. When applying this method to the BCA in this study, assumptions are made regarding the number of households categorized as each type.[39]

$$Net\ Benefit_{Households} = \sum_i \left[\Delta CS_{act_i} \cdot n_i\right] + \left[I - m_{pay} - \Delta Aid\ \right] \cdot n \qquad (4.4)$$

In addition, deadweight loss is generated by both the flood aid program and subsidized insurance. Deadweight loss associated with flood aid (DWL_{aid}) and insurance (DWL_I) is equal to the area between the actuarially fair rate and household demand curve. From an economic perspective, this deadweight loss exists because households of Type 3 and 4 value flood compensation less than the cost borne by taxpayers. This holds both for compensation in the form of aid and insurance. Deadweight loss will increase with the amount of the subsidy and will decrease with demand for coverage.

Net benefits to society are equal to aggregate benefits, less costs across all stakeholders. Taxpayers bear the cost of the information campaign, subsidized premium payments, and administrative costs, but incur lower flood aid payments for insured households. Insured households benefit from subsidized premiums, limited flood aid, and consumer surplus, but must pay the subsidized portion of insurance premiums. The net social benefit of the information campaign is equal to the households' change in consumer surplus above the actuarially fair premium relative to the status quo of *ex post* flood compensation, less the cost of the information campaign, administrative cost of insurance, and deadweight loss.

[39]As discussed in the Methods section, the base case assumes the following distribution of household types: 44% Type 1, 44% Type 2, and 11% Type 3, based on the characteristics of new policyholders in Chapter 3.

$$Net\ Benefit_{Society} = \sum_i [\Delta CS_{act_i} \cdot n_i] + [\Delta Admin_{aid} - \Delta Admin_I - Info \mp \Delta DWL_{aid} - DWL_I] \cdot n \tag{4.5}$$

Social welfare implications of the information campaign will differ considerably based on *ex ante* awareness of insurance. As the proportion of households that are Type 1 and 2 increases (i.e. those that have high demand but incomplete information), social benefits of the intervention are depicted in Figure 4.3, panel A. The shift in demand due to the campaign results in an increase in consumer surplus, both attributable to households willing to pay more than actuarially fair rates and those who only find insurance attractive at subsidized premiums. The total benefit of the information campaign to households is equal to the area of ΔA +ΔB+ΔC. Deadweight loss (ΔD) is associated with these new policyholders since the cost to government of subsidizing insurance (ΔB+ΔC+ΔD) is greater than the value that policyholders derive from the subsidy (ΔB+ΔC). Deadweight loss can be created by both aid and insurance, as depicted in Figures 4.1 and 4.2. The sign of the net social benefit of the campaign (compared to status quo) is indeterminate and depends on the relative magnitude of the consumer surplus above the actuarially fair premium and deadweight loss.

However, if households are fully aware of insurance at baseline, and thus make an informed decision not to purchase, net benefits of a campaign that encourages new policy purchases are those represented in Figure 4.3, panel B. In this case, households of Types 1 and 2 would have purchased insurance prior to the intervention. Therefore, only Type 3 and 4 households would be targeted by the information campaign. If no households are convinced that the value of insurance exceeds the actuarially fair price, then net benefits are equal to ΔC. These benefits accrue to insurance policyholders. However, from the perspective of society, there are no social benefits associated with this consumer surplus since benefits are associated with subsidized premiums and the cost of subsidies must be incurred by taxpayers. In fact, net social benefits would be negative given the cost of the information campaign and deadweight loss of subsidized premiums.

4.3.3 Observations from Conceptual Framework

Several important observations can be drawn from the conceptual framework. First, the distribution of subsidies is largely skewed towards higher income households, under either an *ex post* aid or flood insurance program. Aid programs can especially benefit higher income households when compensation is based on the magnitude of the property damages, but less so when fixed payments are distributed to all households. Under a subsidized insurance program, subsidies received increase with coverage level. Since higher income households are both more likely to purchase insurance and to purchase higher coverage levels, subsidies will largely accrue to these households.

Second, as flood aid (*Aid*) approaches maximum insurance coverage (I_{limit}), the more attractive the aid program will be to households. From the taxpayer perspective, the relative attractiveness of aid and insurance is ambiguous and depends on the magnitude of the subsidy for insurance payments, and the cost of the information campaign.

Third, the closer in magnitude wealth at risk (I_{wealth}) and I_{limit} become, the less attractive insurance is relative to aid. This implies that low-income households with wealth at risk below I_{limit} will perceive flood aid to be more attractive than wealthier households. Aid will cover a relatively large portion of wealth at risk for these low-income households.

Fourth, net social benefits of the information campaign depend heavily on household demand for insurance and baseline awareness of insurance. The largest benefits are associated with households with high demand for insurance that are unaware of the program. As baseline awareness increases, net social benefits decrease. Furthermore, as the demand curve becomes more convex, the less attractive insurance will be (since the area of $A_2 + B_2 + C_1$ will decrease). As mentioned previously, a limitation of the analysis is that no data exists for household demand for subsidized flood insurance in Bangkok. Therefore, the study makes illustrative calculations based on assumed demand curves for a typology of households.

4.4 Fieldwork, Data, and Methods

4.4.1 Fieldwork and Data

Fieldwork for the two sources of data used in this BCA was conducted in Greater Bangkok Metropolitan area, within some of the communities most affected by the 2011 flood. Communities included in both studies were a mix of low-income and middle-income areas (Chapter 3; Nabangchang et al. 2015). Data from the field experiment described in Chapter 3 are used to specify several BCA parameters including the level of flood compensation and treatment effect of the information campaign. Responses are used from 397 participants in the field experiment. Households included in the study owned their home, were not insured against flooding, and were affected by the 2011 flood. The field experiment included two rounds of household surveys. A second data source, Chapter 1), is used for insurable flood loss estimates that are an input for estimating household insurance demand, as described in Section 4.4.3, below. The survey of 469 households involved two rounds of in-person questionnaires that inquired about economic costs incurred during the 2011 flood and socioeconomic status.

4.4.2 Methods

The focus of this BCA study is to present illustrative calculations that demonstrate how welfare implications could be estimated for an information campaign to increase subsidized insurance uptake in Bangkok. The assessment analyzes how net social benefits differ between the status quo (flood aid) and the information campaign. A hypothetical information campaign is assumed to target a population of 500,000 households that reside in areas inundated by the 2011 Thailand flood. The treatment effect of the campaign is assumed to be 4% for all household types (Types 1 to 3), based on the findings of Chapter 3. Net benefits to society of each alternative are equal to aggregate benefits, less costs across all stakeholders. Taxpayers bear the cost of the information campaign, subsidized premiums, and administrative costs, but incur lower flood aid payments for insured households. Insured households benefit from subsidized insurance payments, limited flood aid, and consumer surplus, but must pay the subsidized insurance premiums. The net social benefit to society is equal to the households' change in the portion of consumer surplus above the actuarially fair premium, less the cost of the information campaign, administrative cost of flood aid and insurance, and deadweight loss. All benefit and cost categories are described in Section 4.4.3.

While the information campaign occurs only once, costs and benefits will accrue to stakeholders over a period of several years. The BCA assumes that annual costs and benefits of a one-time information treatment in year 1 unfolds over a ten-year period.[40] Streams of costs and benefits across this period are estimated in net present value (NPV) terms, using a social discount rate of 4% (in the base case). The persistence of the treatment effect is unknown since no prior information experiments have been conducted for insurance and the outcomes of the first experimental study were measured six months after treatment (Chapter 3). Base case assumptions regarding the durability of the treatment effect are developed based on Michel-Kerjan et al. (2012). The base case assumes a logarithmic decline in insurance uptake among

[40]Ten years in the median length of policy tenure in the base case, based on Michel-Kerjan et al. (2012). It is also the length of time found by Gallagher (2014) for post-disaster increase in insurance uptake to decline to baseline levels.

new policyholders. Therefore, 4% of targeted households are expected to purchase insurance immediately after the information campaign, but this number of policyholders in subsequent years declines due to non-renewal of policies. New policies are assumed to be purchased only immediately after the campaign. The rate of decline reported in Michel-Kerjan et al. (2012) is adjusted for the median length of residency reported by Bangkok households.[41] This trajectory implies that about half of policies will still be in-force nine years after the intervention.

4.4.3 Definitions and Estimation of Cost and Benefit Categories

This section describes definitions and estimation techniques for cost and benefit categories included in the analysis. Many categories represent transfer payments, which are perceived as costs to some stakeholders, but benefits to others. Table 4.3 summarizes parameter values included in the BCA for base, downside, and upside assumptions. In the BCA, each category, with the exception of information campaign cost, is estimated for three types of households (Types 1-3) and then multiplied by the number of new policyholders assumed to be of a given household type.

Household Insurance Demand

Limitations of estimating insurance demand in Bangkok are acknowledged. Little information is available regarding insurance demand in Thailand. Demand cannot be constructed using observed purchases due to the presence of (i) a fixed premium rate and therefore no price variation across households and (ii) a purchase mandate for households with mortgages.

[41] Michel-Kerjan et al. (2012) analyzes length of flood insurance tenure for all new policies issued in the U.S. from 2001- 2009. Findings suggest that much of the decrease in uptake of new policies can be explained by relocation. Importantly, the average annual rate of relocation is much greater in the U.S. (16%) than among Bangkok households that participated in the information field experiment (3.5%).

Table 4.3 Key parameters for Benefit Cost Analysis

Cost category	Description	Value estimates (US$ per insured household) Base case	Downside	Upside
Aid	*Ex post* flood compensation provided by national government	800	320	3200
Aid (all households)	Portion of aid automatically distributed to all households in designated disaster-affected areas	160	320	0
Aid (only uninsured households)	Portion of aid distributed via application to uninsured households	640	0	3200
$Admin_{aid}$	Administrative cost associated with distribution of flood aid	177	32	800
I	Annual expected claims for an NCIF insurance policy with US$ 3200 in coverage	25	25	25
m_{pay}	Portion of annual insurance premium, paid by households	16	16	16
m_{sub}	Portion of annual insurance premium, subsidized by government	9	9	9
$Admin_I$	Administrative cost associated with insurance marketing, communication with policyholders, and claim adjustment	2	2	1
Info	Cost of information campaign	1.3	1.9	0.7

Other parameters	Description	Parameter Value Base case	Downside	Upside
Admin cost: insurance	Administrative cost of insurance (% of premium)	12%	15%	8%
Admin cost: flood aid	Administrative cost of flood aid (% of annual expected compensation)	22%	12%	27%
Treatment effect (%)	Increase in insurance uptake attributable to the information campaign	4.3%	2.3%	11%
Flood probability	Probability of a flood similar in magnitude as the 2011 event	0.008	0.010	0.007

With limited information, demand is estimated for households of Type 1-3 (i.e. households that are most likely to purchase insurance after receiving information from the campaign). In Chapter 3, I find that all new policyholders selected the maximum coverage level (US$ 3,200). This suggests that insurance is most attractive for those with insurable flood losses equal to or greater than I_{limit}.[42] Furthermore, insurable losses (i.e. cost of repair and replacement for house, contents, and vehicles) during the 2011 Bangkok flood were relatively low. Median insurable losses were US$ 1,443 and about one-third of households had losses below the median level of government flood aid (US$ 800) (Nabangchang et al., 2015). Households with insurable losses nearly equal to the value of flood aid would be expected to forgo insurance. Only 28% of households had insurable losses greater than I_{limit}.

The household demand curves used for the BCA are based on two assumptions. First, households are expected to insure all losses if the premium is zero. Among households likely to purchase insurance (i.e. those with insurable losses greater than I_{limit}), median insurable losses during the 2011 Bangkok flood were US$ 6,538 (THB 204,300). For all household types, it is assumed that at a premium of zero, households demand US$ 6,538 in insurance coverage. Second, the demand response function for flood insurance in Bangkok is assumed to be linear. Demand is estimated for three types of representative households that are likely to purchase insurance after the information campaign (Types 1-3).

For each of these household types, the assumed linear demand function connects the horizontal intercept (i.e. coverage level selected at a premium of zero) and demand at the actuarially fair or subsidized premium rate (Table 4.4). Type 1 households are assumed to be willing to pay the actuarially fair rate (c=p) for US$ 3,200 in coverage, while Type 2 are

[42]Insurable losses are out-of-pocket expenses to repair and replace house structure, contents, and vehicles. These losses do not include foregone income or value of household time devoted to repair, recovery, or greater travel time.

assumed to be willing to pay the subsidized rate. Meanwhile, Type 3 households are willing to pay the subsidized rate only after the information campaign. Table 4.4 also presents the implied elasticity values for each household type at the actuarially fair and subsidized premium rates. Demand is more elastic at subsidized premiums compared to actuarially fair, which follows the findings of Landry and Jahan-Parvar (2011).

The base case assumes the following distribution of household types: 44% Type 1, 44% Type 2, and 11% Type 3, based on the characteristics of new policyholders in Chapter 3.[43] In sensitivity analysis, the upside assumption is that all new policyholders are Type 1, while the downside case assumes new policyholders are Type 3. In the upside case, the information campaign serves to raise awareness of the NCIF program among households with relatively high demand for insurance. In contrast, the downside case assumes that households have full information prior to the information campaign. Therefore, the households for whom insurance is a rational purchase will be insured at baseline (Types 1 and 2).[44]

[43]This base case assumption is based on the nine households that purchase insurance after the information campaign in Chapter 3. At baseline, four households are willing to pay the actuarially fair rate or greater for US$ 3,200 in coverage. These four households are considered to be Type 1 since they stated that the information campaign made them aware of flood insurance and/or program details. In addition, four households are willing to pay the subsidized rate and were not aware of flood insurance and/or program details at baseline (Type 2). One household is not willing to pay the subsidized rate at baseline, but purchases insurance after the information campaign (Type 3).

[44]There is some evidence against this case. Insurance appears to be a rational purchase for nearly one-third of households included in Nabangchang et al. (2015). Yet, only about 11% of these households (14 out of the 133 households with losses greater than US$ 3,200) are insured.

Table 4.4 Estimated Household-level Coverage Demand, by household type

Demand for I_{limit}	**Type 1** WTP $c=p$	**Type 2** WTP subsidized rate	**Type 3** Choke price $c=p$ (at baseline); WTP subsidized rate (post-intervention)		**Weighted Avg.** Across all household types
			Pre-intervention	**Post-intervention**	
Household demand					
Demand function	$I = -13{,}559{,}000 \cdot c + 204{,}300$	$I = -20{,}860{,}000 \cdot c + 204{,}300$	$I = -26{,}559{,}000 \cdot c + 204{,}302$	$I = -26{,}559{,}000 \cdot c + 232{,}795$	
Elasticity at actuarially fair price (coverage in terms of % of losses)	-1.0	-3.7	-	-7.2	
Elasticity at subsidized price (coverage in terms of % of losses)	-0.5	-1.0	-1.9	-1.3	
Choke price (rate)	0.015	0.010	0.008	0.009	
Choke price (US$)	48.2	31.3	24.6	28.0	
Consumer Surplus (above actuarially fair)					
$\text{Aid}_{\text{uninsured}}$	4.1	1.2	0.0	0.4	2.4 †
$\text{Aid}_{\text{insured}}$	0.6	0.2	0.0	0.1	0.3 *
Insurance	8.9	2.5	0	1.3	5.2 *
Deadweight Loss					
$\text{Aid}_{\text{uninsured}}$	0	0	0.38	0	0.0 †
$\text{Aid}_{\text{insured}}$	0	0	0.02	0	0.0 *
Insurance	0.0	2.4	5.6	3.1	1.4 *

Note: † Represents average value across three types of households for status quo flood aid program (pre-intervention).
* Represents average value across three types of households for information campaign (post-intervention).

Consumer surplus and Deadweight loss

The principal economic benefit that insurance provides is consumer surplus above the actuarially fair premium, as discussed in Section 4.3. Therefore, the 'consumer surplus' reported in the BCA results refers to the benefits that accrue to policyholders who are willing to pay more than the actuarially fair rate. Consumer surplus is also incurred due to subsidized premiums. However, this surplus is already accounted for in the claims that households receive and is equal to total claims, less the premium payment.

The consumer surplus of flood aid and insurance is equal to the area between the household demand curve and actuarially fair rate.[45] The base case assumption is that insured households receive a small, automatic cash transfer ($aid_{insured}$=US$ 160), while uninsured households also receive additional aid available through an application in addition to the automatic transfer ($aid_{uninsured}$=US$ 800). In the base case, the consumer surplus for an average new policyholder is the weighted average total consumer surplus for the three types of households. In the status quo scenario, the weighted average consumer surplus (above the actuarially fair price) of flood aid is US$ 2.4 each year.[46] The weighted average consumer surplus (above the actuarially fair premium) of insurance claims for new policyholders in the base case is US$ 5.2 each year. Consumer surplus of insurance exceeds deadweight loss for all household types except Type 3 (as shown in Table 4.4). Therefore, as the proportion of Type 3 households increases, the information campaign will have a lower net social benefit.

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[45]The consumer surplus associated with the two levels of aid is estimated as $\int_0^{aid_i} I(c)dc - \int_0^{aid_i} c_p = \frac{1}{2}(c_{Choke}-c_p)\cdot aid_i$, where *i=insured, uninsured*. The term c_p is the actuarially fair rate of insurance, while *I* is the household demand curve for flood compensation. Similarly, the consumer surplus associated with an insurance purchase is estimated as $\int_{aid_{uninsured}}^{I_{limit}} I(c)dc - \int_{aid_{uninsured}}^{I_{limit}} c_p = \left[\frac{1}{2}(c_{Choke}-c_p)\cdot I_{limit}\right] - \left[\frac{1}{2}(c_{Choke}-c_p)\cdot aid_{uninsured}\right]$.

[46]In order to report average consumer surplus estimates, the weighted average must be taken across all three household types included in the estimation of benefits. The weights are based on the proportion of households classified as each type. The base case assumes the following distribution of household types: 44% Type 1, 44% Type 2, and 11% Type 3.

Deadweight loss associated with flood aid is equal to the area between the actuarially fair rate and household demand curve, and between compensation values of zero and the flood aid level. The deadweight loss of insurance is equal to the area between the actuarially fair rate and household insurance demand curve, and between compensation values of the insurance coverage level and flood aid received by uninsured households.[47] In the base case, the deadweight loss for an average new policyholder is the weighted average deadweight loss for the three types of households. Deadweight loss will increase with the amount of the subsidy. The weighted average deadweight loss of insurance claims for new policyholders in the base case is US$ 1.4 per year, which is entirely attributable to insurance uptake. In the status quo scenario, the weighted average consumer surplus of flood aid (above the actuarially fair premium) is US$ 0.04.

Flood aid and associated administrative cost

Aid represents a transfer payment between taxpayers and households. In Thailand, insured households must forgo most flood aid.[48] Both of these options provide limited compensation for flood losses. Flood aid that is displaced due to increased insurance uptake is a gain for the taxpayer, but a loss for insured households.[49] The status quo scenario assumes that uninsured households receive US$ 800 in flood aid after a flood occurs. Under the information

[47]The deadweight loss associated with the two levels of aid is estimated as $\int_0^{aid_i} c_p - \int_0^{aid_i} I(c)dc$, where *i=insured, uninsured*. The term c_p is the actuarially fair rate of insurance, while I is the household demand curve for flood compensation. Similarly, the deadweight loss associated with an insurance purchase is estimated as $\int_{aid_{uninsured}}^{I_{limit}} c_p - \int_{aid_{uninsured}}^{I_{limit}} I(c)dc$.

[48]All Thai households are entitled to receive flood aid that is automatically dispersed after a disastrous event. After the 2011 flood, all registered households received US$ 160 immediately after the flood. Yet, additional aid that might become available via an application would not be available to insured households (up to US$ 960 in 2011). Therefore, flood insurance displaces a large amount of aid.

[49]Flood aid and insurance claims are only paid if a flood event occurs. Therefore, values of flood aid and claims are converted to annual expected values by multiplying by the annual probability of a flood similar in magnitude to the 2011 event (p=0.008).

campaign, it is assumed that insured households receive only the small, automatic cash transfer distributed immediately after a disaster (US$ 160), in the base case.[50] Insured households will not be eligible for additional aid that is available via application (up to US $960). Administrative costs of distributing flood aid are assumed to be about 20% of disbursed aid (DDPM, 2013; Threemingmid, 2015). Sensitivity analysis tests how net social benefit estimates change under downside and upside assumptions regarding flood aid. The downside case assumes that an automatic transfer of US$ 320 is available to all households, while the upside case assumes aid of US$ 3,200 (equal to insurance coverage) is only available via application to uninsured households.

Insurance claims, premium payments, and administrative costs

The net benefit of subsidized insurance to households is equivalent to the annual expected claim, less the annual premium and loss of flood aid (compared to the status quo). Insurers are assumed not earn economic rents. Insurer revenues from policyholders plus subsidies received from government are equal to the claims paid and administrative costs. The value of premium payments is estimated as the premium rate multiplied by the coverage level. It is assumed that all new policyholders select the highest coverage level (I_{limit}) of US$ 3,200 and pay an annual premium of US$ 16. The annual expected claim (US$ 25) is greater than the premium paid by households (US$ 16).[51] The difference between these two values (US$ 9) is the subsidized portion of the insurance premium which is paid by government (taxpayers). In addition, taxpayers pay the administrative costs of insurance. Administrative costs are assumed

[50]All registered households in Thailand are eligible for automatic flood aid (Threemingmid, 2015). However, insured households are not able to apply for additional aid for documented repair expenses.

[51]Regardless of flood risk level, households in Thailand pay a fixed premium rate of 0.5%. The return period of a flood similar to the 2011 event is assumed to be 130 years, which implies p=0.008 (DHI, 2012). It is assumed that if a flood similar to the 2011 event occurs, the households that are targeted for the information campaign will be flooded. The probability that high-risk households are flooded (0.8%) exceeds the premium rate (0.5%).

to be 12% of the premium, with a range from 8 to 15%, based on estimates from the National Catastrophe Insurance Fund (Threemingmid, 2015). The cost of administering insurance policies includes marketing, communicating with potential policyholders to clarify contract terms, and claim adjustment.

Cost of information campaign

The cost of the information campaign includes cost of information materials and delivery to households. Costs are estimated for an information campaign that targets 500,000 uninsured households in the Greater Bangkok area. Insured households are not targeted and can be identified from NCIF purchase records. Delivering two rounds of information requires labor, transportation, printed materials, and a short video. Cost components are summarized in Table 4.5. Labor to deliver the first-round of information is expected to be compensated at US$13 per day. It is expected that meeting with households and conveying the information will take an average of 25 minutes. Labor to drop-off the second-round information leaflet is compensated at the minimum daily wage rate of US$10. Transportation costs are estimated to be less than US$ 2 per day for each enumerator. Administrative costs are incurred in the form of field supervisors and a campaign manager.[52] Under these assumptions, the total cost per targeted household is about US$ 1.30, while the cost per new policyholder is US$ 30. Costs of the information campaign are assumed to range from nearly US$ 1 to US$ 2 per targeted household.[53]

[52]Each field supervisor oversees a team of 12 enumerators and daily compensation is four times the minimum daily wage rate. The campaign manager oversees the field supervisors and is compensated US$ 63 per day. Campaign manager compensation is much greater than median civil servant wages, US$36 (Nabangchang et al., 2015).

[53]Under downside assumptions, the campaign cost is US$ 1.91 per targeted household. This assumes a video cost of US$500, daily wage rate of US$ 16, and first-round transport cost of US$ 2.6 per day. Field supervisors oversee 15 enumerators and are compensated at three times the minimum daily wage rate. The campaign manager is compensated at US$ 32 per day. The upside assumptions include zero cost for the video (by using the pre-existing video from the field experiment), daily wage rate of nearly US$ 10, and first-round transport cost of US$ 1 per day. Field supervisors are assumed to oversee ten enumerators and administrators are compensated at base case rates.

Table 4.5 Costs of Information Campaign

	Base Case		Downside	Upside
n= 500,000 targeted households	**Total Cost (US$)**	**Per targeted household**	**Total Cost (US$)**	**Total Cost (US$)**
First round (practical information)				
Information materials				
Development of short video	300	-	500	0
Informational brochure	32,000	0.06	32,000	32,000
Delivery of information				
Labor	333,333	0.67	500,000	200,000
Transport	50,000	0.10	80,000	30,000
Second round (social information)				
Printed material: leaflet	8,000	0.02	8,000	8,000
Delivery of information				
Labor	50,000	0.10	80,000	30,000
Transport	8,333	0.02	16,667	5,000
Administrative cost	155,556	0.31	236,444	63,037
Cost per targeted household	1.28		1.91	0.74
Cost per newly insured household	30		82	17

Note: Exchange rate US$ 1 = THB 31.25, October 2013

4.5 Results

4.5.1 Base Case Results

Streams of costs and benefits over the study period are estimated in net present value terms and summarized in Table 4.6. Results indicate that the information campaign does not deliver net social benefits relative to the status quo flood aid program, under base case assumptions. The expected net benefit to society of the status quo flood aid program is US$ 49,336 (US$ 2.3 per household), assuming a 4% discount rate.[54] In contrast, the information campaign results in a net cost to society of US$ 347,215 total, or about US$ 16 per household.

[54]This is the net cost of providing aid at baseline to the 23,806 households that are expected to purchase insurance after the information campaign.

Under base case assumptions, the status quo flood aid program appears to be preferable to the information campaign, both from the perspective of society and taxpayers.

The status quo flood aid program is associated with one social benefit category (consumer surplus above the actuarially fair premium) and one social cost (administrative cost of flood aid). Taxpayers bear the cost of flood aid payments and associated administrative cost. Meanwhile, households receive benefits of the flood aid and associated consumer surplus. Under the information campaign, consumer surplus remains the only social benefit and amounts to US$ 776,232. The largest social cost is the implementation of the information campaign, which has an expected net present value of US$ 613,002. This cost is borne in the first year and benefits are generated into the future. Since the bulk of costs are borne early on, NPV estimates slightly change with the discount rate assumption. As the discount rate increases, greater weight is given to costs in early years and therefore the NPV estimate decreases. Other social costs include the administrative cost of new insurance policies (US$ 230,027) and administrative cost of flood aid (US$ 101,147). In addition, deadweight loss is associated with new insurance policies since some households are only willing to purchase insurance at subsidized premiums and therefore do not value insurance more than the actuarially fair premium.

Taxpayers are also worse off under the information campaign since they incur greater costs (US$ 2.5 million) than in the status quo scenario (US$ 1.3 million). Greater costs are largely due to expenses associated with the information campaign and subsidizing household insurance premiums. The annual premium subsidy (US$ 8.6 per new policyholder) is greater than the median level of flood aid in the status quo scenario (US$ 6.2). This is due to the large premium subsidy and greater coverage offered under the insurance program. If the premium subsidy and flood aid for policyholders were eliminated, taxpayers would prefer the information campaign (assuming that increased insurance uptake remained the same). New policyholders benefit from the information campaign due to the greater coverage levels offered by insurance, compared to flood aid. The benefit to new policyholders is much greater under the information campaign (US$ 2.3 million total, or US$ 107 per new policyholder) compared to the status quo (US$ 1.4 million total, US$ 64 per new policyholder).

Table 4.6 Benefit-Cost Results: Base Case

	Status Quo: Net Benefit	**NPV 2% (US$)**	**NPV 4% (US$)**	**NPV 6% (US$)**	**Information Campaign: Net Benefit**	**NPV 2% (US$)**	**NPV 4% (US$)**	**NPV 6% (US$)**
Newly insured households	Aid	1,188,465	1,073,134	973,796	Aid	514,265	457,676	409,326
	CS_{act}	325,369	293,794	266,598	CS_{act}	853,853	776,232	709,069
					I	3,370,998	3,077,287	2,822,351
					m_{pay}	-2,191,149	-2,000,237	-1,834,528
	Subtotal	1,513,834	1,366,928	1,240,394	*Subtotal*	2,547,967	2,310,959	2,106,218
Insurance Providers					$m_{sub} + m_{pay}$	3,370,998	3,077,287	2,822,351
					I	-3,370,998	-3,077,287	-2,822,351
					Subtotal	0	0	0
Taxpayers	Aid	-1,188,465	-1,073,134	-973,796	Aid	-514,265	-457,676	-409,326
	$Admin_{aid}$	-262,651	-237,163	-215,209	$Admin_{aid}$	-113,653	-101,147	-90,461
					m_{sub}	-1,179,849	-1,077,050	-987,823
					$Admin_{I}$	-251,982	-230,027	-210,971
					Info	-625,022	-613,002	-601,436
	Subtotal	-1,451,116	-1,310,296	-1,189,005	*Subtotal*	-2,684,771	-2,478,903	-2,300,017
Total (Society)	CS_{act}	325,369	293,794	266,598	CS_{act}	853,853	776,232	709,069
	$Admin_{aid}$	-262,651	-237,163	-215,209	$Admin_{aid}$	-113,653	-101,147	-90,461
					$Admin_{I}$	-251,982	-230,027	-210,971
					Info	-625,022	-613,002	-601,436
	DWL_{aid}	-8,080	-7,295	-6,620	DWL_{aid}	-2,350	-2,065	-1,823
					DWL_{I}	-194,119	-177,205	-162,525
	Total	**54,638**	**49,336**	**44,769**	**Total**	**-333,273**	**-347,215**	**-358,147**

Note: All costs and benefits represent annual expected values. Premiums and administrative costs are incurred each year. Payouts of flood aid and insurance claims are only incurred after a flood event, and therefore these values are converted to annual expected values by multiplying by the annual probability of a flood similar in magnitude to the 2011 event (p=0.008).

Table 4.6. (Continued)

	Information Campaign: relative to status quo	NPV 2% (US$)	NPV 4% (US$)	NPV 6% (US$)
Newly insured households	ΔAid	-674,200	-615,457	-564,470
	ΔCS_{act}	528,484	482,438	442,470
	I	3,370,998	3,077,287	2,822,351
	m_{pay}	-2,191,149	-2,000,237	-1,834,528
	Subtotal	1,034,133	944,031	865,823
Insurance Providers	$m_{sub} + m_{pay}$	3,370,998	3,077,287	2,822,351
	I	-3,370,998	-3,077,287	-2,822,351
	Subtotal	0	0	0
Taxpayers	ΔAid	674,200	615,457	564,470
	$\Delta Admin_{aid}$	148,998	136,016	124,748
	m_{sub}	-1,179,849	-1,077,050	-987,823
	$Admin_I$	-251,982	-230,027	-210,971
	Info	-625,022	-613,002	-601,436
	Subtotal	-1,233,655	-1,168,606	-1,111,012
Total (Society)	ΔCS_{act}	528,484	482,438	442,470
	$\Delta Admin_{aid}$	148,998	136,016	124,748
	$Admin_I$	-251,982	-230,027	-210,971
	Info	-625,022	-613,002	-601,436
	ΔDWL_{aid}	5,729	5,230	4,797
	DWL_I	-194,119	-177,205	-162,525
	Total	**-387,912**	**-396,551**	**-402,917**

Note: All costs and benefits represent annual expected values. Premiums and administrative costs are incurred each year. Payouts of flood aid and insurance claims are only incurred after a flood event, and therefore these values are converted to annual expected values by multiplying by the annual probability of a flood similar in magnitude to the 2011 event (p=0.008).

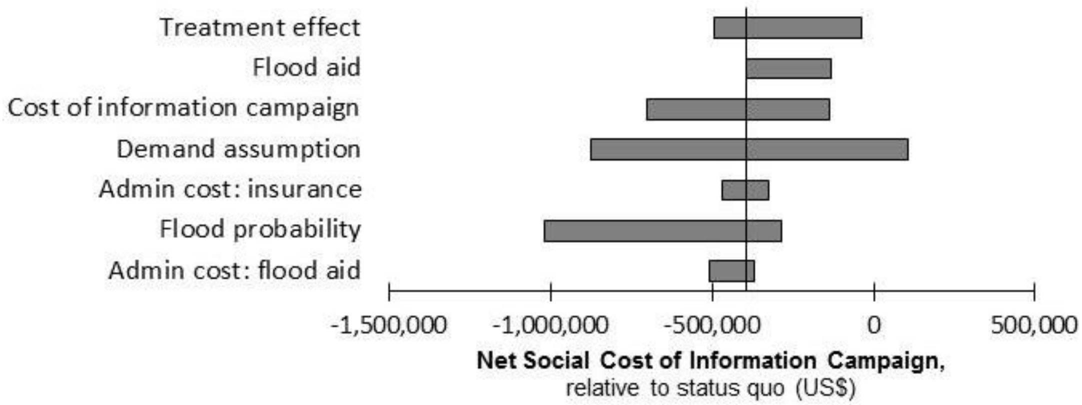
4.5.2 Sensitivity Analysis

Base case results suggest that the status quo policy is preferred to the information campaign from the perspective of a benefit-cost criterion. Yet, under certain conditions, the information campaign might be preferred. Deterministic sensitivity analysis tests parameter assumptions by calculating NPV estimates under upside and downside values of all key parameters. Parameter values are summarized in Table 4.3 for base, downside, and upside cases. Each key parameter is modeled as an uncertain value (e.g. the upside and downside values are used in lieu of the base case assumption), while holding all other parameters at base case values. Particular focus is placed on assumptions regarding insurance demand and insurance policy tenure.

From the perspective of society, net benefit estimates of the intervention are most sensitive to the insurance demand assumption, flood probability, cost of information campaign, and the treatment effect (Figure 4.4). The only assumption that makes the information campaign preferable over the status quo is higher insurance demand. It should be noted that the base case assumes relatively high demand since a linear demand function is assumed. In contrast to demand, costs of the intervention greatly increase with higher flood probability.[55] Cost of the information campaign is not low enough, even under the upside assumption (US$ 0.7 per target household) to make the information campaign less costly than the status quo policy. Overall, results of the sensitivity analysis imply that the viability of an information campaign greatly depends on flood probability and insurance demand.

[55]Both flood probability and the insurance demand assumption drive the magnitudes of consumer surplus and deadweight loss. The actuarially fair rate of insurance is equal to the flood probability. Therefore, as the probability of a flood increases, consumer surplus associated with insurance decreases while deadweight loss rises.

Figure 4.4 Sensitivity of NPV estimates to key parameter values (logarithmic decline in insurance uptake)



Insurance demand

Assumptions regarding insurance demand greatly influence net social benefit estimates through their influence on the relative magnitude of consumer surplus (above the actuarially fair premium) and deadweight loss. In the upside case, all households that purchase insurance after the campaign are assumed to be Type 1. These households are willing to purchase insurance at premiums above the actuarially fair rate, but lack information regarding the insurance program. Therefore, the information campaign serves to raise awareness and inform these households about conditions of the flood insurance policies. Under this assumption, the information campaign is less costly than the status quo policy at discount rates of 2% and 4%.

In the downside case, all new policyholders are assumed to be of Type 3. These households are persuaded by the information campaign that insurance is worth purchasing at subsidized rates. They do not value insurance above the actuarially fair rate. Therefore, there is no consumer surplus (above actuarially fair) under this downside assumption and the information campaign is much more costly that the status quo (Figure 4.4). Given that many Thai households were unaware of the insurance program prior to the intervention, the upside demand assumption appears to be more likely than the downside assumption.

Duration of treatment effect

Sensitivity analysis is conducted for the durability of the treatment effect. The base case assumes that new policyholders will gradually fail to renew their policies. If greater policy retention exists, then the information campaign will be less costly than in the base case. The upside case assumes all new policyholders retain their insurance policies over the ten-year study period. Findings from Kousky (2011) support this assumption.[56] The cost of the intervention assuming constant uptake (US$ 261,736) is about 20% less than the base case (US$ 347,215). Coupled with optimistic assumptions of other key parameters, the information campaign can become preferred to the status quo (Figure 4.5).

The downside case assumes that new policies attributable to the information campaign will follow a linear decline such that, by the end of the study period, all new policyholders have allowed their insurance to lapse. This is based on observations from Gallagher (2014), which examines how insurance uptake in the U.S. responds to a flood event.[57] Under this pessimistic assumption, flood aid is the only parameter that can allow the information campaign to be less costly than the status quo (Figure 4.6).

[56]Kousky (2011) evaluates insurance tenure using all policies active in St. Louis County, Missouri from 2000-2006. The study finds that the majority of lapsed insurance policies can be explained by the annual relocation rate of 14%. Kousky (2011) provides evidence that insurance tenure in Bangkok might be expected to be relatively stable, given long median residency periods among Bangkok households (20 years) compared to U.S. households (5 to 6 years) (U.S. Census Bureau 2015). Kousky (2011) might offer advantages over Michel-Kerjan et al. (2012) since it includes all policies-in-force, not only the small portion of policies that are newly written.

[57]Gallagher (2014) finds that insurance uptake rapidly increase during the year after a flood and then steadily decreases to baseline after nine years. The downside case is considered to be the least likely scenario since Gallagher (2014) does not control for household relocation and the type of treatment (i.e. flood occurrence) differs from the information campaign.

Figure 4.5 Sensitivity of NPV estimates to key parameter values (upside insurance uptake assumption)

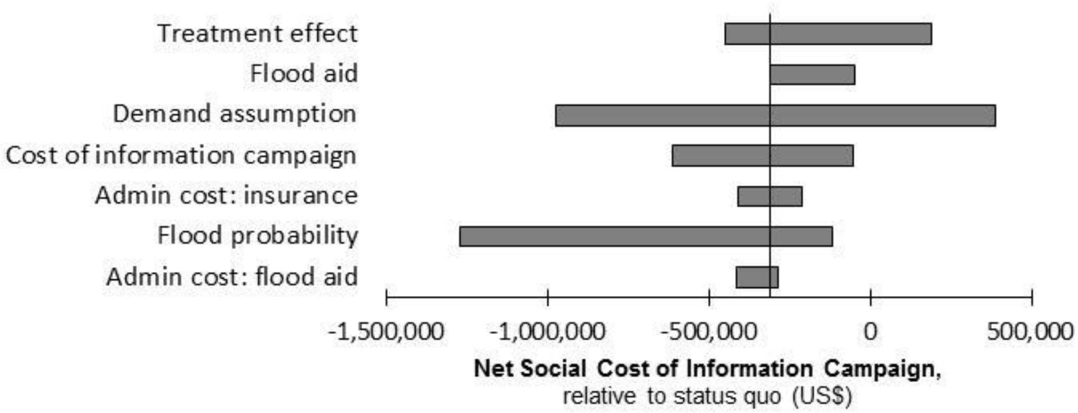
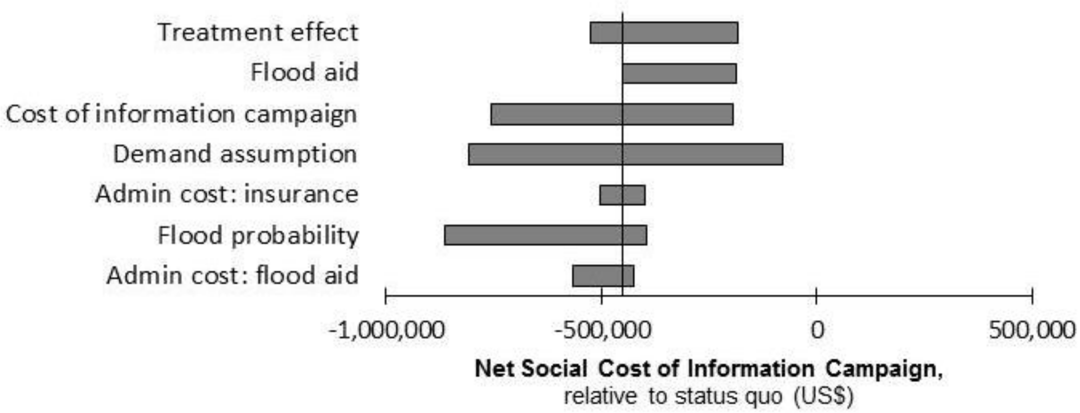


Figure 4.6 Sensitivity of NPV estimates to key parameter values (downside insurance uptake assumption)



4.6 Discussion

This analysis reveals several important insights regarding flood insurance and interventions to encourage voluntary purchase of new policies. First, the information campaign does not pass a cost-benefit test. The intervention only has a modest effect on insurance uptake. Furthermore, the intervention to encourage insurance uptake results in net costs to society due to subsidized premiums and the cost of the information campaign. However, the intervention fails to produce net benefits when accounting for economic costs and benefits across all stakeholders. While mandatory insurance programs offer the potential to spread fixed costs across many policyholders, the costs of voluntary programs will tend to be spread across relatively fewer individuals.

Second, the information campaign is not justifiable on the grounds of serving a vulnerable population or reducing the burden on public budgets. Taxpayers incur greater costs under the information campaign (US$ 2.5 million) than in the status quo scenario (US$ 1.3 million). This greater burden on taxpayers is largely due to subsidized premiums. In addition, the conceptual framework reveals that the distribution of subsidies is largely skewed towards higher income households. Flood insurance does not benefit low-income households since only those that own enough property at risk are likely to purchase insurance policies. Therefore, the information campaign will shift benefits towards higher income households, while taxpayers bear greater cost. As an alternative policy, lump sum aid payments could shift benefits to low-income households.

Third, disaster aid and insurance programs should be better coordinated. A variety of interactions between these two strategies influence household decision making, taxpayer burden, and the economic cost of disaster policy. The presence of disaster aid can reduce demand for insurance and hinder the establishment of a flood insurance program. As the magnitude of flood aid approaches the maximum insurance coverage, the more attractive relying on aid will be to households. In Bangkok, many low-income households received flood aid that exceeded their insurable losses due to the 2011 flood.[58] In order to reduce the incentive for households' to underinsure, flood aid could be limited to low levels.

Fourth, both the conceptual framework and sensitivity analysis of insurance demand imply that the largest benefits of the information campaign are associated with better informing households that have high insurance demand. Less benefit is associated with persuading households with low demand to purchase insurance at subsidized rates. The information campaign could be economically attractive under optimistic assumptions regarding persistence of the campaign treatment effect and household insurance demand. Further research is warranted regarding these two important parameters. This finding has implications for other information interventions. Social norm interventions have become increasingly popular as a means of influencing individual behavior. Yet, the net economic benefits of these social norm interventions are unknown. It appears likely that social norm interventions that are intended to inform households (e.g. about other household's behavior so that learning about optimal behaviors can occur) will offer larger benefits than those intended to persuade (e.g. social pressure to motivate behavioral change).

Overall, the BCA finds that limited government flood aid is preferable to an information campaign to increase insurance uptake in Thailand. This suggests that *ex post* flood aid could be a reasonable policy in cases where the alternative is a voluntary insurance program with subsidized premiums.

[58]Lower-income households in Bangkok are less likely to find flood insurance attractive. In the flood cost survey of households in Bangkok conducted by Nabangchang et al. (2015), nearly half of low-income households (103 out of 210 low-income households) received more government aid than their direct house and content losses.

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CONCLUSION

Overall, the four chapters offer insight into the role of information in mitigating the costs of natural disasters. As communities around the world consider risk mitigation and adaptation options, greater knowledge of disaster impacts and household response can inform crucial policy decisions. Furthermore, information provision could improve decisions related to flood risk mitigation since households often lack of complete information. The major findings and limitations of each of the four chapters are summarized below.

Chapter 1 demonstrates that it is practical and feasible to collect household-level data on flood costs. These microeconomic data produce a more comprehensive view of disaster impacts. Furthermore, they are an important input for the evaluation of flood control mitigation and preventive measures. The use of household surveys offers the ability to capture a wide range of cost types from a broad range of households. This is especially true in developing countries where record keeping tends to be poor and considerable economic activity occurs in the informal sector. Results indicate that median household flood costs were about US$ 3,089 due to the 2011 flood in three of the most severely affected neighborhoods of greater Bangkok. This cost is equal to about six months of self-reported household expenditures. Economic costs were higher for middle-income households than for poor households because they had more property at risk. While the total flood cost was substantial for many households, structural damages to homes were surprisingly low, given the depth and duration of the flood. Building practices in Thailand, such as concrete dwellings, may have lessons for flood-prone communities around the world seeking to reduce potential losses. Houses did not incur permanent structural damage; therefore repair costs were relative low (about 2% of the self-reported market value of the house).

The two main limitations of Chapter 1 are related to the survey instrument design. The design relied on self-reported flood costs and omitted several cost categories. Self-reported costs can be prone to bias since flood-affected households might have incentive to overestimate damage, especially if the estimate influences the distribution of aid (UN and World Bank, 2010). Future research could identify recorded disaster costs and use these estimates either in lieu of or to cross-check survey responses. Data sources could include insurance claims or approved flood aid applications. Future work could also include omitted cost categories such as residual losses and motor vehicle scrappage value. In addition, several cost categories were omitted. Chapter 1 did not account for property damaged that households did not repair or replace. Also, if a motor vehicle was rendered inoperable due to the flood, the survey instrument did not capture a specific scrappage value. Future work could estimate accurate scrappage value by accounting for vehicle model, year, and mileage.

Chapter 2 finds that social media use allowed households to reduce losses during the 2011 flood in Bangkok. Propensity score matching reveals that social media use enabled households to reduce mean total losses by 37%, using a nearest neighbor estimator. Average loss reductions amounted to US$ 3,708 to US$ 4,886, depending on the matching estimator. These reductions are in relation to comparable households (i.e. those who are well-educated, higher-income, and have multi-story houses), rather than the general population. Social media offered information that was not available from other sources, such as localized and nearly real-time updates of flood location and depth. With knowledge of current flood conditions, households could move belongings to higher ground before floodwaters arrived. It appears that social media households focused their *ex ante* mitigation efforts on moving belongings as high as possible. These findings suggest that using social media users as sensors could better inform populations during natural disasters, particularly in locations that lack real-time, accurate flood monitoring networks. Therefore, expanded access to the internet and social could especially be useful in developing countries, ungagged basins, and highly complex urban environments. User updates on social media could especially be useful if they were aggregated and used as input for user-generated flood maps. There is also an enormous opportunity for disseminating government disaster communication through social media. Overall, this study demonstrates the enormous potential of social media for effective flood preparation. Disaster preparedness requires accurate, timely, and readily accessible information to guide household decisions. Social media sites have the potential to provide crucial information that could save lives and reduce property damage.

Limitations of Chapter 2 include self-reported online behavior and possible non-observable differences between social media users and others. Future work could make use of observed internet usage during disasters on social media sites. However, such analysis would need to match observed usage with credible estimates of disaster losses. Future work could also address potential differences between social media users and other households that were not captured in this study. An experimental research design would be a methodically desirable way for capturing the true effects of social media on disaster losses. However, implementing such a design in a disaster situation could raise moral concerns.

The experiment presented in Chapter 3 demonstrates that the combination of practical and social information can encourage flood insurance purchases and thus reduce household welfare losses due to floods. Results indicate that the information intervention increased insurance purchases by about four percent, but no effect was detected for home retrofits. This effect is nearly equal to the increase in uptake that the national insurance program in Thailand has achieved through all other means since its establishment. If scaled up to include all uninsured, flood-prone households in the Bangkok Metropolitan Area, nearly 60,000 additional households could be insured. Results from this experiment are important for the Thai Government's flood insurance strategy, and may have relevance for flood prone areas around the world. The study contributes to the literature on experimental evaluation in the field of environmental policy as well as household demand for flood insurance. The results suggest that well-designed information interventions could increase household uptake of flood insurance, without additional mandates or premium subsidies or mandates.

Limitations of the experiment are that only short-term treatment effects are measured and outcomes are self-reported. Future work could use recorded purchase data and capture long-term treatment effects. The persistence of the effect is unknown beyond six months after treatment and it is unclear how long new policyholders retain their policies. In addition, testing less costly information interventions, such as mass media campaigns, could also be useful in order to determine how information deliver mode affects household response to treatment. More generally, expanding field experiments to other types of climate adaptation actions could produce valuable lessons for public policy.

Chapter 4 presents a benefit-cost analysis of a practical and social norm information intervention. Rigorous accounting of costs and benefits across all stakeholders is crucial to inform policy. Results suggest that the information campaign to increase voluntary insurance purchases will not raise social welfare, under base case assumptions. Furthermore, the information campaign is not justifiable on the grounds of serving a vulnerable population or reducing the burden on public budgets. Yet, the campaign could be economically attractive if base case assumptions regarding insurance demand and policy tenure do not hold. Sensitivity analysis of insurance demand suggests that the largest benefits of the information campaign are associated with better informing households that have high insurance demand. Less benefit is associated with persuading households with low demand to purchase insurance at subsidized rates. This finding has broad implications for other information interventions. It appears likely that social norm interventions that are intended to inform households (e.g. learning about optimal behaviors can occur through knowledge of other household's behavior) likely offer larger benefits than those intended to persuade via social pressure or other means.

Two data limitations in Chapter 4 are household insurance demand and the length of insurance policy tenure. Little is known about either of these, particularly in developing countries. Further research is warranted regarding persistence of the campaign treatment effect and household insurance demand.

Each of the four chapters provides insight into how flood impacts can be mitigated and managed in the face of urbanization and climate change. Low-lying megacities, such as Bangkok, present new challenges for disaster risk mitigation. In these productive urban centers, neither massive evacuations nor limits on concentrations of people and assets are desirable. Rather than encourage relocation of people and assets, risk mitigation strategies in megacities must focus on how to reduce expected losses. Information could play a vital role in allowing individuals to take effective actions to reduce flood losses. Further research is needed to determine the types and sources of information that are most useful to households and how incomplete information compares to other barriers to risk mitigation.

APPENDIX A: PROPENSITY SCORE MATCHING –ESTIMATION OF BALANCING SCORE

Table A1. Descriptive Statistics for Propensity Score Matching, Full Sample

	Full sample (N=469)				Social Media Households(N=55)				Households without social media (N=414)				
Variable	Mean	Std Dev	Min	Max	Mean	Std Dev	Min	Max	Mean	Std Dev	Min	Max	
Outcome Variable													
Total Flood Losses (US$)	4,903	6,069	13	48,914	6,665	6,244	780	29,180	4,669	6,014	13	48,914	†
Household and Housing Characteristics													
Annual Household Expenditure (US$)	8,459	6,214	990	38,835	14,214	8,073	2,990	38,835	7,694	5,499	990	36,112	†
Cars owned (number)	0.9	1.0	0	5	1.5	1.1	0	5	0.8	0.9	0	5	†
Household members (number)	4.3	2.0	1	17	3.9	1.6	1	9	4.4	2.0	1	17	
Size of property (sq. m)	287	235	18	2400	334	194	120	880	281	239	18	2400	
One-story building	0.3	0.5	0	1	0.1	0.3	0	1	0.4	0.5	0	1	†
Low-income neighborhood	0.5	0.5	0	1	0.1	0.4	0	1	0.6	0.5	0	1	†
Survey Respondent Characteristics													
Age of Respondent	49.2	12.1	19	80	42.0	10.2	19	70	50.1	12.0	19	80	†
Married	0.8	0.4	0	1	0.7	0.4	0	1	0.8	0.4	0	1	
Education level													
High School or Vocational	0.33	0.47	0	1	0.20	0.40	0	1	0.35	0.48	0	1	†
College or higher	0.29	0.45	0	1	0.64	0.49	0	1	0.24	0.43	0	1	†

† denotes significant difference at the 5% level between households with and without social media use

Table A2. Logit Regression Estimates for Balancing Score

	Coefficient		z-statistic
Household and Housing Characteristics			
Annual Household Expenditure (Thai baht)	2.5E-06	***	3.370
	(0.00)		
Cars owned (number)	0.23	***	3.100
	(0.07)		
Household members (number)	-0.38	**	-2.500
	(0.15)		
Household members, squared	0.02		1.250
	(0.01)		
Size of property (sq. m)	0.00		-0.110
	(0.00)		
One-story building	-0.90		-1.190
	(0.75)		
Low-income neighborhood	-0.70		-1.230
	(0.57)		
Survey Respondent Characteristics			
Age of Respondent	-0.08	***	-5.550
	(0.01)		
Married	-0.50	***	-2.640
	(0.19)		
Education level			
High School or Vocational	-0.24		-0.740
	(0.33)		
College or higher	0.50		0.940
	(0.53)		
Constant	2.22	**	2.24
	(0.99)		
Observations	469		
Likelihood ratio test	-124		
P-value	0		
Psuedo R^2	0.27		

Clustered standard errors are in parenthesis.

Table A3. Balancing Score Estimates

	Statistic						
Matched Sample	Mean	Std Dev	Min	Max	Obs inside common support	Obs in each sample	% excluded
Treatment	-1.01	1.41	-4.99	1.43	48	55	-13%
Comparison	-3.23	1.61	-6.97	0.65	345	414	-17%

Note: The last column (% excluded) refers to observations outside the region of common support, which is defined as the maximum of the minimum values and the minimum of the maximum values.

APPENDIX B: CONCEPTUAL FRAMEWORK FOR INFORMATION FIELD EXPERIMENT

In order to conceptualize the possible channels through which information might influence insurance and home retrofit decisions, I develop a conceptual framework that slightly modifies the expected utility (EU) model. The central assumption of EU theory holds – that households will maximize expected utility. The model presented represents a comprehensive decision in which a household simultaneously considers insurance, self-protection, and self-insurance options.

Consider a utility-maximizing household with wealth W that is making a decision on the level of flood insurance coverage (I) to purchase as well as expenditures on self-protection (S_a) and self-insurance (S_b). The household faces two states of the world, floodwaters entering their property or not, with annual probabilities of p and $1-p$ of these two states. To some extent, the probability and loss associated with floods is endogenous since actions can be taken to self-protect or self-insure.

The probability that floodwaters enter the house is influenced by an exogenous component and S_a. The exogenous component of risk will vary across households based on a variety of factors including precipitation patterns, topography, and proximity to waterways. The monetary and time costs of S_a and S_b will be incurred regardless of whether or not flooding occurs. If the house floods, the household will incur a loss (L). The magnitude of L will be influenced by W, an exogenous component of loss (X_L), and S_b.

The cost of insurance per unit of coverage is c. If the house is flooded, the household will receive an insurance claim of I and may receive disaster relief and compensation (D). When deciding to purchase insurance or undertake home retrofits, a household may bear costs of searching for information (F). Thus, if the house does not flood, the household will still pay the annual insurance premium (cI) and F.

The household is assumed to be risk averse, with strictly increasing and concave utility functions. The optimal amount of insurance, self-protection, and self-insurance can be determined by maximizing expected utility $E[U(I, S_a, S_b)]$:

$$E[U(I,S_a,S_b)] = p\left(X_p,S_a\right)\cdot U[W - L(W,X_L,S_b) + I - cI - F - S_a - S_b + D] + \left(1 - p\left(X_p,S_a\right)\right)\cdot U[W - cI - F - S_a - S_b] \qquad \text{(B.1)}$$

where $0 \le I \le L$

Based on this model, a household will take action if the difference in EU between states of taking an action and no action is greater than the cost of the action. For insurance, the amount of I selected will be partly influenced by L (selected coverage increases with L) and the relative magnitudes of p and c (which will influence the decision to incur F). In order to determine the optimal level of insurance coverage (I^*), the household's expected utility must be maximized over I. The first order condition for insurance purchase is:

$$p\cdot U'[W - L + I - cI - F - S_a - S_b + D](1 - F - c) - (1 - p)U'[W - cI - F - S_a - S_b](F + c) \quad = 0 \qquad \text{(B.2)}$$

Therefore, a household will only purchase insurance if the marginal utility in the state with flooding is equal to the marginal utility in the state without flooding. The benefit of insurance must equal its cost. If the insurance premium (c) is set at an actuarially fair price, such that the premium is equal to the probability of flooding, then the expected insurance payout received by the household will be zero. In this case, where c=p, the first order condition for insurance purchase becomes:

$$U'[W - L + I - cI - F - S_a - S_b + D] - U'[W - cI - F - S_a - S_b] \quad = 0 \qquad \text{(B.3)}$$

This implies that when insurance is offered at an actuarially fair price, the optimal level of coverage (I^*) is equal to the total flood loss (L), less any disaster compensation that is anticipated by the household. A risk averse household will be expected to purchase full insurance if insurance is offered at actuarially fair rates and if no compensation is anticipated. However, this actuarially fair premium (equal to cL) is not realistic for a private insurer. In order to cover operating costs and/or make a profit, private insurers charge a loading factor and therefore the household would be expected to purchase less than full coverage (i.e. the selected policy will have a deductible).[59] In addition, the household may anticipate some level of disaster compensation. As insurance coverage decreases in response to premium prices, so does the extent of moral hazard that could be encouraged by full coverage (Arrow, 1962). Yet, if coverage decreases in response to anticipated compensation, then the extent of moral hazard does not decline.

This conceptual model does not assume that information is freely available, as in the classic EU model. Furthermore, it improves upon the model of insurance choice by Kunreuther et al. (2009) by (i) defining the hazard event as floodwaters entering a household's property rather than flood occurrence, and (ii) considering a comprehensive insurance, self-protection, and self-insurance decision. Defining the hazard event in this way allows households to influence the probability (through self-protection) and loss (through self-insurance) associated with the event. In addition, considering a household's overall flood risk protection decision allows trade-offs between different types of strategies to be accounted for.

This study relies on this conceptual model rooted in EU theory for understanding household flood mitigation behavior. However, it should be noted that some major underlying

[59]A loading factor is a specified percentage of the total premium that will allow the insurer to make a profit and cover operating costs such as marketing and claim adjustment.

assumptions may not hold when households face low probability risks. When evaluating low frequency hazards, households may rely on heuristics and demonstrate biases (Kahneman and Tversky, 1974; Slovic, 1987).

Expected Effects of Information Treatment

Households often lack perfect information when making decisions regarding insurance, self-protection, and self-insurance. Yet, information is necessary to be aware of actions that can be undertaken, accurately assess probability and magnitude of a loss, and know the costs and possible benefits of various actions. Particularly for low-probability events, such as large floods, households tend to lack adequate risk information. In the absence of information, individuals rely on subjective assessments of risk. If risk is underestimated, then even cost-effective actions may seem too costly.

The information treatment used in this study was expected to address the information failure regarding flood risk mitigation strategies and influence households in three ways. First, it raises awareness of flood insurance and several home retrofit options. Second, the information provides useful inputs into a household risk mitigation decision such as the probability and magnitude of flood loss faced by Bangkok households, insurance premiums and coverage levels, and how to purchase insurance. Last, the social information could lead households to update their risk perceptions, perceived utility gain of actions, and their investment decision based on the behavior of others.

Raising awareness alone might be an effective strategy in encouraging households to take action. The government catastrophe insurance agency in Thailand, the National Catastrophe Insurance Fund, has not conducted household-level communication campaigns, perhaps because there is a mandatory insurance purchase requirement for households with mortgages

(Threemingmid, 2013). Yet, the vast majority of Thai households remain uninsured against flooding due to the prevalence of households without mortgages and thus not being bound by the mandatory purchase requirement. Past communication efforts by the NCIF have been limited to press conferences and informational materials to be distributed by insurance and real estate companies.

Next, the practical component of the information treatment is expected to reduce the cost of searching for information (F) as well as increase the accuracy of perceived probability and magnitude of flood loss. In order to make informed decisions, households require information regarding flood risk, costs of possible actions, and how to undertake actions. With the practical information, households can update perceptions of exogenous flood risk (X_p, X_L) and become aware of the insurance premiums (c) and coverage levels available in Thailand. A household often lacks perfect information on risk characteristics (e.g. probability and magnitude of loss) and options for insurance coverage levels and premiums. An individual will not devote time and expenditures to collecting information if the costs of searching are perceived to be high relative to possible benefits of protective action (Kunreuther and Pauly, 2004).

Lastly, the social information component of the treatment could enable social learning regarding a household's optimal level of insurance coverage (I). This is particularly relevant for households that are uncertain about their production function, as shown by Beshears et al. (2015) and Cai et al. (2009). Households are highly influenced by actions of their neighbors, even when they are not aware of the motivations underlying those actions (Somanathan, 2010). Through social information, households may update their perceptions of flood risk and utility gain of insurance. In addition, households may re-evaluate their risk mitigation decisions.

Based on this conceptual framework, the study hypothesizes that household inaction in Bangkok is partially driven by a lack of awareness of insurance and home retrofit options and how to execute these actions. By receiving practical and social information, treatment households should have greater awareness of mitigation options. Furthermore, treatment households should be more likely to seek further information on flood insurance, how to protect against flood damage, and flood risk in their area.

APPENDIX C: METHODOLOGY OF INFORMATION FIELD EXPERIMENT

The randomized field experiment was designed to test the effect of practical and social information on the uptake of flood insurance and home retrofits. It was conducted in two districts of Bangkok most affected by the 2011 Thailand flood. The 364 participating households were first interviewed in-person in October and November, 2013. During this baseline in-person interview, respondents were asked about their flood risk perception, prior flood experience, previous home retrofits to reduce flood loss, and socioeconomic characteristics. Also during the baseline interview, treatment households received practical information. Two weeks later, social information treatment was delivered. A follow-up interview was conducted by telephone in May 2014 to measure outcomes.

Information Intervention

The information intervention included both practical and social information. The practical information was delivered via an informational pamphlet and a short video (2 minutes) about flood risk in Bangkok and how to purchase insurance and undertake home retrofits. The pamphlet also compared damage costs that a household might face with and without insurance. For example, if a flood similar to 2011 occurs, households may face average home and content damage of THB 85,000, based on survey work by Nabangchang et al. (2015). However, if a household is insured, then such damages would be covered, and the net cost to the household would be the annual premium (e.g. 500 baht if coverage of 100,000 baht is selected). The pamphlet also provided a contact list of insurance companies.

The social information treatment was delivered as a front gate hanger. It conveyed a description of average household losses from the 2011 Bangkok flood and prevalence of flood insurance uptake by households within a respondent's district. Within the two districts selected for the study, insurance uptake was 24% in Bang Bua Thong and 15% in Don Mueang (NCIF, 2013).[60] These insurance coverage rates were conveyed in the social information treatment as "one in four households" in Don Mueang and "one in six households" in Bang Bua Thong. The social information treatment also included a second copy of the information sheet on how to purchase insurance and a contact list of participating companies.

Information Spillover

This study accounted for possible information sharing between treatment and control households. If control households received the intervention information, this might spur them to purchase insurance and thus result in an underestimation of the treatment effect. The extent of spillover is controlled through the information treatment design. Only treatment households could receive the short video and in-person explanation of information provided in the practical information brochure. Therefore, possible spillover is limited to printed materials and second-hand descriptions of the in-person treatment. While many experimental studies do not address the extent of spillover, this study does so by asking during follow-up survey whether or not households received flood insurance information from their neighbors.

Baseline and follow-up survey implementation

Household survey instruments were designed based on literature reviews and revised based on feedback from local collaborators and the results of pre-test interviews. Trained enumerators and field supervisors administered the baseline survey and information treatment in-person in October and November 2013. A follow-up survey was administered via Skype and telephone in May 2014 to record outcome variables. A total of 448 valid baseline surveys were

[60]A district is analogous to a county in the United States and is divided into sub-districts. Insurance uptake at the district level in Bang Bua Thong and Don Mueang districts is moderate, 24% and 15% of the population, respectively. Yet, within the 11 sub-districts of these two districts, uptake varies from 2 to 72% (DOPA 2013; NCIF 2013). Within the four sub-districts selected for the study, insurance uptake ranges from 2 to 25%.

completed. In the follow-up survey, the attrition rate was 19%. Not answering the phone and refusal (rate of 6%) were the most prevalent reasons why households were not included in the follow-up survey.

The baseline survey consisted of questions on socioeconomic characteristics, knowledge regarding flood risk and behavior, exposure to flood informational messages, and household home retrofit actions to reduce flood loss. Both at baseline and follow-up, households were asked about awareness of flood insurance being available as well as awareness of Bangkok generally being a flood prone area. Risk perception in terms of flood probability and expected damage was also recorded both at baseline and follow-up. The survey elicited respondents' perceived probability of a flood of similar magnitude as the 2011 event, within the next five years, on a scale of 0 (will not occur) to 10 (will certainly occur). Perceived level of damage from a flood of similar magnitude as the 2011 event was recorded as high, somewhat high, somewhat low, or low.

The follow-up survey collected key outcome variables, such as insurance purchase and nine types of home retrofits. All key outcome variables are represented as binary indicators of whether or not a household took a particular action. In addition, households were asked about their progress in making an insurance purchase decision – whether they had not thought about it, decided not to buy, or decided to buy but had not done so before the follow-up interview. Information seeking, knowledge variables, and risk perception were also of interest. The follow-up survey inquired whether respondents had contacted an insurance company regarding flood insurance. Households also reported whether or not they had sought information about flood risk in their area, how to protect against flood damage, and flood insurance.

Sampling procedure

A multistage cluster sampling procedure was used to select participant households. This procedure included three stages – (1) sub-district, (2) community, and (3) household. While a sampling frame was available for sub-districts and communities, one was not available for individual households within a community. Therefore, sub-districts and communities were randomly sampled with probability proportional to size, while households within a community were sampled via a 'random walk'. In the first stage, two sub-districts were randomly selected among the sub-districts in Don Mueang and Bang Bua Thong districts that had less than 30% flood insurance coverage. The selected sub-districts in Bangkok were Don Mueang (2% insurance coverage) and Sanambin (2%), while the selected sub-districts in Nonthaburi were Bang Bua Thong (21%) and Bang Rak Phatthana (25%) (DOPA, 2013; NCIF, 2013). In the second stage, communities were stratified into income groups (low-income and upper-income) and sampled with probability proportional to size – resulting in seven low-income and seven upper-income communities.

In the third stage, households were selected within the 14 chosen communities. To select households, a random walk procedure was followed. Within a given neighborhood, half of enumerators interviewed households located on the left side of the street, while the other half of enumerators conducted interviews on the right side of the street. For each community, an interval of houses to visit was determined based on total number of houses in the community. The intervals helped to cover a large portion of the neighborhood and reduced the ability of enumerators to only interview households that were at home during the first visit. To participate in the baseline survey, respondents were required to (i) be homeowners, (ii) not currently have flood insurance, (iii) not planning to move within a year, and (iv) willing to provide a telephone number for a follow-up interview. Once an eligible household was identified, enumerators used block randomization sequences to assign the household to a treatment group. Block randomization sequences were created within each of the 14 study neighborhoods in order to obtain treatment and control groups of equal size at each site.